Abstract
What is the efficacy of credit boom dynamics in predicting financial crisis? Are credit booms dangerous for the sake of financial stability? Do lending booms increase the vulnerability of the banking and thus the financial sector? If so, does all credit booms, without distinction, matter? Or a discrimination in its main components may turn out to be necessary?

The aim is to answer the listed above questions and give a contribution in terms of macro-prudential policy in order to prevent banking crisis as they play a crucial role of "transmission" from the financial system to the real economy.

The work is structured in four main chapters.

In the first chapter, after highlighted the importance of the financial system and its development, a definition of financial (in)stability, is offered. In addition, an exhaustive investigation on the pathological event of this instability, namely a financial crisis, is carried out.

The second chapter presents a brief overview of the main tools designed so far in order to detect financial instability. A satisfactory taxonomy of EWIs is offered.

The third chapter is devoted to the construction of the model. Starting from the preeminent paper of Schularick and Taylor (2012) the total bank credit to the PNFS variable and other credit-related variables are used to explain the behavior of EU country-specific banking indexes constructed for the purpose. Predicting these indexes become essential to detect financial stress events. In a final empirical exercise the HAR-RV model of Corsi (2008) is applied on the country-specific banking indices.

The fourth chapter reports the results of the model on the main EU countries, whereas the fifth chapter suggests some policy implications deriving from the preceding analysis.

The last section concludes.

ACKNOWLEDGMENTS

The first though is devoted to my professor Fulvio Corsi which made this journey even more sensible and interesting.

Secondly, I would like to thank all Ca' Foscari University members, professors and staff because every day they contribute somehow to my education and that of all the Cafoscarini.

Last, but not least a great acknowledgment to my Family and all the people that believe in me.

To All my sincerest gratitude.

TABLE OF CONTENTS

INTRODUCTION

A bubble involves a non-sustainable pattern of price changes or cash flows; this implies that, sooner or later, bubbles are going to implode [1]. A bubble is dangerous since its implosion may lead to great losses in the *microsystem* in which it booms, whereas it may reveal a catastrophe to the extent in which its burst flows beyond the borders of the microsystem it arises from and floods the entire financial system jeopardizing the financial stability.

This paper aim to give a contribution to the macro-prudential policy research from a practical standpoint, which could be of more immediate use for macro-prudential oversight.
In this sense the central scope consists in the creation of an early warning model capable to detect signals of alarm when one or several measures of financial stress and systemic risk are likely to reach critical value in the future.
Predicting the different imbalances scenario such as imbalances in asset price or credit development that can culminate in banking crisis endangering the financial stability is part of the aim as well.

Although the interest is towards all kind of crisis, the focus is on banking crisis and the role of credit in the eco-financial system. The formers are important since they play a crucial role of "transmission" from the financial economy to the real one. The latter is fundamental to the extent in which it represents a strong catalyst factor for the former.
In this direction, starting from the paper of Schularick and Taylor "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008", I study in a deeper way several credit variables to find the best predictor for financial stress events.

Practically speaking, three main steps are taken in order to get the model.
First, starting with a set of potential key early warning indicators/variables for systemic financial instability and widespread imbalances for the Eurozone. I examine the most relevant EU countries that have been affected by the financial stress events.
Second, starting from a baseline model (1) various specifications are analyzed for each credit-related predictor. The target is to end up with *the most efficient early warning model* for each EU country object of analysis.
Finally, predicting the country-specific banking indices by applying the HAR-RV model of Corsi (2008).

Regarding the work structure, it is organized as follows.
The first chapter summarize the main literature results about financial crisis with a focus on banking crisis since they represent the pillar of the analysis. To allow a full understanding of the severity of events of financial stress and the consequences that generate on the entire financial system, the concept of financial stability is reported as well.

[1] See Kindleberger (1978).

The second chapter presents a brief overview of the main tools designed so far to detect the financial instability. At this aim a taxonomy of EWIs is offered.
The third chapter illustrates the model. The main innovation consists in the construction of EU country-specific banking indexes. Predicting the behavior of these synthetic indexes become essential for detecting financial stress events. To this scope, credit variable and other credit-related variables are used.
Subsequently, the model is tested on the main EU countries depending on the data availability. These results are shown in the fourth chapter along with HAR-RV model results.
Finally, some policy implications are extrapolated by the previous findings.
The last section concludes.

Chapter 1
LITERATURE REVIEW

This chapter is dedicated to the main findings offered by the literature. Its aim is to provide the reader with all the concepts and definitions needed to allow the best possible understanding of the theoretical and empirical findings about the topic. This may turn out to be useful later when dealing with the Early Warning Model (EWM) developed in the third chapter.
I exploit this space to report the concept of *financial stability*.
Despite formulating a unique definition accepted *ab omnibus* is of difficult realization, I try to give different definitions, stemming from several authors and institutions, and highlight its growing importance over time.
As a second step, an exhaustive overview of the main type of financial crisis is offered.
The focus here is, among all kind of events of stress, on *banking crisis* and their implications against the financial stability and the real economy.

Finally, the attention is shifted on the role of credit in the macroeconomic system. Starting from Irving Fisher's work on *debt deflation*, passing through Schumpeter, Minsky up to Keen, the main findings and developments about the credit dynamics are offered.
The changes in the interplay between money and credit over the last century are deepen, as well.

1.1 FINANCIAL DEVELOPMENT VS FINANCIAL STABILITY

The onset of the investigation about the role played by the finance in the economic system, specifically in the economic growth, is not recent. The debate has been active for decades offering different viewpoints about the effect of finance on economic growth.
Probably, the first studies which tackle this issue date back to Bagehot (1873) and Schumpeter (1911). Their conservative opinion is that there exists a relationship between finance and growth and define this interaction as positive and non-trivial.
Other views space from Lucas (1988) which judges the implications of finance on economic growth as "inconsequential and overstressed", to Miller (1998) according which the interplay is "obvious".
Although the direction of the causal relationship between the development of a country's financial sector and its growth rate has been frequently questioned (Robinson, 1952), the first author that empirically investigate this interaction is Goldsmith (1969). He finds a positive correlation between the size of the financial sector (as indicator of financial development) and the economic growth in the long term. Goldsmith and Bencivenga & Smith (1991) later, emphasize the importance of the intermediation process carried out by the financial sector, stating that the intermediation make savings better channeled into productive investment[2].

[2] IMF, WP/15/173

Other studies address the causality "finance - economic growth" in a much clearer manner. As suggested by a paper of the IMF on the financial development[3] many authors attempt to demonstrate this positive correlation between these two variable. The pioneers in this direction are probably King & Levine (1993) founding some financial development indicators strongly correlated with growth.
Similarly, Rajan & Zingales (1998) show that the development of financial intermediaries and markets has a non-proportionate large positive effect on more external financing-dependent sectors.
In addition, Levine & Zervos (1998) provided further evidence of this finance-growth causality finding that the development of financial institutions (banks and financial markets), promotes growth, capital accumulation, and increased productivity, even after controlling for economic and political factors[4].

The contribution of financial development is not limited to the economic growth but also include the reduction of inequality.
Besides the main findings explained above there is another body of literature studying the relationship "financial development - inequality". In this sense, Beck et al (2007) find out that financial development affects not only economic growth but also income inequality. More precisely, the study suggests that the positive effects on the income of the poorest quintile, due to the long-term impact of financial development, can be split into two components, economic growth and a reduction in income inequality.
Similarly, Jalilan & Kirkpatrick (2002, 2005) find a similar poverty reducing effect of financial development in low-income countries.
Finally, Jeanneney & Kpodar (2011) suggest that a more developed financial system contributes in reducing inequality by mitigating poverty; this is possible thanks the McKinnon (1973) conduit effect[5] and the aggregate growth channel.

1.1.1 FINANCIAL DEVELOPMENT: BENEFITS VS COSTS

Thanks to the literature framework set out above and other studies, the consensus about the importance of the role played by the financial system in the whole economic system is widely recognized.
On the other hand, the financial development seems to bring with it some side effects. In fact, Beck et al (2007), Jalilan & Kirkpatrick (2002, 2005) and Jeanneney & Kpodar (2011) also warn that financial development generates instability offsetting some benefits on poverty reduction.
This results give rise to another well-accepted pattern in the "finance - growth literature", that is, the statement according which the relationship between financial development and growth is not linear. Under this view, various studies emphasize several forms of non-linearity.

[3] IMF, WP/15/173
[4] IMF, WP/15/173
[5] McKinnon (1973) and Shaw (1973) were the first to explicate the notion of financial repression. They argues that financial development, in the form of a reduced financial repression, increases domestic savings, lowering borrowing costs and stimulating investments. McKinnon *conduit effect* refers to raising interest rate which increases the volume of financial savings through financial intermediaries which increases investible funds.

For instance, Rioja & Valev (2004), through an interesting study on the development of financial systems, suggest that the marginal effect of additional financial development on growth is not constant, finding cases of even uncertain impact. In particular, they detect three different bands which correspond three different levels of financial development – the low level, the intermediate level and the developed one. The marginal effects of augmenting financial development depend on the current level of the financial system' development with uncertain effects at the low band, large and positive effects at the intermediate band and smaller positive effect in economies with developed financial systems.
Similarly, Aghion et al (2005) define a specific threshold of financial development and argue that economies above this level front a positive but diminishing return from additional financial development and converge to the same level of long-term growth whereas economies below this bound reach a lower long-term growth level.
In addition to the above, other authors study this tradeoff between benefits and costs.
Again, Arcand et al (2012), focusing on the size of the financial sector, argues that beyond a certain point the further deepening turns out to be harmful for the growth.
Rajan (2005) in a prophetic work studies the velocity of a financial sector expansion finding an interesting result. He suggests that if the expansion is rapid it should be alarming since the financial sector becomes more vulnerable to left tail events. This is true because now the financial sector is capable to bear more risk but also increases its current level of risk taken thus ending up with a much higher systemic risk.
Finally, Beck et al (2012), analyzing ten years of developed economies (from 1996 to 2006), explains that the financial progress of that period was accompanied by higher level of economic growth but also higher level of economic volatility and idiosyncratic bank fragility. In hindsight, that growth turned out to be a bad illusion because unhealthy.

The literature exposed so far suggests that when valuing the role of finance played in the entire system, both faces of the same coin have to be taken into account.
Before deepening benefits and costs floating from the development of a financial system, it seems appropriate spending a few words about its composition. At this aim, a definition of Garry J. Schinas[6] is adopted.
A financial system includes three separable but closely related components:

- Financial intermediaries;
- Financial markets;
- Financial infrastructure.

Financial intermediaries comprise all financial institutions that pool funds and risks and allocate them in their competing uses.
Financial markets directly match savers and investors, allow investors the rebalancing of portfolios' risk-return as economic and financial condition change.
Financial infrastructure includes private and public institutions, monetary, accounting, legal, regulatory and surveillance infrastructures[7].
Therefore, as defined by Garry J. Schinas in his work "Safeguarding Financial Stability: Theory and Practice":

[6] Safeguarding Financial Stability: Theory and Practice.
[7] Safeguarding Financial Stability: Theory and Practice, p.80.

"The financial system consists of the monetary system with its official understanding, agreements, conventions and institutions as well as the processes, institutions and conventions of private financial activities."

Coming back to the ***benefit hand side***, as illustrated above, the development of financial system has important implications on economic growth and beyond. In fact, financial institutions allow to:

- further economic growth and capital accumulation;
- increase productivity;
- reduce inequality in terms of income and mitigate poverty through McKinnon (1973) conduit effect and the aggregate growth channel.

Besides this relevant contribution, financial systems perform other functions which are intrinsic to its nature. It is worth here to remind some of these apparently basic but fundamental features.

A financial system, among others, permits users of financial assets[8] (from now on financial agents) to carry out the following actions.

1) *Clear and set payments*

- By providing *market liquidity* → trading mechanisms between sellers and buyers;
- By setting the execution of contracts → make sure that agreements are honored.

2) Pool resources and subdivide shares

- On the business sector side, firms may raise funds in three ways:
  - by borrowing from banks;
  - by issuing bonds;
  - by sharing ownership in the firm.
- On the government sector side, governments may:
  - print money through central banks;
  - raise funds by increasing tax revenues;
  - raise funds by issuing treasury bonds.

3) Transfer resources across time and space (shifting the purchasing power over time)

- In high-earning periods agents may invest their surplus in financial assets;
- In low-earning periods (retirement) agent may sell financial assets maintaining consumption stable.

4) Manage risk allocating it in an efficient manner

- Financial systems permit to exchange and control risks:
  - *Insurance* enables the pooling and sharing of risks;
  - *Hedging* enables the transfer of risk to more risk-lover agents (speculators);
  - *Diversification* allow the compensation between profitable and non-profitable investments by exploiting the correlation effect.

[8] The users of the financial environment may be grouped, in a broad sense, in two sectors:

1) Private sector (households and business sector);
2) Government sector.

5) *Provide some guidance on how to handle the separation of ownership from management*

- Executive should maximize the value of shares, that is the firm value;
- Agency problems – managers pursuing interests not in line with shareholders' interests – may be tackled by means of stock option rather than cash, or a mix or by recruiting external auditors.

6) *Price efficiency*

- Prices act as signals impounding all relevant information possessed by traders. Thus, the competitive price system of financial market works as a communication network by transmitting information from one agent to another one.

7) *Market efficiency*

- Weak efficiency: the current price reflects information embodied in past price movements;
- Semi-strong efficiency: the current price reflects information embodied in past price movements and public information;
- Strong efficiency: the current price reflects information embodied in past price movements and both public and private information.

On the ***cost hand side***, as shown previously, the development of financial system has unfortunately non-negligible side effects. These negative effects can be encase in a single concept, that is, *financial instability*.
When there is financial instability, financial systems do not run correctly anymore. Markets are no longer efficient and the price of financial products does not reflect the actual value.
During the typical build-up phase of financial fragility, the portion of risk that financial markets intrinsically create – which is part of financial systems and that under normal conditions do not create problems – amplify its effects. Information asymmetry rises steadily and the small shocks that Allen and Wood (2005) define micro-instability – such as the default of a single bank that has not systemic importance or the impromptu fluctuations of stock market that take form spontaneously in the market and are instrumental to the smooth functioning of an economic system – may assume a systemic range. In short, small shocks may have large and devastating effects.

It is clear from what illustrated so far that financial development is essential for the functioning of the whole economic system due to the role it performs. This is especially true in a globalized economy. Markets are increasingly globalized and a financial system is essential to ensure financial agents the full satisfaction of their market needs. Unfortunately, while a flourishing financial sector promotes growth opportunities, excessive and rapid expansions may create financial instability leading to crises. Therefore, crisis represent the main potential cost of financial development. In other terms, ***crisis are the results of an overdeveloped and unhealthy financial system***.
By keeping all the benefits and contributions of financial systems, the urgent task consists in preventing these crisis events by monitoring and controlling for financial instability.
In this sense, central banks should act with the same energy and priority as they do for price stability. For this last purpose, policy-makers operate by setting a mid-term inflation target and steer monetary policy by the means of interest rate adjustments according the

fluctuation of inflation around a specific range. Here, the target is the inflation (price stability), the yardstick is an inflation range and the instrument is the interest rate[9].
Since the inflation is not directly controllable by the central bank, policy-makers keep it under control by affecting the quantity of money present in the system.
Similarly, in order to maintain a financial system stable (target), policy-makers need to know when take actions and in which way carry out their interventions. At this aim, a financial tool (instrument) is essential for measuring the instability in the system and prevent financial crisis.

1.1.2 DEFINING FINANCIAL (IN)STABILITY

Before dealing with the creation of an instrument of financial policy capable to detect signals of stress in the system, it seems appropriate dwelling on what the tool is going to measure. It's hard measuring something whose entity is not clearly known; thus, this step is fundamental as well as logical.
Whereas it is common ground that the concept of financial stability cannot be reduced to a single definition, it remains however a challenge formulating a theoretical framework able to consistently embrace the various facets underlying this concept.
Therefore, I would like to offer the concept through different viewpoints or definitions elaborated so far by authors and/or institutions.

For instance, according to the definition used by the ***ECB***:
"… financial stability is a condition in which the financial system – comprising financial intermediaries, markets and market infrastructures – is capable of withstanding shocks and the unravelling of financial imbalances."[10]

In a similar and broad way ***Garry J. Schinasi*** affirm that:
"A financial system is in a range of stability whenever it is capable of facilitating (rather than impeding) the performance of an economy, and of dissipating financial imbalances that arise endogenously or as a result of significant adverse and unanticipated events."[11]
Therefore, a financial system is defined stable if three fundamental features are satisfied:

1. Efficiency in allocating economic resources by savers to investors and effectiveness of economic processes, such as wealth accumulation and economic growth;
2. Financial risks should be assessed, priced, allocated and managed;

[9] A central bank may use interest rates either directly or indirectly.
In the first case, the financial institution acts by affecting the interest rate itself, which varies according the central bank. For instance, the Federal Reserve employs the rate on the Fed Funds as the key interest rate; the ECB uses the rate on the repo and the Bank of Japan uses the rate of intervention on deposits.
In the second case, the central bank employs the interest rate in a different manner. For example through repo agreements, the discount window or the reserve coefficient. In addition to the conventional instruments listed so far, another unconventional mean widely used in the aftermath of the 2007-2008 financial crisis by FED and ECB (already used in Japan) is the Quantitative Easing.
[10] See, for instance, European Central Bank (2005).
[11] See Schinasi (2004).

3. Ability to absorb external shocks and/or imbalances, thus keep performing its key functions also under stressed periods.

Also, **Tommaso Padoa-Schioppa** (2003)[12], from the ECB's executive, describes financial stability by recalling the concept of financial system and highlight the danger of cumulative processes. Financial stability is a condition:
"... where the financial system is able to withstand shocks without giving way to cumulative processes, which impair the allocation of savings to investment opportunities and the processing of payments in the economy."

Similarly, the ***Deutsche Bundesbank***'s definition seems to embrace the classical and previously described functions of a financial system, specifying that these key functions are fulfilled during extraordinary periods as well.
It states that the financial stability:
"... broadly describes a steady state in which the financial system efficiently performs its key economic functions, such as allocating resources and spreading risk as well as settling payments, and is able to do so even in the event of shocks, stress situations, and periods of profound structural change."[13]

Another interesting viewpoint is that of ***Michael Foot*** (2003)[14] from *U.K Financial Services Authority*. In an interesting speech he defines financial stability as a *contemporary subsistence* of four conditions:

a. Monetary stability (lowering the mean and the variance of inflation rate);
b. Employment levels close to the economy's natural rate;
c. Confidence in the operation of the generality of key financial institutions and markets in the economy;
d. There are no relative price movements of either real or financial assets within the economy that will undermine "(a)" or "(b)" conditions.

Interesting as well operational is the definition given by ***Ben Bernanke*** and ***Mark Gertler***[15] in a prominent paper on the financial fragility and economic performance. They argue that:
"... financial stability is best understood as depending on the net worth positions of potential borrowers."
Their definition comes from the problem of agency costs associated with the investment process. In fact, they define a financially fragile situation the one where potential borrowers (with greatest access to productive investment projects) have low wealth compared with the size of their investments. This situation (which might occur for example after a debt-deflation period) leads to high agency costs and bad performance in the overall economy.

Otherwise, financial stability is defined by explaining its opposite.

[12] See Padoa-Schioppa (2003).
[13] Deutsche Bundesbank (2003).
[14] See Foot (2003).
[15] See Bernanke and Gertler (1990).

In this direction, ***Roger Ferguson*** (2003)[16] from Board of Governors of the U.S. Federal Reserve System states that:
"It seems useful...to define financial stability...by defining its opposite: financial instability.
In my view, the most useful concept of financial instability for central banks and other authorities involves some notion of market failure or externalities that can potentially impinge on real economic activity."
In addition, the author specifies that financial instability may be described as a situation characterized by three criteria:

1) some important set of financial asset prices seem to diverge sharply from fundamentals; and/or
2) market functioning and credit availability, domestically and perhaps internationally, have been significantly distorted; with the result that
3) aggregate spending deviates (or is likely to deviate) significantly, either above or below, from the economy's ability to produce.

Another interesting definition is given by **Frederick Mishkin**[17] of Columbia University. He offers a contribution in this concept within the framework of information asymmetry and affirm that financial instability:
"occurs when shocks to the financial system interfere with information flow so that the financial system can no longer do its job of channeling funds to those with productive investment opportunities."

Andrew Crockett[18] from the "Bank for International Settlements and Financial Stability Forum" define financial stability as an absence of instability, which describes as follows:
"… a situation in which economic performance is potentially impaired by fluctuations in the price of financial assets or by an inability of financial institutions to meet their contractual obligations."
This definition is interesting because, beyond the mere concept, the author addresses several and important issues. In fact, other than underling that instability should imply real economic costs and that it is the potential for damage rather than actual damage which matters, he specifies that the definition allows him to address the question of whether banks are special and states that:
"all institutions that have large exposures – all institutions that are largely interconnected whether or not they are themselves directly involved in the payments system – have the capacity, if they fail, to cause much widespread damage in the system."

I would like to conclude this section by presenting the viewpoint of the economist **Hyman P. Minsky**[19]. This author and its thinking will be encountered again later since it represents one of the main catalysts factors of the idea underling the EWM developed in the third chapter.
According his thinking, financial instability can be defined as:
"… a process in which rapid and accelerating changes in the prices of assets (both financial and capital) take place relative to the prices of current output."

[16] See Ferguson (2003).
[17] See Mishkin (1999).
[18] See Crockett (1997).
[19] See Minsky (1992).

1.2 FINANCIAL CRISES: DEFINITION AND IDENTIFICATION

In the following section some crisis definitions are offered, as well as a brief discussion of the main types of crisis. As previously stated, crises represent the main potential cost of financial development. A financial system overdeveloped and unhealthy is prone to generate instability which in turn, if not countered in time and with the appropriate instruments, may culminate in a crisis. Therefore, a crisis may be seen as the pathological event of financial instability.
For the purpose of this work, the attention is focused on banking crises due to their importance for the economy in terms of scale and span of the negative effects that ensue (causal effects). In addition, the interplay between banking crises and credit dynamics is introduced. These illustrations will be useful later when dealing with the EWM.

When talking about crises a myriad of articles and books could be cited.
I would like to start this little digression with the support of an outstanding work by Carmen M. Reinhart and Kenneth S. Rogoff.[20] Their contribution shall be used to give a skeleton to the paragraph. However, crisis definitions are enriched with contributions from other authors. This because, on one hand, the definitions offered by Reinhart and Rogoff have the advantage to be clear and to provide the reader with objective parameters for the identification and dating of the crisis. On the other hand, the two authors do not provide a descriptive definition of all types of crises, particularly regarding inflation and currency crises.
In their "This time is different", the authors identify and define crises according two main criteria, by quantitative thresholds and by events. Consequently, the first group of crises is classified by using strictly quantitative definitions whereas the second set is defined on the basis of qualitative and judgmental analysis.

1.2.1 Crises defined by quantitative threshold

Under this criterion shall be collocated currency crises (which include inflationary crises as well as currency devaluations), and sudden stop crises.

Currency and Sudden Stop Crises
Claessens and Kose (2013) associate a currency crisis to a speculative attack on the currency capable to entail one of the following consequences:
- a devaluation or sharp depreciation of the currency;
- forcing the authorities to defend the currency by expending large amount of international reserves;
- a sharp increase of interest rates;
- imposing capital controls.

Theoretical and empirical framework on Currency and Sudden Stop Crisis

[20] Reinhart e Rogoff (2010).

The literature about *Currency Crises* has highly evolved over the last decades. Theories on currency crises that initially focused on their fundamental causes, moved towards multiple equilibria and the role of financial variables, particularly changes in balance sheets, in triggering currency crises.
In explaining this kind of crises, three generations of models are mainly used.
The pioneers of the first generation of models are Krugman (1979) and Flood and Garber (1984). These "KFG" models identify in the investors' rationality the cause of a sudden speculative attack. In fact, the rational investor, which is able to correctly predict the situation in which the government is in excessive deficit financed with central bank credit, continues to hold the currency as long as he/she expects the exchange rate regime remain intact, getting rid of it when the peg is about to end. Consequently, the central bank rapidly loose its liquid assets and is no longer able to support the exchange rate.[21]
The second generation of models shows that doubts about whether a government is willing to maintain its exchange rate peg could lead to multiple equilibria and currency crises (Obstfeld and Rogoff, 1986). Stated roughly, investors attack the currency simply because they expect other investors doing the same.
The third generation of models, widely motivated by the Asian crises of the late 1990s, focuses on rapid deteriorations of balance sheets associated with fluctuations in asset prices (including exchange rates) in explaining currency crises[22] as well as on the roles played by banks and the self-fulfilling nature of crises.[23]

Empirically it has not possible to distinguish among these models the best one able to characterize more accurately currency crises.
In fact, while the KFG model worked well in cases where macroeconomic fundamentals grow explosively, it was not successful when fundamentals are merely highly volatile and money-demand unstable (Claessens and Kose, 2013).
Later studies moved towards dependent variable models, e.g., Logit/Probit models, to estimate crisis probabilities based on a wide range of lagged variables (Eichengreen, Rose and Wyploz (1996), Frankel and Rose (1996), Kumar et al (2003)). The result of this literature is that some indicators are found to be associated with crises but the timing of crises is hard to predict.

Sudden Stop Crises are crises triggered by the cessation of foreign capital flows in favor of a country. Therefore, a sudden stop refers to an event in which a country's domestic economy is no longer able to get access to international capital markets, since foreign providers of capital suddenly stop doing it. The first authors that introduce the term "sudden stops" are Dornbusch, Goldfajn and Valdes[24], while the first analytical framework is developed in Calvo (1998).
These models of disruption in the supply of external financing focus, as the third generation of model, on balance sheet mismatches (currency and maturity) in financial and corporate sectors (Calvo et al., 2006), but assign a greater weight to the role of

[21] For a detailed demonstration see Krugman (1979) and Flood and Garber (1984).
[22] See, for example, Chang and Velasco (2000).
[23] See McKinnon and Pill (1996), Krugman (1998), and Corsetti, Pesenti, and Roubini (1998) for the detailed explanation, according which vulnerabilities stemming from over-borrowing by banks, arising from government subsidies (governments would bail out failing banks), may trigger currency crises.
[24] See Dornbusch, Goldfajn and Valdes (1995).

international factors (such as changes in international interest rates or spreads on risky assets) in causing “sudden stops” in capital flows.

Practical Issues on Currency and Sudden Stop Crisis: Identification, Dating and Results
In order to define currency crises, Reinhart and Rogoff (2010), as previously said, adopt a less descriptive and more quantitative approach. In addition, while the Claessens and Kose (2013) definition englobes all the facets of a currency crisis, Reinhart e Rogoff subdivide this kind of crisis in three subcategories: inflationary crises, the mere currency crises and currency debasements.
With regard to the first type, *inflationary crises*, pointing out the difference between inflation and hyperinflation (inflation rates equal to 40 % per month) and explaining that hyperinflation is a much recent phenomenon as opposed to the inflation levels prior to the WWI, Reinhart and Rogoff adopt a threshold of inflationary crisis equal to a 20 % per year.
As regards the *currency crises*, the authors, starting from the approach of Frankel and Rose[25], extend the definition by considering other variables such as reserve losses and interest rate increases and establish an annual depreciation of 15 %. Even in this case, as for the inflation, the figures take into consideration the quantitative differences between the pre- and post-WW2 (in which the limit applicable to define a severe crisis would be too high for the preceding period). As for episodes of inflation, it is not considered solely the starting date of the collapse (as in Frankel and Rose, and Kaminsky and Reinhart) but the entire period in which the annual rates of depreciation exceed the threshold.
Lastly, *currency debasement*, mainly refer to currency conversions and their dimensions. The “debasement” may be of two types. The Type I consists in a reduction in the metallic content of coins in circulation of 5% or more whereas the Type II coincides with a currency reform that replaces a much-depreciated earlier currency in circulation with a new one. In the sample used for their work the authors find conversions in all hyperinflation episodes as well as after periods of high but not necessarily hyperinflation.[26]
Another measurement aspect about currency that is worth to report is the situation in which pressures/attacks on the currency do not cause significant adjustments. In such a case, the fluctuations in the rate are prevented or alleviated. In particular, exchange rate pressures are cushioned by movements in international reserves or interest rates’ adjustments. To study these episodes, starting from Eichengreen, Rose and Wyplosz (1996), several methods have been implemented. For instance, a composite index to gather speculative attacks is realized based changes in actual exchange rates and in international reserves and interest rates. To avoiding one component dominating the index, the weights are chosen to equalize the components’ variance.[27]

Also, sudden stop along with balance-of-payments crisis may be identified and classified in a quantitative and objective manner. Calvo, Izquierdo and Mejía (2008), starting from

[25] The authors define a currency crisis as a depreciation of at least 25% cumulative over a 12-month period combined with a depreciation of at least 10% greater than in the preceding 12-months. For more details see Frankel and Rose (1996).
[26] The most striking episodes are represented by China, with a conversion ratio of three million to one, and Zimbabwe, with a conversion ratio of ten billion to one.
[27] For reviews see Frankel and Saravelos (2012) and Glick and Hutchison (2011).

the definition of Calvo, Izquierdo and Talvi[28], offer a twofold identification criterion. First, in the period considered there is to be one or more year-on-year collapse in capital flows being at least two standard deviations below its sample mean. Second, the sudden stop onset (ending) depends upon the capital flow variation: it starts (ends) when the annual change falls (exceeds) one standard deviation below (above) its mean[29].

Capital flow data may be used also to identify balance-of-payment crisis. Even though the approaches implemented by authors are pretty different, both in conceptual terms (for example regarding the way reserve losses are treated) and statistical terms (regarding the threshold choice: a unique account deficit threshold for all countries or a country-specific threshold), the sample of events detected is nearly the same.
An interesting contribution is offered by Forbes and Warnock (2012) which analyze, for a large set of countries, the gross capital flows rather than the common current account variable. Using quarterly data and differentiating by foreign and domestic actors they identify four episodes. "Surge" and "Stop" associated to periods of large gross foreign capital inflows and outflows respectively. "Flight" and "Retrenchment" related to periods of large gross capital outflows and inflows respectively but carried out by domestic residents.

1.2.2 Crises defined by events

The ratio for adopting an event approach is explicable by the shortage of data series for extensive time periods which prevents a dating in quantitative terms analogous to the one adopted for inflationary and currency crises. According this criterion, Reinhart and Rogoff define foreign and domestic debt crises as well as banking crises.

Foreign and Domestic Debt Crises
The sovereign debts topic is extremely delicate. Without entering into much detail, this section offers a theoretical framework developed, over the last decades, around this non-recent problem. In addition, some definitions and practical aspects are presented.

Before delving the main issues concerning with foreign and domestic debt crises, it is worth to clarify that the main discriminating factor between the two kinds of debt is represented by the jurisdiction which regulates them.[30]
Therefore, a foreign debt crisis implies a country's default on its *foreign* debt obligations. Analogously, a domestic debt crisis implies a country's default on its *domestic* debt obligations.

[28] Calvo, Izquierdo and Talvi (2004) define systemic sudden stop events as episodes in which output crashes coincide with large capital flow reversal.
[29] See Mauro and Becker (2006).
[30] The foreign debt includes a country's overall debt exposure to foreign creditors. Analogously, the domestic debt of a country is composed of all its outstanding positions issued under national regulations and therefore subject to national jurisdiction, regardless of the creditor nationality or the currency denomination of the debt. The authors include also the domestic public debt denominated in foreign currency. It comes to debt issued under national regulations but expressed in (or pegged to) a foreign currency.

Theoretical and empirical framework on Foreign and Domestic Debt Crisis
The issue that concerns the fulfillment of debt obligations dates back to the period labeled by Reinhart and Rogoff of "the first default" (XVI-XVIII century). From that time until the twentieth century, the *gun-boat* diplomacy represents a common praxis for lenders in order to seize collateral from another country when it refuses to honor its debt obligations. In the modern era, the idea of resorting to these *hard manners* to get the loans paid back does attract little lender governments, given the risks and the huge costs (higher than benefits) that would follow, as well as the borrowers' debt diversification[31].
Thus, why debtors should repay their debt? Or, stated differently, which other means do creditors have at their disposal to induce debtors to honor the international (sovereign) debt?
This issue has been addressed for the first time by Eaton and Gersovitz (1981). They find an explanation in the theory of reputation which emphasizes the importance of financial markets as a mean to smooth idiosyncratic income shocks, thus, especially during recessions or to carry out significant infrastructure projects. At this aim, the advantages of lender governments resulting from a constant access to capital markets may force themselves to honor maturity repayments, even in the absence of a legal body that oblige the fulfillment. This approach has the benefit that institutions are not involved, in the sense that the theory does not depend upon juridical and political structures of individual states (in principle it could explain the indebtedness in the Middle Ages as nowadays) but it seems too simplistic and hardly realistic.

Differently, the Bulow and Rogoff[32] institutional approach focuses on the legal aspects, rather than on reputation, associated to a sovereign default on debt. They argue that, instead of relying solely on reputation, the repayment of foreign debt, especially those of emerging countries, could be claimed by creditors in the judicial courts of creditors' countries. By doing so, a country, considering the option of defaulting on debt, shall account for other costs rather than the exclusion from future loans, i.e. potential disruptions to their commerce as a result of the need to divert trafficking and financial movements to avoid creditors. Thus, if a country default on long term loans, creditors can exert strong pressures against anyone attempting to finance commercial receivables in favor of that country. This would imply important restrictions, since national and international commerce is strongly dependent upon short term banking credits to finance goods during shipment but prior receipt. Practically, however, creditors and debtors negotiate a partial default, meaning that forced expropriation actions are rarely carried out.

In addition to the costs listed above, drawbacks resulting from a lowering of FDI should be counted as well. A country's default would have negative costs on its FDI, in terms of loss of both capital inflows and knowledge, benefits typically offered by an FDI[33].

[31] Debts are typically diversified across Europe, Japan and US, making it even weaker for a single country the incentive to use the force.
[32] See Bulow and Rogoff (1989a,b).
[33] As Reinhart and Rogoff (2010) report, a foreign company willing to make a FDI in an insolvent country shall consider the risk that its plant and equipment may be seized.

Notwithstanding the loss of reputation, the potential exclusion from capital markets and disruptions in the trade seem to support loan flows albeit with different weights depending upon the specific country's situation, these models are not able to fully explain the reasons that induce creditors to lend as much as they do. Besides, they generate multiple equilibria and fragility. This fragility seems to be correlated with countries being in a specific circumstance: heavily indebted and dealing with the renewal of short term loans.

As introduced previously, the domestic debt is the debt that a country has towards itself. Even though domestic debt crises occurred frequently throughout history, this kind of crises received less attention than foreign debt crises, probably due to a greater discretion and a less noise in the international scene, since in this kind of crises important foreign creditors are not involved[34].

The domestic public debt theory is not less complicated than the foreign one.

Models on domestic debt crises treat the argument with less importance than the one dedicated to foreign debt crises. This because governments' debt obligations are typically considered risk-free assets by assumption. In addition, the majority of models tend to assume the Ricardian equivalence making government debts less relevant.

Whatever, debt crises are not to be underestimated and considering that, as reviewed by Reinhart and Rogoff (2010), domestic debt crises occur as much as foreign debt crises with few countries avoiding the default but with poor economic consequences[35], the argument should be tackled with a different approach.

In domestic debt crises models, as for foreign one, the problem of multiple equilibria is underlined. One of the main challenges concerning this topic is represented by the countries' ability to bear different types of domestic and foreign debt.

As stated above, the fragility in the models increases when countries are highly indebted with short term debt. Nevertheless, governments seem to raise international debt either in the short term or in the long run but with interest rates linked to short term loans. This praxis seems to be bound to structural conditions of the countries considered, especially developing countries. For instance, Diamond and Rajan (2001) hold that banks in developing countries seem to be forced to borrow short term to finance illiquid investments, considering the low-quality of institutions they operate in.

Jeanne (2009), instead, explain the short term usage as an incentive to follow more disciplined policies. In fact, as short term indebtedness raise financial crises risks, due to difficulties renewing loans, debtor countries are constrained to adopt more disciplined policies. By doing so, a mutual benefit is created improving the economic performance of both debtors and creditors.

[34] Reinhart and Rogoff evidence that by reporting the case of Argentina. Since 1980 this country defaulted on the domestic debt three times: among these only 1982 and 2001 default, which culminated with a foreign debt default, appealed international attention, whereas the 1989 default, which did not involve non-residents creditors, seems to be little known in the literature.

[35] Governments may default on debt through an indirect way, that is, high inflation. They often abuse of their monopoly on currency issuance, printing as much money as retained useful in order to make the currency strongly depreciated or devaluated. The costly consequences are both direct, in terms of high fiscal costs to stabilize inflation, and indirect, associated with a loss of confidence in the currency by the users.

Practical Issues on Foreign and Domestic Debt Crisis: Identification, Dating and Results
Although foreign default dates are usually well defined and less controversial than, for example, banking crises (for which it is often difficult to define the ending period), Reinhart and Rogoff (2010), while cataloging the number of times that a country defaults, make use of their experience (subjectivity) too, by classifying all the failures occurring within two years from a previous default as part of the same episode.
Some studies date the end of a default as when countries regained the access to private financial markets, whereas others use as identification criterion a certain credit rating[36].
In addition, Reinhart and Rogoff (2010) use two further qualitative variables that embrace the crucial crisis period: the year in which the default occurs and a seven year window centered on the default date. The logical presupposition is that the three-year period pre- and post-crisis is not «smooth». In this way it is possible to analyze, over this crisis window, the behavior of various economic and financial indicators in terms of time and space (among different countries).
However, the identification of external sovereign defaults seems pretty easy since they imply a single event, the default on payments. Differences subsist, instead, with regard to the methodology adopted. The main issues deal with the magnitude of default (widespread vs one class of claims), the default by type of claims (bank or bond claims, private or public claims) and the length of default (missing one or several payments).

Domestic debt crisis, instead, seem less easy to identify.
The difficulties that may be encountered when analyzing the domestic debt are due primarily to a shortage of this kind of data. Governments are never clear enough when it comes to publishing data on public debt, tending to hide and/or mask them. This is especially true when default events on domestic debt have to be reported.
Besides the data challenge, the identification of domestic defaults is not as obvious as for external sovereign defaults. In fact, countries may even choose the way through which default on their debt obligations. Governments can default either directly or indirectly, through periods of hyper-inflation or simply high inflation, or currency debasing or various form of financial repression. Despite the great progress, made by Reinhart and Rogoff (2010) and Abbas et al (2011), in putting together historical series on domestic debt (and not only), as Reinhart and Rogoff affirm the cataloguing of inflation-related default events remains notably ambiguous.

Banking Crises
Banking crisis, also associated with the term financial crisis, are significantly different from other types of crisis. They are rare events but they have occurred over centuries and exhibited some common patterns. Notwithstanding, they seem to be the least understood kind of crisis, especially in terms of timing of occurrence.
Since banking crises represent the central topic of the work, particular room is devoted to this section. The structure is similar to the previous one about currency and foreign and domestic debt crisis with the only difference of a brief appreciation regarding the importance of this kind of crisis. Then, after a definition of banking crises, some theoretical and practical aspects are presented.

[36] See IMF (2005 and 2011).

How important are banking crisis?

First and foremost, it is necessary to point out that although many economies, that are now advanced, have been able to win the challenge of serial defaults on sovereign debt or inflationary crises at high rates, the overcoming of banking crisis turned out to be illusory[37]. <u>The case of banking crisis still persists, becoming even more pronounced over the last decades</u>.

While the frequency of default or restructuring on foreign debt is considerably lower in advanced economies with respect to emerging markets, banking crisis have struck poor countries as well as rich countries throughout history. Surprisingly, the number of crisis is significantly high in world financial centers, such as France, UK and US. For example, in the US the period in which banking crisis are common starts with the 19th century and stopped after the Great Depression thanks to the introduction of deposit insurance[38]. A recent example of bank run in an advanced economy is the case of Northern Rock, a bank specializing in housing finance[39]. Frequent runs are also experienced by emerging markets and developing countries in recent decades: the Indonesia case is the classical example during the 1997 Asian financial crisis. Therefore, <u>the banking crisis phenomenon seems to be a menace with equal opportunities</u>.

Events of <u>banking crisis seems to be accompanied by recessions that are deeper and last longer than other recessions</u>. In this regard, Ben Bernanke[40] affirms that one of the main reason that made The Great Depression lasting such a long time is primarily due by the collapse of the financial system (probably the same applies to The Second Great Contraction). When the financial system is involved, for example throughout the failure of a considerable number of banks, the replenishment of the financial system's ability to concede credit takes long time.

Last but not least, <u>banking crisis may be of (or assume a) systemic nature</u>.

Coming to a definition of a banking crisis, I adopt the one of Reinhart and Rogoff (2010), which seems shared enough in the literature and in practice.

A banking crisis is identified by two types of events:

1) banking panic (bank runs) leading to the bankruptcy, forced merger or acquisition by the public sector of major financial institutions to absorb capital losses (as in Venezuela 1993 or Argentina 2003); and
2) if there are no bank runs, the bankruptcy, merger, acquisition or the public intervention on a large scale in favor of a major financial institution (or group) that trigger the inception of a series of similar operations for other financial institutions (as in Thailand 1996-1997).

Whereas, a banking crisis is defined as systemic[41] if two conditions are met:

1. Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or banking liquidations)

[37] Reinhart and Rogoff's analysis from 1800 to 2008 shows that the banking crisis phenomenon is recurrent.

[38] See Calomiris and Gorton (1998).

[39] See Shin (2011).

[40] See Bernanke (1983).

[41] See Laeven and Valencia (2012) in this regard.

2. Significant banking policy intervention measures in response to significant losses in the banking system.

According to the two authors, the first year in which both criteria are met is considered to be the year when the crisis became systemic. In addition, they specify that policy interventions in the banking sector are significant if at least three out of the following six measures are used:

1) Extensive liquidity support (5% of deposits and liabilities to non-residents)
2) Bank restructuring gross costs (at least 3% of GDP)
3) Significant bank nationalizations
4) Significant guarantees put in place
5) Significant asset purchases (at least 5% of the GDP)
6) Deposit freezes and/or bank holidays[42].

Before entering into detail of the major theoretical results achieved in the field of banking crisis, a brief premise seems appropriate. As it emerges from the work of Reinhart and Rogoff, two kind of banking crisis may be identified.
The former is actually a domestic default, disguised in a banking crisis, that governments make use in countries where the financial repression[43] represents an important form of taxation. Obviously, this is the case of poor and developing countries.
The latter coincides with the real banking crisis, namely those that occur in advanced and emerging economies. When referring to banking crisis, henceforth, it means the pure banking crisis.

Theoretical and empirical framework on Bank runs and Banking Crisis
Financial intermediaries' activity is inherently risky and fragile. This is due to the nature of the functions they perform. Fragility enhances in specific moments and under particular conditions that may be encased in a unique term, namely, financial distress.
As Diamond and Dybvig (1983) hold, the bank's main role of maturity transformation and liquidity creation – the transformation of readily available funds floating from short run deposits into long term loans – make them particularly vulnerable to sudden demands for liquidity, the so called "bank runs".
In more detail, the typical bank activity consists in borrowing short term, by drawing from saving deposits and current account, and simultaneously granting loans with longer maturity. This basic but fundamental function of maturity transformation, in order to

[42] See Laeven and Valencia (2012) for a detailed explanation of the measures implementable.
[43] Financial repression explicated firstly, as introduced previously, by McKinnon and Shaw (1973) refers to the notion that a set of government regulations, laws and restrictions are applied, by the means of financial intermediaries, to depositor citizens. On one hand, depositors have few choices, if none, regarding the types of financial assets they are allowed to hold, reducing the choice towards very low interest rate deposits (governments impose a low maximum threshold). On the other hand, financial intermediaries, lend huge amount of their funding to governments at near-zero interest rate. In this way, governments oblige banks to use deposits to finance public debt. In addition, they make the taxation even heavier by creating an inflation much higher than the maximum thresholds on deposits.

provide the market with the liquidity demanded, reflects preferences of consumers and borrowers.
In normal times, this process does not cause problems but when financial distress affects the economy some complications may arise. In fact, when the confidence of depositors remains intact, the liquid assets (in the form of bank reserves) are more than sufficient to cope with an increase in the deposit withdrawals. But during a banking panic episode, the confidence in the soundness of the financial intermediary collapses and a large number of customers withdraw their deposits, since they believe the bank is, or might become, insolvent. At this stage, the bank is obliged to liquidate its assets, at bargain prices, to meet customer redemptions. This "selling off" process may involve some illiquid assets with particular features, for instance lending to local businesses for which the bank is better informed than other borrowers, as well as a wider variety of assets if the panic contaminates other banks and the crises becomes systemic[44].

Even though a bank would be absolutely solvent in the absence of a bank run, its financial conditions can be devastated by the need to sell off assets at bargain prices. This trigger a feedback loop called "self-fulfilling prophecy". In other words, as bank runs keep going on, it generates their own momentum: more customers withdraw their deposits, this increases banks' probability of default encouraging further withdrawals.
The one just described is another example of multiple equilibria, analogous to the case in which a country's creditors refuse, all together, to refinance short term debt. In the bank panic case, the depositors decline to refinance the bank as a result of a loss of credibility.

The good news is that there exist many instruments banking systems may adopt to tackle the shortage of liquidity resulting from a bank run. Unfortunately, these are mainly useful if the panic affects only a single bank. In such a case, the deposit insurance can eliminate concerns of small depositors and can help reduce coordination problems: the distressed bank may borrow from a pool of other private banks that lend money to each other thanks to a mechanism of collateral on deposit assurance.

According to the model of Diamond and Dybvig[45], deposit insurance may prevent episodes of banking panics. However, they neglect the circumstance in which a lack of efficient regulations may lead banks to take excessive risks[46].
Other means commonly used during financial distress periods are the lender of last resort (LLR) facilities and policy interventions by public sector[47]. The former provide the banks with the short-run liquidity during periods characterized by high financial stress, whereas the latter, consisting in public guarantees, capital support and purchases of non-performing assets alleviate systemic risk in the presence of financial turmoil.

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[44] In this worst-case scenario, the confidence between financial intermediaries falls and banks do not lend money to each other anymore (interbank crisis). The most recent example is the 2007 subprime mortgage crisis born in the US.
[45] See Diamond and Dybvig (1983).
[46] Deposit insurance have been first introduced in the US in 1933. This instrument, adopted after WWII firstly by advanced countries and then by developing countries (Demirguc-Kunt, Kane and Laeven, 2008), may reduce the bank run risk but is accompanied by some negative side effects, such as an increase in the moral hazard, implying a greater risk taking.
[47] See Claessens and Kose (2013).

The theoretical and empirical literature on financial crisis mainly focuses on the effects induced on the real activities and therefore on the real economy.

The contribution offered by Ben Bernanke in its relevant paper on the Non-monetary effects of Financial Crisis in the propagation of the Great Depression, about the role of credit as an amplifier of shocks, is not general. The author, in fact, enter into details by highlighting that the economic agents who suffer most from a credit crunch/contraction, during a recession, are the small-medium sized companies. This because they cannot benefit from the brand popularity as big companies do. Thus, they have less chance to draw on alternative form of financing such as fixed-income and equity. Later studies corroborate this greater difficulties for small-medium sized firms in overcoming strong recessions.

Besides the contribution in the 1983, Ben Bernanke shows, along with Mark Gertler[48]and through a theoretical model, the importance of imperfections in the financial market. These defects in the form of information asymmetry between creditors and debtors may trigger an amplification effect on monetary policy interventions.
In the Bernanke-Gertler model, a reduction of income due, for instance, to a decline in the productivity generates a more than proportional effect on production. This because firms are constrained to cut their investment projects since a much higher share of their investments has to be financed with external and more expensive money, rather than internal resources (profits). Basically, the losses on collateral assets, caused by recessions, amplify their effects through the financial system.

A similar issue is presented by Kyotaki and Moore[49] in their contribution on credit cycles, in which they investigate the interplay between credit constraints and aggregate economic activity over the business cycle. They construct a model of dynamic economy where durable assets play a dual role serving as factor of production and collateral for loans. Lenders cannot force borrowers to pay back their debt unless the debt is secured. The authors show that a fall in the asset price used as collateral, such as a land price collapse like the Japanese one in the 1990th, may prejudice firm collaterals resulting in a decrease in investments that, in turn, causes a further lowering of durable asset prices and so forth. In other terms, borrowers' credit limits are affected by the prices of the collateralized assets whereas these prices are affected by the size of the credit limits. Even in this case, relatively small and/or temporary shocks may persist, amplify and spread out fluctuations in output and asset prices.

Coming to more empirical contributions, Reinhart and Rogoff analyze the correlation between capital mobility and the banking crisis incidence. The authors show, by using an index computed with the same criterion adopted by Obstfeld and Taylor[50], that the international capital mobility turns out to be an important factor in explaining banking crisis. In particular, during high international capital mobility periods a lot of international banking crisis occurred. This is true historically speaking and not only with reference to episodes that received great resonance, as in the 1990th.

[48] See Bernanke and Gertler (1990).
[49] See Kyotaki and Moore (1997).
[50] See Obstfeld and Taylor (2004).

Another empirical work which deserves attention is the one of Kaminsky and Reinhart. They illustrate, through an analysis conducted over the period subsequent to 1970, formal evidences concerning the relationship between banking crisis and financial liberalization[51]. In more detail, they present empirical findings which demonstrate that the conditional probability of a banking crisis given a financial liberalization carried out in the previous years (five or less) is higher than the unconditional probability of a banking crisis.

Demirgüç-kunt and Detragiache (1998) also find some evidence about the negative impact of financial liberalization. In particular, the authors, based on a sample of 53 developed and developing countries over the period 1980-95 and using a multivariate logit model, show that the financial liberalization has an independent negative effect on the banking sector, being one of the culprits of the banking sector fragility. This is true even when some specifications are adopted, for instance, when real interest rate are controlled for.

The interconnections between deregulation and banking crisis seem to be important. Caprio and Klingebiel (1996) carry out a stylized evidence which brings to hold that an inadequate regulation and a poor supervision, during the implementation phase of a liberalization, may play a crucial role in explaining the interconnectedness. Even in this case, this is true for both developed and developing economies.

Other regularities or common features that seem to accompany banking crisis in different countries and over time deal with the interaction among international flows of capitals, credit and asset prices (mainly real estate and equity).

An interesting study in this regard is the paper of Reinhart and Reinhart (2009). The authors formulate a criterion to define a fortuitous[52]capital inflows, named «capital flows bonanzas», in order to catalogue booms episodes, country-by-country, over the 1960-2006 period. Starting from banking crisis and capital flow bonanzas dates, the interplay between the two kinds of events is computed as follows. For each country of the analysis, both conditional and unconditional probabilities are computed and then compared. If capital flow bonanzas make really a country more crisis-vulnerable, then the conditional probability of a crisis given a boom within the three years before and after one or more years of boom should be higher than the unconditional probability of a crisis. Actually the results confirm the authors' intuition.

[51] See Kaminsky and Reinhart (1999). Actually, their findings are not limited to the interplay between banking crisis and financial liberalization. They find links between banking and currency crisis, such as the fact that problems in the banking sector typically precede a currency crisis, with the currency crisis deepening the banking crisis and thus triggering a vicious spiral. However, here the focus is on the importance of financial liberalization.

[52] Meaning "broadly". Practically, they fixe a common threshold, in this case the 20th percentile, to allow a uniform treatment across countries but at the same time flexible enough to permit keeping into account cross-country non-negligible differences in the current account balances. For example, for a relatively closed country like India the cutoff for a bonanza is a current account deficit/GDP of 1.8% whereas for a trade-oriented country, such as Malaysia, the inherent cutoff is a deficit/GDP of 6.6%.

Core sample, 1960-2007

Probability of crisis (in percent)	External Default	Currency Crash	Inflation Crisis	Banking Crisis
High Income				
Conditional on a bonanza (three-year window)	0.2	9.5	2.6	11.9
Unconditional	0.0	8.2	2.1	11.2
Difference	0.2	1.3	0.5	0.7
Middle and low income				
Conditional on a bonanza (three-year window)	29.6	31.5	31.7	20.7
Unconditional	21.0	22.7	23.5	14.3
Difference	*8.6*	*8.8*	*8.2*	*6.4*
All countries				
Conditional on a bonanza (three-year window)	22.2	25.8	24.2	18.4
Unconditional	15.7	19.1	18.0	13.2
Difference	*6.5*	*6.7*	*6.2*	*5.2*
Percent of countries for which conditional probability is greater than unconditional				
	42.2	65.6	59.4	60.9

For the 61% of the countries there is a higher propensity to experiment a banking crisis over capital flow bonanzas' periods. In addition, bonanza episodes turn out to be prone not only to banking crisis but also to others types of crisis[53].

Capital flow bonanzas seem to be linked also with credit cycles. In line with empirical regularities identified in conjunction with credit cycles is the contribution of Mendoza and Terrones (2008). The authors, while adopting a specific methodology, the threshold method, study the micro- and macro-economic features of credit booms in both developed and developing countries. Among the others, they found that capital flow bonanzas, in emerging economies, are followed by credit booms. Specifically, the frequency of credit booms is higher when preceded by periods of large capital inflows and not when preceded by domestic financial reforms or gains in total factor productivity (TFP) as for developed countries. In addition, the authors detect a link between a credit boom and an increase in asset prices.

The relationship between bubbles in asset prices, mainly real estate and equity, and banking crisis takes wide room in the literature.
Reinhart and Rogoff[54] analyze the behavior of real house prices in conjunction with all banking crises occurred after the WWII in advanced economies. In particular, by focusing on the five major crisis[55], they find a clear relation between the housing market and banking crisis: real house prices experience a boom in the period preceding the crisis whereas during the year of the crisis and following it house prices shrink markedly.

[53] It is worth to specify that roughly one-third of the countries in the core sample are high income.
[54] See Reinhart and Rogoff (2008b).
[55] The so called "Big Five": Spain (1977), Norway (1987), Finland and Sweden (1991) and Japan (1992).

Similarly, Bordo and Jeanne (2002), by analyzing advanced economies over the 1970-2001 period, found that banking crisis tend to occur either when the ascent in real house prices reaches the peak or immediately after its collapse.

Again, Gerdrup (2003), focusing on the Norway case over the period 1890-1993, shows in a convincing manner the connections between banking crises and the booms and the crashes of house prices.

I would conclude the discourse on the interplay between the real estate prices behavior and banking crisis by reporting some results offered by Reinhart and Rogoff (2010).
By comparing wide-spread episodes of banking crisis, from the Big Five to the Big Six[56], including emerging market crisis, such as Argentina (2001-02) and Colombia (1998), as well as recent episodes of Hungary (2008) and of advanced economies[57], two main features may be extrapolated:

- The duration of real house prices cycle, in both emerging and advanced economies, is typically within the range four-six years;
- The extent of reductions of real house prices in conjunction with banking crisis, from the peak to the minimum value, is not significantly different among the two kind of economies.

The findings illustrated above seem to confirm the thesis that banking crisis represent a menace with equal opportunities.

Practical Issues on Banking Crisis: Identification, Dating and Results

The correct identification of the starting and especially the ending date of banking crisis is a challenge. As previously specified, this kind of crisis are typically dated using a qualitative approach based on the occurrence of a particular event or a combination of events ranging from forced closure, mergers or government takeover of a considerable number of financial institutions to in-depth assessments of financial conditions (Claessens and Kose, 2013). At this regard, the two major contributions in dating banking crisis are the work of Reinhart and Rogoff (2010) and of Laeven and Valencia (2012) whose classifications largely overlap. Their qualitative approach, based on the banking crisis definitions[58], bear the non-negligible drawback of inaccuracy as regards the starting date: it could date crisis too early/late. In addition, it gives no information about the ending date of the crisis.

The differences in the dating of crisis are extremely important to the extent in which they affect the analyses. An example is the Japan's banking crisis dated by Reinhart and Rogoff as of 1992 whereas by Leaven and Valencia as of 1997.

The difficulties drastically decrease when it comes to date asset prices and credit booms and busts. The availability of the data for these variables makes their identification in nominal or real terms pretty feasible. However, the classification of booms, busts and crunches presents considerable variations owing to differences in the approaches adopted.

[56] The "Big Six" refers to the six major crisis that hit Asia during the 1997-98 period.

[57] Countries that experienced house market bubbles during the 2007: Iceland, Ireland, Spain, UK and US.

[58] See the definitions in the section "How important are banking crisis?".

For instance, Gourinchas, Valdes and Landerretche (2001) rather than setting the threshold first, they limit the number of episodes they want to classify.
In particular, the authors, after defining a lending boom as an episode in which the private credit-to-GDP (in nominal terms) deviates from a rolling retrospective country-specific stochastic trend, identify an episode when the deviation from the trend is larger than a certain threshold. This may be a relative or an absolute deviation pointing out respectively the comparison of the additional lending size to the banking sector size and to the size of the economy. By doing so they detect 80 booms episodes.

Another interesting method is that adopted by Mendoza and Terrones (2008). As introduced earlier, they propose a *threshold method* which basically splits real credit per capita in each country into its cyclical and trend components, and signalizes a credit boom when credit exceeds its long-run trend by more than a given "boom" threshold. The peculiarity of this approach is that booms and duration sills are tailored to each country's standard deviation of credit over the business cycle, thus, reflecting country-specific cyclical credit expansions[59].

Claessens, Kose and Terrones (2012) in their study of business and financial cycles and their interactions, identify peaks and troughs making use of the classical[60] business cycle approach. In more details, working on a database of 44 countries of which 21 advanced OECD economies and 23 emerging countries, they analyze the interaction between economic (GDP) and financial variables (credit, house and equity) by looking at the level of real asset prices and credit over business cycles. Then, in order to determine booms, busts and/or crunches, they focus on the top and bottom quartile changes.

Anyway, when dealing with frequency and distribution of crisis one should be aware about the ambiguity that accompany the identification and dating of financial crisis. This because various kind of crisis may overlap[61] and often do not occur as independent episodes. Indeed, one type of crisis may be triggered by another type or two or more kind of crisis may happen contemporaneously as they are cause by common factors. As Reinhart and Rogoff (2010) posit crisis come in clusters.

1.3 BANKING AND THE ECONOMY

In this last section of the first chapter, after outlining the contours in the previous two sections, we come to the key point: the theory behind the model.

1.3.1 The endogenous cycle view of financial (in)stability

Many studies have been devoted to the importance of credit and in particular of credit expansion and its velocity as the main root of financial crisis. To explore the topic, among

[59] For more details see Mendoza and Terrones (2008).
[60] The definition of classical cycles dates back to the pioneering work of Burns and Mitchell (1946) who laid the grounding for the business cycles' analysis in the US.
[61] See Kaminsky and Reinhart (1999) for the so called twin crisis: currency overlapping banking crisis. See also Laeven and Valencia (2013), they detect a more than 15% of overlapping episodes (68 as twin and 8 as triple crisis out of 431 crisis episodes).

the most relevant papers, I chose to start with the works of Minsky (1982) and Kindleberger (1978). Both authors reach the formulation of a model of financial instability funding their contributions on the thesis whereby the financial system is inherently fragile and the build-up phase of the crisis takes place when there is stability in the system yet. This fragility of the financial system can culminate in instability giving rise to crisis for several reasons but one of this shared by the two authors is the expansion of money and credit, in particular the instability in the supply of credit.
One of the main differences between them is methodological: Minsky make use of a pure economic approach and through this construct a model of financial instability whereas Kindleberger adopts an empirical and historical approach thus analyzing the previous crisis episodes in order to detect the elements shared.

The idea underlying the model of Minsky is that the financial system is inherently fragile and this fragility is an endogenous feature, meaning that it depends on the financial system structure itself. In particular, he focus on the pro-cyclical changes in the supply of credit and maintains that the fragility in the financial contracts and, consequently, the likelihood of financial crisis rises as a result of increases and decreases of the credit supply during, respectively, good times (booms) and economic slowdowns. These pro-cyclical changes in the supply of credit are driven by the investors which inhabit the financial system.
In more details, the Minsky's theory of a capitalist process relies on two main pillars.
First and foremost, the author highlights the conceptual difference to keep in mind in order to carry out a proper analysis/model of the financial system. This concern with the way economic reality is conceived. In fact, if in a standard economic theory the economic reality is analyzed by studying markets for commodities and services, when studying a capitalist process the structuring of economic reality into commodities and markets is of secondary importance; what is fundamental and has to assume primary importance is the analysis of cash flows, consisting in receipts and payments. The standard theory looks at the economy as producing and consuming outputs whereas what he calls the Wall Street perspective views the economy as producing and allocating profits. This economy consists in a set of balance sheets in which assets generate cash receipts and liabilities state payment commitments. Thus, the problem faced by the theory is how assets generate cash and how relations among cash payment commitments, anticipated cash flows and realized cash flows affect the performance of the system.
The second aspect concerns the financial system structure. In fact, the financial system is populated by three kind of actors: *hedged-finance* units, *speculative-finance* units, and *Ponzi-finance* units. Each of these units make use of the credit instrument, as financing, in different quantities according their needs that are intrinsic to their nature.
Therefore, considering both assets and liability sides, two time series must be taken into account to judge the feasibility of an investment.

1) The set of anticipated quasi rents or gross profits (revenues-running expenses, before taxes):
$$AQ_1 \dots AQ_n$$
2) The set of payment commitments:
$$PC_1 \dots PC_n$$

An investment is practicable only if cash in exceeds payment commitments:
$\sum_{i=1}^{n} AQ_i > 0$

$\sum_{i=1}^{n} AQ_i > \sum_{i=1}^{n} PC_i$

In addition, Minsky splits the two variable into a wastage and net income part:

$$AQ_i \begin{cases} AQ_i(a), & \textit{the amount of gross profit representing the consumption of capital} \\ AQ_i(y), & \textit{the net income part of the quasi rent} \end{cases}$$

$$PC_i \begin{cases} PC_i(a), & \textit{the amount of payments on debts that is a repayment of principal} \\ PC_i(y), & \textit{the net income part of the payment commitments} \end{cases}$$

By ignoring the temporal subscripts:

$$AQ(y) = AQ - AQ(a)$$

$$PC(y) = PC - PC(a)$$

A *hedge-finance* unit, identified with a covered investor, is *always* able to pay interests and principal on debt thanks to the remuneration arising from the investment, and has the following features:

- $AQ_i > PC_i \quad \forall\, i, s.t.$
- $AQ_i - PC_i > 0 \quad \forall\, i$
- $E = \sum_{i=1}^{n} k_i\ (AQ_i - PC_i)$

Note that the firm's capitalization value (E) of the cash flows takes into account their uncertainty through the factor k_i which depends on the market interest rates linked to the risk of different assets' classes.
This unit is not subject to a present-value reversal when interest rates change.

A *speculative-finance* unit, identified with a speculative investor, continues to roll over the debt but paying solely the interests portion and thus maintaining unchanged the principal share. For this unit:

- $AQ_i < PC_i \quad (i = 1, \dots, m,\ \ m\ small)$
- $AQ_i > PC_i \quad (i = m + 1, \dots, n)$

In addition, over the first *m* periods

- $\sum_{i=1}^{m} AQ_i(y) > \sum_{i=1}^{m} PC_i(y)$

Such a unit can fulfill its payment commitments only if it runs down its money assets or succeeds in placing new debt. Some examples are business firms that roll over bank debt and commercial paper, banks and other financial institutions and treasuries with floating debt. The normal functioning of such units depends upon their ability to place liabilities and thus on the normal functioning of financial markets. This type of unit is therefore subject to present-value reversal: the value will be positive for low interest rate and negative for high interest rate.

A *Ponzi-finance*[62] unit is a special kind of speculative unit that is not able to obtain an adequate remuneration even to repay debt services and are forced to fulfill their

[62] The term "Ponzi finance" that now is generally used for a non-sustainable pattern of finance memorializes a Boston "swindler" Carlos Ponzi who run a small loans company in one of the Boston suburbs in the early 1920s. He promised his depositors a 30% monthly interest; the financial transactions went smoothly for three months but in the fourth month the cash inflows from new

contractual obligations by placing more and more debts. This is because the income portion of payment commitments exceeds the income portion of cash receipts and this is true for all periods except some terminal periods:

- $AQ_i < \; PC_i \quad (i = 1, \dots, n-1)$
- $AQ_i \gg \; P_i \quad (i = n)$

In addition,

- $AQ_i(y) < PC_i(y) \quad (i = 1, \dots, n-1)$
- $AQ_i(y) \gg \; PC_i(y) \quad (i = n)$

A classic example is a deal that involve holding assets which carrying cost is higher than the income earned, so that the investment is profitable only if the asset appreciates. Naturally, the present value of these units too is sensitive to interest rate changes and as:

$$AQ_i(y) < PC_i(y) \quad (i = 1, \dots, n-1)$$

The outstanding debt of a unit engaged in a Ponzi-finance rises at a faster rate the higher the interest rates because when (short term) rates rise $PC_i(y)$ increases and simultaneously $AQ_i(y)$ decreases as discounting factors rise.

To complete the framework the demand for money:

$$M_D = \sum_{i=1}^{m} T_i\,(X_i) + \; L_i(PC_i)$$

for each of these units according their needs. The rationale of this variable is that some cash or cash-equivalent assets are kept on hand as insurance against disruptions in cash receipts. These holdings are related to near-term running expenses X_i and payment commitments on contracts PC_i.
Again, the need for money is small for hedge units as anticipated total revenues exceed running expenses and total payments in each period. For a speculative-finance unit the demand for money and money market assets is more a function of the payment commitment due to debts with respect to a hedge unit. This because the portion of PC_iX_i of the former unit is greater than the latter portion.

Concluding, the bottom line of the theory is that the fragility in the system is a function of both the mix of units populating the system and the conditions of the financial markets. Whereas a rise in interest rates lowers the *E* of a hedge unit but does not affect its ability to meet payment commitments, it may well affect the terms on which additional debt can be issued. Since debt issuing terms affect investments, these will be reduced. Inasmuch as speculative and especially Ponzi-finance units are vulnerable to present-value reversal investments will be cut and more debt will be issued. But the ability to issue new debt depends on the *E* and if the firm value strongly decrease a downgrading towards a higher risk class will occur.
At this stage the financial system composition is fundamental. In fact, the higher the portion of speculative and Ponzi-finance units the higher the fragility. In normal times threats are latent but as soon as some inefficiencies occur, such as cash flow receipts' changes (expected to validate liabilities) and/or a rise in interest rates, a greater share of speculative units declass in Ponzi units and Ponzi units come to fail. The spiral lead to financial crisis. A financial system formed mainly by hedge units has a greater staying

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depositors was not sufficient to cover interest payments promised to the older borrowers. Finally, he went to prison.

power. Only massive changes in revenues at the macroeconomic level (i.e. after an economic crisis) could make a healthy financial system collapse.

The financial-instability hypothesis theory of Minsky poses important points.
As introduced previously, the financial system is inherently fragile and this fragility is endogenous depending on the financial system structure.
In fact, as a second point, the theory emphasizes the financial relations that are special to capitalism. These rely on assets and liabilities' cash flows and their mutual sustainability. This sustainability, in turn, depends upon the pro-cyclical changes in the supply of credit driven by the investors which inhabit the financial system. The likelihood of financial crisis soars to the extent in which assets receipts are no longer able to support the outstanding as well as the new liabilities. At this stage maybe too late.
Last but not least, the role of the LLR. The author holds that the greater the proportion of speculative and Ponzi finance in the structure of financial relations the greater the importance of the central bank's LLR function. When business organizations are unable to validate a debt structure heavily weighted o short term finance, the central bank as the LLR has the responsibility to facilitate the restructuring of debts so that the share of speculative and Ponzi finance in the system is decreased. Also, the central bank has the responsibility, either by legislation or by its operations, to exert a preventive function and steering the financial system towards a structure in which the actual and potential weights of risky classes are constrained.

Kindleberger, in line with the thinking of Minsky, maintains that the foundations or the build-up phase for the crisis comes from the instability which is typically associated to the evolutionary attitude of the economy and the financial system. As previously anticipated, Kindleberger adopts an historical approach thus analyzing the previous crisis episodes in order to detect and formalize the typical evolutionary stages that characterize a financial crisis, specifying that a financial crisis imply the involvement of financial markets. The Kindleberger's approach, for its nature, is less quantitative and more descriptive than the Minsky's theory.
The author presents an economic model of a general financial crisis that covers the booms and the subsequent busts and focuses on the episodic nature of manias, and the following crisis. Manias are frantic and dramatic episodes generally associated with the expansion phase of the business cycle (but only a few economic expansion are associated with a mania) as the euphoria that accompany them lead to increases in consumption and investment spending. These increases are fueled by rises in the prices of real estate, stocks, or in one or more commodities that in turn flow into accelerations in the economic growth rates. Macro manias, instead, are associated, in particular, with economic mania of firms that become increasingly up-beat and boost investment spending as credit abounds. In fact, the thesis of his contribution is that cycles of manias and panics results from the pro-cyclical changes in the supply of credit[63].
In line with the Minsky's model, the inception phase of the build-up pattern is called "***displacement***". The term encapsulates some exogenous, outside shocks to the macroeconomic system. The nature of the shock changes from one speculative boom to

[63] See "Manias, Panics and Crashes: a history of financial crisis".

another[64]. If the shock is sufficiently large and wide-spread, the anticipated profit opportunities come out in at least one important sector of the economy, resulting in an increase in the corporate profit share of GDP. This because an effective increase in the demand for goods and services takes place, pushing up market prices as the production capacity remain unchanged in the short run. This, in turn, raises profits attracting more investments which increase the growth rate of national income that, due to the development of positive feedback, induce additional investment resulting in an acceleration of the growth rate of national income. At this point the "***euphoria***" stage might develop. The best word to describe this phase is optimism. On one hand, euphoria leads to a raise in the optimism about both the rate of economic growth and the rate of increase in corporate profits. On the other hand, the decline of lenders' losses on their loans make them more optimistic and the result is a reduction in the minimum down payments and the minimum margin requirements. Even if bank loans raises, the leverage (debt-to-capital or equity) of most borrowers decline because their net worth increases at a faster rate (asset prices soar). As soon as firms and households notice the easy profit from speculative purchases a follow-the-leader process develops and banks enlarge the target of potential borrowers to a much wider group of clients to gain market share against other lenders. This leads to a massive expansion of credit and give rise to a subsequent phase called "***overtrading***". The term overtrading, which memorializes Adam Smith and his contemporaries, implies an overestimate of prospective returns and a pure speculation on increases of asset or commodity prices. Investors buy goods and/or securities simply to make profit from the capital gains associated with the anticipated increases in their prices and not for the profitability of the investment itself.

This phase is characterized by a continuum balancing of insiders (who purchased the assets earlier) and the outsiders since outsiders' purchases mean insiders' sales. If the eagerness of the outsider to buy is stronger than the insiders' eagerness to sell, asset prices continue to raise. Otherwise, prices will decline. The "***financial distress***" stage starts when buyers become less eager and sellers become more eager. The term financial distress comes from corporate finance and reflects the firm inability to meet its debt servicing commitments. Translated to whole economy it means that a remarkable portion of businesses and individual investors realize that is time to increase liquidity, by reducing holdings of real estate and stocks and raising holdings of money. At this point, asset prices fall acutely and some highly leveraged investors go bankruptcy as the asset value after the decline is lower than the amount borrowed to buy them whereas others, that continued holding the assets thinking that the decline was temporary, realize that they were wrong and the selling before the decline enhances becomes a need. The liquidation may be disciplined or may degenerate into a panic as investors realize that the buyers are disappearing from the market. The last phase that conduce to the crisis is called "***revulsion***": investors are inundated by a sense of disgust and loathing. This revulsion is accompanied by "***discredit***" from banks which become extremely cautious in their lending on the assets' collateral. Here, some important banks and/or businesses go bankruptcy.

The mix of revulsion and discredit leads to panic that feeds on itself until prices have declined so far that assets' trade is stopped by setting limits on price declines, trading close or a LLR convinces investors that money will be made available in the amount

[64] Probably, the nature of these shocks depends on the historical timeframe over which episodes occur. For instance, the financial liberalization seems to be a pretty common factor in the recent decades but other shocks also include wars or strong policy changes as well as new making-history inventions.

needed to arrest securities' decline due to a shortage of liquidity. To restore the confidence it is not necessary a huge increase in the volume of money as the confidence that one can obtain the money is enough to curb the liquidity demand. However, at this point, as investors fear they will not recover their money anymore, the panic is almost always unrestrainable.

Another aspect that deserves some words is the propagation effect that typically characterizes financial crisis. Kindleberger underlines that Minsky focuses on the instability in the supply of credit in a single country whereas from his historical analysis emerges that the euphoria has often spread from one country to others. In particular, Kindleberger identifies at least three channels of shock. One conduit is represented by the arbitrage, as it ensures that variations in the price of an asset, for example a commodity, in one national market will lead to comparable variations in the prices of the near-the-same commodity in other national markets. A second potential shock transmission channel is constituted by the macroeconomic effect of the GDP raise. In fact, increases in the national income in a country cause increases in the domestic demand for imports, thus increases in counterpart exports in other countries and in turn increases in the national income in these countries. Capital flows are the third connection. This because raises in securities' exports from one country will cause raises in both their prices and their currency value. Finally, psychological factors fuel the contagious as well: investors' euphoria/pessimism in one country affects investors in other countries.

1.3.2 Implications of the Quantity Theory of Credit for the Prevention and Resolution of Banking Crises

Another author which deserves particular attention as his thought about the theory of credit inspired this work and the resulting model is Richard A. Werner.
The last financial crisis revealed great deficiencies in the eco-financial system making both economists and operators in the financial world deeply reflecting with respect to an increasing need for a cooperation. On one side, economists shall pay more attention on finance by including a banking sector in macroeconomic models; on the other side finance and the banking literature have to consider how best to incorporate systemic, macroeconomic feedbacks into their modeling of financial intermediation.
In other words, economics needs more finance and banking, while finance and banking needs more economics. Both disciplines had developed in a way that blindsided them concerning banking crises[65].
In his paper, Richard A. Werner, tackles this special issue of a new interdisciplinary research programme on 'Banking and the Economy' also devoted to the ECOBATE[66]
by focusing on two main points:

1) Pointing out the many empirical challenges that need to be overcome; and as a further step
2) Presenting a concrete model linking banking and the economy via the reflection of the fundamental feature about banks that both finance and economics experts often ignore when dealing with them: ***the process of 'credit creation'***.

[65] See Werner (2012), Towards a New Research Program on 'Banking and the Economy'.
[66] European Conference on Banking and the Economy held on 29 September 2011 at Winchester Guildhall.

I will develop both aspects by focusing on the latter since the theory underlying it inspired my model.

(1)
One of the problems to being solved is the ***velocity decline*** phenomenon and the ***inability to define money***. It is clear and widespread that all the models that neither feature banks nor incorporate monetary variables have not been successful.
The starting point is the well-known ‘quantity equation’:

$$M\,V = P\,Y$$

Where:

M = the money supply measured and defined variously as $M_0, M_1, M_2, M_3 \text{ or } M_4$;
V = the (income) velocity of money[67];
P = the GDP deflator (the appropriate price level);
Y = the real GDP.

In logarithm terms:

$$m + v = p + y$$

The above equation has always been considered a pillar in the macroeconomic models until the mid-80s so much that Friedman famously defined it as:

“uniformity… of the same order as many of the uniformities that form the basis of the physical sciences. And the uniformity is in more than direction. There is an extraordinary empirical stability and regularity to such magnitudes as income velocity that cannot but impress anyone who works extensively with monetary data” (Friedman, 1956, p. 21).

Friedman underlines the empirical stability and regularity in terms of income velocity as well. But this link between the real economy and the financial/monetary sector that he calls “an identity, a truism” decades later[68] loses significance over time as the velocity declines conspicuously and the money demand function becomes unstable. The main consequence of this phenomenon also known as the “mystery as the missing money”[69] is that a reliable interplay between a monetary aggregate and nominal GDP cannot be identified anymore by economists.
After vain attempts in explaining this apparently inexplicable phenomenon as deriving from financial deregulations and innovation (since money is used more efficiently and this lower the velocity but empirically financial deregulation increased the volume of transactions suggesting a higher speed of transactions) [70] the problem remained unsolved and the discipline turned away from it.
The empirical failure in defining money, since one monetary aggregate after another succumbed to an unstable relationship with nominal GDP, represents one of the weaknesses in macroeconomics that remained unsolved. This because economists instead

[67] Originally defined as the number of times gold was said to circulate during an observation period.
[68] Friedman (1992, p. 39).
[69] Goldfeld et al (1976).
[70] See for instance Judd and Scadding (1981); Gordon (1984); Hetzel (1984); Roley (1985); Miller (1986).

of getting to the root of the problem eluded it and operated on the empirical unsustained premise that money and banks did not matter.
Another unsolved puzzle in conventional macroeconomics is the role of banks.
The awareness that banks have special features dates back more than twenty years ago when Blanchard and Fischer (1989) pointed out:

"The notion that there is something about banks that makes them 'special' is a recurrent theme." (p. 478).

Nevertheless, practically speaking, they have always been considered as mere financial intermediaries and for that they have not been explicitly modelled in a meaningful way in major macroeconomic theories and models over the past thirty years. This because conventional approaches failed to identify the nature of this special feature.
Besides what said so far there are other 'anomalies' or empirical facts that seem inexplicable by Keynesian, post-Keynesian and even monetarist theories and models. One of these that deserves single deepening is ***the empirical puzzle of interest rates***.
Theories consider the role of interest rates as the pivotal variable that has significant causal force but empirically they seem far less powerful in explaining business cycles or developments in the economy than theory would have it[71].
In addition, interest rates have not been able to explain major asset price movements (the most emblematic examples is the Japan[72]), nor capital flows[73] – phenomena that in theory should be well explicable through the price of money (interest rates).
Last but not least, the interplay between interest rates and economic activity seems ambiguous in terms of timing: interest rates appear as likely to follow economic activity as to lead it[74].
Again, in order to explain the failure of interest rates in expanding the money supply many attempts take place. These may be collected in two main flows:

a) 'Credit view' literature: includes the 'bank lending view' and the 'balance sheet channel' approach[75]. Proponents of these approaches failed in solving the empirical puzzle because they claimed that credit should just enhance the role of interest rates.
b) 'Liquidity trap' explanation: originating in Keynesian approaches, and subsequently adopted by rational expectations theories (Krugman, 1998) failed since it does not give any answers/explanations to the inefficacy of repeated, over a decade, interest rate reductions in stimulating the economy.

The puzzle of interest rates is a pretty sensitive issue. For interest rates to work efficiently and play the role the theory suggests, the market of money and credit have to be in equilibrium. Probably the problem is that economists simply excluded a priori the

[71] See Melvin (1983) and Leeper and Gordon (1983), who found scarse support for the so-called liquidity effect of interest rates on the money supply.
[72] See Asako (1991) on Japanese land prices and French and Poterba (1991) on Japanese stock prices; see Dokko et al. (1990) on the US real estate market.
[73] See Ueda (1990) and Werner (1994).
[74] For instance, Stock and Watson (1999) find that the nominal rate is a leading business-cycle indicator whereas short-term interest rates, since influenced by central banks, tend to follow nominal GDP growth. The same also seems to apply to long-term interest rates (Werner, 2005).
[75] See Bernanke and Gertler (1995).

possibility that markets may never be in equilibrium but as long as this possibility becomes reality it would not be prices (such as interest rates) that determine outcomes, but quantities (such as the quantity of credit). Under this perspective the quantity and the quality of credit assumes an absolute importance. Blanchard and Fischer (1989) recall this concept in a comment on the missing role of banks in this way:

"A recurrent theme in the literature and among market participants is that the interest alone does not adequately reflect the links between financial markets and the rest of the economy. Rather, it is argued, the availability of credit and the quality of balance sheets are important determinants of the rate of investment" (p. 478).

By the way, even the credit rationing argument itself is not capable to explain why available alternatives to domestic bank credit (foreign bank credit, direct finance, equity issuance) failed to compensate for credit supply constraints. After all, credit rationing is a microeconomic argument without any explicit macroeconomic implications. But here it is macroeconomic issues that require explanation: why have interest rate reductions failed to stimulate the economy, and why could non-bank sources of funding not compensate for lack of bank credit?

Some proposals to these inexplicable facts/anomalies have also come from advocates of real business cycle theories arguing that macroeconomics should tackle the challenges posed by the last financial crisis by including a financial/banking sector into DSGE models. As Werner states, this response seems *"an ad hoc modification of an incompatible approach"*. Instead of an optimal modification of a ready-made but vicious approach a whole new paradigm is needed. To get this target Werner captures the momentum of a shift towards models that are developed by following an inductive research methodology.
In this direction the author points out that this new paradigm, which can only arise from an inductive approach, has to be able to solve at least the following seven central empirical puzzles in macro- and monetary economics:

1) The apparent velocity decline;
2) The identification problem of money and
3) of what makes banks special (while incorporating this feature appropriately into a macroeconomic model);
4) why there are recurring banking crises;
5) the ineffectiveness of over a decade of interest rate reductions in stimulating growth in Japan (and a growing number of other countries), and, more generally, the link between interest rates and growth;
6) the success of the German and East Asian economic model, despite wide-spread government intervention and use of non-market mechanisms; and
7) the ineffectiveness of supply-side reforms (deregulation, liberalization, privatization).

(2)
As said before, Werner uses an inductive method to construct an alternative approach to the mainstream theories. In particular, the author via empirical observations of the key

aspects of banking activity modifies the last common macro model that includes money, that is, the ***quantity equation***.
The best starting point is the original formulation of this equation by Irving Fisher (1911), based on Newcomb (1885) and John Stuart Mill (1848):

$$M\,V = P\,Q$$

The above equality means that the effective money, MV, assumed to circulate and be used for transactions equals the value of transactions, PQ, resulting by summing prices times quantities transacted.
Werner rephrase this statement also known as 'equation of exchange', such that it is "valid under any set of circumstances whatever", as follows:
"The total value of ***transactions*** *during any time period must be the same as the amount of money used to pay for these transactions."*
Here I would focus the attention on two points: on one side, the components of this equality and on the other side the word transaction which I wrote in bold character.
First, while M and P could be readily identified, V is hard to measure thus has to be the unknown variable. The problem is that data on transactions Q, that are necessary, are not officially published by central banks, thus the main flaw of Fisher's equation is that it is inapplicable as is formulated.
This drawback is overcome by Pigou (1917) and his colleagues at Cambridge University by arguing that the stock of money used for transactions should be proportional to 'total nominal expenditures', which could be represented by the expenditure-side of GNP. From there onwards many economists replaced PQ with PY.
This apparently simple but important change in the definition of the quantity equation, in particular on the right-hand side, had some implications on the left-hand as well.
The second point here is what is meant by *transaction*.
For instance, Milton Friedman motivates the change in this way:
"Fisher, in his original version, used T to refer to all transactions – purchases of final goods and services…, intermediate transactions…, and capital transactions (the purchase of a house or a share of stock). In current usage, the item has come to be interpreted as referring to purchases of final goods and services only, and the notation has been changed accordingly, T being replaced by y, as corresponding to real income" (Friedman, 1990, p. 38).

Here, Friedman is right on the kind of transactions that one has to consider when referring to the GDP on the other side of the equation but he does not explain why this is justified and what the implicit assumptions are.
Indeed, as Werner state, Fisher's earlier formulation is a special case that holds only if nominal GDP is a robust proxy for the value of total transactions in the economy for which money is changing hands. Or:

$$P\,Y = P\,Q$$

In addition, if one considers growth rates, more restrictions apply, that is, transactions proxied by GDP are a constant proportion of total transactions. But it is neither clear that GDP accurately reflects all transactions in the economy nor that GDP-based transactions are a constant proportion of total transactions. Actually, GDP statistics reflect income, value added in production and services or expenditure on goods and services only and since capital gains on assets and in general financial transactions (likewise the majority of real estate transactions) affect wealth but are not included in the income definition and hence GDP, the problem is obvious. On one hand, financial transactions cannot be ignored, as many economists acknowledge[76], but on the other hand by keeping the proxy of GDP as the value of ***all*** transactions is not completely correct. Therefore, what is the solution here?

Even though the distinction between GDP-based transactions and non-GDP-based transactions seems pretty clear in the literature, in practice, in the mainstream use of the quantity equation, the corresponding separation of relevant monetary aggregates is not carried out as nominal income is employed.

Werner suggest to:

"disaggregate the general equation of exchange for all transactions into two flows – those of money used for GDP ('real', hence subscript R) and those of money used for non-GDP transactions ('financial', subscript F)."

Moreover, this has been also noted by Friedman:

"Each side of this equation can be broken into subcategories: the right-hand side into different categories of transactions and the left-hand side into payments in different form" (Friedman, 'Quantity Theory', Encyclopedia Britannica, 15th edition, p. 435).

Werner (1992, 1997) implemented successfully this distinction with the quantity equation taking the following form:

$$MV = M_R V_R + M_F V_F$$
$$PQ = P_R Q_R + P_F Q_F$$

Where:
$M_R V_R$= money used for 'real' transactions (that are part of GDP);
$M_F V_F$= money used for 'financial' transactions (that are not part of GDP);
$P_R Q_R$= value of 'real' transactions (that are part of GDP);
$P_F Q_F$= value of 'financial' transactions (that are not part of GDP);

Consequently, it must also hold:

[76] John Stuart Mill (1848) suggested that one must consider the possibility that money is used not for goods (and services), but instead for financial transactions, such as the purchase of securities. Jeremy Bentham (1952-54) did so as well. After them several authors recognized, in theory but also in practice, the importance of discriminating between real and financial transactions.
Fisher, and after him Keynes, suggested to distinguish between transactions arising from the sale or purchase of finished goods and services (which can be measured by GDP) and financial transactions that are not related to national income. For other contributions that use a similar distinction see Selden (1956), Spindt (1985), Cramer (1986), Stone and Thornton (1987), Niggle (1988) and Allen (1989).
Also, the UK's Central Statistical Office (1986) itemized that GDP was merely a subset of transactions involving final output, thus is the total value of transactions that should be used in the quantity equation.

$$M_R V_R = P_R Q_R$$
$$M_F V_F = P_F Q_F$$

Moreover, by proxying the value of GDP-based transactions with the nominal GDP ($P_R Y$):

$$M_R V_R = P_R Y$$

With a constant/stable ‘real’ velocity of money

$V_R = (P_R Y)/M_R$= const.

Regarding growth rates, one may talk about economic growth if the value of economic transactions from one time period to the subsequent one increases. Thus, in terms of net changes in the quantity equation variables over the period considered:

- the rise (fall) in the amount of money used for GDP-based transactions is equal to the rise (fall) in nominal GDP;
- the rise (fall) in the amount of money used for non-GDP transactions is equal to the change in the value of non-GDP transactions.

Stated in the form of equation:

$$\Delta(M_R V_R) = \Delta(P_R Y)$$
$$\Delta(M_F V_F) = \Delta(P_F Q_F)$$

From the framework outlined above an important and clear observation can be extrapolated: ***an asset bubble can be caused if more money is created and injected into asset markets***.

<u>*Measuring the left-hand side of the Quantity Equation*</u>

At this point, after setting up the structure of the new paradigm of the quantity equation, it only remains to define the details, i.e., solving the practical matter of measuring the quantity of money actually used for all transactions, MV.

The inability to define money, as illustrated before, has been one of the major anomalies. As a rule, after the war, almost all economists, among which Fisher and Keynes, have used the deposit aggregates, ranging from M0 to M4, to represent the amount M in the quantity equation. By the way, this approach revealed several drawbacks.

First and foremost, by definition, the original equation of exchange defines M as the purchasing power that is actually exerted when transactions occur whereas the ‘M’-aggregates, as traditionally defined, mainly consist of money deposited with banks or the central bank. Thus, they measure subsets of private-sector savings and hence money that, at the moment of measurement, is not used for transactions. The original equation of exchange however requires a measure of that money that is used for transactions, namely, money in circulation, not money out of circulation.

One of the author which stresses this point is John Stuart Mill (1848). He defines the quantity equation as a transactions equation, as described later by Fisher and by Werner but successive authors tended to neglect it. He underlines this concept thus:

"Whatever may be the quantity of money in the country, only that part of it will affect prices which goes into the market of commodities, and is there actually exchanged against goods. Whatever increases the amount of this portion of the money in the country, tends to raise prices. But money hoarded does not act on prices. Money kept in reserve by individuals to meet contingencies which do not occur, does not act on prices. The money in the coffers of the Bank, or retained as a reserve by private bankers, does not act on prices until drawn out, nor even then unless drawn out to be expended in commodities" (Book III, Chapter 8, par. 17, p. 20).

Another important limitation is noted by Friedman (1956), which stated that:

"dollars of money are not distinguished according as they are said to be held for one or the other purpose" (p. 61).

This means that by using cash/deposits as money in the quantity equation does not allow to discriminate between money used for one purpose (GDP-based transactions) rather than another one (financial transactions). Again, within the two macro distinctions it would be interesting differentiating between money used for productive investments and money simply spent, something that would be impossible by employing any M-aggregates.
Therefore, how could money used for transactions be represented?
To answer this crucial question Werner, instead of the deductive method, utilizes the already mentioned inductive approach, i.e., starting with empirical facts, which are used to identify patterns and formulate theories, and then testing these theories against the facts again. Thus, the starting point should be to understand how money is created and injected in our present-day system and then implementing in the quantity equation and finally testing it.
Empirically, we are interested in the behavior of the amount of money used for transaction and, specifically, its increase/decrease. Since we are no longer in a gold standard but we are operating under a fiat money system in which about 97% of the money supply is created and allocated by private profit-oriented enterprises, namely the banks, the attention should be shifted on them[77].
Banks create money 'out of nothing' when they credit borrowers' bank accounts with sums of money that nobody transferred into these accounts from other parts of the economy. This process of ***credit creation***, as Werner (1992, 1997, 2005) argued, allow banks to invent about 97% of the money supply when they simply grant loans, extend bank credit (or purchase other assets).
This concept of credit creation is so simple that human being and thus the majority of economists repel it. J. K. Galbraith (1975) says about it:

"The process by which banks create money is so simple that the mind is repelled. When something so important is involved, a deeper mystery seems only decent" (p. 18f).

[77] See Werner (2012).

However, there exist also several authors that well recognize the fact that banks create the money supply[78], but despite this it failed to become the mainstream view probably due to the fixation on legal tender or metallic money.
Even Schumpeter (1954) highlights the *interchangeability* of money with credit:

"As soon as we realize that there is no essential difference between those forms of 'paper credit' that are used for paying and lending, and that demand, supported by 'credit', acts upon prices in essentially the same manner as does demand supported by legal tender, we are on the way toward a serviceable theory of the credit structure…".[79]

This recognition that credit may have the same economic effect as money appears quite difficult also because of their technical differences. As Schumpeter states,

"… the mere practitioner will in general be impressed by the technical differences rather than by the fundamental sameness."[80]

The substitutability between money and credit and thus the linkage between credit and the macroeconomy represents one of the major breakthrough well recognized already at the inception of the twentieth century so much that in the Enzyclopedia Britannica (1911 edition) is claimed:

"The immense growth of credit and its embodiment in instruments that can be used as substitutes for money has led to the promulgation of a view respecting the value of money which may be called the Credit Theory. According to the upholders of this doctrine, the actual amount of metallic money has but a trifling effect on the range of prices, and therefore on the value of money. What is really important is the volume of credit instruments in circulation. It is on their amount that price movements depend. Gold has become only the small change of the wholesale markets, and its quantity is comparatively unimportant as determinant of prices" (italics added).[81]

From what reported so far emerges clearly that what does really matter in the modern eco-financial system is credit rather than money. The fact that banks create the money supply in an economy with a banking system, means that bank credit creation should have a direct impact on transaction volumes, demand, and hence also prices, as Mill (1848) and Bentham (1952-4) suggested.
By reflecting this in the quantity equation, as Werner does, gives the following equations:

$$C\,V = P\,Q$$
$$CV = C_R V_R + C_F V_F$$
$$PQ = P_R Q_R + P_F Q_F$$

Thus:

$$C_R V_R = P_R Q_R$$
$$C_F V_F = P_F Q_F$$

[78] Among others Pollexfen (1697), Law (1720), Thornton (1802), John Stuart Mill (1848), Macleod (1855/56).
[79] Schumpeter (1954), p. 718f.
[80] Schumpeter (1954), p. 719, emphasis as in original.
[81] Encyclopedia Britannica (1910-1911).

By proxying the value of all GDP-based transactions, $P_R Q_R$, with the nominal GDP, $(P_R Y)$, as previously explained:

$$C_R V_R = P_R Y$$

With a constant/stable 'real' velocity of credit:

$V_R = (P_R Y)/C_R$= const.

Similarly, for the financial sector:

$$C_F V_F = P_F Q_F$$

With a constant/stable 'financial' velocity of credit:

$V_F = (P_F Q_F)/C_F$= const.

In terms of growth:

$$\Delta(C_R V_R) = \Delta(P_R Y)$$
$$\Delta(C_F V_F) = \Delta(P_F Q_F)$$

The model of disaggregated credit described above gives also an answer to the puzzles/anomalies previously identified.

(1) As Werner (1997, 2005) illustrates, the right quantity equation, which is disaggregated at least into the two streams of GDP and non-GDP based transactions, should not suffer from a velocity decline.

(2) The identification problem of money is explained as well. Credit created by the banking system (including the central bank), not only solves the problem of what M-aggregate choosing but is also more consistent with what the definition of quantity equation requires. This because credit creation measures only purchasing power that is actually used for transactions at the time of measurement – which is what deposit aggregates cannot deliver. Indeed, credit always represents effective purchasing power, as borrowers take out loans to engage in transactions. Obviously, only the net creation of new transferable purchasing power is included in the definition. For instance, the issuance of corporate debt or government bonds, does not in itself constitute credit creation, since in these cases already existing purchasing power is simply transferred between parties. In addition, thanks to sectoral loan data we may get information about the ***direction of purchasing power***, i.e., what share of purchasing power is primarily spent on 'real' transactions that are part of GDP and which part is primarily used for financial transactions.[82]

(3) At this point it is easy to recognize why banks are so special. Banks ration ad allocate credit in the economy (well known in the literature) but since banks create the money supply (not well recognized), ***credit rationing has macroeconomic***

[82] Werner (2012).

implications.[83] In other words, the quantity and the quality of credit creation are key factors shaping the economy. And since neither non-bank financial institutions, nor debt and equity markets can create credit, non-bank sources of funding can never compensate in aggregate for a lack of bank credit.

(4) To understand why banking crisis are so recurring we have to consider the last equation of the quantity equation model modified for credit:

$$C_F V_F = P_F Q_F$$

It is clear that ***asset inflation is caused by the creation of credit*** (and hence new money) ***by banks for asset transactions***, $C_F V_F$, that boosts asset prices. These, increase as far as credit creation for asset transactions continues. As soon as this is not forthcoming sufficiently, asset prices must be expected to fall, which will render speculators out of pocket and asset loans nonperforming. The most important consequence is a drop in the present value of the loan portfolio (e.g. due to non-performance) which will cause a complete erosion of the majority of bank's equity due to the modest capital cushion in the banking system. This would render the banking system subject to either runs or avoidance in the inter-bank market.[84]

Another consequence of the driving force exerted by bank credit creation towards asset prices (in aggregate terms) is that ***a large and enough sustained extension of credit for financial transactions will produce a Ponzi scheme***, whereby early entrants (buying the assets that are driven up by bank credit creation) have a chance to exit with profits, while the late entrants (buying near the peak of an asset bubble, as the opportunity of making profits comes out from shadows) will lose.

(5) The answer to the puzzle why interest rate reductions failed to stimulate the Japanese economy is in this equation:

$$C_R V_R = P_R Y$$

As we may notice nominal GDP growth, $P_R Y$, is determined by credit creation used for GDP-based transactions; interest rates do not appear in the equation. In addition, Werner, by investigating the link between credit growth and interest rates illustrates that there is not a robust negative correlation between the two[85]. Thus, the key variable driving economic growth is the credit rather interest rates.

(6) The success of the German and East Asian economic model may be explained by looking at the direction of the purchasing power. These economies achieved a superior economic performance, namely, a high nominal GDP growth with a proportional low inflation without asset price cycles and maintaining financial stability because they concentrated the creation of credit on productive and sustainable investments and not on consumption and asset transactions.

(7) Last but not least, the ineffectiveness of supply-side reforms. As we know, "supply-side reforms" include deregulation, liberalization, privatization and thus act on the supply side of the economy. However, these structural reforms failed

[83] See Werner (1992, 1997).
[84] Werner (2012).
[85] See Werner (2005).

to stimulate the economy. This because the supply side has not been supported by the demand side. In other words, structural reforms may raise the potential growth rate, but if a lack of credit creation does not allow the demand side to expand, the economy will continue to grow below its potential. In this scenario, the more the potential growth rate is raised through supply-side reforms, the greater the deflationary pressure would be. This because nominal GDP growth is restricted by credit creation for GDP transactions[86].
Again, the ‘credit quantity equation’ shows clearly what said:

$$C_R V_R = P_R Y$$

By summarizing, in this last subsection of the first chapter devoted to the quantity theory of credit I reported the amendments that Werner applied to the quantity equation and the motivations that support the theory behind it. I will use empirically this theoretical framework in the third chapter when constructing the EWS for the prevention of banking crisis.

[86] See Werner (2012).

Chapter 2
DETECTING AND MEASURING FINANCIAL (IN)STABILITY

After defining the financial (in)stability concept through various definitions and viewpoints it's time to tackle the delicate issue of how to practically measure it. This is what the second chapter aim to do. It is essentially divided into two subsections.
Firstly, some analytical perspectives are going to be delineated. In the last decade several tools have been employed to measure financial instability depending on the way it is defined. Thus, the specific approach used for modelling financial crisis/episodes of financial stress lays the groundwork for the operational framework. Subsequently, a taxonomy of the main instruments *potentially usable* in the measurement process is offered.

2.1 MODELLING FINANCIAL INSTABILITY

In order to set up the operational framework for choosing the appropriate yardstick it has to be clear, before, the analytical approach which the operational framework refers to, namely, what we are going to measure. This because the analytical approaches, that vary considerably, have different and important implications for how to set up the yardstick.
For this purpose, I follow the working paper of Borio and Drehmann (2009). They try to explain the reasons why developing a satisfactory operational framework is still far away despite the numerous efforts made by economists and policymakers. The major challenge complicating this task is the *"fuzziness"* with which financial (in)stability can be measured. In addition, the authors argue that this fuzziness in measurement does not prevent further progress towards an operational framework, as long as it is appropriately accounted for.
Borio and Drehmann suggest to discriminate among approaches by using three dimensions, or rather, defining these according to the way financial instability is modelled. In this direction, the dimensions are defined in terms of whether financial crises/episodes of financial stress are seen as:

1) self-fulfilling or driven by "fundamentals";
2) the result of endogenous financial cycles or of exogenous negative "shocks" amplified by the system (the "endogenous cycle" versus "exogenous shock-amplification" views) and
3) reflecting mainly shocks to systematic risk factors or idiosyncratic shocks amplified through spillovers across the system.

(1) In the first case, as previously seen in the section dedicated to the banking crisis models, the distinction is between the type Diamond and Dybvig (1983) model, characterized by multiple equilibria (crisis occurs/crisis does not occur) and the unique equilibrium model type in which a crisis can occur only if the value of the assets falls below a certain threshold and thus driven by fundamentals or threats to solvency. In the first type, the panic is triggered by a casual and adverse event that give rise to a crisis. Under the second category, the root stands in the

depositors who make an analysis of the fundamentals and realize the bank's poor soundness.

The view of banking panics as a kind of random events self-confirming equilibria in settings with multiple equilibria seems quite common. To this first class of models, in which the causes of adverse events are the changes in agents' beliefs that are not related to the real economy, belongs the previously mentioned paper of Diamond and Dybvig (1983). In particular, the authors construct a two-period economy model assuming that consumers have at their disposal only two investment technologies: demand deposits and a two-period investment technology. While demand deposit contracts provide the improvement in terms of better risk sharing among people who need to consume at different random times, they have an undesirable equilibrium, a bank run, which causes real economic problem as even healthy banks can fail provoking a disruption in the loans and in productive investments. The investment technology provides low levels of output per unit of input if operated for a single period but high output levels if operated for two periods. In this framework, bank runs are triggered by sunspots: the depositors, losing the confidence in the bank's ability to pay back at the end of the second period, shift their expectations and immediately withdraw their money. Since the share set aside as reserve is not sufficient to cover all depositors' requests, banks become insolvent.

A more pragmatic and less mysterious view about the matrix of banking panics is the one of Bryant (1980). The pioneer model of banking crisis developed by this author shall be counted in the second category. In Bryant's seminal model bunk runs are triggered by aggregate loan risk and asymmetric information about loan payoffs. Bank's customers will realize that the intermediary's ability in paying back deposits decrease substantially owing to the rise of non-performing loans.

Another model in which bank runs are primed by real shocks to the economy is the Gary Gorton alternative, based on the hypothesis for which depositors receive a noisy signal about the value of bank assets. Panics are linked to some variable predicting the riskiness of bank deposits and occur when a specific threshold value of that variable is reached. Analyzing the US National Banking Era, the results suggest that panics come from depositors' reaction to changing perceptions of risk, due to the arrival of new information about a coming recession, rather than random events. The bottom line of Gorton's study is that bank panics are more likely to occur close to a business cycle peak with recessions on the horizon, because of depositors' concerns that loans do not get paid back.

Interesting is also the work of Chari and Jagannathan (1988). In their model the runs always come from withdraws triggered by new information about the bank, but here some other factors contribute to the panic. In fact, the onset of the panic due to information for which future returns are likely to be low is fueled by withdraws of uninformed individuals as well. Besides, some other clients, for reasons different from those based on new information, may need to withdraw their money. If this group of customers is unusually large then uninformed individuals are misled and as a large volume of withdraw imply liquidation costs, bank runs force social costs.

The solutions offered by the authors of both kinds of models are various. A quite shared response to bank runs is represented by deposit insurance. According to Diamond and Dybvig (1983), deposit insurance avoid runs by removing the incentive, for patient depositors, to join bank runs. Similarly, Bryant (1980) posit that deposit insurance removes incentives to collect costly information that is socially useless. Other solutions space from the suspension of convertibility for solvent banks combined with a sort of banks' assessment to verify their solvency to investor, up to clearing houses to facilitate interbank loans and the LLR. Even though these instruments reduced consistently the frequency of bank panics they still happen.

(2) The second dimension is crucial for laying down the basis of an operational framework: the dichotomy between the endogenous cycle and exogenous shock-amplification views of financial instability.
The former standpoint, belonging to an older intellectual tradition, is associated to the contributions of Minsky (1982) and Kindleberger (1996) illustrated in detail in the last section of the first chapter. Here, I would like to quickly recall that their "model" is fundamentally dynamic with the financial system itself playing a key role in generating what may appear as the exogenous "shock" triggering distress (e.g., a fall in asset prices from unsustainable levels).
The latter and more recent literature falls in the shock-amplification category. The supporters of these models assume a probability distribution for exogenous "shocks" that, given the rest of the structure of the economy, may result in financial distress if the realization is sufficiently negative (e.g., a bad harvest, a fall in productivity).
While there is abundance of economic models based on the exogenous shock-amplification view[87], no formal micro-founded model able to capture satisfactorily the endogenous cycle view of instability has as yet been developed.

(3) The third dimension is defined in terms of whether financial stress reflects shocks to systematic risk factors or idiosyncratic shocks amplified through spillovers across the system. The former are shocks that typically affect exposure that are common across institutions whereas the latter relate to the channel through which the crisis propagates. It is worth to say that in models that consider the financial sector as a unique entity, as it is common, no such distinction exists[88]. Among models that assume multiple intermediaries the first kind of shocks is claimed by approaches that underline a common deterioration due to shared exposures, such as by holding the same assets[89]. The second type of shocks is explained in model that focus on credit chains, payment and settlement system links or runs primed by the inability to distinguish solvent from insolvent institutions[90]. These approaches assume that the original deterioration takes place in a specific institution and then is transmitted elsewhere through ripple effects, as a result of the balance sheet/behavioural connections that keep the financial system together.

[87] See, for example, the model of Kiyotaki and Moore (1997) illustrated in the first chapter; and Bernanke et al (1999).
[88] This is the case of the Diamond and Dybvig (1985) "systemic" model.
[89] See for instance Cifuentes et al (2005), Allen and Gale (2004).
[90] See Kiyotaki and Moore (1997), Allen and Gale (2000b), Rochet and Tirole (1996a,b), Freixas and Parigi (1998), McAndrews and Roberds (1995), Aghion
et al (1999).

Some consideration may be extrapolated by the approaches illustrated above.
First, all of them suggest strengthening the robustness of the financial system to shocks.
Second, improving the information available to economic agents in order to limit the risk of unjustified contagion.
Third, ameliorate the so called and known "buffers" in the system.
Of course, all these actions may be carried out in several ways and depending on the details of the models. Here the aim is not to analyze these potential options since it is not the correct venue but simply to recall them.

2.2 MEASURING FINANCIAL INSTABILITY: A TAXONOMY

As seen above the definition of what we are going to measure is fundamental as well as necessary in order to use an appropriate yardstick. For example, from a practical standpoint, the approaches vary considerably in terms of their ability to measure the risk of financial stress in real time to the extent in which, analytically, crises are modelled as self-fulfilling, since the probability of stress is impossible to measure. By contrast, endogenous cycle models allow a concrete and, at least conceptually, an easier assessment of financial stress in the system.
The above explained approaches are different also for what concerns the importance assigned to various factors in that context, for instance between liquidity and solvency or interconnections in the financial system and direct plain exposures to systematic risk not related with those connections and so forth. Also, all these discrepancies entail divergences in terms of the most promising areas for policy actions.
Therefore, if we make a confrontation between the exogenous shock-propagation paradigms and the endogenous-cycle approach, the latter put more emphasis on the willingness of containing risk-taking in the expansion phase.
However, these policy aspects will be tackled in detail in the last chapter dedicated to the policy considerations.
Coming back to our measurement process, it is worth to say that the role of measurement is twofold as it is not only finalized at the mere role of "measuring" the instability in the system but also to designate the entities/institutions that should be responsible for the task itself.
This dual role performed by the measurement process imply that it requires two distinct measurement tools. On one hand, the authorities' responsibility in assuring the accomplishment of the task materializes by means of *ex post measurement* of financial instability. On the other hand, the support for implementing the chosen strategy to achieve the target in real time lean on *ex ante measurement*.
The former tool is aimed to assess whether financial instability prevailed or not *at some point in the past* whereas the latter evaluates whether the financial system is fragile or not *today*.
When dealing with ***ex post measurement*** difficulties may be more or less challenging depending on whether an event that may qualify as financial distress occurs or not during the relevant period.
Thus, two scenarios have to be taken into consideration:

- If this event happens the measurement difficulties are more manageable because policymakers, to claim that the system was not stable, should
  (a) recognize financial stress ex post; and

(b) finalize a judgement about the level of stress and recognize that it was much larger than the simple exogenous (and thus unavoidable) "shock". In other words, being able to understand that financial stress was the result of financial instability rather than extreme shocks.

- If such an event does not occur, ex post assessment is less manageable since it is quite hard to measure financial stress that actually has not materialized. The point here is that the system may actually be unstable (fragile) even if no financial distress has emerged. Given the sporadic nature of financial stress events (fortunately) and the length of the window during which the system can be fragile but does not experience crisis, judging whether and how the authorities are doing their task may prove tricky for quite a long time.

In both cases, as we have seen above, the assessment is not immediate and the room for fuzziness certainly does not lack.
For instance, even though financial stress does take place, one might ask how 'large' should be the losses among financial intermediaries and the associated costs for the real economy before the episode can qualify as one of 'financial distress'? Or, how large should the 'shock' be?
Again, how to discriminate between crisis prevention and crisis management?
For example, if the authorities intervene to manage the first signs of strain and thereby avoid the failure of institutions (e.g., through early recapitalizations or the issuance of guarantees), is that distress or its prevention?
For ex ante measurement the fuzziness is even more pronounced.
Possible questions may include: what would have happened had the system been hit by a shock? Or, in the endogenous cycle view of financial instability, were imbalances building up that simply happened not to unwind during the period?
All these questions will, hopefully, receive an answer in the last part dedicated to policy measure suggestions.
By contrast, ***ex ante measurement***, requires solutions much more demanding and ambitious than for accountability, for several reasons.
First, this tool is inevitable to the extent in which when the financial distress comes out the damage is already done. In this sense, requirements are particularly exigent when supporting discretionary measures for *preventive action*. Practically, this translates in measuring, in real time, the probability and cost of future events of stress *with a sufficient lead and confidence*. The measurement can be less exigent when serving for the calibration of *built-in* stabilizers, such as through the indexing of prudential tools. For example, it would be sufficient to link prudential measures to rough estimates of the financial cycle, based on some long-term averages.
Second, ex ante measurement aims to the development of leading tools rather than contemporaneous ones, namely, for *barometers* rather than *thermometers* of distress. But the utility of such instrument is its dual function: given the lead-lag relationships involved, such measures would also be good thermometers of financial instability. In this direction, the prominent challenge is the ***paradox of instability***, that is, the financial system can appear strongest precisely when it is most fragile. Thus, being able to recognize when the system is in this "status" would be a great breakthrough.

In designing a measurement tool, it is worth to specify that, unfortunately, we have to distinguish between what an ideal measure would be and what has been reached in

practice. This because the empirical models and instruments used so far are still far away, as a reliable solution, from what the problem requires.
Borio and Drehmann (2009) design this ideal measure of financial (in)stability *M* as some transformation of the output of a structural model[91] of the economy *f(.)* linking a set of variable *X* to policy tools *I* and exogenous shocks *u*. In symbols:

$$M \leftarrow f(X, I, u)$$

Such an ideal model would allow policymakers to run both ex post/ante measurements. In the former case, the recognition of instability in the system may be carried out by splitting the past into shocks and the endogenous response of the system.
In the latter case, the model may be used to generate the ex-ante probability distribution of outcomes, and hence of financial distress, by simulating the shocks or, alternatively, to generate scenarios (i.e. trace the behaviour of the system conditional on specific shocks).
By the way, as anticipated before, the reality falls well short of this ideal paradigm. Actually, it falls well short even of the less demanding field of monetary policymaking that represents the main source of inspiration for those working on financial stability[92]. In fact, while policymakers have models that link instruments to the goal (mixing inflation and output) and use them to make forecasts and carry out policy simulations[93], for analyzing the stability in the system there are no satisfactory models of the economy as a whole linking balance sheets in the financial sector to macroeconomic variables.

Before moving to an overview of the main indicators that are actually used at present in policy institutions and that could be potentially usable, I would like to recall the three dimensions that Borio and Drehmann (2009) mention in order to classify these tools:

1) Capability to deliver leading rather than contemporaneous measures of stress (barometers vs thermometers);
2) Ability to capture behavioural interactions that underlie episodes of financial distress (endogenous nature of aggregate of risk vs collective behaviour)[94];
3) Capability to "tell a story" about the transmission mechanism of financial stress (trade-off between granularity for policy evaluation or communication vs accuracy in measurement)[95].

2.2.1 Balance sheet vs Market Price Indicators

[91] The term structural model, as opposed to the reduced form, is often used to refer to models whose parameters do not change with respect to policy interventions (so called "deep parameters"), so that policy simulations can be properly carried out.
[92] See Goodhart (2006).
[93] See (Nelson (2008).
[94] Since its failure would imply underestimating the probability of financial distress.
[95] A typical example in econometrics are simple models, like autoregressive specifications, that may even outperform the true model of the data generating process in forecast performance (Clements and Hendry (1998) but they are not granular enough for policy evaluation/communication.

In illustrating the roundup of indicators I choose to follow the taxonomic structure of Borio and Drehmann (2009), thus starting from the simplest kind of indicator, i.e. statistics based on ***balance sheet items***. Most of the so-called "Financial Soundness Indicators" listed by the IMF fall in this category[96]. They include measures of banks' capitalization, non-performing loans (NPL), loan loss provisions (LLP), items of the balance sheets of households and corporations and so forth. In a typical build-up phase of crisis, ie when risk is taken on, profit tend to be high and provision low. However, the main drawback of these statistics is that, given their nature and the accounting rules which they are subject, taken alone they are not able to give predictive signals: they are thermometers rather than barometers. Therefore, given the backward nature of these balance sheet variables as well as income leverage variables, in order to serve as leading indicator, they need to be embedded in a "theory" of the dynamics of instability, such as the endogenous cycle view, that links them explicitly to future episodes of financial distress.

Next to the above indicators taken individually, ***indices*** that mix balance sheet variables into a single number to generate an index of stress have been developed. The main advantage of these indices is their capability to summarize more information into one indicator but at the same time they are not much see-through. To the risk of making confusion it must be added the above limitation given their construction.

One step ahead with respect to balance sheet variables may be done by considering ***ratings*** issued by credit rating agencies or by supervisory authorities constructed on more confidential information. Since these indicators are essentially estimates of the likelihood of default or expected loss of single institutions taken in isolation they have the indices' advantage of combining more information into a single indicator and, above all, they are (should be) forward-looking. By contrast, they are not free from limits. The principal is that they concern individual institutions and fail to capture the second dimension, ie common exposures and behavioural interactions among participants in the system. In addition, their reliability is quite questionable mainly because of their (in)ability to function as truly leading indicators of financial stress. This is especially true for credit agencies' rating and especially after the latest financial crisis where downgrades seemed to be rather "sticky" thus not reflecting the arrival of new information. Reporting the expression of Borio and Drehmann (2009) such ratings seek to be "through-the-cycle" rather than "point-in-time" estimates of default as they filter out the influence of the business cycle and resulting better in evaluating the structural and idiosyncratic determinants of default than its evolution over time.

Other options or possibilities to the balance sheet statistics and their variants are indicators of financial distress based on ***market prices***. Again, within this category there are several variations. For instance, if we consider raw indicators such as volatilities and quality spreads, these may be employed singularly or in combination with poor or no theoretical restrictions.

However, wishing to be more demanding, one could rely on pricing models based on specific assumptions and constructed using as inputs prices of fixed income securities and equities in order to derive estimates of probabilities of default or expected losses for individual institutions and sectors. A typical example is expected default frequencies (EDFs), namely, probabilities of default obtainable from equity prices recalling the

[96] See IMF (2008).

Merton's scheme[97], according which equity can be seen as a call on the firm's assets just as its debt is a put on them. Again, these individual inputs can be aggregated, based on some estimates of correlations across the firms' assets in order to obtain a measure of stress for the corresponding sector.
Valuing the pro and cons of such indicators we can say that they have multiple benefits but also some drawbacks. On the benefit hand side, they are forward-looking and point-in-time measures of risk due to their ability of incorporating all the information available to market participants at a particular point in time. In addition, given their nature, they also implicitly embed views about any common exposures and interactions that may exist within the sector covered and are available at high frequencies.
By contrast, the main disadvantage is their potentially narrow coverage depending on the specific features of the entities involved. This because market prices are not available for all market participants as few institutions may be publicly quoted. Moreover, the market nature of such indicators entails the problem of the risk premium. In more detail, it is important to discriminate between the market's view of future cash flows and the price it assigns to them, namely, the risk premium. Since the target is to identify future distress, rather than measuring the current conditions (price linked to this stress) the influence of the risk premium should be filtered out. The point is that any biases in the market's assessment would be embedded in the estimates. This would translate in estimates of risk derived from market prices unusually low as vulnerabilities build up serving as contemporaneous indicators of stress rather than leading.
Last but not least a practical shortcoming. Empirical evidence seems to confirm that the lead with which market prices suggest financial stress is uncomfortably short for policy actions. For instance, unusually low volatilities and narrow spreads prevailed across a broad spectrum of asset classes until the turmoil started in the summer of 2007, when they then rose sharply[98].

2.2.2 Early Warning Indicators (EWIs)

Another class of indicators that offer plenty of choice is represented by the so-called ***early warning indicators***. They are intended to overcome the limits seen above for the previous statistics. In fact, they are designed to identify episodes of financial distress in advance.
Essentially, two main methodologies have been employed in the empirical studies of the Early Warning Systems for different kinds of crises: signaling and discrete-choice approaches. However, in addition to these two classical methods, some other approaches have been used in the literature. To illustrate them, I take advantage of the contribution of M. Chui and P. Gai and Frankel and Saravelos (2010)[99].

A. *The Signalling Approach*

Following a chronological order, the "signals" approach, which essentially optimizes the signal to noise ratio for the various potential indicators of crisis, is the first adopted. Pioneers of this approach are the work of Kaminsky and Reinhart (1996) and Kaminsky, Lizondo and Reinhart (1998) (from now on KLR).
Kaminsky and Reinhart (1996) lays the groundwork for the subsequent "signal approach" in KLR. By focusing primarily on the link between banking crisis and balance of payment

[97] See Merton (1974).
[98] See BIS (2007).
[99] See M. Chui and P. Gai (2005). In their book there is an entire section devoted to early warning models and their evaluation.

crisis, analyze the behaviour of several macroeconomic variables in months before and after the crisis. The authors employ a methodology developed for predicting the turning points of business cycles in order to identify variables that act as "early warning signals" for crises. As a result, a loss of foreign exchange reserves, high real interest rates, low GDP growth and a decline in stock prices seem to be the best signals.

The seminal paper is the work of KLR, which examines the empirical evidence on currency crisis and proposes a specific early warning system. Their "signal approach", that still remains a reference point, consists in monitoring the evolution of various economic variables and issuing a signal when one of these variable deviates from its normal level beyond a certain level, functioning as threshold. For each indicator a country-specific threshold is defined according to the percentiles of the distribution of that indicator. Important is the arbitrarily chosen signaling horizon within which a crisis may follow or not a signal (depending on it is a god or bad signal).

The signaling approach gets a direct measure of the importance of each candidate explanatory variable by imputing a one (for crisis) or a zero (no crisis) signal from each explanatory variable at each point in time in the sample. This is carried out by two steps. First, the creation of an index. In the KLR case an exchange rate pressure index is defined as a weighted average[100] between the changes in the nominal exchange rate and that in the stock of foreign exchange reserves:

$$erpi = \frac{\Delta e}{e} - \frac{\sigma_e}{\sigma_r} * \frac{\Delta r}{r}$$

Or, for country *i* at time *t*, the ERPI_{it} is expressed as:

$$\text{ERPI}_{it} = \frac{e_{it} - e_{it-j}}{e_{it-j}} - \frac{s_{e_i}}{s_{r_i}} * \frac{r_{it} - r_{it-j}}{r_{it-j}}$$

where:

e_{it} = nominal exchange rate of country i's currency against the U.S. dollar at time t;

r_{it} = stock of foreign exchange reserves held by country i at time t;

j = *n* of months on which the percentage change is computed;

$s_{e_i} and\ s_{r_i}$ = standard deviations of the nominal exchange rate and the stock of foreign exchange reserves, respectively.

Second, the ERPI_{it} is converted into the binary variable c_{it} and a crisis hitting country *i* at time *t*, is defined by a simple rule, namely, whenever *ERPI* exceeds its sample mean by an arbitrarily chosen number η of its sample standard deviations:

$$c_{it} = \begin{cases} 1\,, if\ \text{ERPI}_{it} > \overline{\text{ERPI}_\iota} + \eta\sigma_{\text{ERPI}_i} \\ 0\,, \qquad\qquad\qquad\qquad otherwise \end{cases}$$

where:

$\overline{\text{ERPI}_\iota}$ = (country–specific) mean of the exchange rate pressure index;

σ_{ERPI_i} = standard deviation of the index.

[100] In such a case the weights are chosen as the sample standard deviations of the two components.

A quantitative assessment of the value of the variable as a crisis indicator is carried out by signal-to-noise ratios computed for each explanatory variable over the whole sample period. This is the ratio of the success rate of crisis predictions relative to the false alarm rate (good vs bad signal or 'noise').
In symbols, assuming a signaling horizon of twenty-four months, the following matrix is used to define the above ratio:

	Crisis (within 24-months)	**No Crisis** (within 24-months)
Signal was issued	A	B
No signal was issued	C	D

The noise-to-signal ratio is the ratio of the portion of bad signals or false alarm to the portion of good signals, namely:

$$Noise - to - signal\ ratio = \frac{B}{B+D} \Big/ \frac{A}{A+C}$$

Where:
A = *n* of months in which the indicator gives a good signal;
B = *n* of months in which the indicator gives 'a noise';
C = *n* of months in which the indicator fails to give a signal, that would have been good;
D = *n* of months in which the indicator did not give a signal that would have been bad.

Finally, two kind of error may occur:

1) share of ***type I errors*** (event occurring but no signal issued as a share of A + C, that is, $\frac{C}{A+C}$) or simply the share of missed crisis;
2) share of ***type II errors*** (event not occurring but signal issued as share of B + D, that is $\frac{B}{B+D}$) or simply the share of false alarms.

The variable/indicator is 'useful' if the NtS ratio is less than one. A value of one means that the indicator provides purely random signals.

Berg and Pattillo (1999a) and Edison (2000) re-estimate the KLR results with revised data while further investigating this method. In particular, Berg and Patillo (1999) by using Kaminsky *et al.*'s (1998) signal approach develop a forecast for the 1997 Asian currency crisis and show that out-of-sample performance from KLR approach is not superior to a simple probit-based model.

The other major representative of the above approach are Kaminsky and Reinhart (1999), which apply it not only to currency but also to banking crisis in parallel. I particular, in their influential and widely-cited study on the twin crises they first compute the conditional and then the unconditional probabilities of crisis and found that, actually, problems in the banking sector normally precede a currency crisis, and a currency crisis, in turn, could increase the risk of a banking crisis.
Another contribution that deserves to be mentioned when dealing with the signaling extraction approach is the work of Reinhart (1999). The author, in order to assess the

overall probability of an incumbent crisis, put together the information provided by all the indicators of the economy. In practice, Kaminsky computes a composite index for each country and at a particular point in time that offers information on the vulnerability of that country at that time. To get this scope one way could be to count the number of signal issued by the different indicators at a certain point in time and, the larger the number of signal, the higher the probability of a crisis. This is a simple equally-weighted aggregation in which all the indicators are equally important in predicting a crisis. To account for the divergences in indicator performances, Kaminsky suggests a different weighting scheme.
In more detail, the composite index, I_t, for each country at time *t*, is a weighted average of the number of indicators which issue a signal. In symbol:

$$I_t = \sum_{j=1}^{n} S_t^j / \omega^j,$$

where,
$S_t^j = 1$, if indicator *j* issues a signal at time *t*;
n = total number of indicators;
ω^j = NtS ratio of indicator *j*.

These composite indices aggregated with both the equally-weighted and NtS ratio weights give information on a country's evolution in terms of vulnerability: by looking at the indices' series, in the time-period analyzed, we can say if a country become more/less vulnerable. In addition, this index variant of the signal approach allows the calculation of the probability of a future crisis. In particular, the probability that a crisis is going to occur within *h* months from *t*, conditional on the fact that the index stays between a specific range of values, is expressed as:

$$P\left(crisis_{t,t+h} \middle| \underline{I} < I_t < \overline{I}\right) = \frac{n.of\ months\ with\ a\ crisis\ occurring\ between\ t, t+h\ given\ \underline{I} < I_t < \overline{I}}{n.of\ months\ with\ \underline{I} < I_t < \overline{I}}.$$

Particularly interesting among the signaling approaches is the paper of Borio and Lowe (2002). The authors constructed aggregated indexes with the aim of identifing financial imbalances ex ante. In particular, their aggregated indexes, composed by asset prices, credit and investment variables, would trigger a crisis signal only if all the variables included in the composition crossed their thresholds simultaneously. Their results suggest that a sustained rapid credit growth combined with large raises in asset prices seems to increase the likelihood of a financial instability episode. In particular, they emphasize the role of monetary policy in maintaining financial stability and hold that while low and stable inflation promotes financial stability it also creates the presuppositions for a typical build-up phase of a crisis to the extent in which it raises the probability that excess demand pressures flow mainly into credit aggregates and asset prices rather than in goods and services prices.
Similarly, Davis and Karim (2008) construct composite indicators, again, with the aim of put together several variables on the basis of their individual NtS ratio. The main and not

negligible difference is that they allow composite indexes to issue a signal without necessarily that all its components surpassed their cut-off.

B. The Discrete-Choice approach

The relatively more recent-used and maybe popular approach consists in using probit or logit models. These models are also called parametric (i.e. regression-based) approaches. The main difference between parametric and non-parametric approaches (i.e. crisis signal extraction) is that while the latter aims to extract a 'crisis signal' from each individual indicator, the former evaluate directly the condition probability of a crisis, given a group of indicators. The idea underlying this approach consists in splitting different countries and time periods in two discrete episodes: a crisis and a tranquil period. The choice of indicators is suggested by the theory *a priori*. Then, the selected set of indicators is mapped into a known probability distribution of these episodes such that it is possible to evaluate the likelihood of a crisis by using Logit/Probit methods. Before deepening these models, it is worth to say that they are employed with the aim to overcame the limitations of the much more simple to estimate and use Linear Probability Model (LPM)[101]. In fact, Logit/Probit models are more sophisticated ***binary response models*** primarily interested in the ***response probability***

$$P(y = 1|\boldsymbol{x}) = P(y = 1|x_1, x_2, \dots, x_k),$$

where:

y = crisis variable assuming a value of either 1 or 0 if a crisis occurs or does not occur, respectively;

$\boldsymbol{x}$ = full set of explanatory variables.

Broadly speaking, Logit and Probit are two kinds of models that fall into the general class of binary response models which take the following form

$$P(y = 1|\boldsymbol{x}) = G\ (\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k) = G(\beta_0 + \boldsymbol{x\beta}),$$

where:

$G(\cdot)$ = a cumulative distribution function (cdf) taking on values strictly between zero and one, that is, $0 < G(z) < 1$ for all real numbers *z*;

$\boldsymbol{\beta}$ = a vector of parameters;

$\boldsymbol{x\beta} = \beta_1 x_1 + \ldots + \beta_k x_k$.

From the above general definition it is easy to achieve Logit/Probit models by substituting the specific function $G(\cdot)$.

In more detail, to get a ***logit model***, $G(\cdot)$ must be the cumulative distribution function for a standard logistic random variable. This logistic function, which is between zero and one for all real number *z*, is expressed as follows:

$$G(z) = exp(z)/[1 + exp(z)] = \Lambda(z)$$

Thus, by substituting:

[101] The two most important drawbacks LPM are that the fitted probabilities can be < 0 or > 1 and the partial effect of any explanatory variable (appearing in level form) is constant. For a more detailed description see "Introductory Econometrics: A Modern Approach, 4th Edition", section 7.5.

$$P(y = 1|\boldsymbol{x}) = exp(\boldsymbol{x\beta})/[1 + exp(\boldsymbol{x\beta})].$$

In the ***probit model***, $G(\cdot)$ is the standard normal cumulative distribution function, expressed as the following integral:

$$G(z) = \Phi(z) \equiv \int_{-\infty}^{z} \phi(v)dv,$$

where $\phi(z)$ is the standard normal density

$$\phi(z) = (2\pi)^{-\frac{1}{2}} exp(-z^2/2).$$

The function $G(\cdot)$ is an increasing function in both logit and probit models. In addition, both cdf, $\Lambda(z)$ and $\Phi(z)$, increase most quickly at $z = 0$. Moreover, $G(z) \rightarrow 0$ as $z \rightarrow -\infty$, and $G(z) \rightarrow 1$ as $z \rightarrow \infty$.

The decision about using logit or probit (normal distribution) is essentially arbitrarily given that the two distribution are quite similar. In fact, the shape of the standard normal cdf is very similar to that of the logistic cdf.

I would like to conclude this digression on Logit/Probit models by spending a few words on the parameter vector $\boldsymbol{\beta}$.
While ordinary least squares and weighted least squares may be used to estimate the LPM, they are not applicable in nonlinear cases due to the nonlinear nature of $E(y|\boldsymbol{x})$.
In such cases **the maximum likelihood estimation** (MLE) in a valid solution. Here the estimator will not be shown in detail as it is not the primary goal but some important features concerning logit and probit models are delineated[102].
As said above, for estimating limited dependent variable models (**LDV**), that is, models treating a dependent variable whose range of values is substantially restricted (a binary variable is an example), maximum likelihood methods are needful.
In order to obtain this estimator, since it is based on the distribution of y given $\boldsymbol{x}$, the density of y_i given $\boldsymbol{x}_i$ is necessary. In symbol, by including the intercept into the vector $\boldsymbol{x}_i$:

$$f(y|\boldsymbol{x}_i;\boldsymbol{\beta}) = [G(\boldsymbol{x}_i\boldsymbol{\beta})]^y\,[1 - G(\boldsymbol{x}_i\boldsymbol{\beta})]^{1-y}\,, y = 0, 1.$$

It is clear that when $y = 0$, we get $1 - G(\boldsymbol{x}_i\boldsymbol{\beta})$, whereas when $y = 1$, we get $G(\boldsymbol{x}_i\boldsymbol{\beta})$.
The ***log-likelihood function*** is obtained by taking the natural logarithm of the above function:

$$\ell_i(\boldsymbol{\beta}) = y_i log[G(\boldsymbol{x}_i\boldsymbol{\beta})] + (1 - y_i) log[1 - G(\boldsymbol{x}_i\boldsymbol{\beta})],$$

where,
$\ell_i(\boldsymbol{\beta})$ = log-likelihood function for observation *i* and is a function of the parameters and the data $(\boldsymbol{x}_i y_i)$;

[102] For a deepening see the appendix.

$G(\cdot)$ = strictly between zero and one for logit and probit, thus $\ell_i(\boldsymbol{\beta})$ is well defined for all values of $\boldsymbol{\beta}$.

Assuming a sample size of *n* the log-likelihood is the summation of the above function across all observations:

$\mathcal{L}(\boldsymbol{\beta}) = \sum_{i=1}^{n} \ell_i(\boldsymbol{\beta})$.

Finally, the MLE of the vector parameter $\boldsymbol{\beta}$, denoted $\widehat{\boldsymbol{\beta}}$, is the one that maximizes the log-likelihood. Again, the *logit estimator* is the $\widehat{\boldsymbol{\beta}}$ in which $G(\cdot)$ is the standard logit cdf whereas if the $G(\cdot)$ is the standard normal cdf, then $\widehat{\boldsymbol{\beta}}$ is the *probit estimator*.

The first studies adopting this approach as mentioned in the first chapter[103] are Eichengreen, Rose and Wypslosz (1996), Frankel and Rose (1996), and Kumar *et al.* (1998) regarding currency crises, and Demirguc-Kunt and Detragiache (1998) for banking crises.

Eichengreen, Rose and Wypslosz (1995) analyze the contagious nature of currency crises empirically. In particular, they estimate a binary probit model linking the dependent variable (taking on a value of one for a speculative attack and zero otherwise) to their controls with maximum likelihood, including additional regressors to capture the effects of macroeconomic and political influences that affect crisis incidence. By relying on thirty years of panel data from twenty industrialized countries, they find evidence of contagion more pronounced and spread to countries that are closely linked by international trade connections than to countries in similar macroeconomic circumstances.

Frankel and Rose (1996) retrace the work of Eichengreen *et al.* (1996) and estimate probit models linking their binary crash measure to several variables (mainly debt-related variables, external variables, domestic macroeconomic variables). In more detail they use a multivariate model to employ all variables simultaneously and pool all the available data across both countries and time periods and estimate probit models using maximum likelihood. By using a panel of annual data for over one hundred developing countries from 1971 through 1992 they found that a low FDI-to-debt ratio is consistently associated with a high probability of a crash.

Kumar et al. (1998) employ binomial logit models to predict again currency crashes. Their results seem in favor of the use of a binomial discrete dependent variable approach to forecast financial crises.

The work of Demirguc-Kunt and Detragiache (1998) and their evidence about the negative impact of financial liberalization are already explained in the first chapter. Here I would like to stress their methodology: they estimate the probability of a banking crisis using a *multivariate logit model*, and test the hypothesis that the dummy variable capturing whether the financial system is liberalized or not significantly increases the probability of a crisis when other factors are controlled for.

One step ahead with respect to binomial logit/probit models in order to introduce a third possible outcome in the regression, beyond the classical tranquil and crisis status is the ***multinomial logit/probit*** approach. It still belongs to the family of the limited dependent variable models but differently from its binary version it allows for more than two outcomes.

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[103] See "Theoretical and empirical framework on Currency and Sudden Stop Crisis".

Let us assume that there are *j* possible outcomes in the data. Then, the dependent variable *y* can take *j* values, e.g. 0,1,…,j-1.
In our context, we are modelling crisis status and by considering the *post crisis bias*[104] hypothesis, *j* may assume three possible outcomes, that is:

- $j = 0$, for tranquil periods;
- $j = 1$, for crisis times;
- $j = 2$, for post-crisis years.

With the above status, the ***multinomial logit model*** is expressed as follows:

$$P(y = j|\boldsymbol{x}) = exp(\boldsymbol{x}\beta_J)/[1 + exp(\boldsymbol{x}\beta_1) + exp(\boldsymbol{x}\beta_2)],$$

where,
$\boldsymbol{x}$ = usual vector of explanatory variables (regressors).

By adopting the calm period $(y = 0)$ as the control group, the vector of coefficients β_1 will represent the marginal effect of the independent variables $\boldsymbol{x}$ on the likelihood of being in crisis period relative to the probability of being in a tranquil period whereas β_2 will represent the marginal effect of $\boldsymbol{x}$ on the probability of being in a post-crisis period relative to the likelihood of being in a tranquil period. Thus, in symbol:

$$P(y = 1|\boldsymbol{x}) = exp(\boldsymbol{x}\beta_1)/[1 + exp(\boldsymbol{x}\beta_1) + exp(\boldsymbol{x}\beta_2)],$$

$$P(y = 2|\boldsymbol{x}) = exp(\boldsymbol{x}\beta_2)/[1 + exp(\boldsymbol{x}\beta_1) + exp(\boldsymbol{x}\beta_2)],$$

Finally,

$$P(y = 0|\boldsymbol{x}) = 1 - P(y = 1|\boldsymbol{x}) - P(y = 2|\boldsymbol{x}) = 1/[1 + exp(\boldsymbol{x}\beta_1) + exp(\boldsymbol{x}\beta_2)].$$

Consequently, the relative probabilities are simplified in following way:

$$\frac{P(y = 1|\boldsymbol{x})}{P(y = 0|\boldsymbol{x})} = \exp(\boldsymbol{x}\beta_1)$$

And,

$$\frac{P(y = 2|\boldsymbol{x})}{P(y = 0|\boldsymbol{x})} = \exp(\boldsymbol{x}\beta_2).$$

As for the binomial model, the maximum likelihood estimator (MLE) keeps on being valid for the multinomial as well, given their common non-linear features. The main difference which makes interpretation of the coefficients more difficult than for binary choice models is that now there are two parameter vectors, β_1 and β_2.

The authors that adopted for the first time the multinomial logit approach described above are Hardy and Pazarbașioĝlu (1999). Even though they were keen to prepare the ground for what would have solved the *post-crisis bias*, their contribution on the prediction of banking crises still represents the very first attempt to introduce a third possible outcome in the regression, beyond the classical (0,1) status supported by the binomial approach.

[104] It will be explained later in this section of this second chapter when some conclusion about the pros and cons of the examined techniques will be drawn.

In particular, their research complements the one of Demirguc-Kunt and Detragiache seeking to outweigh their major critical points, in particular:

- the poor usefulness of their findings in predicting crisis in advance;
- the focus on coincident indicators that does not allow to identify turning points, i.e., dynamic features of the lead-up to banking crises;
- inability of discriminating between tranquil periods and what Minsky would define the build-up phase of a crisis, namely, periods in which banking sector difficulties may be incubating but have not yet reached crisis levels;
- differentiating by region or severity of banking crisis, by contrast to their common methodology applied to the full sample.

C. *Analyzing variables' behaviour around crisis occurrence*

This third category represents a technique which consists in employing a qualitative and quantitative analysis of the behaviour of several variables around the occurrence of a crisis event. In particular, the countries sample is split into two groups, the crisis and non-crisis control group and the variables, that are going to be analyzed may be either chosen by the literature or by mean of a specific technique. This kind of event analysis approach, unlike the more recent literature, consist of panel studies in which the focus is on trying to predict the date at which a crisis happens, rather than on the cross-sectional incidence of crisis.
These techniques are predominantly used in the earlier literature of leading indicators by Kamin (1988), Edwards (1989), Edwards and Montiel (1989), Edwards and Santaella (1993) which use some of the largest samples.

D. Innovative approaches

The last class of techniques is the more recent used in early warning contributions. As in the previous subsections, there are several examples but the most important may be grouped into three techniques: binary recursive trees, artificial neural networks and genetic algorithms and Markov switching models.
Following the chronological order in which these techniques have been employed, I would start with Markov-switching models and then move to examine the two mostly used Artificial Intelligence Techniques (AIT).
Indeed, ***Regime switching models*** have a pretty old root. Early work on these models date back to Quandt (1958), Goldfeld and Quandt (1973) and Hamilton (1990). Nevertheless, this tool becomes common in applications only during the 90's with the enhancing of computers technology. Markov-switching models with constant transition probabilities are employed in several contributions, such as, to interest rates and subsequently to analyze GNP (Hamilton 1988, 1989), to stock returns (Cecchetti, Lam and Mark 1990) and to floating exchange rates (Engel and Hamilton 1990). However, these earlier models suffer from an important limitation, that is, the restriction of constant transition probabilities. Later, Lee (1991) and Diebold et al. (1994) extended the baseline model to allow for time-varying transition probabilities and use it in modelling swings in the dollar-pound rate. Next, Filardo (1993, 1994) analyzes business cycles.
Coming back to the EWMs, the first authors that employ this technique for crisis studies are Cerra and Saxena (2001) and Martinez-Peria (2002). Indeed, before them, Jeanne and Masson (1998) and Fratzscher (1999) develop currency crisis models in which multiple

equilibria are possible and switches between these equilibria are modeled by a Markov-switching variable. The limitation is that in both contributions the likelihood of switching from one equilibrium to another is constant.
Cerra and Saxena (2001) use a Markov-switching model with time-varying probabilities to empirically model currency crises. The authors investigate whether the 1997 Indonesian crisis is due to domestic fundamentals, common external shocks ("monsoons") or contagion from neighboring countries. In particular, to endogenize the probability of a crisis in Indonesia, measured by a done-on purpose Market Pressure Index (MPI) gauging exchange rate pressure (high when there is pressure on the currency and low otherwise), they first set the fixed transition probability model (FTP) and then estimate a time-varying transition probability model (TVTP). In more detail, the fixed transition probability Markov-switching model (FTP) MSM estimates the switch, on average, of the Indonesia MPI in the two states (pressure-crisis/no pressure-no crisis). The model is composed by a measurement equation with mean switching and fixed transition probabilities, as follows:

$$MPI_t - \mu_{s_t} = \phi\left[MPI_{t-1} - \mu_{s_{t-1}}\right] + \sum_{i=1}^{3} \beta_i F_{i,t-1} + e_t;$$

$$\mu_{s_t} = (1 - s_t)\mu_0 + s_t\mu_1;$$

$$Pr(s_t = 0/s_{t-1} = 0) = q, \qquad Pr(s_t = 1/s_{t-1} = 1) = p.$$

Where:
MPI ~ AR(1) process with two means (μ_0 for low pressure and μ_1 for high pressure);
F_i = predetermined fundamental variables pointed out by the previously run OLS;
p = probability of remaining in a crisis state between t-1 and t;
q = probability of remaining in a non-crisis state between t-1 and t;
s_t = unobserved state.

Subsequently, the authors estimate a time-varying transition probability (TVTP) Markov-switching model in order to check if, after controlling for the fundamentals, pressures in the Indonesian exchange market could be explained by movements in MPIs of Thailand and Korea. In this second model, the likelihood of a crisis in Indonesia switches between high and low states according to one period lags of the MPIs of Thailand and Korea. Thus, the transition probabilities are expressed as follows:

$$Pr(s_t = 1/s_{t-1} = 1) = p_t = \frac{\exp\left[p_0 + p_1 MPI_{j,t-1} + p_2 MPI_{k,t-1}\right]}{\left(1 + exp\left[p_0 + p_1 MPI_{j,t-1} + p_2 MPI_{k,t-1}\right]\right)};$$

$$Pr(s_t = 0/s_{t-1} = 0) = q_t = \frac{\exp\left[q_0 + q_1 MPI_{j,t-1} + q_2 MPI_{k,t-1}\right]}{\left(1 + exp\left[q_0 + q_1 MPI_{j,t-1} + q_2 MPI_{k,t-1}\right]\right)}.$$

Here, $MPI_{j,t-1}$ and $MPI_{k,t-1}$ are the lagged MPI for Thailand and Korea, and p and q are changing over time in response to movements in these MPIs. Their results show that when MPIs of neighboring countries are accounted for, there is much more variation in the estimated probabilities and that crisis are caught with greater accuracy in a TVTP and without delays. In addition, they also test for contagion in stock market by estimating similar FTP and TVTP models for changes in Indonesia's stock market index. Again, stock market changes in Thailand and Korea helped predict stock market movements in Indonesia.

The contribution of Martinez-Peria (2002) is closely related, from a methodological viewpoint, to the work examined above. She also estimates a Markov-switching model with time-varying probabilities but to model speculative attacks on the EMS over the period 1979-1993. The author evaluates the extent in which five specific variables (domestic credit growth, import-export ratio, unemployment rate, fiscal deficit and interest rates) determined crisis vulnerability in the EMS. Her results in assessing the ability of the Markov-switching model to capture crisis episodes are quite encouraging: the method turns out to be able to identify all the crisis episodes identified previously by Eichengreen et al. (1995) with their binary probit model.

Another important paper for the development of EWSs using the Markov-switching technique, among the first studies, is the contribution of Abiad (2003). The author extends the work of Martinez-Peria (2002) in several aspects. First, he employs the model primarily as an early-warning system by including a larger set of indicators and assessing the model's predictive ability both in sample an out-of-sample. In addition, unlike Martinez-Peria (2002) that assumes the model's parameter to be uniform across countries, he finds that different indicators matter for different countries and the parameter constancy assumption gives a poor performance.

Binary recursive trees are typically used to determine leading indicator crisis thresholds. The authors that first employ this technique are Ghosh and Ghosh (2002) and Frankel and Wei (2004).

Ghosh and Ghosh (2002) try to identify structural determinants of currency crisis by examining the role of corporate sector vulnerabilities in currency crisis using a panel dataset covering a mix of 40 advanced and emerging economies over the 1987-1999 period. The methodological innovation of their work is the usage of the ***Binary Recursive Tree*** (BRT). This is a decision-theoretic classification technique particularly suited to situations characterized by threshold effects and non-linear relationships between the explanatory variables. In particular, a binary classification tree is a partitioning algorithm that identifies the indicators and the respective thresholds in a recursive manner. These indicators and threshold are chosen such as to generate the best division of the sample in the relevant classes, for instance pre-crisis and calm periods. Formally, it is a sequence of rules for predicting a binary variable, *y*, given a vector of explanatory variables, x_j , $j = 1, \dots, J$. The tree structure consists of one *root node* and just two (hence "binary") branches leaving each *parent node*, entering in a *child node* and multiple *terminal nodes* (or "leaves"). The splitting is repeated along the various sub-branches until a terminal node is reached. In their specific work, *y* is the binary variable (1,0) for crisis and otherwise, respectively and $\hat{x}_j$ represents some of the threshold value of one of the explanatory variables into two sub-branches. The sample is randomly divided in a "core" sample and a smaller test sample. The latter is used for out-of-sample robustness check whereas for the former the algorithm looks for sequential splits, each consisting of the explanatory variable and the relative threshold that best differentiate between crisis/no crisis group. The discrimination between crisis and non-crisis countries is carried out by minimizing the sum of the two kind of errors. Indeed, for each explanatory variable, the algorithm keep on searching over its observed values in the sample until the threshold value, x_j, that minimizes the sum of type I and type II errors is found. The root node is represented by the variable (and its associated threshold x_j) with the lowest error score[105]. Observations with explanatory variable level (in their case a current account deficit) lower than $\hat{x}_j$ fall in the left sub-branch of the tree whereas the ones with a current account deficit higher than $\hat{x}_j$ fall in the right side. This process could be repeated, at least in principle, until each observation has been placed into each own branch. Since this would be equivalent to include as many explanatory variables as observations in a standard regression, some termination rule is required. This because there is a trade-off in extending the number of branches between the improvement of fit and parsimony. After the split the improvement is balanced with a "branch" penalty and if the penalty is larger than the improvement the branch is terminated in the previous node.

Frankel and Wei (2004), in their work on crisis prevention and management, try out different methodologies, among which the regression tree analysis, to discern determinants of economic performance. By using a large dataset including the most visible crises of the 1994-2002 period (Mexico, Thailand, Korea, Indonesia, Malaysia, Russia, Brazil, Turkey, and Argentina) the authors, first, run a simple probit analysis to verify if the variables suggested in the literature are able to predict the increased likelihood of a currency crisis on an annual basis. Then, a regression tree analysis is carried out in order to make the data choosing freely which variables matter the most. Finally, they apply the conventional regression analysis to a cross-section of countries to explain the performance during the most recent decade (taken to be 1990-2002, which includes both the boom and bust phase).

Artificial neural networks (ANNs) and *genetic algorithms* (GA) have been employed in the economics literature since the beginning of 1990th and mainly in two kind of applications: economic agents' classification and time series prediction.
For instance, in one of the earliest studies, Bell et al. (1990), employ a back-propagation neural network (BPN) technique along with eleven predictor variables to establish whether selected banks are bankrupt or not. Besides, by comparing the performance of a logit model with the one of an ANN, they find that the latter is better than the former in determining marginally distressed banks.
However, the first studies that employ the ANN and GA techniques to create an EWM are the contributions of Nag and Mitra (1999) and Apoteker and Barthelemy (2000).

Nag and Mitra (1999) use ANNs to set an early warning system, based on sixteen variables, with the aim of capturing exchange rate crisis in Indonesia, Malasia and Tayland over the 1980-1998 period. In addition, they compare the results with those of the signal approach. In their comparison, they find that ANN model has a superior

[105] Robustness check is carried out by applying the threshold value for each variable to the test sample returning a second error score.

forecast ability than the KLR (Kaminsky, Lisondo and Reinhart) model, particularly on comparing out-of-sample predictions[106].

Apoteker and Barthelemy (2000), instead, try to understand and quantify country risk levels though another Artificial Intelligence Techniques (AIT)[107], that is, Genetic Algorithm (GA). In their model, that is based on the evaluation of five "fundamental balance" charts[108], a genetic algorithm is employed to identify quadrants in the balance charts that are most associated with four kind of crises: transfer crises, liquidity crises, exchange rate crises and cyclical development crises. In particular, the authors create a tool/indicator, called Vulnerability, measured as a distance to an optimal combination computed as a risky pattern by a genetic algorithm and regularly updated with new official data. The GA generates a set of conditions associated with crises and Vulnerability is gauged by how many of these conditions are satisfied at a given point in time.

As seen above ANNs and GAs are both part of the AITs. For a detailed description please refer to the paper mentioned above. Here, instead, the aim is to offer a basic understanding of the two techniques as made for the previous one.
Artificial neural networks (ANNs) are a kind of statistical learning algorithm that looks like biological neural networks that, as stated by Graupe (2007), consists of neurons (called nerve cells) and are used to estimate functions that may depend on a large number of generally unknown inputs. ANN resembles the brain in two aspects:

- knowledge is acquired by the network through a learning process; and
- knowledge is stored by using the "synaptic weights", i.e., interneuron connection strengths.

ANN model uses nonlinear function approximation tools that test the relationship between independent (explanatory) and dependent (to be explained) factors. In more detail, the model involves a group of artificial neurons that "communicate" among them through the connectionist approach, namely, the network units are connected by a flow of information. According to the specific way the information flows through the network during the learning phase (external vs internal information), the structure of the model changes. A message is transferred from one neuron to the other in a simple way: as soon as a neuron receives signals equal to or higher than their threshold values it triggers sending an electric signal of constant level and duration through axon. The neurons or the processing units may have several input paths corresponding to the dendrites and,

[106] Nag and Mitra (1999) offer a brief description of neural networks in their Appendix I. However, for a more satisfactory survey see Kuan and White (1994) and Lewbel (1994).
[107] For a detailed description of AIT, see Oztemel (2003). Briefly, he distinguishes artificial intelligence techniques in four main classes: Expert Systems, Artificial Neural Networks (ANNs), Genetic Algorithm (GA) and Fuzzy Logic.
[108] These are, essentially, scatterplots illustrating aspects of a country's economy. In more detail, the authors use five "fundamental balance charts" (Growth, Financing, Foreign Exchange, Cyclical and Banking System Balance), each built as a scatter graph based on two different composite indicators, with a "risk threshold" defined for each of them enabling to represent non-linearity. Both the indicators and thresholds are incrementally adjusted to obtain the best statistical fit with existing crises. For instance, the Cyclical Balance combines a monetary pressure indicator (domestic liquidity in relation with the previous inflation and economic growth rates) with an indicator of real economic pressure (a leading indicator of the pressure in domestic demand, built from moving elasticities to imports and the exchange rate).

generally, they are combined by a simple summation, that is, the weighted values of these paths. A basic (of single hidden layer) representation of artificial neural network is the following:

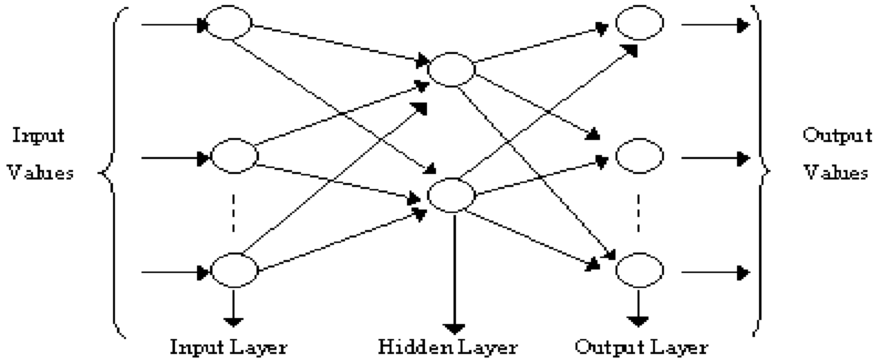


Figure 2.2 Graphical representation of single hidden layer artificial neural network.

Figure 2.2 shows that the artificial neural networks do not join randomly, but in three different layers, in parallel with each other in each layer (Oztemel, 2003):

- *Input Layer*: consists of explanatory variables and are responsible for *transferring* the input variables to hidden layers without processing any of the input information;
- *Hidden Layer(s)*: responsible for *processing* the input variables and transferring them to the output layer;
- *Output Layer*: works as the hidden layer, that is, each input coming from the hidden layer is processed and the required result is produced.

The processing phase is carried out by three steps as Haykin (1999) shows:

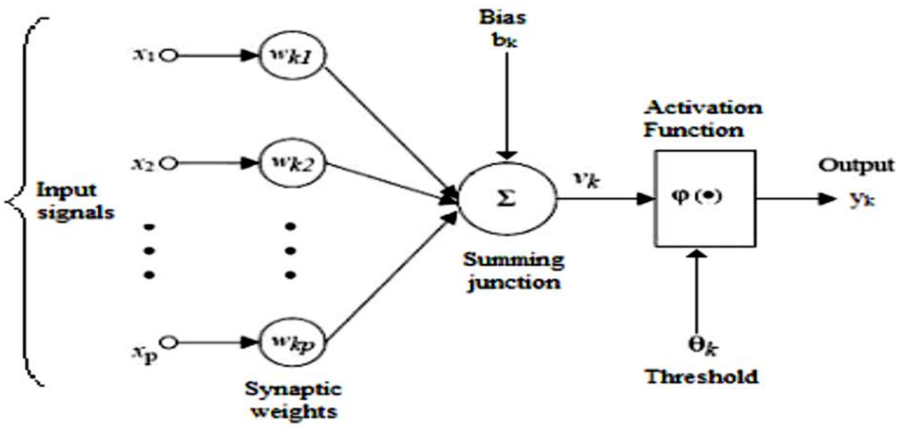


Figure 2.3 The mathematical model of a neuron.

1) Inputs are multiplied by connection weights (the weight is a number, and represents the synapse) as they enter the hidden layer that consists of hidden units;
2) In the hidden layer, linear combinations take place. These means summing together all the inputs and modifying them by the weights. A negative weight

reflects an inhibitory connection, while positive values designate excitatory connections;

3) Lastly, the activation function controls the amplitude of the output by transforming the combinations in a value between a range, i.e. an acceptable range of output is usually between 0 and 1, or it could be -1 and 1.

Finally, the output of the neuron, y_k, would be the outcome of some activation function on the value of its interval activity, defined as:

$$v_k = \sum_{j=1}^{p} w_{kj} x_j.$$

Let’s now turn our attention towards the other technique.

Genetic algorithm (GA), first introduced by Holland (1975), is a machine learning optimization method. As the name suggests, it is based on a metaphor of the evolution process observed in nature. This procedure is based on the evolution of a population of individuals, represented by a vector of possible solutions. The steps to carry out the GA, as stated by Apoteker and Barthelemy (2000), may be summarized in four:

1) Initialize a population of individuals.
   In this first stage a population of individuals is created. Everyone is represented by a character string that represents the chromosome or genotype and each character represents a gene. The algorithm simulates an evolution process.
2) Evaluate individuals of this population.
   The evaluation is carried out by means of an evaluation function. In particular, the optimization process is achieved by minimizing or maximizing the function which allow to measure the performance of each individual (or string) and to give a fitness value.
3) Select best individuals and do random changes.
   In this third phase, that allow to select the basic individuals of the next generation, the selection method is important. Nowadays, several methods are available[109] even though the most common, initiated by Holland (1975) and also used by the author is the “Roulette Wheel” selection. It is a fitness-proportionate selection method, meaning that the number of times an individual will be selected is equal to his fitness divided by the fitness mean of the whole population.
   After the selection of individuals, some of them are chosen to cross parts of themselves: the reproduction in a GA is represented by a *crossover*.

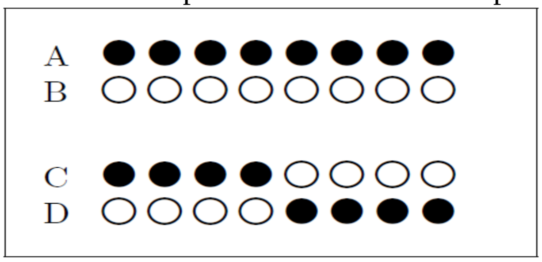


Figure 2.4: Single Point Crossover: (A,B) are parents and (C,D) are childs.

It is a crucial innovation as it is aimed to prevent the population from moving toward a local optimum. The most common way to do crossover is the single point crossover as illustrated by the figure on the left.

[109] Many new selection algorithms are now available. Among others: sigma scaling, Boltzmann selection, rank selection, tournament selection and so forth.

4) Test for stopping criterion: return the solutions/individuals if satisfied or go to step 2 if not.

As it is clear from what said so far, GA are not designed to create models, like standard Neural Networks, but rather to obtain topologies or selections for an optimal combination. It is pretty similar to *simulated annealing* but instead of using just one individual moving around a possible solution with random increments (figure 2.5a), GA search for an optimum with a vector of individuals (a vector of possible solutions), and the vector will follow the best evaluations, taking care of local optima.

Figure 2.5a: Simulated Annealing.

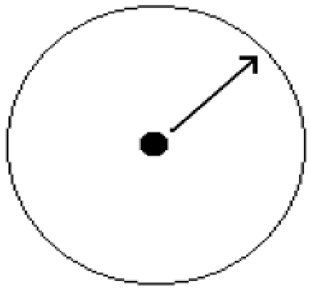
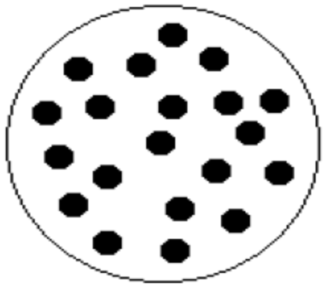


Figure 2.5b: Genetic Algorithms.



In addition to the innovative techniques explained above, there are other methods used to predict (currency) crises[110]. The most numerous are the ***value-at-risk*** models proposed firstly by Blejer and Schumacher (1998), the ***autoregressive conditional hazard*** (ACH) models, first proposed by Zhang (2001) and then developed by Hamilton and Jorda (2002), the ***VAR*** model, that will be examined apart in the next section, and ***Fisher discriminant analysis*** employed by Burkart and Coudert (2000) in their analysis of currency crisis[111].

An overall comparison of EWIs

This subsection on EWIs is going to be concluded by an overall comparison. In this direction, it is worth to specify that the comparison carried out here has a twofold nature, that is, intra- and inter-comparison.

Let's see, firstly, an ***intra***-assessment on EWIs.

As illustrated above, there are numerous techniques that the class of EWI offers. Numerous are also the pro and cons when assessing among these approaches. Going in order, we've seen that the "*signaling approach*" of KLR allows a direct ranking of variables as crisis indicators (by imputing a 1 for crisis and 0 otherwise) and provides a quick focus on the source of the crisis (assuming an encompassing set of indicators).

However, this method has several deficiencies.

First and foremost, the transformation of the exogenous variable into a binary one translates in a loss of information on the relative importance of the independent variable

[110] As it is clear from the illustration of the different kind of models, these are primarily focused on currency crisis, especially the seminal studies. However, later, EWMs also focus on other type of crisis, as banking crises.

[111] Here, I mentioned the most used. To get a full survey see Appendix I in Abiad (2003).

values. This means that the one percent threshold crossing of a variable has the same meaning of a fifty percent crossing.
Second, this approach does not take into consideration strong correlations among indicators which has a negative impact on the construction of a composite indicator (Eliasson and Kreuter, 2002).
Third, it does not provide a framework for statistical testing or calculation of crisis probabilities in the future. In addition, it suffers the misclassification errors that can bias the conclusions of the analysis. As Vlaar (2000) points out, the signalling method provides the best results when the behaviour of variables in the pre-crisis period is clearly different from their behaviour in a tranquil period[112].

A valid alternative to this method is the *discrete-choice approach* consisting of logit/probit models. As previously seen, one of the first authors that question the signal approach are Berg and Patillo (2000) which add two new indicators to the KLR model and update the data through 1996 to try to predict the Asian crisis. In comparing this predictive performance with three probit-based alternatives, they find that the probit model with untransformed variables performs better than the signal-based models. Indeed, Eichengreen et al. (1996) are the first that employ a binary probit model to analyze, empirically, the contagious nature of currency crises. The main difference with the signalling approach is that the independent variables are continuous, while the dependent variable remains binary or multinomial. The econometric model gains several advantages over the signalling method.
First, the significance of an additional variable is easily checked since the method analyses the significance of all the variables simultaneously.
Second, this approach has the benefit of providing a framework for statistically measuring the magnitude and significance of the effects of various potential explanatory variables on the onset of a crisis.
Third, the model allows to estimate the likelihood of a future crisis occurrence given projected or anticipated values of the explanatory variables.
Even this approach is not free of limitations. The main drawback is that the model does not overcome the issue of independence of crisis occurrence from one period to another one, except indirectly through serial correlations existing in the explanatory variables. Since the model heavily rely on the crisis dummy variable, further serial correlation may be unawares introduced depending on the way the dummy variable is constructed. For instance, exclusion windows (the crisis variable automatically is set to zero for k periods immediately following a time point rated to be in crisis) establishes perfect correlation between a crisis time point, and the next k periods following it.
Finally, due to the non-linear nature of the probit/logit function, the contribution of a single variable is not constant and depends on the values of all the other variables, so it is not possible to directly define the relative signalling power of a single indicator (KLR)[113].

[112] Nevertheless, this approach is employed nowadays yet. Several studies after the KLR and Kaminsky and Reinhart (1999) seminal paper has been carried out; among others, Borio and Lowe (2002a), (2002b), (2004) and Alessi and Detken (2009) that use the method to predict episodes of macroeconomic imbalances.
[113] Even in this case, many studies use the discrete/choice approach despite it limitations. After Eichengreen et al. (1996), Frankel and Rose (1996) employ probit regression, Klein and Marion (1997) applied logit specification in their analysis of the collapse of exchange rate regimes in Latin America. Subsequent important papers applying the binomial probit model are: Goldfajn and Valdes (1997),

Innovative techniques also find large room among the empirical methods employed for EWIs. One of the first adopted, as illustrated above, is the *Markov-switching model* by Jeanne and Masson (1998), Fratzscher (1999) and Abiad (2003). The authors try to exploit the benefits associated with this technique in order to encompass the possibility of multiple equilibria. As Abiad (2003) claims, the main innovation of these models consists in a sharp reduction of the subjectivity of the decision maker. To be more specific, these models do not depend on an arbitrary decision about fixing the onset of a (currency) crisis, which is based on the signal provided by the index of speculative pressure, that in turn depends on the choice of the threshold value and the time horizon of the crisis. This because the parameters evaluated in the model along with the data obtained reveal the state of the economy.
Markov-switching model has several advantages with respect the two previous methods. The most important consist in avoiding potential misclassification errors in the probit data, addressing the serial correlations inherent in crisis occurrence, allowing to measure and test significance of indicator variables and delivering forecast probabilities of future crises conditional on projected future values of indicator variables.

Last, but not least, some words on the two most used techniques among the AITs.
Artificial neural networks (ANNs) and *genetic algorithms* (GA) employed first, in constructing EWMs, by Nag and Mitra (1999) and Apoteker and Barthelemy (2001), respectively, have several benefits, among which, a superior forecast ability than the KLR model, particularly on comparing out-of-sample predictions. In addition, these models are characterized by a high flexibility in their specification and a great ability to encompass complex interactions between variables (Abiad, 2003).

Regarding the pro and cons of other innovative methods used as EWIs to predict crises (VaR, ACH, VAR, Fisher discriminant analysis, and others) please see Abiad (2003).

Coming to the ***inter***-comparison of EWIs, as emerged from how illustrated so far, these indicators have several attractive features with respect to the other instruments as well as some shortcomings. It is worth to say that the following considerations may vary tool by tool, thus they should be taken with tweezers.
First, unlike balance-sheet and market-based indicators, they are explicitly forward-looking and represent statistically rigorous attempts in identifying basic relationships in the historical data. In addition, they implicitly capture any interactions that have existed in previous episodes. Finally, EWIs could be able to give a concrete contribution in piecing together broad and not immediate stories about the factors behind the distress.
A partial benefit may be the ability of this kind of indicator to provide information about the costs associated with the potential financial crisis. Partial because due to their nature and the way they are constructed, EWIs provide only an estimate of the probability of distress, not of its cost. However, a solution may be to quantify costs by looking at the past losses associated with the episodes of distress used in the calibration.
Naturally, this instrument is not free of shortcomings.

Esquivel and Larrain (1998), Berg and Pattillo (1998a and 1998b), IMF(1998), Kruger, Osakwe and Page (1998), Caramazza, Aziz and Salgado (2000), Schardax (2002), Kumar, Moorthy and Perraudin (2002) and Collins (2003). Eliasson and Krauter (2001) and Bussiere and Fratzscher (2002) apply the multinomial logit.

Broadly speaking, they are criticized mainly on the relationship between the past and the future. In other terms, there is no guarantee that past connections will hold in the future. In more detail, from a policy perspective, an important drawback is often quite short forecasting horizon. This may help investors rather than policymakers. Second, as Kaminsky and Reinhart (1999) point out, the forecast may involve information that is actually not available at the time the prediction is made.

Finally, the choice of independent variables may be excessively data driven with thr risk of overfitting at the cost of out-of-sample performance.

However, some of these limitations are overcome, for instance, with the contribution of Borio and Lowe (2002a,b) that rely on a longer time horizon (from one to four years) and on information that is available at the time the predictions are made, i.e. they are truly real-time (Borio and Drehmann 2009). Therefore, despite their drawbacks, EWIs still represent one of the best alternative.

2.2.3 Single-module measures: VARs

Vector auto-regressions (VARs) are proposed for the first time in empirical economics by Sims (1980). The author demonstrated that VARs offer a flexible and manageable framework for analyzing economic time series. VARs or in general macro models draw on the financial accelerator literature. A Vector auto regression model posits a set of relationships between past lagged values of all variables in the model and the current value of each variable in the model (LeSage 1999). In symbol, a VAR pattern that contain *n* variables may be expressed as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{nt} \end{bmatrix} = \begin{bmatrix} A_{11}(\ell) & \cdots & A_{1n}(\ell) \\ \vdots & \ddots & \vdots \\ A_{n1}(\ell) & \cdots & A_{nn}(\ell) \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{nt} \end{bmatrix} + \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix}$$

where:

- $A_{ij}(\ell)$ = model which parameters take the form of $\sum_{k=1}^{m} a_{ijk}\ell^k$, where ℓ is the lag operator defined by $\ell^k y_t = y_{t-k}$ and *m* is the length of the lag set by the modeler;
- y_{it} , $i = 1, \dots, n$ = *n* variables in the model at time *t*;
- C_i = constants;
- ε_{it} = independent disturbances.

The VAR has several nice features that justify its usage in practice.

First and foremost, VARs, by construction, are widely data-driven representations of the economy, with few theoretical restrictions. Broadly speaking, in a typical VAR model, a rather small set of variables interact dynamically, with the dynamics ultimately driven by a set of exogenous shocks. Thanks to simulations, the approach may generate a probability distribution of outcomes for the endogenous variables and hence a measure of the probability of distress *over any given horizon*. A peculiar usage of this technique could consist in assuming a specific set of shocks and then, conditional on this set, the model could generate the implied value for the variable of interest. Moreover, to the extent in which the selected shock are not included in the typical range observed in the sample, this procedure take the form of a stress test[114].

Finally, this technique represents a potential useful tool in the absence of structural econometric models for carrying out stability analysis.

As it emerges from what seen above, VARs have a lot of benefits that make them quite appealing. One of the major shortcomings of the previously analyzed technique, within the perspective of an anticipatory tool, is the short time horizon with which signals are issued. Well, the flexibility in this direction, i.e. modeling the time horizon up to several years before the crisis event, represents one of the major advantage of VARs. This means that, depending on the horizon over which the forecasts are made, they can truly act as barometers rather than as thermometers of financial distress, providing a rich representation of the range of potential outcomes. In addition, they account for interactions between variables and hence feedback effects (Borio and Drehmann 2009).

Unfortunately, in practice, this technique turns out to be not much convenient. The main drawback, in fact, is data limitations. Especially in capturing financial distress, the variables that are typically employed are rather rudimentary and poorly modelled.

Another negative aspect concerns the assumptions on which this approach is based. Specifically, as Borio and Drehmann (2009) point out, these models generally assume that the underlying relationships interact in a (log)linear fashion[115]. This would be acceptable if the underlying data generating process (DGP) was linear or the VAR was used to study the impact of small shocks around the equilibrium of the process. But it is rare that stress tests consider small shocks, and it is even less likely that the relevant DGP are all log-linear over the relevant range (Borio and Drehmann 2009).

2.2.4 Multiple-module measures: Macro stress tests

This last section is devoted to the ultimate tool that, according the structure of the Borio and Drehmann's work, I decided to deepen, that is, macro-stress test.

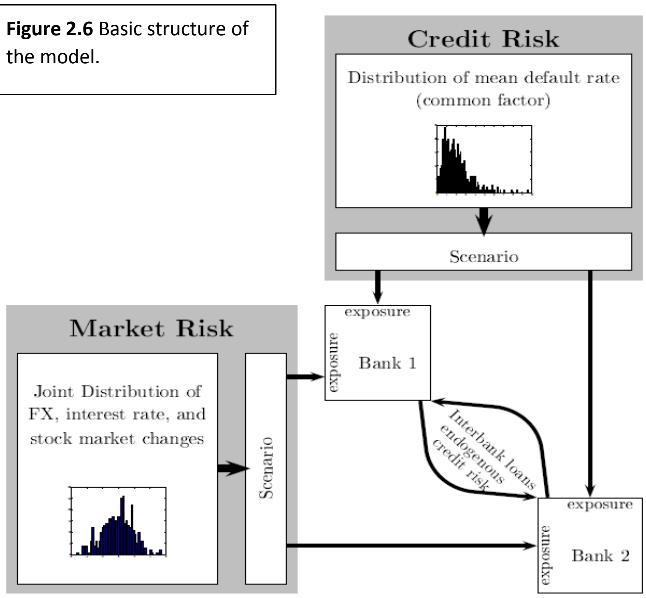
This tool finds room left by the absence of fully-fledged structural models and by the limits of VARs. This kind of technique is inspired by the "negative exogenous shock-amplification" view of financial instability. In fact, as stated by IMF and World Bank (2003), macro stress tests, analogously to the stress tests for the portfolios of individual institutions, are designed to form a view of how the system, as a whole, would behave under exceptional but plausible adverse circumstances, namely, in response to negative "shocks" drawn from the tail of the underlying probability distribution.Macro stress tests are different but at the same time similar as they have some features in common. In particular, the way in which the test is run and the rationale behind is the same. A "shock trigger" is employed to generate the shock and/or to trace out a scenario for macroeconomic variables, that is, the changes in the assumed "systematic risk factors". These are then used to shock the balance sheets of the relevant sector for assessing more precisely their impact on its financial strength, measured in a variety of ways (Cihak (2007). The "shock trigger" is a macro engine (Borio and Drehmann, 2009) and may vary from a tradition macro model (eg, Bunn et al. (2005)) or a macro model linked to market risk drivers (Elsinger et al. (2006)) to a VAR (eg, Pesaran et al. (2006)).

[114] See the next section.

[115] This would imply that, for instance, a three standard deviation shock has exactly the same impact as three times a one standard deviation shock.

One of the earliest multi-module measurement models is the one of Elsinger et al. (2006). The authors suggest a fully operational model for assessing the banks' risk, but systematically rather than individually. The systematic nature of their approach is dictated by the complicated network of mutual credit obligations that can make the actual risk exposure of banks invisible at the level of individual institutions.

Figure 2.6 Basic structure of the model.



The authors combine standard risk management techniques with a network model of interbank exposures and analyze the consequences of macroeconomic shocks for bank insolvency risk. In addition, the model integrates four kind of risk in the interbank sector: market risk, credit risk, interest rate risk and counterparty credit risk. Banks are exposed to shocks from credit risk
and market risk according to their respective exposures whereas interbank credit risk is endogenously explained by the network model (see figure 2.6). In more detail, these four type of variable represent different states of the world and for each of them, the network model determines endogenously actual interbank payment flows. Then, default frequencies of individual banks across states are computed by explicitly accounting for the feedback between banks from mutual credit exposures and mutual exposures to aggregate shocks. Finally, the model is able to discriminate between fundamental and contagious defaults by distinguishing bank defaults that arise directly as a consequence of movements in the risk factors and defaults which arise indirectly because of contagion.

Macro stress test are widely used and popular just like the stress tests for individual institutions. They also have several benefits. First, they are able to cover a broad range of scenarios, not constrained by the probability distributions derived in estimation. In fact, can be more granular than the other approaches relating scenarios to features of individual balance sheets. In addition, like EWIs, they are explicitly forward-looking and allow tracking the propagation mechanism from shock to outcome and hence in story telling and communicating concerns (Borio and Drehmann 2009).
However, as mentioned above for individual modules, regardless of the macro engine used, be a VAR or a macroeconomic model, these macroeconomic modules make a very scares performance in incorporating financial variables. Finally, their utilization is closely restricted to stress episodes driven by macro factors since the macro model is the source of all shocks in these applications (Borio and Drehmann 2009).

Chapter 3
AN EARLY WARNING MODEL (EWM) FOR BANKING CRISES

In the first chapter the financial (in)stability concept through various definitions has been illustrated. Subsequently, the delicate issue of how to practically measure it has been addressed. In more detail, we have seen that the modeler has a wide range of tools among which to choose for concretely measuring financial crises episodes. Unfortunately, many of these instrument work as thermometers rather than barometers and fail to give predictive signals or, when this occur, the time horizon is too short to allow policy makers to intervene with an efficient response.
However, positive aspects came out as well. Broadly speaking, a tool turns out to be useful from a policy standpoint when provide signal of alarm with a sufficient lead of time. “Sufficient” means a time span that is at least greater than one year. Naturally, the higher the lead the better for the users especially for policymakers[116]. In this anticipatory direction, the benefits appear to raise sharply when shifting from balance-sheet to market price indicators. This restricts the choice of the modeler to essentially two broad class of indicators, i.e. EWIs and Macro Stress Tests. Each of this tool has its own advantages and drawbacks and, above all, each kind of indicator best suits to specific contexts and needs. Probably, one of the capabilities that the modeler cannot miss is precisely to be able to choose, among instruments, the best one to fulfill the duties for which it is called upon to answer.
This third chapter is aimed to illustrate the design of the model and its main components. After an introductory section explaining the theory underlying the model, the methodology and the data employed are described.

3.1 THE THEORY UNDERLYING THE MODEL: CREDIT BOOMS GONE BUST

This work starts primarily by the preeminent contribution of Schularick and Taylor that examines the role of the monetary policy and the link between financial leverages and financial crisis in the long run, namely from 1870 to 2008. Their paper, beyond a new long-run historical dataset, offer an answer to different puzzles that may arise when analyzing the quantitative history of money and credit, especially in a broader, systematic and cross-country way.
The role of these two variables in the macroeconomy has strongly changed throughout the history[117]. The last century has given birth to different economic standpoints that may be grouped in three main “views” associated to their different periods.

- Late 19th : the “Money view”, that owes its foundation to the seminal contributions of Friedman and Schwartz (1963), dominates;
- Late 20th : the “Irrelevance view” of Modigliani-Miller (1958), according which real economic decisions became independent of financial structure altogether, gains influence;

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[116] An EWI might be employed not only for policy purposes but also by investors. Of course, for the latter users a year is more than enough.
[117] See Freixas and Rochet 1997, chapter six.

- End 20th : the “Credit view”, founded on the ideas of Fisher (1933) and enhanced by Mishkin (1978), Bernanke (1983) and Gertler (1988), captured a growing attention. Under this viewpoint, the mechanisms and quantities of bank credit became much more important, beyond the level of bank money, due to its macroeconomic implications.

As one may notice, the standpoints delineated above diverge greatly. This divergence is even more pronounced when considering the role of credit, within the credit view. One strand of literature, that sustains the *financial-accelerator models*[118] claims that credit is passive, a simple propagator of shocks not a source of it whereas *multiple equilibria models*[119] consider plausible also feedback effects. A more radical strand of literature, with an older tradition and on which my model rely on, is the one of Minsky (1977) and Kindleberger (1978) for which the financial system, that is endogenously instable due to endogenous credit bubbles with waves of euphoria and anxiety[120], is prone to generate economic instability.
The first aim of Schularick and Taylor (2012) is to make some clarity among the above disparate views by establishing stylized facts about the variables of money and credit and their interactions with the crises over the past one hundred and forty years. In this sense, due to monetary and regulatory changes after WW2, i.e., the passage gold-to-fiat money, the raising role of activist monetary policies and an increase in the bank supervision and deposit insurance as well as in the role of the Lender of Last Resort (LLR), two eras of finance capitalism may be detected:

1) In the first era, going from 1870 to 1939, the “money view” looks plausible. Money and credit are volatile but in the long run they maintain a stable relationship to each other and to the size of the economy (GDP).
2) In the second era, going from 1945 to 2008, credit and bank assets show an increasing trend and overcome their pre-1940 levels on GDP. In more details, from 1970 onwards, the credit variable raises more than broad money (in addition to GDP). This is due to a mix of a higher leverage and, especially after the ‘70s, a substantial funding via nonmonetary liabilities of banks, mainly debt securities. This, in turn, increased the financial risk in the system.

One important consequence deriving from the changes described above is that crisis dynamics in the two eras changed as well. Crises occurring in the postwar era have not been accompanied by a collapse of broad money due to a strong support of money base growth by central banks. However, a more activist monetary policy response to crises could have contributed to fuel the uninterrupted leverage growth occurred in the postwar financial system. Governments tried to cushion the impact of financial crises through policy activism. But at the same time, the financial sector has grown and increased leverage, expanding the size of the threat even as the policy defenses have been strengthened. As a result, the shocks hitting the financial sector might now have a potentially larger impact on the real economy, absent the policy response[121].

[118] Among others, Borio (2008), Hume and Sentence (2009).
[119] Among others, Bernanke and Gertler (1995) and Kiyotaki and Moore (1997).
[120] See section 1.3.1 “The endogenous cycle view of financial (in)stability”.
[121] See Schularick and Taylor (2012).

The second purpose of their contribution consists in a twofold empirical analysis using a sample of long-run data for 14 developed economies. In more details, they first use an event analysis approach to study the coevolution of money and credit aggregates and real economic activity in the five-year window following a financial crisis. The results of this first part reveal that financial crises in the prewar are accompanied by pronounced deflation and a stagnation of narrow and broad money growth whereas in the postwar era financial crises are associated with upwards pressure on inflation relative to normal. This is probably due to the much more active monetary policy response, as shown by the expansion of narrow money.

Subsequently, the authors investigate the sources of the recurrent financial instability in more developed countries[122]. In particular, the look at role of the credit system and check if, actually, the financial system itself create economic instability by means of endogenous lending booms.

Practically speaking, they estimate a probabilistic model of financial crisis event in country *i*, in year *t*, as a function of a lagged information at year *t*, in one of two forms,

1) OLS Linear Probability: $p_{it} = b_{0i} + b_1(L)\, D \log CREDIT_{it} + b_2(L)\, \mathbf{X}_{it} + e_{it},$
2) Logit: $logit\,(p_{it}) = b_{0i} + b_1(L)\, D \log CREDIT_{it} + b_2(L)\, \mathbf{X}_{it} + e_{it}.$

On the left-hand side, $logit\,(p) = \ln(p/(1-p))$ is the log of the odds ratio. The dependent variable is a dummy equal to one when a financial crisis, according their definitions[123], occurs and zero otherwise.

On the right-hand side, the main object of study is the lag polynomial $b_1(L)$. It contains only lag orders greater than or equal to one, and the target is to check if the lags of credit growth are informative. The CREDIT variable is defined as the total bank loans variable deflated by the CPI. Other possible causal factors are included, if present, as additional variables in the vector **X** and controlled by the lag polynomial $b_2(L)$[124].

Their analysis starts with an OLS Linear Probability model with simple pooled data in its baseline version consisting of five annual lags of the real loan variable as regressors and no controls. Then, the country fixed effect and the year effects are added with only the latter statistically significant implying that there exists a time component steering financial crises[125]. Unfortunately, such time effects are unknown ex-ante, thus, in practice, it cannot be used for predicting purposes. In addition, due to Linear Probability model shortcomings in the form of fitted values not constrained to the unit interval relevant for a probability outcome, a switch to the logit version is offered. The first results

[122] Much of the recent literature is focused on developing countries, in which financial crises are often triggered by currency turmoil or sovereign debt problems. In addition, developing economies often suffer institutional weaknesses and credibility problems that soil the analysis making it difficult to understand the real causes of the financial crisis.

[123] The authors, by corroborating the crisis histories from Bordo et al. (2001) and Reinhart and Rogoff (2009) with alternative databases compiled by Laeven and Valencia (2008), define a financial crisis an event during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions.

[124] Actually, the authors consider up to five annual lags of any regressor to keep the lag structure reasonable.

[125] As one may expect given the consensus view that financial crises have tended to happen in waves throughout history.

already confirm that a credit boom over the previous five years is indicative of a heightened risk of a financial crisis.
In the second part, Schularick and Taylor test the important claim for which credit aggregates are better than monetary aggregates as financial crises predictors. In this sense, they take several perturbations of the baseline model by replacing the five lags of credit with alternative measures of money and credit, i.e. real broad money instead of real loans, narrow money in lieu of loans and real loans replaced first by loans-to-GDP ratio and then by the loans-to-broad-money ratio. Robustness checks (by splitting the sample in pre- and post-WW2) confirm the similar predictive power of different forms of credit volume whereas credit cannot be well proxied by broad money. Findings in this part corroborate what said above, namely, in the pre-WW2 the ‘money view’ of the financial system is an adequate simplification as money and credit move together whereas in the post-WW2 credit delinks from money aggregates raising the issue of which aggregate effectively steers macroeconomic outcomes.
Finally, the authors submit their “credit view” based model to robustness tests. Specifically, they add 5 lags of real GDP growth, inflation rate, nominal short-term interest rate, change in the investment-to-GDP ratio and the interaction of the five-year moving average of credit growth with real investment growth[126]. None of these variables reveals able to ameliorate the predictive power of the model or to affect the credit strength.
As a final robustness exercise, the authors include asset prices and controls for the level of financial development to check if the role of credit grow in generating financial instability is affected. Regarding the former, while asset prices slightly contribute to provide further signals of future financial crisis (changes in real stock prices rather than nominal), their overall contribution is relatively small. Concerning the latter, the credit to GDP ratio, as a proxy for financial depth, is added. The purpose is to test if crisis events are more likely in larger financial systems. The result is positive raising immediately the predicting power of the model measured by the AUROC. The variable is significant if both stock prices and credit levels are included suggesting that the risk of financial crises grows with a higher credit-to-GDP level[127].

Overall, the results from their predictive analysis of large, long-term, cross-country dataset suggest policy implications that is worthwhile to recall.
First, monetary aggregate may be the appropriate instrument when supporting the price stability is the scope. Instead, when the goal shifts to financial stability a better pillar might make use of credit aggregates given their superior predicting power towards financial crises.
Second, the financial depth/dimension of the system is important as well. Specifically, even though in the initial phase of financial development, run-ups in equity markets are much less dangerous, stock market booms become more problematic with larger financial sectors.
Finally, the relevance of credit growth history as a predictor of financial crises and the robustness of the results to the inclusion of other key macro variables support the theories

[126] According to other studies results. For instance, Demirgüç-Kunt and Detragiache (1998) find inflation to contribute to crises whereas according to Kaminsky and Reinhart (1999) the rising of interest rates to defend a peg may contribute to trigger crises.
[127] This recall the claim, as argued by Rajan (2005), for which larger and/or more complex financial systems may be inherently more risky.

of Minsky and Kindleberger for which the financial sector is quite capable of creating its very own shocks.

3.2 THE MODEL

Following on the previous point, the model developed in this paper is, theoretically, inspired to the endogenous view of financial instability and the findings of Schularich and Taylor (2012) illustrated so far whereas from a practical standpoint it differs in some aspect. Stated differently, by relying on a different model specification I try to check if the financial sector generates its own instability. However, there are several differences both in terms of model construction and purposes that need a satisfactory explanation.
As abundantly said in the second chapter, the choice of the model depends, among others, upon the scope prefixed by the user. In other words, the definition of what we are going to measure is fundamental as well as necessary to utilize an appropriate yardstick. The first substantial difference is precisely this. While Schularick and Taylor aim to check, among others, if the past credit growth has a good predicting power of financial crises, I'm mainly interested in testing whether the history of credit and other credit-related variable are useful for explaining the *instability/stress in the banking system*. Therefore, as said so far, the attention is restricted on the banking sector, which is the pillar of the financial system, and thus on banking crises. The relevance of these kind of crisis and the interest towards them has been explained previously[128]; what is worth to highlight here is that the focus is on the level of stress and not necessarily on the financial crisis event itself, meant as the ending point where the stress cumulated over time culminates.
In this direction, particular attention is dedicated to the behaviour of the banking stress in the Eurozone along with the credit dynamics over a determined lagged time window. The nature of the scope and the specific interest illustrated above justify the choice of the model. Being interested in the credit dynamics on the banking sector over time rather than all at once the model consists of a simple Finite Distributed Lag (FDL) model, as the baseline version, where on the left-hand side there is the banking sector proxied by appropriately constructed banking indexes while on the right-hand side the past credit-related variables as regressors. In addition, various specifications of the base model are adopted.

3.2.1 The dependent variable

The choice of dependent variable is the main innovation of the present work. It consists of a country-specific banking index constructed for the specific purpose, even though it may be employed in different ways. As mentioned before, these country-specific banking indices serve as proxies for the banking sector and the main advantage is that they are continuous variables thus, as opposed to discrete measures, they do not waste information. Avoiding this loss of information assumes relevance to the extent in which the user is not only interested in obtaining information about the mere occurrence of a crisis event but also in investigating and monitoring the level of stress in the banking system. In this direction, the quality of information that a continuous variable may offer with respect to a zero-one variable is appreciable.
Unfortunately, these banking indices for EU countries are not available or when they are the time length is really restricted making hard the conduction of a reasonable analysis.

[128] See the sections devoted to banking crises and banking and the economy.

In more detail, these banking indices are available for a very few countries, namely, France, Italy, Germany and Spain. However, they do not go much back in time: the best case is the French *EPSFBQ* Index that starts from 30th December, 1998. The German *3BV9X* Index starts from 25th March, 2008 whereas the Italian *IT8300* Index starts from 19th December, 2008. The worst case is the Spanish *IBEXBAN* Index starting from 25th November, 2015.

In addition, these already constructed sectorial indices have a different design with respect to the indices created in the present work due to the differences in the purposes for which they are built. While the above indices have inbound and outbound rules, as well as to stay in, the indices here created have not such bounding rules. This is coherent with the nature of the target. Since the role of the banking index in my analysis is to proxy the banking sector of the country/region considered, it is logical that the country-specific banking system is represented by all the banks operating in that country at the time considered. Also, it seems logical that each bank entity takes a different weight according the influence effectively exercised on the banking system.

For the reasons explained above, I tried to replicate the indices in a similar but different way, given the different scope they pursue, and considering data availability.

For this aim, I took advantage of the Index Mathematics Methodology document by S&P Global[129] where different kind of index with several aggregation methods are illustrated. Among others, I decided to employ the capitalization-weighted scheme for two reasons. First, making a trade-off between the complexity in aggregating and the consistency from a conceptual standpoint, this technique seems appropriate enough. It is reasonable that the banks with higher market capitalization are associated with more weight and able to steer the index more than small banks since the former can affect and move the market more than the latter.

Secondly, the most widely quoted stock indices, like S&P 500, the S&P Global 1200 and indices from other index providers (sometimes with some subtle difference) such as MSCI's indices, FTSE's indices and Russell's use this aggregation technique.

However, as said before, some divergence exists.

In more detail, the index formula, sometimes called a "base-weighted aggregative" method, is generated by a modification of a *LasPeyres* formula, which uses base period quantities (in such case share counts) to calculate the price change. In fact, a LasPeyres index would assume the following form:

$$Index = \frac{\sum_i P_{i,1} * Q_{i,0}}{\sum_i P_{i,0} * Q_{i,0}}, \qquad (1)$$

where the numerator represents the total cost of purchasing a certain quantity of goods at *current* prices with respect to the cost of purchasing the same quantity but at a different cost, that is, the *base-period* prices represented by the denominator.

To obtain the index formula, the quantity measure in the numerator, Q_0, is replaced by Q_1, so that the numerator becomes a measure of the current market value, whereas the product in the denominator is replaced by the so-called *divisor*. The formula net of the above modifications becomes:

[129] See the document "S&P Dow Jones Indices: Index Mathematics Methodology" which covers the mathematics of index calculations.

$$Index\ Level = \frac{\sum_i P_i * Q_i}{Divisor}. \qquad (2)$$

At this stage, it is worth to say that as S&P Dow Jones Indices' market cap-weighted indices are float adjusted, the Q_i in the above final formula would be replaced by the product of outstanding shares and the IWF:

$$Q_i = IWF_i * Total\ Shares_i\,. \qquad (3)$$

In other words, the number of shares outstanding would be reduced to exclude closely held shares from the index calculation, because such shares are not available to investors, by means of the calculation of an Investable Weight Factor (IWF) for each stock representing the percentage of total shares outstanding that are included in the index calculation.
However, for the sake of simplicity in the computation this step is not run making the index constructed here not float-adjusted. Nevertheless, as shown later the results are quite coherent with the index already constructed.
A fundamental step, instead, is the computation of the divisor. Divisor adjustments are crucial for the index maintenance to the extent in which changes in shares outstanding, capital actions, addition or deletion of stocks to the index should not change the level of the index.
Let's see how the divisor is calculated and updated to reach the final formula.
Let us consider the time subscript and let us set the market value for the divisor and the current market value as follows:

- $MVD_t = P_{t-1} * Q_t$ (4)
- $MVC_t = P_t * Q_t\,.$ (5)

Now, as emerges from the S&P Global document, the divisor formula in time *t* has the following expression:

$$D_t = \frac{\sum_i MVD_t}{I_{t-1}}, \qquad (6)$$

from which,

$$I_{t-1} = \frac{\sum_i MVD_t}{D_t}. \qquad (7)$$

Equations (6) and (7) may be defined as the inception formula since they are used solely in time one and zero, respectively. In fact, in time *t=0*, the index becomes:

$$I_0 = \frac{\sum_i MVD_1}{D_1}, \qquad (8)$$

where I_0 is the starting value of the index chosen arbitrarily. It may assume several values such as 100, 1000 or 10000 depending on the kind of the index. For instance, the Italian *IT8300* Index base value is equal to 20000 on 19th December, 2008 starting date whereas the German *3BV9X* Index base value equals 100.13 on 25th March, 2008 starting date.

Once assigned the base value in time zero the index series can start and it is easy to roll on the computation. The value of the index in time *t*, I_t, with *t = 1, 2, …, T* is calculated, as pointed out previously, by the final formula, that is, equation (2).
To get equation (2), here rearranged in market value terms and by keeping the time subscript, two steps are made.
First, the index in time *t*, I_t, must be equal to the last closing price of the index, I_{t-1}, adjusted solely for the stock price changes:

$$I_t = \frac{\sum_i MVC_t}{\sum_i MVD_t} * I_{t-1} . \qquad (9)$$

Second, by substituting (7) into (9) we obtain:

$$I_t = \frac{\sum_i MVC_t}{D_t} . \qquad (10)$$

Finally, as anticipated before, *any change to the stocks in the index that alters the total market value of the index* <u>while holding stock prices constant</u> will require a divisor adjustment. To this scope, a divisor formula in time *t+1*, D_{t+1}, with *t = 1, 2, …, T* is needed[130]. Analogously to the formula for the index level, the divisor D_{t+1} relies on the previous divisor value D_t. The formula takes the following form:

$$D_{t+1} = D_t + \frac{\Delta MV_{t+1}}{I_t} , \qquad (11)$$

where ΔMV_{t+1} is the aggregate change in market value of the index resulting from additions and/or deletions of stock, that is, variations in the number of shares. Note that the adjustments are made using the index closing price. Also, it is easy to check that when there are no variations, i.e. $\Delta MV_{t+1} = 0$, the divisor remains unchanged.
By employing the above formula, I constructed, as previously said, banking indices starting from January, 1985 until the mid-2016 for the main EU countries according data availability. However, the choice has not been immediate since I compared the above method, i.e. the capitalization-weighted scheme, with other two versions using different weights. In more details, I tried to replicate the country-specific banking indices with the equally-weighted and the Index of Capital and Liquidity (ICL)-weighted scheme as well. The former, as the name suggests, consists in attributing an equal share of the index price to all its components. The latter version consists in using the ICL of each bank stock as a weight for the final index. The ICL is a weighted average of capital and liquidity (proxied by the volume) of the stock considered. Briefly, the index in time *t*, $Index_t$, with *t=1,2,… ,T* assumes the following expression:

$$Index_t = \sum_{i=1}^{n} \left(\frac{p_{it}}{p_{it-1}} * WICL_{it} \right) * initial\ value ,$$

Where,

[130] Recall that the divisor formula (6) is used solely in *t=1* in the form of $D_1 = \frac{\sum_i MVD_1}{I_0}$, where I_0 is fixed.

$$WICL_{it} = \frac{ICL_{it}}{\sum_i^n ICL_{it}},$$

And

$$ICL_{it} = Wcap_{it} + \ am(Wvol_{it}) .$$

Obviously, $Wcap_{it}$ and $Wvol_{it}$ are the capitalization-weighting factor and the volume-weighting factor of stock i in day t computed as the average (daily) historical market capitalization of stock i divided by the total capitalization of all stocks and the volume (daily) of stock i on the total volume, respectively.
αm, instead, is a sensitivity factor expressed as follows:

$$\alpha m = \frac{\sum_i^n cap_{it}}{\sum_i^n vol_{it}}.$$

In particular, if αm is higher than a certain fixed figure, that I set to a quite high threshold, than $\alpha m = 0$. This because an $\alpha m > 25{,}000$, for instance, does not make much sense as it means that the portion of capital is 25,000 times higher than the volume one[131]. Actually, the ICL is somewhat used as an inclusion parameter threshold for some indices obviously set at a much lower threshold but I employed it as a weight, due to the different nature of my banking indices.
To get an idea of the shape of these indices and the consistency with the sectorial indices already constructed have a look at figure 3.1. It shows the Italian IT8300, the French EPSFBQ, the German 3VB9X and the Spanish IBEXBAN in black, compared to the respectively three techniques, i.e. equally-weighted in red, ICL-weighted in yellow and cap-weighted in light blue. Graphically, the indices' behaviour may be sometimes misleading, for instance, the ItaBI (ICL-w) seems to perfectly track the IT8300 index by overlapping it for all the series. However, as the correlation tables point out, the first important result is that the correlation between the "original" indices and the indices constructed with the cap-weighted method is always the highest reaching, in the poorest German case a 0.889 and in the best Spanish case a 0.999. The second observation that can be made is that the equally-weighted scheme is the second most diligent one in replicating the original indices. Also, it is worth to notice that the longer the time series replicated the harder the replication task and the better the benefits of the cap-weighted techniques may be appreciated. In the Spanish case, we have only six months of history making negligible the differences in correlation terms especially for the two best methods (0.993 vs 0.999). However, if we consider the longest French series the benefits of the cap-weighting scheme are highly appreciable both graphically and from a correlation viewpoint.
Therefore, by adopting this method I replicated 22 banking indices for EU countries and by applying the same logic I constructed a EU banking index. The figure 3.2 reports all the realized indices which, according the length of the series, are employed as dependent variable in the analysis.

3.2.2 The predictor variables

[131] I would like to recall that 25,000 is purely arbitrary, chosen so high, according to the data sample, to make alpha never equal to 0.

The right-hand side of the model is mainly composed of the past credit variables as regressors. Let us see in more detail what are these predictor variables. The principal object of study is going to be the total bank credit granted to the *private non-financial sector* (PNFS). In addition, the Credit-to-GDP variables are followed with particular attention as well. The focus on these variables for two reasons. First, they are found to be significant and with a high predictive power in the paper of Schularick and Taylor (2012). Second, the credit and particularly the Credit-to-GDP gap pointed out by the Basel Committee on Banking Supervision (BCBS)[132] as an important starting point for predicting the excess of aggregate credit growth that have often been associated with the build-up of system-wide risk.
Both variables above are also considered in their variants according the changing in the borrowers/lenders or in the unit type (percentage of GDP or domestic currency value). For instance, it is possible that the total bank credit of the country-considered commercial banks granted to the PNFS is considered in market value terms as well as in percentage of the GDP. The same for the country-considered 'all sector credit' granted to PNFS or to NFCs, non-financial corporations (both private-owned and public-owned).
Regarding to Credit-to-GDP variants, these include Credit-to-GDP ratios with actual data, Credit-to-GDP trend constructed with an HP filter and Credit-to-GDP gaps with actual trend defined as the difference between the credit-to-GDP ratio and its long-run trend.
According data availability, some regression may include credit granted by all sector to households and non-profit institutions serving households (NPISHs), residential and commercial property prices or debt service ratios (DSR) for the household, the non-financial corporation and the total PNFS. This newly-discovered variable has been found to provide important information about financial-real interactions and early warning signals for systemic banking crises[133].

3.2.3 Data

The analysis is conducted by using quarterly time-series data from the main EU countries and accounting for data availability. The sample starts from January 2, 1985 for the longest banking indices and at the earliest available date for the rest. It ends in 2016 Q1.
The data used in the present work comes from different sources. With regards to the data used for the construction of banking indices, they are from Bloomberg and Factset. They consist of the last price, the average historical market capitalization and the volume of all the bank stocks included in the index. These are daily observation. In fact, the banking indices are designed in a daily frequency and then converted quarterly. A list of all bank stocks treated and included in the indices is available in table C1.
Also, it is useful to highlight that the last price of the bank stocks included in the indices have already been converted in the euro currency by Factset. Unfortunately, this is not true for the BIS credit variables (expressed naturally in levels) which are expressed in domestic currency. However, they are converted when needed since the entire analysis is expressed in euro currency.
The regressor, instead, are mainly BIS statistics. In more detail, as mentioned before, they are essentially the long series on total credit to the private non-financial sector (PNFS), the total credit to the government sector, the Credit-to-GDP gaps, DSRs and on the

[132] See the "Basel III: A global regulatory framework for more resilient banks and banking systems" (2010).
[133] See Drehmann and Juselius (2012).

property prices. When the variables are deflated the BIS consumer price statistics are used as deflator.
It is worth to note that while the total credit BIS statistics are very useful as input data because they facilitate comparability across countries, the credit-to-GDP gaps published by the BIS may differ from credit-to-GDP gaps considered by national authorities as part of their countercyclical capital buffer decisions[134]. Thus, for the sake of consistency, I preferred to use essentially BIS statistics among regressors.

[134] See the BIS website (https://www.bis.org/statistics/c_gaps.htm).

Chapter 4

EMPIRICAL RESULTS ON THE EU COUNTRIES

In the previous chapter, we have seen the theoretical standpoint underlying the model. In addition, the design of the model and the main innovation, that is, the EU country-specific banking indices employed as dependent variable has been deepen. This fourth section tackles the delicate step of building up, in practice, the model along with its main components. Illustrating the main empirical results is the central part of the chapter's scope.
The first part is devoted to the construction of a chronology of stress events in the Eurozone by exploiting the indices under the form of another variable. Subsequently, the simple linear regression lagged model with credit-related variable as predictors is run with various specifications.
Finally, the HAR-RV model of Corsi (2008) is applied to the Italian Banking Index.

4.1 A chronology of Banking Stress Events in the Eurozone

The second empirical exercise, after the construction of the banking indices, consists in the realization of a chronology of banking stress events in the Eurozone. For this scope, I make use of the previously constructed banking indices and compute the level of stress in the country considered by means of a nice tool, i.e. the CMAX[135]. Indeed, the choice has been made between two alternatives. The first method of Patel and Sarkar (1998) calculates an indicator, the above mentioned CMAX, which detects extreme price levels over a given period (for example 12 or 24 months). The second method of Mishkin and White (2002) identify crises as falls in the price of a security or an index below a certain threshold (set arbitrarily at 20%) over a chosen time period (which may be a week, a month, a year, etc.). Obviously, each method has its own benefits and disadvantages and have some differences, even though they rely on the same working logic, that is, defining a crisis/stress event as the price decline of a stock or an index over a time window. The choice has been dictated by two reasons. First, I moved toward the method that needs of less arbitrariness in setting the yardstick. Second, the tool that offers more continuity, in line with the indices, has been preferred. In this direction, while the Mishkin and White's method (2002) allow to identify solely the crisis event once fixed both, an arbitrary threshold and the window over which the price decline has to occur, the CMAX indicator may be employed in a much continuous way such that the user can identify not only the crisis event itself but the level of stress over time. This monitoring action throughout the CMAX does not waste information that the continuous index provides. In addition, in the way I employ it, less subjectivity is required as I'm going to illustrate.
According Patel and Sarkar's approach (1998), to identify periods of significant price declines in the history of the EU countries analyzed, I make advantage of the CMAX indicator. The CMAX in time *t*, $CMAX_t$, with *t = 1, 2, …, T* takes the following form:

$$CMAX_t = \frac{P_t}{max[P_{t-m}, \dots, P_t]},$$

[135] The CMAX is largely utilized by equity market practitioners. The Morgan Stanley, for instance, used it in the monthly publication "MSCI perspective". See also Patel and Sarkar (1998) that first use it for stock market crises and Coudert and Gex (2006).

where m is usually equal to twenty-four months and P_t is the index price at time t. However, I also try to set m = *12* but in this way too much period of stress/crisis are identified[136].

The range of the $CMAX_t$ variable spaces between *0* and *1*. In particular, if the index price increases over the window considered the indicator equals *1*, whereas the more the price falls the closer the variable gets to *0*. The crucial point when using the CMAX, making the time window fixed to twenty-four months (as a rule of thumb), is the number of standard deviations to subtract to the mean of the CMAX series. Two or three standard deviations below the mean are considered when fixing the threshold. Here, as anticipated previously, I am interested in exploiting the continuity in the information offered by the indices. Thus, all three standard deviations from the mean are taken, corresponding to three different level of stress, namely, the first order stress (yellow code), the second order stress (orange code) and the third order stress (red code).

Before appreciating some CMAX graphs, additional technical details may be useful. One that is worth to notice is the starting point of the CMAX and the corresponding thresholds. Indeed, the indicator as well as the thresholds should start after the m window by construction. However, to make the variable starting from the unit and the first observation of the banking index, the index price in time *t*, P_t, with $t \leq m$ is divided by the maximum value between time zero and time *t* instead of excluding the first *m* time window. This to avoid losing too much information. Also, if a stress period starts too early, namely before one year from the inception of the CMAX series, it is not counted. In this way, the indicator series does not start with a truncation at some point between *0* and *1* and even though the initial information is not necessary usable (if a stress period immediately occurs it is not counted) it may always be useful to know the first 24-months history of the index CMAX.

The figure 4.1 (a, b) shows the CMAX of the Italian Banking Index with *m* set equal to 12- and 24-months respectively, and the three level of stress. Also, the CMAX is complemented by the banking index with shadows corresponding to the stress periods and a table summarizing this events and their depth.

First, it should be noted that at a first glance the CMAX variable recognizes well-known crisis events. In fact, it is worth to say that, by construction, the indicator is not designed for identifying the turning points since the fall in the share price is already well under way when it signals a crisis, but rather the indicator detects the point at which there has already been an abnormal drop in the price[137].

As pointed out in 4.1 tables the number of stress periods, the depth and the duration change by changing m. In more detail, when m is shorter the thresholds are something higher and the CMAX variable is prone to identify too much stress periods and of a greater duration and intensity. When m=*24* the CMAX variable is more conservative. In the former case, 4 first order stress events, 1 second order stress event and 3 third order stress events are identified. In the latter case, the first and second order stress events remain the same but only one third order stress event is signaled, that is, the 2007-08 financial crisis. In addition, the 12-months CMAX signals the ICT bubble as a second order gravity (whereas the 24-months gives a yellow code) and the 2012-13 crisis as well as the 2016 italian banking stressed period as red code.

[136] As it is going to be shown later, the event of stress identified with the CMAX are then compared with other crisis datasets.

[137] Coudert and Gex (2006).

However, as previously said, given the nature of this indicator and the scope in this context, these divergences assume a relative weight.
A further technical issue that cannot be neglected concern the way the thresholds are constructed concerning some special cases. As previously illustrated, the thresholds are obtained by subtracting once, twice and thrice the standard deviation from the mean, both computed on the entire CMAX series. This procedure gives reasonable thresholds and works well in its simplicity. Unfortunately, this is not always the case. It may be that some indices experience too much period of stress or that the period of loss are too much extended making the weight of the periods of negative performances in the series excessive, for threshold purposes, compared to the periods of positive performances[138]. In such a situation, if the usual procedure is applied the more restrictive thresholds are even negative. This is, for example, the case of the Greece and Ireland that have been overwhelmed by the last global financial crisis. For these two countries, a special treatment is carried out. In particular, to exploit as much information as possible, I restrict their sample by eliminating, partially or totally if needed, the 2007-08 financial crisis period. In more detail, for the Greek case, the last 2,200 day observations (something like 34 quarters) are removed so that the mean and the standard deviations are calculated until the end of 2007. In the case of Ireland, reasonable thresholds may be obtained by removing only three years of data, that is, from the inception of 2008 until the end of 2010[139]. The figure 4.2 (a, b) shows the CMAX complemented by the banking index with shadows corresponding to the stress periods and the related tables for both Greece and Ireland. One may note that the number of stress events affecting these countries is not particularly greater than the other's one. Probably, the frequency of stress episodes is even lower compared to the frequency of other more diligent countries but the intensity of the damages suffered by crisis events, especially those arising from the last financial crisis' losses is frightening.
At this stage, it is useful to illustrate how the CMAX variable is employed to develop a chronology of crisis/stress events in the Eurozone. Let us consider, in line with the work of Patel and Sarkar (1998) but with some differences[140], the following definitions.
I define the *beginning of the crash* as the first day in which the CMAX variable falls below the threshold set for the first order stress, i.e. one standard deviation from the mean. Analogously, the *date of recovery* is the first date in which the indicator overcomes the first order threshold coming back to "green ground". In addition, to avoid counting the same crisis twice the CMAX has to remain over the threshold for at least three quarters[141]. This means that additional triggers occurring within a crisis, that is, within nine months

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138 In such a situation, the length of the time series is important as well. A longer series would probably help to construct reasonable threshold also for these special cases to the extent in which additional information would raise the share of increasing returns.
139 Patel and Sarkar (1998) face a similar problem by splitting the sample period in two equal parts and taking the more stable one.
140 For instance, Patel and Sarkar (1998) set two thresholds to define a stock market crash, i.e. a more than 20 and 35 per cent of the regional price index decline relative to the historical maximum for developed and emerging market respectively, whereas I compute the price decline by applying the definition of starting and ending date of the stress period according the 3 standard deviation thresholds.
141 This "distance" is purely arbitrary. Some authors take six months, others one year. I take a half measure. It is true that stock prices tend to move and adjust in pretty fast way but maybe two quarter are really poor whereas a year may be abundant. However, it is worth to highlight that the choice of considering three quarters a reasonable window for a banking index to recover the previous losses is completely subjective.

from the first trigger (beginning of the crash) are considered part of the same crisis, instead of indicating a new crisis. The *beginning of the stress/crisis*, instead, is defined as the first day in which the CMAX falls from the unit and does not reach it anymore, keeping on the collapse until the threshold is broken. Note that I prefer to talk about stress rather than crisis since the focus here is, as previously said, on the level of stress affecting the banking system rather than solely on the final catastrophic event. This assumes importance to the extent in which the ItaBI CMAX, for example, signals a yellow code by broking the first order threshold, which is not so dangerous at that moment but may prepare the ground for an orange or red code[142]. In fact, the alarm codes observing in the table in figure 4.1 (c) reflect the intensity of the collapse/fall during the crash period. The 2007-08 financial crisis, for instance, is classified as a third code alarm since the indicator breaks all three thresholds by falling below three standard deviation from the mean. Finally, the *date of trough* is the last day in which the CMAX variable reach the lowest point during the crash period, i.e. from the beginning of crash to the date of recovery.

At this point, it is easy to identify the various stress periods and their related features. For this purpose, in line with Patel and Sarkar (1998), I define the *months to trough* as the period between the beginning of stress and the date of trough. Analogously, the *months to recovery* is the time window starting from the beginning of stress and ending in the date of recovery. Finally, the *smooth period* is the time passing from the previous recovery date up to the next stress during which the variable is in the “green ground”.

Subsequently, to get a grasp of the banking indices behaviour around a stress period, I compute the price decline to trough as well as the index return before and after the stress/crisis for a three-year window and both annually and cumulated. Index returns are expected to be positive in the period before the beginning of stress and negative but increasing in the period after the stress. The results confirm the expectations. Figure 4.3 shows the price decline to trough, and the index returns over the three-year window preceding and following the event of stress for Italy, France, Germany and Spain[143].

First, as it should be, the price decline to trough increases as passing from the first to the third order stress. When comparing the yellow and the orange code the difference is not always crystalline since in some cases the latter is lower than the former. As an example, consider the 2011/12 second order German stress and the last first order stress. In such a case, it is true that the latter price decline to trough is greater than the former’s (-60% vs -56%) but it is also true that the months to trough in the orange code are much lower than the ones of the yellow code (6 months and 26 days vs 29 months and 13 days). Therefore, the months to trough are complementary to the price decline information when valuing the intensity/gravity of a stress and ignoring it may be misleading. However, the gap among the three kind of stress is particularly marked when considering the red code, for which the price decline is not less than 70 per cent and reaches embarrassing figures such

[142] As it will be explained better later the yellow code is not considered a “crisis” but the typical turmoil of a financial market environment. Instead, for counting crisis events for dataset purposes only the orange and red code are considered.

[143] However, the chronology is also available for other EU countries such as Austria, Belgium, Cyprus, Czech Republic, Denmark, EU, Finland, Greece, Hungary, Ireland, Malta, Netherland, Poland, Portugal, Slovakia, Sweden and United Kingdom. Here, four main countries are taken as an example but later the second and third order stress events (which are considered crisis for dataset purposes) of all countries are summarized. For some country, whose banking index has less than 20 years of history, the chronology is not developed as it is not employed in the analysis, i.e. Bulgaria, Romania.

as the 100 per cent of decline, i.e. the maximum loss, in the case of the Greece and Ireland during the 2007-08 financial crisis.
Coming back to the indices' behaviour around the three-year window, one may easily notice that the trend of indices' return is positive and increasing as one approaches to the stress episode, especially in the last two years before the beginning of the stress. Also, the cumulated returns are generally positive over the window considered by reflecting the build-up phase of a crisis. There are, however, few exceptions in which the cumulated return before the beginning of the stress is something negative. Probably, these cases are a continuous of the previous crisis, namely, the banking sector of the country considered has never completely healed from the last stress.
Analogously, for the window after the episode. The first two years are the worst in terms of returns and the recovery in positive ground seems to occur solely in the third year. However, one may notice that, generally, apart for some yellow codes, three years are not enough for the banking sector to recover the previous losses as the cumulated returns shows.
Let us see now the chronology of stress events, as analyzed above, considered enough deep to be classified as crisis events. As anticipated above, the yellow code is not accounted for this purpose. Thus, to being classified as a crisis affecting the banking sector of the country considered, the CMAX has to signal an orange or red code. In this way, by refreshing that the banking indices available for the analysis (whose history is not shorter than 20 years) are twenty-one, including the EU banking index, the crisis events correspond to 49 episodes. Observing the crisis dataset in figure 4.4 one may notice, at a first glance, that, apart Malta and Portugal, all the EU countries analyzed have experienced at least one red code. Also, this is usually triggered by the 2007-08 financial crisis. The only countries for which the CMAX variable recognizes the latest global crisis but not identifying it as a third order stress are the Czech Republic, Finland and Poland. Malta seems to be the country less affected by crisis experiencing only one orange code whereas the Spain is the country most affected by crisis, i.e. five episodes among which one red code. The countries that experience more red codes, instead, are the Cyprus, Slovakia and Sweden with two cases. In addition, by looking at the countries with lowest price decline to trough, besides the previously mentioned Greek and Irish cases, it is worth to notice the Belgium case with a -94 per cent in less than two years (21 months), and the Polish case with a -90 per cent in 14 months.
Finally, the general considerations made for the chronology of stress events, about the CMAX behaviour around a crisis/stress window of three years, are naturally valid for this crisis dataset as well.

4.2 A simple Finite Distributed Lag model

This subsection is completely devoted to the finite distributed lag (FDL) model designed in the previous chapter. In line with the contribution of Schularick and Taylor (2012), the interest of the present analysis is to check whether there exists an evidence for credit growth–induced financial instability but focusing on the EU banking systems. Indeed, the primary purpose is to check if effectively credit booms are dangerous for the banking instability. A key innovation here is represented by the banking indices constructed for the specific purpose and employed as continuous dependent variables. The model, therefore, assuming the following form:

$$D\ log(y_{it}) = b_0 + b_1(L) D\ log X_{it} + e_{it}\ .$$

Where y contains the country-specific banking index time series returns, in real terms unless differently specified, whereas X can almost always be interchanged with the CREDIT variable, which is represented by the several credit-related variables that are object of study[144]. However, the focus and thus the starting point will be the total bank credit granted to the Private Non-Financial Sector (PNFS) deflated by the CPI. Also, much attention is devoted to other variables of credit, especially the credit-to-GDP variables. The predictors are examined one at a time. Naturally, the primary object of study in the model is the lag polynomial $b_1(L)$ that contains only lag orders greater than or equal to one. This to investigate if the lags of credit growth or another variable, for instance the DSR's growth, in a country i are informative on the health state of the banking sector of that country. Finally, e_{it} is the well-known error term.

Before proceeding with the analysis, it is necessary to spend few words about the model lag structure. As it will be shown during the analysis various lag structures are adopted. In more detail, for each credit-related regressor the lags are computed on three and five years with three different specifications for each temporal horizon, reflecting the lag frequency. For instance, in the three-year horizon case we will have the first specification (3YS1) consisting of three yearly lags, the second specification (3YS2) reporting six half-yearly lags and the third specification consisting of twelve quarterly lags. Analogously for the five-year window.

Last but not least, the difference-log relation. In line with Schularick and Taylor, I keep the differences of the logarithm of the variable under study as interested in the variable's growth rate but differently from the authors the first and the fourth difference are taken instead of the first one solely. In this way, some technical issues bounded to the quarterly data used are overcome. To be more precise, the fourth difference allows to work around the seasonality problem that characterizes the quarterly credit series whereas, since at this point the series are not stationary, the first difference deals with stationarity. The *logarithmic transformation* allows to obtain the month-to-month change in the year-over-year *percentage change* in the data (or, equivalently, the year-over-year difference in the month-to-month percentage change in the data)[145]. Also, note that D includes both the first or non-seasonal differencing, Δ_1, and the seasonal span differencing, Δ_s, where $s = 4$ when dealing with quarterly data. Also, note that the order in which the differencing is performed is of no consequence as the differencing operators, $\Delta_1$and Δ_s are commutative. However, from a step-by-step as well as logical standpoint, the non-seasonal difference is applied first on the logged regressor and then, as the data show some seasonality, the seasonal difference is run[146]. In symbol:

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[144] See the Data section on the variables used as regressors.

[145] All the advantages of using the log are well known. For example, log returns give the simplicity of multiperiod returns, i.e. k-period log return is the sum of single-period log returns rather than the product as for gross returns. In addition, the log stabilizes the variance of a variable whose conditional standard deviation is proportional to its conditional mean. See "Statistics and Data Analysis for Financial Engineering".

[146] It is worth to add that the seasonal adjustment revealed a critical point here. There exist various techniques to remove seasonality from a time series depending on various factors. Among others I also considered the programs of the US Census Bureau, known as X-13ARIMA-SEATS. However, due to the form of the variable employed, i.e. taking the compounding rate proxied by difference of logarithm, the Box-Jenkins modeling approach seemed more appropriate.
See "Box, G. E. P., G. M. Jenkins, and G. C. Reinsel. Time Series Analysis: Forecasting and Control. 3rd ed. Englewood Cliffs, NJ: Prentice Hall, 1994".

$$\Delta_s \Delta_1 y_t = \Delta_s (y_t - y_{t-1}) = (y_t - y_{t-1}) - (y_{t-s} - y_{t-1-s}) = \Delta_1 \Delta_s y_t \, .$$

4.2.1 Empirical Results from the FDL model

This subsection is dedicated to collect and summarize the empirical results from analyzing the main EU countries. Particularly, the analysis cover mainly the EU countries whose banking indices' time series are complete, that is, data are available from January, 1985 keeping into account the credit data availability as well.

Italy

The first country analyzed is Italy. This country, fortunately, from the 20th century going on does not experienced well-known banking crisis even though it has been strongly affected, as the most of EU countries, indirectly by the last global financial crisis. However, given the personal interest it is the same and first examined. The analysis starts with the Italian banking sector proxied by the Italian Banking Index (ItaBI) deflated by the ItaCPI, as dependent variable, and the total bank credit granted to the PNFS as regressor. The credit variable, on which the lags are applied, has been previously deflated by the ItaCPI and preprocessed to deal with stationarity, as pointed out above.
Following, tables 4.1 reports the best results for the first ItaBI regressions on both horizons. The matlab code reports all the models for the temporal horizon specified and lastly the best models according the criteria adopted. I report solely the most significant model for each specification. This is carried out with the aim of some criteria to select among models. Specifically, I mainly make benefit of the Akaike Information Criterion (AIC) even though the Adjusted R-Squared is considered in a complementary manner[147]. However, along with the model quality and the goodness-of-fit, also the precision of predictions is considered, thus the SE is monitored as well.
As the code indicates, AIC prefers the 3YS1 model whereas the Adjusted R-squared the 3YS3 model. This is not surprising given the different model structure's length.
Let us have a look at the regression content. Unfortunately, as a general observation, the history of bank credit granted to the PNFS in Italy seems not to be significant in predicting the Italian banking sector movements in the three-year specifications. The p-value of both lag specifications is poorly high (0.15 and 0.21) and the goodness-of-fit poorly low (0.02 and 0.03). The results do not improve when considering the 5-year horizon. If considering the best model in terms of AIC, the credit lags are not significant in predicting the banking index movement with a p-value of 0.19 and an Adjusted R-Squared of 0.02. The situation does not change when taking the real banking stock returns by deflating for the ItaCPI.

[147] The Adjusted R-Squared rather than the R-Squared since the former is adjusted for various factors such as the low number of observations.

Table 4.1 – Baseline model (1) with no aggregation.

```
The best linear model in terms of AIC for the three year horizon is :

Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                         Estimate        SE        tStat      pValue
                                       __________    ________    ________    _______

    (Intercept)                        -0.0097153    0.017743    -0.54757    0.58504
    L4_D_log(Bank credit to PNFS/CPI)     -1.2224      1.2988    -0.94117    0.34857
    L8_D_log(Bank credit to PNFS/CPI)     -1.8732      1.3205     -1.4185    0.15873
    L12_D_log(Bank credit to PNFS/CPI)     1.5585      1.3192      1.1813    0.23988


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.194
R-squared: 0.045,  Adjusted R-Squared 0.0203
F-statistic vs. constant model: 1.82, p-value = 0.147
```

```
The best linear model in terms of Adjusted R-Squared for the three year horizon is :

Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 13 terms in 12 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0098439	0.01765	-0.55772	0.5782
L1_D_log(Bank credit to PNFS/CPI)	1.0592	1.4084	0.75206	0.45367
L2_D_log(Bank credit to PNFS/CPI)	-0.18704	1.4417	-0.12974	0.89702
L3_D_log(Bank credit to PNFS/CPI)	0.12742	1.4624	0.087125	0.93074
L4_D_log(Bank credit to PNFS/CPI)	-0.41504	1.4577	-0.28473	0.7764
L5_D_log(Bank credit to PNFS/CPI)	-3.1148	1.5133	-2.0582	0.041999
L6_D_log(Bank credit to PNFS/CPI)	-0.13609	1.5465	-0.088002	0.93004
L7_D_log(Bank credit to PNFS/CPI)	-0.24676	1.5484	-0.15936	0.87368
L8_D_log(Bank credit to PNFS/CPI)	-1.6526	1.5207	-1.0867	0.27959
L9_D_log(Bank credit to PNFS/CPI)	-0.38125	1.4801	-0.25759	0.79722
L10_D_log(Bank credit to PNFS/CPI)	2.4639	1.4849	1.6593	0.099985
L11_D_log(Bank credit to PNFS/CPI)	-1.187	1.4669	-0.80914	0.42023
L12_D_log(Bank credit to PNFS/CPI)	1.1918	1.4358	0.8301	0.40833

```
Number of observations: 120, Error degrees of freedom: 107
Root Mean Squared Error: 0.193
R-squared: 0.129,  Adjusted R-Squared 0.0319
F-statistic vs. constant model: 1.33, p-value = 0.214
```

```
The best linear model in terms of AIC for the five year horizon is :

Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.010923	0.017744	-0.61561	0.53938
L4_D_log(Bank credit to PNFS/CPI)	-1.0884	1.3056	-0.83364	0.40623
L8_D_log(Bank credit to PNFS/CPI)	-2.2795	1.3495	-1.6891	0.093939
L12_D_log(Bank credit to PNFS/CPI)	1.2155	1.4096	0.86234	0.39031
L16_D_log(Bank credit to PNFS/CPI)	-1.6174	1.4097	-1.1473	0.25366
L20_D_log(Bank credit to PNFS/CPI)	0.83221	1.4906	0.55829	0.57774

```
Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.194
R-squared: 0.0634,  Adjusted R-Squared 0.0223
F-statistic vs. constant model: 1.54, p-value = 0.182
```

A slight improvement, instead, seems to occur when first aggregating the regressors and then both the dependent and the predictor variable. This is done with a matlab function used by Corsi (2008) in the HAR-RV model, namely, the "AggregateInMean" function[148]. Following, the best answers from the code when suggesting first to aggregate the credit variable before computing the lags and subsequently to aggregate both side of the model. It is worth to say that the when aggregating the left-hand side the length, *n*, over which run the aggregation is chosen by the user in line with the model specification whereas for the regressor all the *n =1,2,3,4* are employed and then the AIC criterion select among the four models according the user input on the left-hand side. Then, the three best specifications are compared again as usual. This because for the dependent variable the best *n* changes depending on the specification[149], and the value for the predictor variable changes consequently (even though often the one year aggregation is selected) so the code selects for the user.

Let us see the regressions with aggregated variables. Table 4.2 shows the baseline (2) model with only the regressors aggregated in mean. For the three-year horizon, the two criteria agree on S1, for which the best aggregation length is *n = 2*, whereas for the five-year horizon the AIC and the Adjusted R-Squared points out the first and the third specification respectively with *n = 2* for both specifications. However, while the longest specification, 5YS3 seems to fit the data better than the first one, 5YS1, it is much less accurate as indicated by the SEs.

Table 4.2 – Baseline model (2) with aggregated regressors.

```
The best linear model in terms of AIC for the three year horizon with the predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    D_log(Bank credit to PNFS/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                              Estimate       SE        tStat       pValue
                                             __________    ________    ________    ________

    (Intercept)                              -0.0095638    0.017475    -0.54729     0.58523
    L4_Aggr_D_log(Bank credit to PNFS/CPI)      -3.3222      1.6046     -2.0704    0.040636
    L8_Aggr_D_log(Bank credit to PNFS/CPI)      -1.6349      1.6019     -1.0206     0.30957
    L12_Aggr_D_log(Bank credit to PNFS/CPI)      2.4887      1.6268      1.5299     0.12877


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.191
R-squared: 0.0738,  Adjusted R-Squared 0.0498
F-statistic vs. constant model: 3.08, p-value = 0.0303
```

[148] As the code reports, the function 'aggregateInMean(x,n)' … "aggregates over a window of length n, the vector x sliding of one element at time. Then the first result is a vector of non-overlapping aggregate of length x/n. The second output is an overlapping aggregate vector of n elements having the same length of the original x…". I employ the second output.

[149] It is worth to specify that to exploit at best the three specifications the length *n* for the dependent variable is changed even though the best aggregation seems to be always n=6.

```
The best linear model in terms of AIC for the five year horizon with the predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0090742	0.017512	-0.51816	0.60535
L4_Aggr_D_log(Bank credit to PNFS/CPI)	-3.2875	1.6106	-2.0412	0.043543
L8_Aggr_D_log(Bank credit to PNFS/CPI)	-1.7938	1.6341	-1.0977	0.27464
L12_Aggr_D_log(Bank credit to PNFS/CPI)	1.9895	1.6697	1.1915	0.23593
L16_Aggr_D_log(Bank credit to PNFS/CPI)	-2.0488	1.7044	-1.202	0.23184
L20_Aggr_D_log(Bank credit to PNFS/CPI)	-1.6195	1.8308	-0.88459	0.37824

```
Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.191
R-squared: 0.0889,  Adjusted R-Squared 0.0489
F-statistic vs. constant model: 2.22, p-value = 0.0566
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with the predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 21 terms in 20 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0096878	0.017131	-0.56552	0.573
L1_Aggr_D_log(Bank credit to PNFS/CPI)	1.5975	2.5809	0.61895	0.53737
L2_Aggr_D_log(Bank credit to PNFS/CPI)	-2.9855	3.7145	-0.80374	0.42347
L3_Aggr_D_log(Bank credit to PNFS/CPI)	2.716	4.018	0.67596	0.50064
L4_Aggr_D_log(Bank credit to PNFS/CPI)	-2.1728	4.2073	-0.51643	0.60671
L5_Aggr_D_log(Bank credit to PNFS/CPI)	-4.5424	4.6551	-0.97579	0.33154
L6_Aggr_D_log(Bank credit to PNFS/CPI)	3.9839	5.092	0.78237	0.43586
L7_Aggr_D_log(Bank credit to PNFS/CPI)	-3.434	5.3033	-0.64752	0.51879
L8_Aggr_D_log(Bank credit to PNFS/CPI)	-2.0799	5.4143	-0.38415	0.70169
L9_Aggr_D_log(Bank credit to PNFS/CPI)	1.9397	5.5896	0.34702	0.72932
L10_Aggr_D_log(Bank credit to PNFS/CPI)	1.3232	5.7654	0.22951	0.81894
L11_Aggr_D_log(Bank credit to PNFS/CPI)	-1.7555	5.7927	-0.30306	0.76248
L12_Aggr_D_log(Bank credit to PNFS/CPI)	4.6213	5.6395	0.81944	0.4145
L13_Aggr_D_log(Bank credit to PNFS/CPI)	-2.0116	5.4735	-0.36752	0.71402
L14_Aggr_D_log(Bank credit to PNFS/CPI)	-2.5558	5.413	-0.47215	0.63786
L15_Aggr_D_log(Bank credit to PNFS/CPI)	1.8368	5.3036	0.34632	0.72984
L16_Aggr_D_log(Bank credit to PNFS/CPI)	-3.9204	4.8821	-0.80301	0.4239
L17_Aggr_D_log(Bank credit to PNFS/CPI)	3.2619	4.4129	0.73917	0.46155
L18_Aggr_D_log(Bank credit to PNFS/CPI)	-4.9439	4.2917	-1.152	0.25211
L19_Aggr_D_log(Bank credit to PNFS/CPI)	10.764	4.0858	2.6346	0.009778
L20_Aggr_D_log(Bank credit to PNFS/CPI)	-8.2574	2.8827	-2.8645	0.0051005

```
Number of observations: 120, Error degrees of freedom: 99
Root Mean Squared Error: 0.187
R-squared: 0.245,  Adjusted R-Squared 0.0923
F-statistic vs. constant model: 1.61, p-value = 0.0662
```

Let us see now the most interesting results offered by the baseline model (3) with both side of regression aggregated. The table 4.3 shows the best results among the three specifications for the two horizons.

Table 4.3 – Baseline model (3) with both the dependent and predictor variables aggregated.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                                 Estimate       SE        tStat       pValue
                                                __________    _________    ________    _________

    (Intercept)                                 -0.0084099    0.0092889    -0.90537      0.36715
    L4_Aggr_D_log(Bank credit to PNFS/CPI)         -2.7323        1.031     -2.6501    0.0091695
    L8_Aggr_D_log(Bank credit to PNFS/CPI)         -1.9069       1.0302      -1.851     0.066714
    L12_Aggr_D_log(Bank credit to PNFS/CPI)         2.0154        1.045      1.9285     0.056239


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.102
R-squared: 0.122,  Adjusted R-Squared 0.099
F-statistic vs. constant model: 5.36, p-value = 0.00172
```

```
The best linear model in terms of Adjusted R-Squared for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
                                                Estimate        SE        tStat       pValue
                                                _________    ________    ________    _______

    (Intercept)                                 -0.008473    0.009216    -0.91938    0.35986
    L2_Aggr_D_log(Bank credit to PNFS/CPI)        -0.4801      1.5143    -0.31705    0.75179
    L4_Aggr_D_log(Bank credit to PNFS/CPI)       -0.72153      2.1323    -0.33839     0.7357
    L6_Aggr_D_log(Bank credit to PNFS/CPI)        -2.5532      2.4243     -1.0532    0.29452
    L8_Aggr_D_log(Bank credit to PNFS/CPI)        -1.8466      2.4461    -0.75491    0.45187
    L10_Aggr_D_log(Bank credit to PNFS/CPI)        2.2788      2.1608      1.0546    0.29384
    L12_Aggr_D_log(Bank credit to PNFS/CPI)       0.46487      1.5401     0.30184    0.76333


Number of observations: 120, Error degrees of freedom: 113
Root Mean Squared Error: 0.101
R-squared: 0.158,  Adjusted R-Squared 0.113
F-statistic vs. constant model: 3.53, p-value = 0.00307
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                              Estimate       SE         tStat       pValue
                                             __________    _________    ________    _________

    (Intercept)                              -0.0075673    0.0090958    -0.83195      0.40718
    L4_Aggr_D_log(Bank credit to PNFS/CPI)      -2.3733       1.0239     -2.3179     0.022238
    L8_Aggr_D_log(Bank credit to PNFS/CPI)      -2.0861       1.0333     -2.0189     0.045842
    L12_Aggr_D_log(Bank credit to PNFS/CPI)      1.9435       1.0275      1.8914     0.061112
    L16_Aggr_D_log(Bank credit to PNFS/CPI)      -2.954       1.0795     -2.7365    0.0072043
    L20_Aggr_D_log(Bank credit to PNFS/CPI)    -0.80585       1.1704    -0.68853      0.49252


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.0992
R-squared: 0.178,  Adjusted R-Squared 0.142
F-statistic vs. constant model: 4.93, p-value = 0.0004
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                              Estimate       SE         tStat      pValue
                                             _________    _________    ________    _______

    (Intercept)                              -0.007657    0.0090978    -0.84163    0.40184
    L2_Aggr_D_log(Bank credit to PNFS/CPI)    -0.99789       1.5638    -0.63812    0.52473
    L4_Aggr_D_log(Bank credit to PNFS/CPI)    0.064471       2.3143    0.027858    0.97783
    L6_Aggr_D_log(Bank credit to PNFS/CPI)      -3.195       2.7473     -1.1629    0.24739
    L8_Aggr_D_log(Bank credit to PNFS/CPI)    -0.98211       2.9447    -0.33352    0.73939
    L10_Aggr_D_log(Bank credit to PNFS/CPI)    0.57126       3.0616     0.18659    0.85233
    L12_Aggr_D_log(Bank credit to PNFS/CPI)     2.3179       3.0744     0.75394    0.45251
    L14_Aggr_D_log(Bank credit to PNFS/CPI)    -1.3595       3.0212    -0.44999    0.65361
    L16_Aggr_D_log(Bank credit to PNFS/CPI)    -2.7727       2.8535    -0.97167    0.33337
    L18_Aggr_D_log(Bank credit to PNFS/CPI)     1.5103       2.4633     0.61312    0.54107
    L20_Aggr_D_log(Bank credit to PNFS/CPI)    -1.9032       1.7293     -1.1006    0.27352


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.0992
R-squared: 0.214,  Adjusted R-Squared 0.142
F-statistic vs. constant model: 2.97, p-value = 0.00244
```

The AIC and Adjusted R-Squared are consistent along the two horizons considered by selecting always the first and second specification respectively. It is worth to add that in the baseline model (3) with both variables aggregated with the 'aggregateInMean' function, the aggregation length considered span always between the 0 - 4 range for the regressand as well as for the regressors[150]. However, the best aggregation length for the dependent variable is *n=4* which gives for the regressors always *n=4* to get the best models.
Let us see in more detail the regression content.
First, all the coefficient estimates in both the S1s, apart the last lag L20 in 5YS1, are significant at least at the 10% confidence interval (CI) which is not the maximum of the attendance but is a great step forward with respect to the inception baseline (1) model. In addition, the first two lags in the 5YS1 are significant at 5%.
Second, even though the joint significance of the lag structure in each S2 model is high at the narrower CI, as the p-value of the F-statistic points out, the coefficient estimates in both S2 are essentially not significant. This is probably due to the nature of the FDL model. One drawback of this class of models, as anticipated before, lies in the multicollinearity. Even if the credit regressor is stationary, as it has been carefully done, when lagging it may be highly autocorrelated making each observation strongly correlated with the previous one, which leads to unreliable coefficient estimates with large variances and standard errors. A possible solution could be to impose some restriction on the lag weights thus ending with a restricted FDL model. In this sense, the most common application is the *polynomial distributed lag* model first explored by Shirley Almon (1965) which, as the name suggests, consists in imposing a shape on the lag distribution to reduce the effects of collinearity, i.e. assume that the lag weights follow a smooth pattern that can be represented by a low degree polynomial, represented in practice by a quadratic function. However, this alternative has its own disadvantages as well. First, it imposes a non-negligible smoothness on the coefficients and, most importantly, imposing restrictions on the parameters leads to bias unless these are true. Since the quadratic lag distribution looks counterintuitive, for example, with lags that swoop into negative values in the middle, giving evidence of misspecification of the model, this way is abandoned.
Coming back to our models, let us check if effectively the collinearity among the lagged regressors is present. For this purpose, I make benefit of the Belsley collinearity diagnostic approach[151]. Look at the table 4.4 in which the collinearity test is run in matlab for all the three specifications over 5 years. If the *Conditional Index* (condIdx) overcome the default threshold of 30, collinearity is present among the lagged regressors. In addition, to check which lagged regressors are affected by collinearity one should look at the variance decomposition proportions identifying individual predictors (columns on the right of condIdx column) for which Belsley suggests a tolerance of 0.5. It is worth to say that Belsley's simulation experiments suggest that condition indices in the range of 5 to 10 reflect weak dependencies, and those in the range 30 to 100 reflect moderate to high dependencies. However, as we can see, even though the index value increases when passing from S1 to S3, it never exceeds the default bound. If one wish to be more conservative by considering a 10 threshold the S3 should be excluded and being strictly

[150] Different from the baseline model (4) in which the moving average of the regressand instead of the aggregation is taken and in which the moving window is allow to exceed the limit of one year.
[151] See Belsley, D. A., E. Kuh, and R. E. Welsch. Regression Diagnostics. Hoboken, NJ: John Wiley & Sons, 1980.

conservative with a condIdx bound equal to 5 only the S1 should be accepted[152]. The collinearity diagnostics may be a further help in selecting the most appropriate model. However, even before the collintest, the choice, by employing this first credit variable, was fallen the same on the S1, in particular on the baseline (3) 3YS1 and 5YS1 models. Also, I would like to precise that I am not going to choose only one absolute model but rather use the best models in a complementary way. In the following economic interpretation, this will be demonstrated.

What does the 3YS1 and 5YS1 result mean from an economic standpoint? At a first glance, the three and five annual lags point out that the relationship between the credit variable employed as regressor and the banking sector proxied by the ItaBI seems to be positive in the short run and negative in the long run with a cycle of three years. In more detail, the results may be interpreted in this way: given, in the year *t*, a 1 per cent increase in the italian total bank credit granted to the PNFS and aggregated over one year, the italian banking sector/index is going to rise of about 2 per cent in the same year *t* (short run), to decrease of about the same percentage in the second year *t+1*, and of about 2.4 - 2.7 per cent in the third year *t+2* (long run).

What about the fourth annual negative lag in S5? Probably, it represents the last year of the previous cycle and therefore is negative. In the framework so depicted, the first positive year of the cycle could represent the build-up phase of the stress in the banking system and the two subsequent years when the stress materializes. Most importantly, if this interpretation is correct, the turning point between the first and the second year or equivalently between the third and second lag when passing from positive to negative sign becomes fundamental to the extent in which it may warn that trouble/stress is likely to follow. However, it is too early to say that.

Finally, before moving to the other version of the bank credit variable, let’s see the baseline model (4). The only difference with respect to the baseline (3) consists in the fact that the left-hand side of the FDL model is aggregated with a moving average (MA) instead of the ‘aggregateInMean’ function and there is no more the limit of one year for aggregating. From a practical standpoint, the ‘aggregateInMean’ function and the MA provide similar results with the latter slightly better. The table 4.4 shows these small improvements.

[152] However, the S2 is on the limit of exclusion since only the last row surpass the bound.

Table 4.4 – Baseline model (4) with a MA dependent variable and predictor variables aggregated as usual. The top panel shows the MA of ItaBI with n = 4 to compare with the 5YS1 baseline model (3) with ItaBI aggregated over the same window.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                              Estimate       SE        tStat       pValue
                                             __________    _______    ________    __________

    (Intercept)                              -0.0024748    0.006687   -0.37009       0.71202
    L4_Aggr_D_log(Bank credit to PNFS/CPI)      -1.6182     0.73354     -2.206      0.029444
    L8_Aggr_D_log(Bank credit to PNFS/CPI)      -2.7303     0.72587    -3.7614    0.00027154
    L12_Aggr_D_log(Bank credit to PNFS/CPI)      1.4023     0.73656     1.9039      0.059511


Number of observations: 115, Error degrees of freedom: 111
Root Mean Squared Error: 0.0716
R-squared: 0.179,  Adjusted R-Squared 0.157
F-statistic vs. constant model: 8.09, p-value = 6.39e-05
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                              Estimate       SE         tStat       pValue
                                             _________    _________    ________    __________

    (Intercept)                              -0.001265    0.0065342    -0.19359       0.84686
    L4_Aggr_D_log(Bank credit to PNFS/CPI)     -1.5102      0.72711     -2.0771      0.040146
    L8_Aggr_D_log(Bank credit to PNFS/CPI)     -2.6386      0.72645     -3.6323    0.00042992
    L12_Aggr_D_log(Bank credit to PNFS/CPI)     1.2475      0.72266      1.7263      0.087131
    L16_Aggr_D_log(Bank credit to PNFS/CPI)    -1.6954      0.75911     -2.2334      0.027564
    L20_Aggr_D_log(Bank credit to PNFS/CPI)    -1.5314      0.82294     -1.8609      0.065454


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0697
R-squared: 0.236,  Adjusted R-Squared 0.201
F-statistic vs. constant model: 6.73, p-value = 1.68e-05
```

Two observations are worth to be cited.
First, as the top panel shows, when using the MA instead of the 'aggregateInMean' function and keeping fixed the window length *n*, both the overall p-value and the one of the coefficient estimates reduce further. In the specific 5YS1 case also the third annual lag, L12, becomes significant at 5% CI.
Second, while for the 'aggregateInMean' function the best *n* between the 0 – 4 range is one year, with the MA the best aggregation length is $n = 6$ since when $n \geq 7$ the model performance starts to decay. In total, the 5YS1 baseline model (4) with an ItaBI MA with $n = 6$ seems to be the best performer. From an economic viewpoint, the interpretation remains unchanged with respect the baseline model (3).

Let us proceed with the analysis of the other bank credit-related variable, namely, that expressed in percentage of the GDP.
When considering the total bank credit granted to the PNFS in percentage of GDP the results seems even more scarce. In fact, some significance appears only in baseline model (3) and (4) as table 4.5 and 4.6 show. As a general observation, it is easy to see that once again the criteria are consistent along the two horizons by choosing the S1 and S2. In more detail, for the bank credit to GDP, unusually, the 3-year horizon models outperform the 5-year horizon ones as the former signal smaller p-values of the overall lag structure with respect to the latter with the 5YS2 even not significant at 10% CI (0.0438 vs 0.0788 for the S1 and 0.0368 vs 0.105 for the S2). Again, the coefficient estimates are not significant especially for S2. The best model, i.e. the 3YS1 has the first two annual lags significant at 10% and 5% respectively. While the relationship between the two variables seems negative, there is too less significant information to draw some conclusion. When taking the MA on the left-hand side, with the best aggregation window, that is, $n = 6$, the framework does not change substantially if not for the strongest significance at the second annual lag but clearly it is affected by the aggregation window.

Table 4.5 – Baseline model (3) with both sides of the regression aggregated in mean.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                          Estimate        SE         tStat       pValue
                                         __________    _________    ________    ________

    (Intercept)                          -0.0071346    0.0095972     -0.7434     0.45874
    L4_Aggr_D_log(Bank credit/GDP)          -2.1306       1.1562     -1.8427    0.067923
    L8_Aggr_D_log(Bank credit/GDP)          -2.5435       1.1561     -2.2001     0.02978
    L12_Aggr_D_log(Bank credit/GDP)         0.88959       1.1625     0.76526     0.44567


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.105
R-squared: 0.0672,  Adjusted R-Squared 0.0431
F-statistic vs. constant model: 2.79, p-value = 0.0438
```

```
The best linear model in terms of Adjusted R-Squared for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
                                          Estimate        SE         tStat      pValue
                                         __________    _________    ________    _______

    (Intercept)                          -0.0075697    0.0094977      -0.797    0.42712
    L2_Aggr_D_log(Bank credit/GDP)           1.4584       1.2574      1.1599    0.24854
    L4_Aggr_D_log(Bank credit/GDP)         -0.60408       1.4922    -0.40483    0.68637
    L6_Aggr_D_log(Bank credit/GDP)          -2.5841       1.6165     -1.5985    0.11272
    L8_Aggr_D_log(Bank credit/GDP)         -0.94637       1.6287    -0.58106    0.56236
    L10_Aggr_D_log(Bank credit/GDP)        -0.57968        1.521    -0.38112    0.70383
    L12_Aggr_D_log(Bank credit/GDP)         0.58658        1.277     0.45935    0.64686


Number of observations: 120, Error degrees of freedom: 113
Root Mean Squared Error: 0.104
R-squared: 0.11,  Adjusted R-Squared 0.0629
F-statistic vs. constant model: 2.33, p-value = 0.0368
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                        Estimate        SE         tStat       pValue 
                                       __________    _________    ________    ________

    (Intercept)                        -0.0077275    0.0096792    -0.79836     0.42632
    L4_Aggr_D_log(Bank credit/GDP)       -0.40281      0.94016    -0.42845     0.66913
    L8_Aggr_D_log(Bank credit/GDP)        -2.4001      0.95944     -2.5015    0.013786
    L12_Aggr_D_log(Bank credit/GDP)       0.23202      0.96537     0.24034      0.8105
    L16_Aggr_D_log(Bank credit/GDP)       -1.3979       0.9882     -1.4146     0.15991
    L20_Aggr_D_log(Bank credit/GDP)       0.46814       1.0263     0.45615     0.64915


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.105
R-squared: 0.082,  Adjusted R-Squared 0.0417
F-statistic vs. constant model: 2.04, p-value = 0.0788
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                        Estimate        SE         tStat       pValue 
                                       __________    _________    ________    ________

    (Intercept)                        -0.0073716    0.0097053    -0.75954     0.44917
    L2_Aggr_D_log(Bank credit/GDP)         1.1643       1.3538     0.86006     0.39164
    L4_Aggr_D_log(Bank credit/GDP)       -0.59789       1.6052    -0.37248     0.71026
    L6_Aggr_D_log(Bank credit/GDP)        -2.1002       1.7415      -1.206     0.23044
    L8_Aggr_D_log(Bank credit/GDP)         -1.423       1.7763    -0.80108     0.42483
    L10_Aggr_D_log(Bank credit/GDP)      -0.50917       1.7686     -0.2879     0.77397
    L12_Aggr_D_log(Bank credit/GDP)       0.53806       1.7799     0.30229       0.763
    L14_Aggr_D_log(Bank credit/GDP)       0.29609       1.8172     0.16294     0.87087
    L16_Aggr_D_log(Bank credit/GDP)       -2.0893       1.8145     -1.1514     0.25207
    L18_Aggr_D_log(Bank credit/GDP)        2.1125       1.6769      1.2597     0.21046
    L20_Aggr_D_log(Bank credit/GDP)      -0.75143       1.4532    -0.51707     0.60615


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.104
R-squared: 0.131,  Adjusted R-Squared 0.0509
F-statistic vs. constant model: 1.64, p-value = 0.105
```

Table 4.6 – Baseline model (4) with a MA dependent variable and predictor variables aggregated as usual.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.00095235	0.0069749	-0.13654	0.89164
L4_Aggr_D_log(Bank credit/GDP)	-0.033665	0.75846	-0.044385	0.96468
L8_Aggr_D_log(Bank credit/GDP)	-2.7666	0.75365	-3.671	0.00037315
L12_Aggr_D_log(Bank credit/GDP)	-0.23099	0.75414	-0.3063	0.75995

```
Number of observations: 115, Error degrees of freedom: 111
Root Mean Squared Error: 0.0746
R-squared: 0.109,  Adjusted R-Squared 0.0854
F-statistic vs. constant model: 4.55, p-value = 0.00479
```

```
The best linear model in terms of Adjusted R-Squared for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.00057538	0.0069735	-0.08251	0.93439
L2_Aggr_D_log(Bank credit/GDP)	1.3168	1.2319	1.0689	0.2875
L4_Aggr_D_log(Bank credit/GDP)	-0.60035	1.6985	-0.35346	0.72443
L6_Aggr_D_log(Bank credit/GDP)	-1.1046	1.9537	-0.56538	0.57299
L8_Aggr_D_log(Bank credit/GDP)	-2.2352	1.9394	-1.1525	0.25165
L10_Aggr_D_log(Bank credit/GDP)	-0.073639	1.6634	-0.044271	0.96477
L12_Aggr_D_log(Bank credit/GDP)	-0.15288	1.1878	-0.12871	0.89783

```
Number of observations: 115, Error degrees of freedom: 108
Root Mean Squared Error: 0.0745
R-squared: 0.135,  Adjusted R-Squared 0.0873
F-statistic vs. constant model: 2.82, p-value = 0.0138
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                        Estimate         SE          tStat       pValue
                                       ___________    _________    _________    ________

    (Intercept)                        -0.00035096    0.0071177    -0.049308     0.96076
    L4_Aggr_D_log(Bank credit/GDP)       -0.060666      0.76526    -0.079275     0.93696
    L8_Aggr_D_log(Bank credit/GDP)         -2.7348       0.7605       -3.596    0.000487
    L12_Aggr_D_log(Bank credit/GDP)       -0.28931      0.76493     -0.37822       0.706
    L16_Aggr_D_log(Bank credit/GDP)       -0.58541      0.78413     -0.74658     0.45693
    L20_Aggr_D_log(Bank credit/GDP)       -0.17275      0.82338     -0.20981     0.83421


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0751
R-squared: 0.114,  Adjusted R-Squared 0.0734
F-statistic vs. constant model: 2.81, p-value = 0.02
```

So far, I treated basically credit granted from banks to the PNFS and the related variables such as in percentage of GDP. Let us see now the total amount of credit granted from all institution (not only commercial banks) to the borrowers and the related variables. Intuitively, the relation between the total credit granted to the PNFS and the banking sector should be less strong with respect the total bank credit and the same banking index granting that credit. The results confirm the expectations.
As for the total bank credit, the 5-year horizon explains better the ItaBI movements. The two criteria disagree along the two horizons: for the shortest one the S1 and S2 are chosen whereas for the longest one both AIC and Adjust R-Squared select S2.

Table 4.7 – Baseline model (3) with both sides of the regression aggregated in mean.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                        Estimate       SE          tStat       pValue
                                       _________    _________    _________    ________

    (Intercept)                        -0.008162    0.0096272     -0.84781     0.39829
    L4_Aggr_D_log(Credit to PNFS/CPI)    -2.5956       1.1594      -2.2388    0.027077
    L8_Aggr_D_log(Credit to PNFS/CPI)     1.4969       1.1662       1.2836     0.20185
    L12_Aggr_D_log(Credit to PNFS/CPI) -0.052783       1.1707    -0.045086     0.96412


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.105
R-squared: 0.0548,  Adjusted R-Squared 0.0303
F-statistic vs. constant model: 2.24, p-value = 0.0872
```

The best linear model in terms of Adjusted R-Squared for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =

Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.0082559	0.0095866	-0.8612	0.39095
L2_Aggr_D_log(Credit to PNFS/CPI)	-0.77831	1.6352	-0.47597	0.63501
L4_Aggr_D_log(Credit to PNFS/CPI)	-2.487	2.2681	-1.0965	0.27519
L6_Aggr_D_log(Credit to PNFS/CPI)	0.63089	2.5795	0.24458	0.80722
L8_Aggr_D_log(Credit to PNFS/CPI)	-0.77904	2.5917	-0.30059	0.76428
L10_Aggr_D_log(Credit to PNFS/CPI)	3.6297	2.302	1.5768	0.11764
L12_Aggr_D_log(Credit to PNFS/CPI)	-1.9984	1.6598	-1.204	0.23112

Number of observations: 120, Error degrees of freedom: 113
Root Mean Squared Error: 0.105
R-squared: 0.087, Adjusted R-Squared 0.0385
F-statistic vs. constant model: 1.79, p-value = 0.106

The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =

Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.0080804	0.0090712	-0.89078	0.37492
L4_Aggr_D_log(Credit to PNFS/CPI)	-2.4659	1.0969	-2.248	0.026498
L8_Aggr_D_log(Credit to PNFS/CPI)	1.3168	1.0999	1.1973	0.23369
L12_Aggr_D_log(Credit to PNFS/CPI)	-0.022323	1.1043	-0.020215	0.98391
L16_Aggr_D_log(Credit to PNFS/CPI)	-4.5018	1.1094	-4.0577	9.1105e-05
L20_Aggr_D_log(Credit to PNFS/CPI)	0.58641	1.1244	0.52154	0.60301

Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.0993
R-squared: 0.175, Adjusted R-Squared 0.139
F-statistic vs. constant model: 4.85, p-value = 0.000463

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                        Estimate        SE         tStat       pValue
                                       __________    _________    _________    _________

    (Intercept)                        -0.0088734    0.0089768    -0.98848      0.32511
    L2_Aggr_D_log(Credit to PNFS/CPI)     -0.8295      0.91756    -0.90402      0.36798
    L4_Aggr_D_log(Credit to PNFS/CPI)    -0.66156      0.96326    -0.68679      0.49367
    L6_Aggr_D_log(Credit to PNFS/CPI)     -2.0455      0.99914     -2.0472     0.043041
    L8_Aggr_D_log(Credit to PNFS/CPI)     0.73914       1.0188     0.72549      0.46971
    L10_Aggr_D_log(Credit to PNFS/CPI)    0.72258       1.0299     0.70163       0.4844
    L12_Aggr_D_log(Credit to PNFS/CPI)     1.0369       1.0343      1.0025      0.31832
    L14_Aggr_D_log(Credit to PNFS/CPI)     -1.211       1.0257     -1.1807      0.24029
    L16_Aggr_D_log(Credit to PNFS/CPI)    -3.2339       1.0117     -3.1964    0.0018212
    L18_Aggr_D_log(Credit to PNFS/CPI)     -1.251      0.98514     -1.2699      0.20682
    L20_Aggr_D_log(Credit to PNFS/CPI)   0.072353      0.94317    0.076713      0.93899


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.0983
R-squared: 0.228,  Adjusted R-Squared 0.158
F-statistic vs. constant model: 3.23, p-value = 0.00113
```

However, as one can notice I also reported the S1 for the 5-year for comparison with the analogous model of bank credit. While the p-value of the overall lag structure is significant, the coefficient estimates here are less significant with respect the bank credit complicating the inference.

Table 4.8 – Baseline model (4) with a MA dependent variable and predictor variables aggregated as usual.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                        Estimate        SE         tStat       pValue
                                       __________    _________    ________    ________

    (Intercept)                        -0.0022799    0.0071187    -0.32027     0.74937
    L4_Aggr_D_log(Credit to PNFS/CPI)     -1.3837      0.68399     -2.0229    0.045483
    L8_Aggr_D_log(Credit to PNFS/CPI)    -0.67717      0.68589    -0.98728     0.32565
    L12_Aggr_D_log(Credit to PNFS/CPI)     1.1165      0.68007      1.6417     0.10349


Number of observations: 115, Error degrees of freedom: 111
Root Mean Squared Error: 0.0763
R-squared: 0.0684,  Adjusted R-Squared 0.0432
F-statistic vs. constant model: 2.72, p-value = 0.0481
```

```
The best linear model in terms of Adjusted R-Squared for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
                                      Estimate        SE         tStat       pValue
                                     __________    _________    ________    _______

    (Intercept)                      -0.0024923    0.0070813    -0.35195    0.72556
    L2_Aggr_D_log(Credit to PNFS/CPI)   -1.0021       1.2622    -0.79389      0.429
    L4_Aggr_D_log(Credit to PNFS/CPI)   -1.4517       1.7183    -0.84489    0.40004
    L6_Aggr_D_log(Credit to PNFS/CPI)  -0.12927       1.9217   -0.067267    0.94649
    L8_Aggr_D_log(Credit to PNFS/CPI)    -1.296       1.9094    -0.67876    0.49874
    L10_Aggr_D_log(Credit to PNFS/CPI)   2.7748        1.683      1.6488     0.1021
    L12_Aggr_D_log(Credit to PNFS/CPI) -0.77058       1.2051    -0.63944    0.52389


Number of observations: 115, Error degrees of freedom: 108
Root Mean Squared Error: 0.0758
R-squared: 0.105,  Adjusted R-Squared 0.0552
F-statistic vs. constant model: 2.11, p-value = 0.0579
```

```
Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                         Estimate        SE         tStat        pValue
                                        __________    _________    ________    _________

    (Intercept)                         -0.0018553    0.0065562    -0.28298      0.77773
    L4_Aggr_D_log(Credit to PNFS/CPI)      -2.0497      0.78833        -2.6     0.010614
    L8_Aggr_D_log(Credit to PNFS/CPI)     0.014306      0.77821    0.018384      0.98537
    L12_Aggr_D_log(Credit to PNFS/CPI)     0.70958      0.78136     0.90814      0.36581
    L16_Aggr_D_log(Credit to PNFS/CPI)     -3.7316      0.78501     -4.7536    6.146e-06
    L20_Aggr_D_log(Credit to PNFS/CPI)    -0.67429      0.79566    -0.84746       0.3986


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0703
R-squared: 0.224,  Adjusted R-Squared 0.188
F-statistic vs. constant model: 6.28, p-value = 3.68e-05
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                            Estimate        SE         tStat       pValue
                                           __________    ________    ________    ________

    (Intercept)                            -0.0022378    0.006429    -0.34808     0.72848
    L2_Aggr_D_log(Credit to PNFS/CPI)          -1.598      1.1614      -1.376     0.17178
    L4_Aggr_D_log(Credit to PNFS/CPI)        -0.41454      1.6185    -0.25613     0.79836
    L6_Aggr_D_log(Credit to PNFS/CPI)         -1.4465      1.9117    -0.75666     0.45096
    L8_Aggr_D_log(Credit to PNFS/CPI)         0.15664      2.0877    0.075029     0.94034
    L10_Aggr_D_log(Credit to PNFS/CPI)        0.84547      2.1801     0.38782     0.69895
    L12_Aggr_D_log(Credit to PNFS/CPI)         1.1545      2.1651     0.53324       0.595
    L14_Aggr_D_log(Credit to PNFS/CPI)        -1.9382      2.0585    -0.94158     0.34859
    L16_Aggr_D_log(Credit to PNFS/CPI)        -1.2766       1.879    -0.67943     0.49837
    L18_Aggr_D_log(Credit to PNFS/CPI)         -2.762      1.5895     -1.7376    0.085234
    L20_Aggr_D_log(Credit to PNFS/CPI)        0.72866      1.1212      0.6499     0.51719


Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0688
R-squared: 0.29,  Adjusted R-Squared 0.221
F-statistic vs. constant model: 4.24, p-value = 5.91e-05
```

When employing a MA of the dependent variable instead of the aggregation in mean the results, as usual, improve event though much coefficient estimates remain not significant and thus unclear. However, by looking at 3YS1 and 5YS1 of baseline (4) model one can notice that the first and fourth annual lag are negative while the third seems positive in 3YS1 (even though with scares significance), which would approach to the economic interpretation given for the bank credit. Nevertheless, the second annual lag still remains not clear to draw the same conclusion with reasonable certainty.

Let us proceed with the analysis of other credit-related variables. As pointed out at the beginning of the analysis, the second most important regressor is represented by the Credit-to-GDP variable. Particularly, the analysis follow the same steps of the credit variable examined so far but henceforth, as several EU countries are going to be analyzed, to avoid dispersion solely the most significant baseline version will be shown and commented. However, all the non-reported regressions are available upon request.
For the present work, the Credit-to-GDP variable, as said in the data section, includes three variants, i.e. the *Credit-to-GDP ratios* with actual data, *Credit-to-GDP trend* constructed with an HP filter and *Credit-to-GDP gaps* with actual trend defined as the difference between the credit-to-GDP ratio and its long-run trend. It is worth to specify that the credit here is not from banks but from all sectors to PNFS.

Let's start with the Credit-to-GDP ratio series. The baseline model (1) with no aggregation is, broadly speaking, not significant over both horizons. Being more precise, the only exception is the 5YS2 with half-yearly lags which is indicated by both AIC and Adjusted R-Squared. The same is true for the baseline model (2). Following, the table 4.9

shows the best baseline model (1) and (2), namely, the 5YS2. Even though the F-statistic p-value is significant at 5 per cent CI the coefficient estimates are not significant and consistent among themselves (large/small and negative/positive alternate without much sense) apart L14 representing the first semester of the fourth lagged year. Unfortunately, this model does not allow to make much inference, thus let us move to the baseline model (3).

Table 4.9 – The best baseline model (1) and (2) are the same: 5YS2.

```
Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                              Estimate       SE        tStat       pValue
                             __________   ________   ________   ________

    (Intercept)              -0.0080962   0.017309   -0.46775     0.6409
    L2_D_log(Credit/GDP)         1.6813     1.2841     1.3093    0.19319
    L4_D_log(Credit/GDP)        -1.5587     1.3265    -1.1751    0.24253
    L6_D_log(Credit/GDP)        0.84297     1.4639    0.57583    0.56592
    L8_D_log(Credit/GDP)         1.4155     1.4884    0.95104    0.34369
    L10_D_log(Credit/GDP)      -0.51574     1.5214   -0.33898    0.73528
    L12_D_log(Credit/GDP)      -0.23859     1.5231   -0.15665    0.87581
    L14_D_log(Credit/GDP)       -3.3157     1.5108    -2.1947   0.030309
    L16_D_log(Credit/GDP)       -1.3594     1.4915   -0.91148    0.36405
    L18_D_log(Credit/GDP)        1.5925     1.3713     1.1613    0.24805
    L20_D_log(Credit/GDP)       0.67684       1.33    0.50891    0.61185


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.188
R-squared: 0.154,  Adjusted R-Squared 0.0769
F-statistic vs. constant model: 1.99, p-value = 0.041
```

The best models for the baseline (3) structure, that is, with both dependent and predictor variables aggregated are shown in the table 4.10. The AIC criterion points out to the S1 whereas the Adjusted R-Squared indicates the second specification as the best model. As one may notice, the overall lag structure is significant at 5 per cent CI in both models but unfortunately the coefficient estimates are not. The only exception is in S1 the fourth annual lag, L16, that has a decent tStat, i.e. higher than 3. Equivalently, the two semesters in the fourth lagged year, L14 and L16, are significant at 10 and 5 per cent respectively. While this fourth lag would suggest the negative relationship between the Credit from all sector to PNFS on GDP and the ItaBI, at least in that year, the information that is significance is really scares to infer some conclusion.

Table 4.10 – Baseline model (3) with both the dependent and predictor variables aggregated.

```
The best linear model in terms of AIC for the five year horizon with both dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                   Estimate        SE         tStat        pValue
                                  __________    ________    _________    _________

    (Intercept)                   -0.0070884    0.0094913    -0.74684       0.4567
    L4_Aggr_D_log(Credit/GDP)      -0.045452      0.87684   -0.051836      0.95875
    L8_Aggr_D_log(Credit/GDP)         0.7277      0.91928     0.79159      0.43024
    L12_Aggr_D_log(Credit/GDP)      -0.89806      0.93184    -0.96375      0.33721
    L16_Aggr_D_log(Credit/GDP)       -3.0258      0.93526     -3.2353    0.0015905
    L20_Aggr_D_log(Credit/GDP)       0.80439      0.90081     0.89296      0.37376


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.103
R-squared: 0.115,  Adjusted R-Squared 0.0758
F-statistic vs. constant model: 2.95, p-value = 0.0152
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with both dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                   Estimate        SE        tStat       pValue
                                  __________    _________    ________    ________

    (Intercept)                   -0.0062715    0.0095092    -0.65952     0.51096
    L2_Aggr_D_log(Credit/GDP)       -0.40369      0.91467    -0.44135     0.65983
    L4_Aggr_D_log(Credit/GDP)        0.27206      0.94942     0.28655       0.775
    L6_Aggr_D_log(Credit/GDP)        -0.7351         1.02    -0.72067     0.47266
    L8_Aggr_D_log(Credit/GDP)         1.1794       1.0393      1.1347     0.25898
    L10_Aggr_D_log(Credit/GDP)      -0.19937       1.0481    -0.19023     0.84948
    L12_Aggr_D_log(Credit/GDP)      -0.28985       1.0532    -0.27522     0.78367
    L14_Aggr_D_log(Credit/GDP)       -2.0022       1.0521     -1.9031    0.059672
    L16_Aggr_D_log(Credit/GDP)        -2.532       1.0367     -2.4424    0.016198
    L18_Aggr_D_log(Credit/GDP)      -0.13547      0.97493    -0.13896     0.88974
    L20_Aggr_D_log(Credit/GDP)       0.95743      0.94251      1.0158     0.31196


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.103
R-squared: 0.155,  Adjusted R-Squared 0.077
F-statistic vs. constant model: 1.99, p-value = 0.0409
```

Let us consider now the Credit-to-GDP trend computed with an Hodrick-Prescott (HP) filter with a quarterly smoothing parameter. The results of the baseline model (1) are poor, especially for the 3-year horizon, for which the coefficient estimates are not significant. Some improvement occurs when considering the longest horizon. Table 4.11 report the best models.

Table 4.11 – Baseline model (1) only 5Y horizon.

```
The best linear model in terms of AIC for the five year horizon is :

Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                    Estimate       SE        tStat      pValue
                                    _________    ________   ________   ________

    (Intercept)                     -0.017638    0.018912   -0.93265    0.35297
    L4_D_log(Credit-to-GDP trend)     0.45349      8.5808    0.05285    0.95794
    L8_D_log(Credit-to-GDP trend)      1.5427      9.1077    0.16938     0.8658
    L12_D_log(Credit-to-GDP trend)    -17.053      9.4129    -1.8117   0.072665
    L16_D_log(Credit-to-GDP trend)     15.939      9.2816     1.7172    0.08865
    L20_D_log(Credit-to-GDP trend)     11.336      9.1441     1.2397    0.21764


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.194
R-squared: 0.0631,  Adjusted R-Squared 0.022
F-statistic vs. constant model: 1.53, p-value = 0.185
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon is :

BESTLM_5Y =


Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 21 terms in 20 predictors]

Estimated Coefficients:
                                    Estimate       SE        tStat      pValue
                                    _________    ________   ________   ________

    (Intercept)                     -0.020198    0.018114     -1.115    0.26753
    L1_D_log(Credit-to-GDP trend)      14.933      13.877     1.0761    0.28449
    L2_D_log(Credit-to-GDP trend)       4.695       15.95    0.29436     0.7691
    L3_D_log(Credit-to-GDP trend)     -7.6127      17.367   -0.43835    0.66209
    L4_D_log(Credit-to-GDP trend)     -13.683      17.346   -0.78881    0.43211
    L5_D_log(Credit-to-GDP trend)      10.788      20.019    0.53891    0.59116
    L6_D_log(Credit-to-GDP trend)      4.1444      20.948    0.19785    0.84357
    L7_D_log(Credit-to-GDP trend)      15.967      21.652    0.73746    0.46259
    L8_D_log(Credit-to-GDP trend)     -5.6907      21.724   -0.26195     0.7939
    L9_D_log(Credit-to-GDP trend)     -43.626      22.236     -1.962   0.052573
    L10_D_log(Credit-to-GDP trend)      24.61      22.523     1.0926    0.27721
    L11_D_log(Credit-to-GDP trend)     24.314      22.544     1.0785    0.28344
    L12_D_log(Credit-to-GDP trend)    -32.486      22.321    -1.4554    0.14873
    L13_D_log(Credit-to-GDP trend)    -25.126      21.822    -1.1514    0.25233
    L14_D_log(Credit-to-GDP trend)     6.2534      21.984    0.28444    0.77666
    L15_D_log(Credit-to-GDP trend)     17.259      21.241    0.81251    0.41845
    L16_D_log(Credit-to-GDP trend)    -10.083      20.422   -0.49376    0.62257
    L17_D_log(Credit-to-GDP trend)     24.009      17.719     1.3549    0.17852
    L18_D_log(Credit-to-GDP trend)     23.406      17.807     1.3144    0.19175
    L19_D_log(Credit-to-GDP trend)    -21.082      16.331     -1.291    0.19973
    L20_D_log(Credit-to-GDP trend)      10.38      14.508    0.71542    0.47603


Number of observations: 120, Error degrees of freedom: 99
Root Mean Squared Error: 0.184
R-squared: 0.265,  Adjusted R-Squared 0.116
F-statistic vs. constant model: 1.78, p-value = 0.0327
```

As usual AIC prefers the S1 whereas Adjusted R-Squared the S3. The lag structure of the former model is not overall significant even though the third and fourth lagged years, L12 and L16, are significant at 10 per cent. The half-yearly lag structure, instead, seems more appropriate for the Credit-to-GDP trend as the F-statistic p-value indicates a 5 per cent of significance. However, the coefficient estimates, apart some exception, are not significant making difficult a reasonable inference.

Let us see the other baseline versions. Table 4.12 shows the result for the baseline model (2) with aggregated regressors. As before only the 5Y horizon results are reported as the 3Y ones are not significant.

One may see that while the S1 is significant at 1 per cent and the S3 at 5 per cent the coefficient estimates are again not significant to draw some conclusion. In addition, the accuracy of prediction is really poor as the SE are extremely high.

Table 4.12 – Baseline model (2) only 5Y horizon.

```
The best linear model in terms of AIC for the five year horizon with the predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                            Estimate      SE         tStat        pValue
                                           _________    _______    ________    __________

    (Intercept)                            -0.018178    0.018498   -0.98268       0.32785
    L4_Aggr_D_log(Credit-to-GDP trend)        12.218      10.591     1.1537       0.25105
    L8_Aggr_D_log(Credit-to-GDP trend)       -8.2102      12.452   -0.65937       0.51099
    L12_Aggr_D_log(Credit-to-GDP trend)      -32.258       12.49    -2.5827       0.01107
    L16_Aggr_D_log(Credit-to-GDP trend)       46.407      12.627     3.6753    0.00036365
    L20_Aggr_D_log(Credit-to-GDP trend)      -2.9503      11.485   -0.25688       0.79774


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.187
R-squared: 0.133,  Adjusted R-Squared 0.0952
F-statistic vs. constant model: 3.5, p-value = 0.00553
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with the predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    D_log(ItaBI_QLP/CPI) ~ [Linear formula with 21 terms in 20 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.021954	0.018105	-1.2126	0.22817
L1_Aggr_D_log(Credit-to-GDP trend)	37.053	24.695	1.5004	0.13669
L2_Aggr_D_log(Credit-to-GDP trend)	-32.137	41.545	-0.77355	0.44104
L3_Aggr_D_log(Credit-to-GDP trend)	17.504	44.196	0.39604	0.69292
L4_Aggr_D_log(Credit-to-GDP trend)	-43.985	45.943	-0.95739	0.3407
L5_Aggr_D_log(Credit-to-GDP trend)	65.448	53.523	1.2228	0.22431
L6_Aggr_D_log(Credit-to-GDP trend)	-56.867	62.148	-0.91502	0.36241
L7_Aggr_D_log(Credit-to-GDP trend)	84.711	63.637	1.3311	0.1862
L8_Aggr_D_log(Credit-to-GDP trend)	-92.983	64.11	-1.4504	0.15012
L9_Aggr_D_log(Credit-to-GDP trend)	11.013	65.888	0.16714	0.8676
L10_Aggr_D_log(Credit-to-GDP trend)	33.644	67.758	0.49653	0.62062
L11_Aggr_D_log(Credit-to-GDP trend)	8.4811	67.783	0.12512	0.90068
L12_Aggr_D_log(Credit-to-GDP trend)	-68.355	66.124	-1.0337	0.30377
L13_Aggr_D_log(Credit-to-GDP trend)	21.089	64.445	0.32725	0.74417
L14_Aggr_D_log(Credit-to-GDP trend)	-6.0252	64.06	-0.094056	0.92525
L15_Aggr_D_log(Credit-to-GDP trend)	30.951	62.721	0.49348	0.62277
L16_Aggr_D_log(Credit-to-GDP trend)	-48.564	54.278	-0.89474	0.3731
L17_Aggr_D_log(Credit-to-GDP trend)	98.635	46.709	2.1117	0.037233
L18_Aggr_D_log(Credit-to-GDP trend)	-49.178	45.013	-1.0925	0.27725
L19_Aggr_D_log(Credit-to-GDP trend)	-0.87886	42.467	-0.020695	0.98353
L20_Aggr_D_log(Credit-to-GDP trend)	15.565	25.798	0.60336	0.54765

```
Number of observations: 120, Error degrees of freedom: 99
Root Mean Squared Error: 0.183
R-squared: 0.278,  Adjusted R-Squared 0.133
F-statistic vs. constant model: 1.91, p-value = 0.0195
```

Following the results of the baseline model (3) with both the ItaBI and the Credit-to-GDP trend aggregated. Once again, while the results for the 3-year horizon are meaningless, the lowest AIC values are obtained when the dependent variable is aggregated over one year and half. In such a case, the code choses the aggregation over 3, 2 and 2 quarters for S1, S2 and S3 respectively. In addition, the former criteria prefer the 5YS1 whereas the latter indicates the 5YS2 as the best model.

Table 4.13 – Baseline model (3) only 5Y horizon.

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                            Estimate       SE        tStat       pValue
                                           _________    _________   _______    __________

    (Intercept)                            -0.017522    0.0072599   -2.4136       0.01739
    L4_Aggr_D_log(Credit-to-GDP trend)        7.4393       4.1563    1.7899      0.076128
    L8_Aggr_D_log(Credit-to-GDP trend)       0.92293       4.8867   0.18886       0.85053
    L12_Aggr_D_log(Credit-to-GDP trend)      -18.427       4.9019   -3.7593    0.00027047
    L16_Aggr_D_log(Credit-to-GDP trend)       4.4084       4.9554   0.88961       0.37555
    L20_Aggr_D_log(Credit-to-GDP trend)       19.813       4.5075    4.3955    2.4919e-05


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.0732
R-squared: 0.241,  Adjusted R-Squared 0.207
F-statistic vs. constant model: 7.23, p-value = 6.54e-06
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                           Estimate       SE         tStat       pValue
                                           _________    _________   ________    _________

    (Intercept)                            -0.016578    0.0072105    -2.2991     0.023406
    L2_Aggr_D_log(Credit-to-GDP trend)       -2.9724       5.6759   -0.52368      0.60156
    L4_Aggr_D_log(Credit-to-GDP trend)        8.7852       8.3406     1.0533      0.29453
    L6_Aggr_D_log(Credit-to-GDP trend)        1.1399       9.2668    0.12301      0.90233
    L8_Aggr_D_log(Credit-to-GDP trend)        1.9133       10.356    0.18475      0.85377
    L10_Aggr_D_log(Credit-to-GDP trend)      -1.8352       10.727   -0.17108      0.86448
    L12_Aggr_D_log(Credit-to-GDP trend)      -7.6144       10.777   -0.70653      0.48136
    L14_Aggr_D_log(Credit-to-GDP trend)      -13.061       10.518    -1.2417        0.217
    L16_Aggr_D_log(Credit-to-GDP trend)      0.94637       9.4716   0.099916      0.92059
    L18_Aggr_D_log(Credit-to-GDP trend)       8.6217       8.5267     1.0111      0.31419
    L20_Aggr_D_log(Credit-to-GDP trend)       16.782       6.0066     2.7939    0.0061536


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.073
R-squared: 0.277,  Adjusted R-Squared 0.211
F-statistic vs. constant model: 4.19, p-value = 6.42e-05
```

As we may notice the overall significance of lag structure is strong for both specifications even though the coefficient estimates are not. Another observation worth noticing is that the Adjusted R-Squared reach the 20 per cent of the variability explained by the model. However, the results may be further slightly improved if we consider the baseline model (4) with the dependent variable aggregated with a MA and the regressors aggregated as usual. Table 4.9 shows the results. As previously said, the best moving window for the ItaBI is n = 6 whereas for the regressors the best models, 5YS1 and 5YS2, are obtained with n equal to three and two respectively.

Table 4.14 – Baseline model (4) only 5Y horizon.

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                            Estimate        SE         tStat       pValue
                                           _________    _________    _______    __________

    (Intercept)                            -0.010448    0.0069789     -1.497       0.13728
    L4_Aggr_D_log(Credit-to-GDP trend)        6.8654       3.8977     1.7614      0.080977
    L8_Aggr_D_log(Credit-to-GDP trend)       0.72221       4.5803    0.15768         0.875
    L12_Aggr_D_log(Credit-to-GDP trend)      -18.435       4.5942    -4.0128    0.00011037
    L16_Aggr_D_log(Credit-to-GDP trend)       4.3039       4.6445    0.92668       0.35614
    L20_Aggr_D_log(Credit-to-GDP trend)       18.713       4.2315     4.4223    2.3207e-05


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0686
R-squared: 0.26,  Adjusted R-Squared 0.226
F-statistic vs. constant model: 7.67, p-value = 3.3e-06
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                            Estimate        SE          tStat        pValue
                                           __________    _________    __________    _________

    (Intercept)                            -0.0095924    0.0069174       -1.3867      0.16849
    L2_Aggr_D_log(Credit-to-GDP trend)        -2.5789       5.6264      -0.45836      0.64765
    L4_Aggr_D_log(Credit-to-GDP trend)         6.4254       8.2971       0.77442      0.44044
    L6_Aggr_D_log(Credit-to-GDP trend)         3.1875       8.9437        0.3564      0.72226
    L8_Aggr_D_log(Credit-to-GDP trend)      -0.030741       9.9117    -0.0031015      0.99753
    L10_Aggr_D_log(Credit-to-GDP trend)       0.10623       10.192      0.010423       0.9917
    L12_Aggr_D_log(Credit-to-GDP trend)        -9.386       10.168      -0.92307      0.35811
    L14_Aggr_D_log(Credit-to-GDP trend)       -11.492       9.8923       -1.1617      0.24803
    L16_Aggr_D_log(Credit-to-GDP trend)      -0.38756       8.8758     -0.043665      0.96525
    L18_Aggr_D_log(Credit-to-GDP trend)        9.1197       7.9758        1.1434      0.25549
    L20_Aggr_D_log(Credit-to-GDP trend)        15.683       5.6284        2.7864    0.0063362


Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0683
R-squared: 0.3,  Adjusted R-Squared 0.233
F-statistic vs. constant model: 4.47, p-value = 3.06e-05
```

The overall significance of the lag structure strengthened as the p-value of the F-statistic fell further in both models. In addition, the model so specified explain a slight more portion of variability as points out the increased Adjusted R-Squared. Unfortunately, SE are still high, especially for S2, and different coefficient estimates remain not significant complicating a deep inference about the behaviour between the variables under analysis.

Let us examine now the last Credit-to-GDP variant, namely, the Credit-to-GDP gap. This variable has been object of a special treatment which deserve some attention. Since the gap assumes also negative values, to take the logarithm I make benefit of the suggestions by Box & Cox when dealing with shifted power transformation[153]. Without going in detail, the authors suggest to add a constant, c, to the x_i observations such that $x_i > -c$. Naturally, to assure the positivity of the lowest observation in the series I set $c = min(x_i) + 10$. The unit is a symbolic figure.
To avoid dispersion, following only the baseline model (3) and (4) which are also the most significant. The first observation is that the 3-year horizon is too short for the Credit-to-GDP gap to explain the ItaBI. Within the longest horizon while the baseline model (4), unsurprisingly, outperform the (3) in terms of both significance and goodness-of-fit, the coefficient estimates in both specification are not significant apart the fourth lagged year. It is worth to specify here that by adding a constant, c, the model lost its elasticity thus the interpretation of the coefficient estimates is no longer as a percentage change.

Table 4.15 – Baseline model (3) only 5Y horizon.

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                          Estimate        SE        tStat       pValue
                                         __________    ________    ________    __________

    (Intercept)                          -0.0089486    0.0093887   -0.95312       0.34255
    L4_Aggr_D_log(Credit-to-GDP gap)       0.076296      0.33305    0.22908       0.81922
    L8_Aggr_D_log(Credit-to-GDP gap)        0.29044       0.3611    0.80432       0.42289
    L12_Aggr_D_log(Credit-to-GDP gap)      -0.44228      0.37617    -1.1758       0.24214
    L16_Aggr_D_log(Credit-to-GDP gap)       -1.3441       0.3805    -3.5323    0.00059575
    L20_Aggr_D_log(Credit-to-GDP gap)      0.096292      0.36569    0.26331       0.79279


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.102
R-squared: 0.123,  Adjusted R-Squared 0.0846
F-statistic vs. constant model: 3.2, p-value = 0.00969
```

[153] See "An Analysis of Transformations", Box and Cox (1964).

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0093069	0.0094136	-0.98866	0.32502
L2_Aggr_D_log(Credit-to-GDP gap)	-0.15055	0.33945	-0.44351	0.65827
L4_Aggr_D_log(Credit-to-GDP gap)	0.16896	0.35173	0.48036	0.63193
L6_Aggr_D_log(Credit-to-GDP gap)	-0.30911	0.39138	-0.78981	0.43135
L8_Aggr_D_log(Credit-to-GDP gap)	0.51189	0.40327	1.2693	0.20702
L10_Aggr_D_log(Credit-to-GDP gap)	-0.21025	0.41461	-0.50711	0.61311
L12_Aggr_D_log(Credit-to-GDP gap)	-0.17752	0.41888	-0.42381	0.67254
L14_Aggr_D_log(Credit-to-GDP gap)	-0.84993	0.4182	-2.0324	0.044548
L16_Aggr_D_log(Credit-to-GDP gap)	-1.1528	0.413	-2.7912	0.0062015
L18_Aggr_D_log(Credit-to-GDP gap)	-0.14082	0.3881	-0.36284	0.71743
L20_Aggr_D_log(Credit-to-GDP gap)	0.22611	0.37989	0.59521	0.55294

```
Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.102
R-squared: 0.162,  Adjusted R-Squared 0.0853
F-statistic vs. constant model: 2.11, p-value = 0.0294
```

Table 4.16 – Baseline model (4) only 5Y horizon.

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.002557	0.0069	-0.37058	0.71167
L4_Aggr_D_log(Credit-to-GDP gap)	0.011438	0.31492	0.036319	0.97109
L8_Aggr_D_log(Credit-to-GDP gap)	0.13199	0.32349	0.40803	0.68406
L12_Aggr_D_log(Credit-to-GDP gap)	-0.68127	0.33505	-2.0333	0.04445
L16_Aggr_D_log(Credit-to-GDP gap)	-1.3309	0.34325	-3.8774	0.00018088
L20_Aggr_D_log(Credit-to-GDP gap)	0.17812	0.34079	0.52267	0.60226

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0737
R-squared: 0.147,  Adjusted R-Squared 0.108
F-statistic vs. constant model: 3.76, p-value = 0.00354
```

```
The best linear model in terms of Adjusted R-Squared for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0037913	0.0068424	-0.55409	0.5807
L2_Aggr_D_log(Credit-to-GDP gap)	-0.68119	0.44013	-1.5477	0.12473
L4_Aggr_D_log(Credit-to-GDP gap)	0.49881	0.60563	0.82361	0.41204
L6_Aggr_D_log(Credit-to-GDP gap)	-0.55367	0.78939	-0.70139	0.48462
L8_Aggr_D_log(Credit-to-GDP gap)	0.70354	0.91623	0.76787	0.44431
L10_Aggr_D_log(Credit-to-GDP gap)	-0.48792	0.97244	-0.50174	0.61691
L12_Aggr_D_log(Credit-to-GDP gap)	0.34671	0.97286	0.35639	0.72227
L14_Aggr_D_log(Credit-to-GDP gap)	-1.5831	0.92473	-1.712	0.08988
L16_Aggr_D_log(Credit-to-GDP gap)	-0.13896	0.81361	-0.1708	0.86471
L18_Aggr_D_log(Credit-to-GDP gap)	-0.91362	0.64862	-1.4086	0.16194
L20_Aggr_D_log(Credit-to-GDP gap)	0.67072	0.4689	1.4304	0.1556

```
Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0726
R-squared: 0.209,  Adjusted R-Squared 0.133
F-statistic vs. constant model: 2.75, p-value = 0.00475
```

Among the remainder variables the most interesting one in terms of significance and goodness-of-fit is the Credit to Non-Financial Corporations (NFCs) reported in the following tables.

Table 4.17 – Baseline model (3) with Credit to NFCs.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                        Estimate        SE          tStat       pValue
                                       __________    _________    ________    ________

    (Intercept)                        -0.0080718    0.0096992    -0.83221       0.407
    L4_Aggr_D_log(Credit to NFCs/CPI)    -0.22266      0.73081    -0.30467     0.76116
    L8_Aggr_D_log(Credit to NFCs/CPI)       1.452      0.77938       1.863    0.064988
    L12_Aggr_D_log(Credit to NFCs/CPI)    0.86966      0.73973      1.1756     0.24214


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.106
R-squared: 0.041,  Adjusted R-Squared 0.0162
F-statistic vs. constant model: 1.65, p-value = 0.181
```

```
The best linear model in terms of Adjusted R-Squared for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 13 terms in 12 predictors]

Estimated Coefficients:
                                        Estimate       SE         tStat       pValue
                                       __________    ________    ________    _________

    (Intercept)                        -0.0088899    0.009374    -0.94836      0.34509
    L1_Aggr_D_log(Credit to NFCs/CPI)     -5.2135       2.045     -2.5493     0.012211
    L2_Aggr_D_log(Credit to NFCs/CPI)      1.5653      3.0226     0.51786      0.60563
    L3_Aggr_D_log(Credit to NFCs/CPI)      4.1735      2.9909      1.3954      0.16578
    L4_Aggr_D_log(Credit to NFCs/CPI)     -2.9587      2.7856     -1.0621      0.29057
    L5_Aggr_D_log(Credit to NFCs/CPI)     -6.3104      3.2425     -1.9461     0.054263
    L6_Aggr_D_log(Credit to NFCs/CPI)      4.2516      3.9872      1.0663      0.28867
    L7_Aggr_D_log(Credit to NFCs/CPI)      6.6774      3.9831      1.6765     0.096568
    L8_Aggr_D_log(Credit to NFCs/CPI)     -4.1805      3.2086     -1.3029      0.19542
    L9_Aggr_D_log(Credit to NFCs/CPI)      -4.802      2.8461     -1.6873     0.094468
    L10_Aggr_D_log(Credit to NFCs/CPI)     2.8947      3.1163      0.9289      0.35503
    L11_Aggr_D_log(Credit to NFCs/CPI)     6.0151      3.1617      1.9025     0.059791
    L12_Aggr_D_log(Credit to NFCs/CPI)    -6.2624      2.1142      -2.962    0.0037662


Number of observations: 120, Error degrees of freedom: 107
Root Mean Squared Error: 0.103
R-squared: 0.174,  Adjusted R-Squared 0.0812
F-statistic vs. constant model: 1.88, p-value = 0.0453
```

```
Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                          Estimate        SE          tStat        pValue
                                         __________    _________    ________    __________

    (Intercept)                          -0.0089701    0.0089987    -0.99683       0.32096
    L4_Aggr_D_log(Credit to NFCs/CPI)       -1.2702      0.78786     -1.6122       0.10969
    L8_Aggr_D_log(Credit to NFCs/CPI)       0.47405      0.84138     0.56342       0.57426
    L12_Aggr_D_log(Credit to NFCs/CPI)     -0.59499      0.83393    -0.71347       0.47701
    L16_Aggr_D_log(Credit to NFCs/CPI)      -3.7478      0.84337     -4.4438    2.0594e-05
    L20_Aggr_D_log(Credit to NFCs/CPI)     0.056524      0.80113    0.070555       0.94388


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.0985
R-squared: 0.189,  Adjusted R-Squared 0.154
F-statistic vs. constant model: 5.32, p-value = 0.000198
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                          Estimate        SE        tStat       pValue
                                         __________    _________   ________    ________

    (Intercept)                          -0.0087811    0.0088006   -0.99778     0.32059
    L2_Aggr_D_log(Credit to NFCs/CPI)        -3.084       1.3146    -2.3459    0.020787
    L4_Aggr_D_log(Credit to NFCs/CPI)        1.2945       1.9743     0.6557      0.5134
    L6_Aggr_D_log(Credit to NFCs/CPI)       -3.5292       2.6951    -1.3095     0.19312
    L8_Aggr_D_log(Credit to NFCs/CPI)        4.7928       3.1779     1.5082      0.1344
    L10_Aggr_D_log(Credit to NFCs/CPI)      -4.4925       3.4888    -1.2877     0.20058
    L12_Aggr_D_log(Credit to NFCs/CPI)       3.9906        3.499     1.1405     0.25658
    L14_Aggr_D_log(Credit to NFCs/CPI)      -6.2839       3.2158     -1.954    0.053258
    L16_Aggr_D_log(Credit to NFCs/CPI)      0.53531        2.762    0.19381     0.84668
    L18_Aggr_D_log(Credit to NFCs/CPI)      -2.1421       2.0492    -1.0453     0.29818
    L20_Aggr_D_log(Credit to NFCs/CPI)       1.8303       1.3619     1.3439     0.18176


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.0964
R-squared: 0.258,  Adjusted R-Squared 0.19
F-statistic vs. constant model: 3.8, p-value = 0.000204
```

First, the two criteria disagree among the different horizons: S1 and, surprisingly, S3 for the 3-year window whereas S2 for the 5-year horizon. However, I also report 5YS1 for comparison purposes. While the 3YS1 is not significant the quarterly specification has an overall significance of 5% CI and, surprisingly, much coefficient estimates (about the half) are significant at least at the weaker 10 per cent with others approaching to it. A similar situation for the half-yearly specification in the longest horizon. Therefore, it seems that the Credit to NFCs prefers smaller than one year lags.

Table 4.18 – Baseline model (4) with Credit to NFCs.

The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =

Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.0027031	0.0068411	-0.39512	0.69353
L2_Aggr_D_log(Credit to NFCs/CPI)	-2.5849	0.95438	-2.7085	0.0078612
L4_Aggr_D_log(Credit to NFCs/CPI)	0.17125	1.3525	0.12661	0.89948
L6_Aggr_D_log(Credit to NFCs/CPI)	-0.10724	1.6064	-0.066762	0.94689
L8_Aggr_D_log(Credit to NFCs/CPI)	0.027606	1.6105	0.017142	0.98636
L10_Aggr_D_log(Credit to NFCs/CPI)	1.6895	1.3646	1.238	0.21838
L12_Aggr_D_log(Credit to NFCs/CPI)	-1.4549	0.95723	-1.5199	0.13145

Number of observations: 115, Error degrees of freedom: 108
Root Mean Squared Error: 0.0733
R-squared: 0.164, Adjusted R-Squared 0.117
F-statistic vs. constant model: 3.52, p-value = 0.0032

Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.002422	0.0063839	-0.37939	0.70514
L4_Aggr_D_log(Credit to NFCs/CPI)	-1.8252	0.61187	-2.9829	0.0035232
L8_Aggr_D_log(Credit to NFCs/CPI)	0.20515	0.63467	0.32323	0.74714
L12_Aggr_D_log(Credit to NFCs/CPI)	-0.77456	0.62507	-1.2392	0.21795
L16_Aggr_D_log(Credit to NFCs/CPI)	-3.5872	0.63752	-5.6268	1.4383e-07
L20_Aggr_D_log(Credit to NFCs/CPI)	-0.51367	0.62283	-0.82473	0.41133

Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0684
R-squared: 0.264, Adjusted R-Squared 0.231
F-statistic vs. constant model: 7.83, p-value = 2.48e-06

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0031729	0.0058666	-0.54084	0.58978
L2_Aggr_D_log(Credit to NFCs/CPI)	-3.3327	0.87316	-3.8169	0.00022984
L4_Aggr_D_log(Credit to NFCs/CPI)	0.9373	1.3069	0.71722	0.47485
L6_Aggr_D_log(Credit to NFCs/CPI)	-3.1237	1.7787	-1.7562	0.082001
L8_Aggr_D_log(Credit to NFCs/CPI)	2.4531	2.0914	1.173	0.24349
L10_Aggr_D_log(Credit to NFCs/CPI)	-2.0561	2.2911	-0.89741	0.37157
L12_Aggr_D_log(Credit to NFCs/CPI)	1.608	2.2913	0.70179	0.48438
L14_Aggr_D_log(Credit to NFCs/CPI)	-3.8338	2.1029	-1.8231	0.07116
L16_Aggr_D_log(Credit to NFCs/CPI)	-0.10921	1.8044	-0.060524	0.95185
L18_Aggr_D_log(Credit to NFCs/CPI)	-2.9047	1.3376	-2.1716	0.032161
L20_Aggr_D_log(Credit to NFCs/CPI)	1.0607	0.88843	1.1939	0.23522

```
Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0628
R-squared: 0.408,  Adjusted R-Squared 0.351
F-statistic vs. constant model: 7.17, p-value = 1.62e-08
```

The results for the baseline model (4) are similar the (3). The best specification for both horizon is the S2, even though I also report the 5YS1. Again, for this credit variable, the half-yearly lags fit better the ItaBI movements. The 5YS2 is the model which deserves much attention. In addition to what said for the baseline (3), which also applies in this case, it is worth to highlight the goodness-of-fit reached with this credit variable that touches the highest level (Adjusted R-Squared equal to 0.35) among all the credit-related variables examined as regressors for this country.
Finally, let's test whether the best predictor, that is, the credit to NFCs' effect on the ItaBI movements is affected by the specific financial system dimension/depth, as proxied by the Credit to GDP ratio. In the table 4.19, the baseline model (5), with the best ItaBI predictor and the financial/bank dimension proxied by the respective credit to GDP ratio, shows the results. Note that the best model when including the bank depth is reached with the variable aggregated over five quarter whereas for the financial depth $n = 4$.

Table 4.19 – Baseline model (5) with the best ItaBI predictor and the financial/bank depth proxied by the respective credit to GDP ratios.

```
Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
                                              Estimate        SE         tStat        pValue
                                             __________    _________    ________    __________

    (Intercept)                              -0.0021536    0.0062773    -0.34307       0.73221
    L4_Aggr_D_log(Credit to NFCs/CPI)           -2.2287      0.62921      -3.542    0.00058765
    L8_Aggr_D_log(Credit to NFCs/CPI)          0.092903      0.62606     0.14839       0.88231
    L12_Aggr_D_log(Credit to NFCs/CPI)          -0.8175      0.61482     -1.3297       0.18643
    L16_Aggr_D_log(Credit to NFCs/CPI)          -3.5539      0.62693     -5.6688    1.2105e-07
    L20_Aggr_D_log(Credit to NFCs/CPI)         -0.50244      0.61233    -0.82054       0.41372
    Aggr_D_log(Bank credit/GDP)                  2.0875       0.9549      2.1861       0.03097


Number of observations: 115, Error degrees of freedom: 108
Root Mean Squared Error: 0.0673
R-squared: 0.296,  Adjusted R-Squared 0.256
F-statistic vs. constant model: 7.55, p-value = 8.93e-07
```

```
Linear regression model:
    MA_D_log(ItaBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
                                              Estimate        SE         tStat        pValue
                                             __________    _________    ________    __________

    (Intercept)                              -0.0032294    0.0062727    -0.51484       0.60772
    L4_Aggr_D_log(Credit to NFCs/CPI)           -1.7114      0.60231     -2.8413     0.0053714
    L8_Aggr_D_log(Credit to NFCs/CPI)           0.17892      0.62273     0.28731       0.77443
    L12_Aggr_D_log(Credit to NFCs/CPI)          -1.0455      0.62449     -1.6742      0.096992
    L16_Aggr_D_log(Credit to NFCs/CPI)          -3.5992      0.62544     -5.7547    8.2152e-08
    L20_Aggr_D_log(Credit to NFCs/CPI)         -0.45215       0.6116    -0.73929       0.46133
    Aggr_D_log(Credit/GDP)                      -1.8629      0.81246     -2.2929      0.023788


Number of observations: 115, Error degrees of freedom: 108
Root Mean Squared Error: 0.0671
R-squared: 0.299,  Adjusted R-Squared 0.26
F-statistic vs. constant model: 7.66, p-value = 7.24e-07
```

In the above two models, while the relationship between the credit to NFCs and the ItaBI is consistent with the previous results, it can be appreciated the improvement in both the CEs and F-statistic significance as well a more crystalline relation between the bank/financial depth and the ItaBI. Also, the goodness-of-fit increases with the addition of the bank depth first and the financial depth then.

Summing up the Italian Banking Sector

According the credit series availability there has been examined and reported seven different credit-related variables, namely, the total bank credit to the PNFS both in absolute and in percentage terms, the total credit (granted from all sector and not only commercial banks) to PNFS again in absolute and percentage terms, the three Credit-to-GDP variants (Credit-to-GDP ratio, Credit-to-GDP trend and Credit-to-GDP gap) and last, but not least, the credit granted to NFCs. Indeed, besides the above variables three further BIS statistics have been tested but with very bad results thus not reported, the credit to households and NPISHs (in absolute and percentage terms) and the DSR.

Comin back to the 'decent' explaining regressors, on one hand, the *bank credit* growth rate revealed, as expected, one of the most important predictor of financial (in)stability even when monitoring the more specific banking stress. On the other hand, surprisingly, the most powerful predictor of the Italian Banking Index (ItaBI) turned out to be the *credit (from all sectors) granted to NFCs*. This is essentially the credit received by entities whose principal activity is the production of market goods or non-financial services[154]. It is evident that the Italian Banking Sector heavily relies upon these real-sector business realities.

Finally, the aggregated bank and financial depth seem to affect and contribute in explaining the ItaBI movements with the former in a positive way and the latter in a negative one.

[154] For NFC is meant the following entities: legally constituted corporations, branches of non-resident enterprises, quasi-corporations, notional resident units owning land, and resident non-profit institutions that are market producers of goods or non-financial services. See the BIS Statistical Bulletin "Credit to the non-financial sector".

Analyzing the 20th Century Banking Crisis in EU: Sweden

For the sake of dispersion, given the elevated number of EU countries that are examinable in terms of data availability, I choose to focus primarily on the countries in the Eurozone that experienced important banking crisis and that are well-known in the literature as well as recognized in banking crisis datasets.

Proceeding in chronological order, the Finnish and Swedish banking crisis in the 90's are the first analyzed. These events are well recognized by important datasets[155] and a good result here from the crisis episode dataset, constructed with the CMAX applied on the county-specific banking indices, is that it clearly identifies these events even with a consistent timing and the appropriate gravity, i.e. red code. Specifically, for the Finnish case, the beginning of stress begins on 1, July 1988 and the beginning of crash about the end of November in the 1991 with a price decline to through of 92% in about 4 years. For the Swedish case, instead, the beginning of stress takes place on 1, August 1989 and the beginning of crash the same on 21, November but one year before the Finnish case, in 1990 with a price decline to through of 90% in 3 years and a quarter.

Unfortunately, the Finnish Banking Index (FinBI) is among the few indices for which very few commercial banks are available with really short time series. Thus, fearing that the FinBI does not adequately represent the Finnish banking sector, it is not analyzed.

Let's see now the Swedish case.

As previously anticipated, I will not list all the baseline models but only the most important in terms of significance and goodness-of-fit.

The first regressor in the bank credit granted to the PNFS. Even though there appears some weak significance in the 5-year horizon of model (1) the most important worth to report are the models with aggregated variables. The table 4.29 shows the baseline model (2) with only the predictors aggregated.

[155] See, for instance, Laeven and Valencia (2008) and Reinhart and Rogoff (2009).

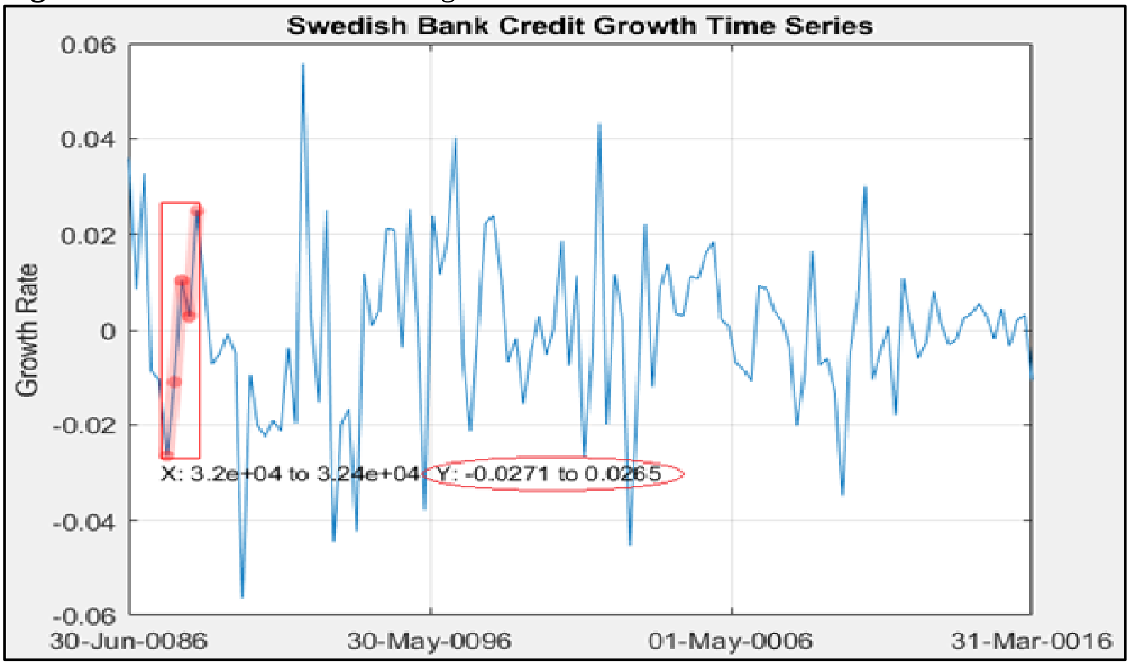
Table 4.20 – Baseline model (2) with only the bank credit to PNFS aggregated.

```
The best linear model in terms of AIC for the three year horizon with the predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    D_log(SweBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                               Estimate       SE        tStat       pValue 
                                              _________    ________    ________    ________

    (Intercept)                               -0.010612    0.022797    -0.46551     0.64244
    L4_Aggr_D_log(Bank credit to PNFS/CPI)       3.7551      2.0562      1.8263    0.070383
    L8_Aggr_D_log(Bank credit to PNFS/CPI)      -2.2949      2.0918     -1.0971     0.27487
    L12_Aggr_D_log(Bank credit to PNFS/CPI)     -5.0559      2.0598     -2.4545    0.015592


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.25
R-squared: 0.0828,  Adjusted R-Squared 0.0591
F-statistic vs. constant model: 3.49, p-value = 0.018
```

```
The best linear model in terms of AIC for the five year horizon with the predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                               Estimate       SE        tStat       pValue 
                                              _________    ________    ________    ________

    (Intercept)                               -0.010016    0.022449    -0.44617     0.65632
    L4_Aggr_D_log(Bank credit to PNFS/CPI)       4.5941      2.0684       2.221    0.028324
    L8_Aggr_D_log(Bank credit to PNFS/CPI)      -2.8213      2.0712     -1.3622     0.17583
    L12_Aggr_D_log(Bank credit to PNFS/CPI)     -5.2085      2.0608     -2.5275    0.012858
    L16_Aggr_D_log(Bank credit to PNFS/CPI)     0.41453      2.0731     0.19996     0.84187
    L20_Aggr_D_log(Bank credit to PNFS/CPI)      4.9624      2.0805      2.3852    0.018718


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.246
R-squared: 0.127,  Adjusted R-Squared 0.0884
F-statistic vs. constant model: 3.31, p-value = 0.00795
```

For this baseline version, the two criteria are consistent by selecting the S1 and for both horizons. Even though not all coefficient estimates are significant we may notice that overall the lag structures provide a reasonable framework and analogously to the Italian economic interpretation, by looking at 5YS1, we can grasp a positive relation in the short run (L20) and negative relations in the long term (L12 and L8) even though L16 in not clear. The 3YS1 appears to say first negative and then positive relation but it all depends from where the inception of the cycle is set. Specifically, given, in the year *t*, a 1 per cent increase in the swedish total bank credit granted to the PNFS and aggregated over three quarters (the code select as the best window *n = 3*), the swedish banking sector/index is going to rise of about 5 per cent in the same year *t* (short run), and to decrease of about 5.2 per cent in year *t+2*, and of about 2.8 per cent in year *t+3* (long run) by keeping the 1 per cent increase each *t*. This scenario is also consistent with the chronology of crisis episode table which report an upward trend before the crisis and a downward trend after the episode. In more details, it is the last year before the beginning of stress that is markedly increasing (42%) with the SweBI returns still negative in the third year after the event. In addition, to further highlight the consistency of the model so specified, if we look at the Swedish bank credit growth rate (figure 4.5) in the period preceding the beginning of the well-recognized banking stress of the 90's, we may well appreciate the growth rate: a ~ 5.4% of increase (from – 2.71% to + 2.65%) from the mid-1987 until the end of 1989 which would translate, according the above model, in an at least 30% increase in the SweBI. It actually increased even more.

Figure 4.5 – Swedish bank credit growth time series.



Tables 4.30 and 4.31 shows the results of the baseline model (3) and (4) respectively. The two criteria disagree among the two horizons, that is, for the 3-year window AIC and Adjusted R-Squared choose S2 and S3 respectively whereas for the 5-year window the model always preferred is S2. I report only the model for the longest horizon and, also, the S1 even not chosen by the code, for comparison purposes.

Table 4.21 – Baseline model (3) with both SweBI and bank credit to PNFS aggregated.

```
Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                                  Estimate       SE         tStat        pValue
                                                 _________    ________    ________    __________

    (Intercept)                                  -0.011213    0.013222    -0.84803        0.3982
    L4_Aggr_D_log(Bank credit to PNFS/CPI)          3.0706      1.3183      2.3292      0.021608
    L8_Aggr_D_log(Bank credit to PNFS/CPI)         -1.3533      1.2903     -1.0489       0.29646
    L12_Aggr_D_log(Bank credit to PNFS/CPI)        -5.0722      1.2805      -3.961    0.00013039
    L16_Aggr_D_log(Bank credit to PNFS/CPI)       -0.38397      1.2902    -0.29759       0.76656
    L20_Aggr_D_log(Bank credit to PNFS/CPI)         4.6994      1.3256      3.5452    0.00057021


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.145
R-squared: 0.202,  Adjusted R-Squared 0.167
F-statistic vs. constant model: 5.78, p-value = 8.53e-05
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y = 


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                                  Estimate       SE        tStat       pValue
                                                 _________    ________    ________    _________

    (Intercept)                                  -0.011634    0.012958    -0.89789      0.37122
    L2_Aggr_D_log(Bank credit to PNFS/CPI)         -2.4274      1.5676     -1.5485      0.12439
    L4_Aggr_D_log(Bank credit to PNFS/CPI)          3.5821      1.8683      1.9173     0.057813
    L6_Aggr_D_log(Bank credit to PNFS/CPI)         -0.3171      2.0495    -0.15472      0.87733
    L8_Aggr_D_log(Bank credit to PNFS/CPI)          1.7499      2.1623      0.8093      0.42011
    L10_Aggr_D_log(Bank credit to PNFS/CPI)        -4.0365      2.2217     -1.8168     0.071995
    L12_Aggr_D_log(Bank credit to PNFS/CPI)       -0.35231      2.2282    -0.15811      0.87466
    L14_Aggr_D_log(Bank credit to PNFS/CPI)        -4.8649      2.1825      -2.229     0.027863
    L16_Aggr_D_log(Bank credit to PNFS/CPI)          2.376      2.0754      1.1449      0.25477
    L18_Aggr_D_log(Bank credit to PNFS/CPI)        -2.1069      1.8884     -1.1157      0.26701
    L20_Aggr_D_log(Bank credit to PNFS/CPI)         4.6783      1.5856      2.9504    0.0038848


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.142
R-squared: 0.269,  Adjusted R-Squared 0.202
F-statistic vs. constant model: 4.01, p-value = 0.000108
```

The first observation is that while some CE are not significant, the overall lag structure of the models is essentially significant at the lowest CI. This again to highlight the jointly importance of some coefficient that alone is not informative. By looking at the 5YS1 one may notice that the first, third and fifth lags are significant with a positive, negative and again positive coefficient. This tendency seems also confirmed by the S2. While, by looking at both specifications, a scenario like the one drawn above for baseline (2) seems plausible, the second and fourth annual lags remain quite unclear.

Table 4.22 – Baseline model (4) with a MA of SweBI and the bank credit to PNFS aggregated as usual.

Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.0071784	0.0087341	-0.82189	0.41294
L4_Aggr_D_log(Bank credit to PNFS/CPI)	0.21612	0.80188	0.26952	0.78804
L8_Aggr_D_log(Bank credit to PNFS/CPI)	0.64776	0.78893	0.82106	0.41341
L12_Aggr_D_log(Bank credit to PNFS/CPI)	-3.6903	0.78455	-4.7038	7.5312e-06
L16_Aggr_D_log(Bank credit to PNFS/CPI)	-2.1743	0.78934	-2.7546	0.0068872
L20_Aggr_D_log(Bank credit to PNFS/CPI)	2.5951	0.79244	3.2748	0.0014178

Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0935
R-squared: 0.284, Adjusted R-Squared 0.252
F-statistic vs. constant model: 8.67, p-value = 6.06e-07

The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =

Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.0086135	0.008541	-1.0085	0.31556
L2_Aggr_D_log(Bank credit to PNFS/CPI)	-2.0719	1.0878	-1.9046	0.059589
L4_Aggr_D_log(Bank credit to PNFS/CPI)	0.99233	1.2365	0.80253	0.42407
L6_Aggr_D_log(Bank credit to PNFS/CPI)	0.066312	1.3424	0.049398	0.9607
L8_Aggr_D_log(Bank credit to PNFS/CPI)	1.4614	1.4089	1.0373	0.30202
L10_Aggr_D_log(Bank credit to PNFS/CPI)	-1.4164	1.4412	-0.98279	0.32799
L12_Aggr_D_log(Bank credit to PNFS/CPI)	-1.5913	1.4443	-1.1018	0.2731
L14_Aggr_D_log(Bank credit to PNFS/CPI)	-2.8047	1.4114	-1.9872	0.049534
L16_Aggr_D_log(Bank credit to PNFS/CPI)	-0.39176	1.3419	-0.29195	0.77091
L18_Aggr_D_log(Bank credit to PNFS/CPI)	-1.1034	1.2229	-0.90233	0.36897
L20_Aggr_D_log(Bank credit to PNFS/CPI)	2.3724	1.0286	2.3064	0.023069

Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0912
R-squared: 0.351, Adjusted R-Squared 0.289
F-statistic vs. constant model: 5.62, p-value = 1.11e-06

When considering the baseline (4) the two criteria agree along the different horizons. The model selected is the S2. As the 3YS2 has only the first and last half-yearly lags significant, I report only the 5-year model accompanied by the 5YS1 even though not selected as the best model from the code. While the goodness-of-fit of the S2 outperform S1, as expected by construction, the SE of the coefficient estimates are higher, pointing out less prediction accuracy. In the 5YS1, the last three lags are highly significant with L20 positive and L16 and L12 negative. If we consider this triennium solely, it would suggest the same previous economic interpretation, featured by a positive relation in the short term (build-up phase in the first year) and negative in the long term (following two years). What change here are the CEs which are slightly more contained. Unfortunately, La and L8 remain unclear, even if we look at the 3YS1 only the third lag is significant, thus we cannot draw a clear conclusion.

Let's move to the bank credit as a percentage of GDP. Some significance appears already in 5Y baseline (1) and in baseline (2) in both horizons. As previously seen, the cycle negative, negative and positive CE repeats in 3YS1 but as we can see from 5YS1 three year are not enough to explain the cycle here and the first lag is positive while the third and fourth negative with the second unclear. Table 4.32 shows this framework.

Table 4.23 – Baseline model (2) with bank credit as a percentage of GDP.

```
The best linear model in terms of AIC for the three year horizon with the predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    D_log(SweBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                         Estimate        SE        tStat       pValue
                                        __________    _______    ________    ________

    (Intercept)                         -0.0094698    0.02292    -0.41317     0.68025
    L4_Aggr_D_log(Bank credit/GDP)          3.0278      1.881      1.6096      0.1102
    L8_Aggr_D_log(Bank credit/GDP)         -3.3713     1.9684     -1.7127    0.089441
    L12_Aggr_D_log(Bank credit/GDP)         -2.804      1.884     -1.4883     0.13938


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.251
R-squared: 0.0724,  Adjusted R-Squared 0.0485
F-statistic vs. constant model: 3.02, p-value = 0.0326
```

```
The best linear model in terms of AIC for the five year horizon with the predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                       Estimate         SE         tStat       pValue
                                      __________    ________    ________    ________

    (Intercept)                       -0.0086651    0.022833    -0.37951     0.70502
    L4_Aggr_D_log(Bank credit/GDP)         2.513      1.9258      1.3049     0.19456
    L8_Aggr_D_log(Bank credit/GDP)       -2.9729      1.9995     -1.4868     0.13983
    L12_Aggr_D_log(Bank credit/GDP)      -2.3854      2.0052     -1.1896     0.23669
    L16_Aggr_D_log(Bank credit/GDP)      0.96686      2.0037     0.48253     0.63035
    L20_Aggr_D_log(Bank credit/GDP)       3.3375       1.941      1.7195    0.088245


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.25
R-squared: 0.0959,  Adjusted R-Squared 0.0563
F-statistic vs. constant model: 2.42, p-value = 0.04
```

While the two criteria choose the S1 and S2 for the 3-year horizon and S1 and, surprisingly, S3 for the 5-year window, I reported for the sake of brevity solely the most informative.
Let's see what happen when aggregating both dependent and predictor variables. The table 4.33 shows the results.

Table 4.24 – Baseline model (3) with both SweBI and the bank credit as a percentage of GDP aggregated.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                       Estimate       SE         tStat        pValue
                                      _________    ________    ________    __________

    (Intercept)                       -0.010124    0.013402    -0.75539       0.45155
    L4_Aggr_D_log(Bank credit/GDP)       4.2003      1.2039      3.4889    0.00068629
    L8_Aggr_D_log(Bank credit/GDP)      -2.2826      1.2355     -1.8476      0.067213
    L12_Aggr_D_log(Bank credit/GDP)     -2.4124      1.2063     -1.9998      0.047862


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.147
R-squared: 0.166,  Adjusted R-Squared 0.145
F-statistic vs. constant model: 7.7, p-value = 9.74e-05
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                        Estimate        SE         tStat       pValue
                                       __________    ________    ________    _________

    (Intercept)                        -0.0099782    0.013279    -0.75142      0.45395
    L4_Aggr_D_log(Bank credit/GDP)           3.71      1.2232      3.0331    0.0029978
    L8_Aggr_D_log(Bank credit/GDP)        -2.1186      1.2406     -1.7077     0.090407
    L12_Aggr_D_log(Bank credit/GDP)       -2.2644      1.2448     -1.8191     0.071526
    L16_Aggr_D_log(Bank credit/GDP)       0.11053      1.2447      0.0888       0.9294
    L20_Aggr_D_log(Bank credit/GDP)         2.467      1.2324      2.0018     0.047681


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.145
R-squared: 0.195,  Adjusted R-Squared 0.16
F-statistic vs. constant model: 5.54, p-value = 0.000133
```

Again, I report solely S1 for the two horizons. This time the two criteria agree pointing out the S1 and S3 for both windows. It is worth to say that apart for the 5YS3 whose best aggregation length is one quarter, the best *n* for all models in baseline (3) is again three quarters as for the previously examined regressor. While both the overall and the CE singular significance improve, the economic interpretation is analogous to the one illustrated for the bank credit growth.

Table 4.34 illustrates the results when applying a MA, with the usual best *n = 6* moving window, and the regressor aggregated as usual. Particularly, the best aggregation length over 3-year horizon is 4, 3, 4 quarters for S1, S2, S3 respectively whereas for the longest horizon 4, 3, 1 quarters are indicated for S1, S2, S3 respectively. In addition, it seems that the bank credit to GDP prefers the lower than 1-year lags since for the shortest horizon the code select always S3 while for the longest one AIC chooses S2 and Adjusted R-Squared S3.

Table 4.25 – Baseline model (4) with a MA of SweBI and the bank credit as a percentage of GDP aggregated as usual.

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                        Estimate         SE          tStat       pValue
                                       __________    _________    ________    _________

    (Intercept)                        -0.0053887    0.0091417    -0.58946      0.55677
    L4_Aggr_D_log(Bank credit/GDP)         2.3615      0.89109      2.6502    0.0092419
    L8_Aggr_D_log(Bank credit/GDP)        -1.0356      0.87593     -1.1822      0.23968
    L12_Aggr_D_log(Bank credit/GDP)       -2.6742      0.87926     -3.0415    0.0029495
    L16_Aggr_D_log(Bank credit/GDP)      -0.65783      0.87816     -0.7491      0.45541
    L20_Aggr_D_log(Bank credit/GDP)        1.9013      0.88265       2.154     0.033439


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.098
R-squared: 0.214,  Adjusted R-Squared 0.178
F-statistic vs. constant model: 5.95, p-value = 6.67e-05
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                        Estimate        SE         tStat        pValue
                                       __________    _________    ________    __________

    (Intercept)                        -0.0078533    0.0086485    -0.90806       0.36595
    L2_Aggr_D_log(Bank credit/GDP)        -4.4207       1.1587     -3.8152    0.00023124
    L4_Aggr_D_log(Bank credit/GDP)           5.02       1.5463      3.2464      0.001573
    L6_Aggr_D_log(Bank credit/GDP)        -2.3558       1.8353     -1.2836       0.20214
    L8_Aggr_D_log(Bank credit/GDP)         1.6148       1.8583     0.86894       0.38688
    L10_Aggr_D_log(Bank credit/GDP)       -2.6625       1.8476     -1.4411       0.15257
    L12_Aggr_D_log(Bank credit/GDP)      -0.52307       1.8436    -0.28372       0.77719
    L14_Aggr_D_log(Bank credit/GDP)       -2.2607       1.8437     -1.2262       0.22291
    L16_Aggr_D_log(Bank credit/GDP)         1.162       1.7991     0.64587       0.51979
    L18_Aggr_D_log(Bank credit/GDP)      -0.97807       1.4928    -0.65517        0.5138
    L20_Aggr_D_log(Bank credit/GDP)        1.9888        1.092      1.8212      0.071451


Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0925
R-squared: 0.333,  Adjusted R-Squared 0.268
F-statistic vs. constant model: 5.18, p-value = 3.88e-06
```

I only report the 5YS2 accompanied by the S1 for comparison purposes. As one may notice the economic interpretation does not change and the two specifications are consistent among themselves, i.e. by analyzing the half-yearly lags two at a time corresponding to the same year, it emerges a positive relationship in the first year (even though the L18 is not clear from the 5YS2) and a negative relation in the long run until the fourth year (L8-L6) with a return in positive field solely in the fifth year (L4-L2).

Let us look now at the total credit (from all sector and not just from the banking sector) granted to the PNFS. As praxis, we will first examine the variable in absolute terms and then as a percentage of GDP.
Table 4.35 and 4.36 show the most significant models, that is, baseline (3) and (4). In both kind of models, the two criteria agree along the different horizons by pointing out always S2. I also report the S1, as usual, for comparison purposes. When observing the results of these best models one may grasp that this variable does not provide very good results compared to the bank credit variables. The overall lag structure of 5YS1 of baseline (3) is not significant even at the 5% CI. In addition, there are too much coefficient estimates that are not informative and clear. If we move to the baseline (4), which generally does improve the results, the framework seems to even get worse.

Table 4.26 – Baseline model (3) with both SweBI and the credit to the PNFS aggregated.

```
Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                              Estimate       SE        tStat       pValue
                                              ________    ________    ________    ________

    (Intercept)                               -0.010441   0.014147    -0.73807     0.46199
    L4_Aggr_D_log(Credit to PNFS/CPI)            2.3019     1.2803      1.7979    0.074841
    L8_Aggr_D_log(Credit to PNFS/CPI)           -2.1396     1.2802     -1.6713    0.097405
    L12_Aggr_D_log(Credit to PNFS/CPI)          -2.0557     1.2813     -1.6044      0.1114
    L16_Aggr_D_log(Credit to PNFS/CPI)          0.33498      1.295     0.25867     0.79636
    L20_Aggr_D_log(Credit to PNFS/CPI)           2.1349     1.3188      1.6188     0.10825


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.155
R-squared: 0.0884,  Adjusted R-Squared 0.0484
F-statistic vs. constant model: 2.21, p-value = 0.058
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                              Estimate      SE        tStat       pValue
                                              ________    _______    _________    ________

    (Intercept)                               -0.010857   0.01357     -0.80007     0.42541
    L2_Aggr_D_log(Credit to PNFS/CPI)            -3.849    1.4137      -2.7227    0.007542
    L4_Aggr_D_log(Credit to PNFS/CPI)            2.6684    1.7611       1.5152     0.13262
    L6_Aggr_D_log(Credit to PNFS/CPI)           0.81141    2.0565      0.39456     0.69394
    L8_Aggr_D_log(Credit to PNFS/CPI)          -0.38214    2.2282     -0.17151     0.86414
    L10_Aggr_D_log(Credit to PNFS/CPI)          -2.3167    2.2992      -1.0076     0.31587
    L12_Aggr_D_log(Credit to PNFS/CPI)          -1.1585    2.3169         -0.5     0.61808
    L14_Aggr_D_log(Credit to PNFS/CPI)         -0.91549    2.2706     -0.40319      0.6876
    L16_Aggr_D_log(Credit to PNFS/CPI)          0.38515    2.1177      0.18187     0.85602
    L18_Aggr_D_log(Credit to PNFS/CPI)         0.017481      1.83    0.0095524      0.9924
    L20_Aggr_D_log(Credit to PNFS/CPI)           2.0587    1.4678       1.4026     0.16358


Number of observations: 120, Error degrees of freedom: 109
Root Mean Squared Error: 0.148
R-squared: 0.201,  Adjusted R-Squared 0.128
F-statistic vs. constant model: 2.74, p-value = 0.00474
```

Table 4.27 – Baseline model (4) with a MA of SweBI and the credit to the PNFS aggregated as usual.

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0064945	0.009659	-0.67238	0.50276
L4_Aggr_D_log(Credit to PNFS/CPI)	-0.33178	0.79715	-0.41621	0.67808
L8_Aggr_D_log(Credit to PNFS/CPI)	0.14424	0.8028	0.17967	0.85775
L12_Aggr_D_log(Credit to PNFS/CPI)	-2.6378	0.80105	-3.293	0.001337
L16_Aggr_D_log(Credit to PNFS/CPI)	-0.62906	0.80816	-0.77838	0.43803
L20_Aggr_D_log(Credit to PNFS/CPI)	1.6195	0.81389	1.9899	0.049111

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.103
R-squared: 0.128,  Adjusted R-Squared 0.0878
F-statistic vs. constant model: 3.19, p-value = 0.00992
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0077907	0.0093727	-0.83121	0.40776
L2_Aggr_D_log(Credit to PNFS/CPI)	-2.4137	0.98044	-2.4619	0.015466
L4_Aggr_D_log(Credit to PNFS/CPI)	0.40688	1.2019	0.33852	0.73565
L6_Aggr_D_log(Credit to PNFS/CPI)	0.30243	1.3979	0.21635	0.82914
L8_Aggr_D_log(Credit to PNFS/CPI)	0.72093	1.5101	0.47739	0.63408
L10_Aggr_D_log(Credit to PNFS/CPI)	-1.2969	1.5551	-0.834	0.40619
L12_Aggr_D_log(Credit to PNFS/CPI)	-1.7179	1.5651	-1.0976	0.27491
L14_Aggr_D_log(Credit to PNFS/CPI)	-1.1793	1.5332	-0.76915	0.44354
L16_Aggr_D_log(Credit to PNFS/CPI)	-0.056546	1.4299	-0.039545	0.96853
L18_Aggr_D_log(Credit to PNFS/CPI)	-0.13123	1.2356	-0.1062	0.91563
L20_Aggr_D_log(Credit to PNFS/CPI)	1.4706	0.99122	1.4837	0.14092

```
Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.1
R-squared: 0.218,  Adjusted R-Squared 0.143
F-statistic vs. constant model: 2.91, p-value = 0.00303
```

As a praxis, this credit variable is examined as a percentage of GDP as well. Even with this variable the results seem to worse with respect to the bank credit. I report solely the baseline model (3) and (4). For the former, the criteria choose S1 and S2 for the 3-year horizon and always S1 for the longest horizon. For the latter, S2 and S3 are preferred over the 3-years while the S2 is always selected for the 5-year horizon. However, as the table 4.37 and 4.38 show, I just report S1 and S2 for comparison.

Table 4.28 – Baseline model (3) with both SweBI and the credit to GDP aggregated.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                  Estimate        SE         tStat        pValue
                                 _________    ________    ________    _________

    (Intercept)                  -0.010535    0.013608    -0.77414      0.44042
    L4_Aggr_D_log(Credit/GDP)       2.8245        1.09      2.5913      0.01079
    L8_Aggr_D_log(Credit/GDP)      -3.0925      1.0992     -2.8135    0.0057574
    L12_Aggr_D_log(Credit/GDP)    0.041664      1.0995    0.037894      0.96984


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.149
R-squared: 0.14,  Adjusted R-Squared 0.118
F-statistic vs. constant model: 6.3, p-value = 0.000535
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                  Estimate        SE         tStat       pValue
                                 _________    ________    ________    ________

    (Intercept)                  -0.010343    0.013717    -0.75401      0.4524
    L4_Aggr_D_log(Credit/GDP)       2.7658      1.1289      2.4499    0.015808
    L8_Aggr_D_log(Credit/GDP)      -2.9879      1.1562     -2.5842    0.011024
    L12_Aggr_D_log(Credit/GDP)     0.17757      1.1703     0.15174     0.87966
    L16_Aggr_D_log(Credit/GDP)     0.15477      1.1698     0.13231     0.89497
    L20_Aggr_D_log(Credit/GDP)     0.59325       1.179     0.50318     0.61581


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.15
R-squared: 0.142,  Adjusted R-Squared 0.104
F-statistic vs. constant model: 3.78, p-value = 0.00336
```

Table 4.29 – Baseline model (4) with a MA of SweBI and the credit to GDP aggregated as usual.

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                   Estimate       SE         tStat       pValue
                                  __________    _________   ________    ________

    (Intercept)                   -0.0059064    0.0096142   -0.61434     0.54025
    L4_Aggr_D_log(Credit/GDP)         1.7244       0.7587     2.2728    0.024964
    L8_Aggr_D_log(Credit/GDP)        -1.4716      0.76039    -1.9353    0.055498
    L12_Aggr_D_log(Credit/GDP)       -1.2664      0.76052    -1.6652    0.098688


Number of observations: 115, Error degrees of freedom: 111
Root Mean Squared Error: 0.103
R-squared: 0.115,  Adjusted R-Squared 0.0909
F-statistic vs. constant model: 4.8, p-value = 0.00351
```

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                   Estimate       SE         tStat       pValue
                                  __________    _________   ________    ________

    (Intercept)                   -0.0057369    0.0096891    -0.5921     0.55501
    L4_Aggr_D_log(Credit/GDP)         1.7303      0.78587     2.2018    0.029786
    L8_Aggr_D_log(Credit/GDP)          -1.34      0.79973    -1.6756    0.096686
    L12_Aggr_D_log(Credit/GDP)       -1.1108      0.80935    -1.3725     0.17272
    L16_Aggr_D_log(Credit/GDP)       0.35094      0.80894    0.43382     0.66527
    L20_Aggr_D_log(Credit/GDP)       0.42242       0.8152    0.51817     0.60539


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.104
R-squared: 0.118,  Adjusted R-Squared 0.0774
F-statistic vs. constant model: 2.91, p-value = 0.0165
```

As it emerges from the tables above the results does not improve even if considering this credit variable as a percentage of GDP. The credit to GDP ratio seems to have a relationship only for the first two lags. This is clear in both 3YS1 and 5YS1.

Let us examine the Credit-to-GDP trend. As for the credit to GDP variable, I report solely the most interesting models, that is, baseline (3) and (4). For the former, the code is consistent among the different horizons by choosing always the S1 with the best aggregation length always equal to 2 quarters for the regressors. For the latter, instead, both criteria select S1 in the 3-year window whereas for the longest horizon the specifications preferred are S1 and S3. Her the best *n* is 4 quarters for 3YS1 and 4 and 2 quarters for 5YS1 and 5YS3 respectively. However, as usual, I report only the first specifications. Tables 4.39 and 4.40 show the results.

Table 4.30 – Baseline model (3) with both SweBI and the credit to GDP trend aggregated.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                           Estimate        SE         tStat       pValue
                                           _________    ________    ________    _________

    (Intercept)                            -0.012141    0.013637    -0.89024      0.37518
    L4_Aggr_D_log(Credit-to-GDP trend)        14.298      5.3267      2.6841    0.0083365
    L8_Aggr_D_log(Credit-to-GDP trend)       -26.361      6.0838     -4.3329    3.1461e-05
    L12_Aggr_D_log(Credit-to-GDP trend)       16.602      5.3807      3.0855    0.0025411


Number of observations: 120, Error degrees of freedom: 116
Root Mean Squared Error: 0.148
R-squared: 0.149,  Adjusted R-Squared 0.127
F-statistic vs. constant model: 6.76, p-value = 0.000304
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                           Estimate        SE         tStat       pValue
                                           _________    ________    ________    _________

    (Intercept)                            -0.013584    0.013893    -0.97771      0.33029
    L4_Aggr_D_log(Credit-to-GDP trend)        14.687      5.3919      2.7239    0.0074675
    L8_Aggr_D_log(Credit-to-GDP trend)       -26.227      6.1821     -4.2425    4.5203e-05
    L12_Aggr_D_log(Credit-to-GDP trend)       16.994      6.3219      2.6881    0.0082624
    L16_Aggr_D_log(Credit-to-GDP trend)      -1.5195      6.3022     -0.2411      0.80991
    L20_Aggr_D_log(Credit-to-GDP trend)        3.992      5.6592      0.7054        0.482


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.149
R-squared: 0.153,  Adjusted R-Squared 0.116
F-statistic vs. constant model: 4.11, p-value = 0.00181
```

Table 4.31 – Baseline model (4) with a MA of SweBI and the credit to GDP trend aggregated as usual.

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
                                               Estimate       SE          tStat       pValue
                                               _________    _________    ________    _________

    (Intercept)                                -0.0070114   0.0094755    -0.73995      0.46089
    L4_Aggr_D_log(Credit-to-GDP trend)             10.457      4.1038      2.5481     0.012198
    L8_Aggr_D_log(Credit-to-GDP trend)            -21.944      4.9099     -4.4694      1.9e-05
    L12_Aggr_D_log(Credit-to-GDP trend)            13.835      4.1038      3.3712    0.0010306


Number of observations: 115, Error degrees of freedom: 111
Root Mean Squared Error: 0.101
R-squared: 0.157,  Adjusted R-Squared 0.135
F-statistic vs. constant model: 6.91, p-value = 0.000261
```

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                               Estimate       SE          tStat       pValue
                                               _________    _________    ________    _________

    (Intercept)                                -0.0082931   0.0097444    -0.85106       0.3966
    L4_Aggr_D_log(Credit-to-GDP trend)             10.831      4.2013      2.5779     0.011274
    L8_Aggr_D_log(Credit-to-GDP trend)            -21.767      5.1191     -4.2521   4.4884e-05
    L12_Aggr_D_log(Credit-to-GDP trend)            13.535      5.3503      2.5297     0.012845
    L16_Aggr_D_log(Credit-to-GDP trend)         -0.072681      5.2435   -0.013861      0.98897
    L20_Aggr_D_log(Credit-to-GDP trend)            2.3756      4.4981     0.52813      0.59849


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.101
R-squared: 0.161,  Adjusted R-Squared 0.122
F-statistic vs. constant model: 4.18, p-value = 0.00165
```

The Credit to GDP trend seems to explain quite well the SweBI movements on a 3-year horizon. By looking at both specifications one may notice that the first three lags are significant at the 5% CI with the second lag even at 1% but the last two lags are not informative. In addition, it is worth to notice the high SEs, symptom of a poor accuracy prediction. The 3YS1 seems the best model by also considering the higher F-statistic and the stronger significance along with a better goodness-of-fit. The situation is analogous for the two baseline models.

Let us analyze the last credit to GDP version, namely, the Credit to GDP gap. For the sake of brevity and considering also the bad performance of this predictor, I report only the baseline (4).

Table 4.32 – Baseline model (4) with a MA of SweBI and the credit to GDP gap aggregated as usual.

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0067767	0.0099664	-0.67996	0.49795
L4_Aggr_D_log(Credit-to-GDP gap)	0.12826	0.14551	0.88147	0.37997
L8_Aggr_D_log(Credit-to-GDP gap)	-0.26577	0.15577	-1.7062	0.090774
L12_Aggr_D_log(Credit-to-GDP gap)	-0.2003	0.14675	-1.3649	0.17505

```
Number of observations: 115, Error degrees of freedom: 111
Root Mean Squared Error: 0.107
R-squared: 0.0525,  Adjusted R-Squared 0.0269
F-statistic vs. constant model: 2.05, p-value = 0.111
```

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0065653	0.010101	-0.64996	0.51708
L4_Aggr_D_log(Credit-to-GDP gap)	0.13558	0.15268	0.888	0.3765
L8_Aggr_D_log(Credit-to-GDP gap)	-0.2541	0.16568	-1.5337	0.12801
L12_Aggr_D_log(Credit-to-GDP gap)	-0.18373	0.1647	-1.1155	0.26707
L16_Aggr_D_log(Credit-to-GDP gap)	0.037687	0.16698	0.2257	0.82186
L20_Aggr_D_log(Credit-to-GDP gap)	0.020223	0.15744	0.12845	0.89803

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.108
R-squared: 0.053,  Adjusted R-Squared 0.00955
F-statistic vs. constant model: 1.22, p-value = 0.305
```

Among the others variables the most informative ones are the credit (from all sectors) granted to households and NPISHs and the residential property prices (RPPs).
Let's see the most significant models for the credit to households and NPISHs. Table 4.43 shows the results.

Table 4.33 – Baseline model (3) and (4) with SweBI as dependent variable and Credit to HHs and NPISHs as predictor.

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                                Estimate      SE        tStat       pValue
                                                _________   ________   ________   __________

    (Intercept)                                 -0.011764   0.013391   -0.87854       0.3815
    L4_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -0.16186     1.5591   -0.10382       0.9175
    L8_Aggr_D_log(Credit to HHs&NPISHs/CPI)        2.0646     1.5403     1.3404      0.18278
    L12_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -3.2742     1.5435    -2.1212      0.03607
    L16_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -4.9518     1.5456    -3.2037    0.0017592
    L20_Aggr_D_log(Credit to HHs&NPISHs/CPI)       5.3876     1.5889     3.3907   0.00095855


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.147
R-squared: 0.182,  Adjusted R-Squared 0.146
F-statistic vs. constant model: 5.07, p-value = 0.000308
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                                 Estimate        SE         tStat       pValue
                                                __________   _________   _________   _________

    (Intercept)                                 -0.0071321   0.0092123    -0.77419      0.4405
    L4_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -0.018141       1.079   -0.016813     0.98662
    L8_Aggr_D_log(Credit to HHs&NPISHs/CPI)         1.8776      1.0374      1.8099    0.073068
    L12_Aggr_D_log(Credit to HHs&NPISHs/CPI)       -2.6494      1.0403     -2.5467    0.012272
    L16_Aggr_D_log(Credit to HHs&NPISHs/CPI)       -4.2399      1.0418     -4.0696   8.939e-05
    L20_Aggr_D_log(Credit to HHs&NPISHs/CPI)        2.3259      1.0709      2.1719    0.032027


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0988
R-squared: 0.202,  Adjusted R-Squared 0.165
F-statistic vs. constant model: 5.52, p-value = 0.000143
```

The best models reveal to always belong to baseline (3) and (4). I reported only the 5YS1 for each version as the most significant. While taking a MA of six quarters on the SweBI

clearly improves both the overall lag structure and the CEs significance, the predictive ability of the 'Credit to HHs and NPISHs' evidently gets better with the second lag turning significant at 10% CI. Unfortunately, the impact effect of L4 on SweBI, as measured by the first beta, is not clear whereas the long-run cumulative effect of this credit variable on the SweBI is quite appreciable with a positive-negative-positive relationship.
Table 4.44 and 4.45 illustrate the framework when the residential property prices (RPPs) are used as predictors in the baseline (3) and (4) respectively.

Table 4.34 – Baseline model (3) with both the SweBI and RPPs aggregated.

```
The best linear model in terms of AIC for the three year horizon with both the dependent and predictor variables aggregated is :

BESTLM_3Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 13 terms in 12 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0098472	0.012318	-0.79941	0.42582
L1_Aggr_D_log(RPPs/CPI)	2.6734	0.67124	3.9828	0.00012449
L2_Aggr_D_log(RPPs/CPI)	0.6609	0.73278	0.90191	0.36913
L3_Aggr_D_log(RPPs/CPI)	-1.3107	0.74903	-1.7499	0.082999
L4_Aggr_D_log(RPPs/CPI)	-1.9917	0.74788	-2.6631	0.0089387
L5_Aggr_D_log(RPPs/CPI)	0.018861	0.81611	0.023111	0.9816
L6_Aggr_D_log(RPPs/CPI)	0.1428	0.81682	0.17482	0.86155
L7_Aggr_D_log(RPPs/CPI)	-0.74582	0.81818	-0.91156	0.36405
L8_Aggr_D_log(RPPs/CPI)	-1.2767	0.81884	-1.5592	0.12191
L9_Aggr_D_log(RPPs/CPI)	0.42785	0.75167	0.56921	0.57041
L10_Aggr_D_log(RPPs/CPI)	0.81497	0.75336	1.0818	0.28178
L11_Aggr_D_log(RPPs/CPI)	-0.29546	0.73844	-0.40012	0.68987
L12_Aggr_D_log(RPPs/CPI)	-0.90821	0.67644	-1.3426	0.18223

```
Number of observations: 120, Error degrees of freedom: 107
Root Mean Squared Error: 0.134
R-squared: 0.358,  Adjusted R-Squared 0.286
F-statistic vs. constant model: 4.96, p-value = 1.74e-06
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    Aggr_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                Estimate       SE        tStat       pValue
                                ________    ________    ________    __________

    (Intercept)                 -0.004385   0.012806    -0.34243       0.73266
    L4_Aggr_D_log(RPPs/CPI)        -4.348    0.72944     -5.9608    2.8652e-08
    L8_Aggr_D_log(RPPs/CPI)      -0.83321    0.75095     -1.1095       0.26954
    L12_Aggr_D_log(RPPs/CPI)      -1.6082    0.76718     -2.0962      0.038278
    L16_Aggr_D_log(RPPs/CPI)      -1.4021    0.76936     -1.8225      0.071008
    L20_Aggr_D_log(RPPs/CPI)      -1.4792    0.75484     -1.9596      0.052479


Number of observations: 120, Error degrees of freedom: 114
Root Mean Squared Error: 0.14
R-squared: 0.259,  Adjusted R-Squared 0.226
F-statistic vs. constant model: 7.96, p-value = 1.82e-06
```

For the baseline (3) the two criteria agree along the 3-year horizon by selecting always the S3 with the best aggregation length equal to one quarter. When considering the 5-year window the best models are the S1 and S3 with *n* equal to 3 and 1 quarter respectively. I report 3YS3 with solely 5YS1. As we can see, while the overall lag structures are both highly significant, the CE's significance decrease as we move from annually to quarterly lags. However, the SEs are really contained and the goodness-of fit is good with respect to the previous models with others predictors. The best performance of this predictor is corroborated by the baseline (4) with a MA of the SweBI aggregated with the usual best 6 quarters window as dependent variable. For this version, given the results, all three specifications are reported. While the goodness-of-fit increases, when moving from the S1 to S3, as expected by construction, the prediction accuracy decreases as the SEs of the CEs indicates. It is worth to notice the high β_1 impact effect of RPPs, representing the first L4 lag, on the SweBI with a subsequent weaker long-run cumulative effect. However, the relationship among the two variables remains negative.

Table 4.35 – Baseline model (4) with a MA of SweBI dependent variable and RPPs aggregated as usual.

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                  Estimate        SE         tStat       pValue
                                 __________    _________    ________    _________

    (Intercept)                  0.00078149    0.0087043    0.089782      0.92863
    L4_Aggr_D_log(RPPs/CPI)         -3.2065      0.52066     -6.1585    1.254e-08
    L8_Aggr_D_log(RPPs/CPI)         -1.2895      0.51636     -2.4973     0.014007
    L12_Aggr_D_log(RPPs/CPI)        -1.0153      0.52551      -1.932     0.055955
    L16_Aggr_D_log(RPPs/CPI)        -1.5464      0.52655     -2.9368     0.004046
    L20_Aggr_D_log(RPPs/CPI)        -1.4093      0.53717     -2.6236    0.0099468


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0925
R-squared: 0.3,  Adjusted R-Squared 0.268
F-statistic vs. constant model: 9.36, p-value = 1.93e-07
```

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                 Estimate        SE        tStat        pValue
                                __________    _________    ________    __________

    (Intercept)                 -0.0034005    0.0081093    -0.41933       0.67584
    L2_Aggr_D_log(RPPs/CPI)         2.7306      0.65946      4.1406    7.0598e-05
    L4_Aggr_D_log(RPPs/CPI)        -3.7827      0.92903     -4.0716    9.1256e-05
    L6_Aggr_D_log(RPPs/CPI)        0.31917       1.1771     0.27114       0.78682
    L8_Aggr_D_log(RPPs/CPI)        -1.5943       1.2743     -1.2511        0.2137
    L10_Aggr_D_log(RPPs/CPI)       0.45879         1.32     0.34757       0.72887
    L12_Aggr_D_log(RPPs/CPI)       -1.2615       1.3232    -0.95341       0.34259
    L14_Aggr_D_log(RPPs/CPI)        0.1124       1.2888    0.087211       0.93067
    L16_Aggr_D_log(RPPs/CPI)       -1.5821       1.1946     -1.3244       0.18828
    L18_Aggr_D_log(RPPs/CPI)       0.75279      0.94274     0.79851       0.42639
    L20_Aggr_D_log(RPPs/CPI)       -1.3776      0.67366     -2.0449      0.043391


Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0864
R-squared: 0.417,  Adjusted R-Squared 0.361
F-statistic vs. constant model: 7.44, p-value = 8.01e-09
```

```
The best linear model in terms of AIC for the five year horizon with both the dependent and predictor variables aggregated is :

BESTLM_5Y =


Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 21 terms in 20 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0041953	0.0077039	-0.54457	0.58734
L1_Aggr_D_log(RPPs/CPI)	5.17	1.2751	4.0547	0.00010351
L2_Aggr_D_log(RPPs/CPI)	-2.2489	2.1871	-1.0283	0.30646
L3_Aggr_D_log(RPPs/CPI)	-3.1351	2.158	-1.4528	0.14961
L4_Aggr_D_log(RPPs/CPI)	2.9573	2.3954	1.2346	0.22007
L5_Aggr_D_log(RPPs/CPI)	0.29929	2.4106	0.12415	0.90146
L6_Aggr_D_log(RPPs/CPI)	-4.4096	2.5293	-1.7434	0.084537
L7_Aggr_D_log(RPPs/CPI)	1.303	2.6463	0.49238	0.6236
L8_Aggr_D_log(RPPs/CPI)	0.54434	2.5808	0.21092	0.83341
L9_Aggr_D_log(RPPs/CPI)	-0.74867	2.5771	-0.29051	0.77207
L10_Aggr_D_log(RPPs/CPI)	-0.24199	2.5815	-0.093739	0.92552
L11_Aggr_D_log(RPPs/CPI)	-0.52889	2.592	-0.20405	0.83876
L12_Aggr_D_log(RPPs/CPI)	-0.16953	2.5949	-0.065334	0.94805
L13_Aggr_D_log(RPPs/CPI)	1.4434	2.61	0.55303	0.58155
L14_Aggr_D_log(RPPs/CPI)	-2.8524	2.6877	-1.0613	0.29129
L15_Aggr_D_log(RPPs/CPI)	0.47613	2.5781	0.18468	0.85388
L16_Aggr_D_log(RPPs/CPI)	1.0478	2.4687	0.42443	0.67222
L17_Aggr_D_log(RPPs/CPI)	-0.9505	2.4196	-0.39284	0.69533
L18_Aggr_D_log(RPPs/CPI)	-0.76666	2.1752	-0.35246	0.72528
L19_Aggr_D_log(RPPs/CPI)	1.3739	2.2138	0.62059	0.53637
L20_Aggr_D_log(RPPs/CPI)	-1.3716	1.2825	-1.0695	0.2876

```
Number of observations: 115, Error degrees of freedom: 94
Root Mean Squared Error: 0.082
R-squared: 0.525,  Adjusted R-Squared 0.424
F-statistic vs. constant model: 5.2, p-value = 1.73e-08
```

Finally, let's test whether the Credit to HHs and NPISHs along with the RPPs' effect on the SweBI movements are affected by the specific financial system dimension/depth, as proxied by the Credit to GDP ratio. In the table 4.46, the baseline model (5), with the best SweBI predictors and the financial/bank dimension proxied by the respective credit to GDP ratio, shows the results. First, for all baseline (5) versions, the relationship between the predictors and the SweBI are consistent with the previous results with the RPPs always negative and the credit to HHs and NPISHs positive in the first lags then negative and again positive. Second, almost all the CEs of the lagged predictors are significant and informative apart the third and fourth lag of the credit to HHs and NPISHs especially when the financial and bank depth is added into the model. However, the overall lag structure of all three versions is abundantly significant at 1% CI with an increasing F-statistic and p-value as the financial/bank depth is accounted for. Finally, note that the best model here, in terms of AIC and goodness-of-fit, is reached with the bank depth aggregated over one year (*n =4*).

Table 4.36 – Baseline model (5) with the best SweBI predictors and the financial/bank depth proxied by the respective credit to GDP.

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	0.0037082	0.0079202	0.4682	0.64062
L4_Aggr_D_log(RPPs/CPI)	-4.1251	0.65353	-6.3121	6.8658e-09
L8_Aggr_D_log(RPPs/CPI)	-2.4769	0.74571	-3.3215	0.0012361
L12_Aggr_D_log(RPPs/CPI)	-1.8005	0.79126	-2.2755	0.024929
L16_Aggr_D_log(RPPs/CPI)	-1.7039	0.69961	-2.4355	0.016574
L20_Aggr_D_log(RPPs/CPI)	-2.0652	0.57956	-3.5634	0.00055427
L4_Aggr_D_log(Credit to HHs&NPISHs/CPI)	1.9791	1.0012	1.9768	0.050708
L8_Aggr_D_log(Credit to HHs&NPISHs/CPI)	4.5705	1.0554	4.3305	3.4351e-05
L12_Aggr_D_log(Credit to HHs&NPISHs/CPI)	1.4889	1.2886	1.1554	0.25056
L16_Aggr_D_log(Credit to HHS&NPISHs/CPI)	-1.1065	1.3457	-0.82219	0.41285
L20_Aggr_D_log(Credit to HHS&NPISHs/CPI)	3.1374	1.2965	2.4199	0.017258

```
Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0823
R-squared: 0.471,  Adjusted R-Squared 0.42
F-statistic vs. constant model: 9.27, p-value = 7.98e-11
```

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 12 terms in 11 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.001495	0.0070359	-0.21249	0.83215
L4_Aggr_D_log(RPPs/CPI)	-3.7005	0.58045	-6.3751	5.2458e-09
L8_Aggr_D_log(RPPs/CPI)	-0.90529	0.71446	-1.2671	0.20798
L12_Aggr_D_log(RPPs/CPI)	-0.68431	0.72486	-0.94405	0.34735
L16_Aggr_D_log(RPPs/CPI)	-2.1455	0.62109	-3.4545	0.00080177
L20_Aggr_D_log(RPPs/CPI)	-1.7201	0.51405	-3.3463	0.001144
L4_Aggr_D_log(Credit to HHs&NPISHs/CPI)	3.4082	0.91799	3.7127	0.0003331
L8_Aggr_D_log(Credit to HHs&NPISHs/CPI)	4.0151	0.93462	4.2959	3.9508e-05
L12_Aggr_D_log(Credit to HHs&NPISHs/CPI)	-0.60317	1.195	-0.50475	0.61481
L16_Aggr_D_log(Credit to HHS&NPISHs/CPI)	-0.958	1.1852	-0.80827	0.4208
L20_Aggr_D_log(Credit to HHS&NPISHs/CPI)	3.4002	1.1426	2.976	0.00364
Aggr_D_log(Credit/GDP)	-3.6431	0.65285	-5.5802	1.9538e-07

```
Number of observations: 115, Error degrees of freedom: 103
Root Mean Squared Error: 0.0725
R-squared: 0.594,  Adjusted R-Squared 0.551
F-statistic vs. constant model: 13.7, p-value = 8.51e-16
```

```
Linear regression model:
    MA_D_log(SweBI_QLP/CPI) ~ [Linear formula with 12 terms in 11 predictors]

Estimated Coefficients:
                                                   Estimate         SE          tStat        pValue
                                                  __________    __________    __________    __________

    (Intercept)                                   -0.0023331    0.0069036      -0.33795        0.73609
    L4_Aggr_D_log(RPPs/CPI)                           -3.218      0.58318        -5.518     2.5688e-07
    L8_Aggr_D_log(RPPs/CPI)                           -1.539      0.66152       -2.3265       0.021948
    L12_Aggr_D_log(RPPs/CPI)                        -0.97896      0.69579        -1.407        0.16245
    L16_Aggr_D_log(RPPs/CPI)                         -2.2652      0.61049       -3.7104     0.00033572
    L20_Aggr_D_log(RPPs/CPI)                         -2.0649      0.49989       -4.1307     7.3709e-05
    L4_Aggr_D_log(Credit to HHs&NPISHs/CPI)            3.187       0.8862        3.5963     0.00049748
    L8_Aggr_D_log(Credit to HHs&NPISHs/CPI)           3.8946      0.91711        4.2466     4.7673e-05
    L12_Aggr_D_log(Credit to HHs&NPISHs/CPI)        0.034042        1.137      0.029939        0.97617
    L16_Aggr_D_log(Credit to HHS&NPISHs/CPI)        -0.23059       1.1697      -0.19713        0.84411
    L20_Aggr_D_log(Credit to HHS&NPISHs/CPI)          3.8735       1.1248        3.4436     0.00083119
    Aggr_D_log(Bank credit/GDP)                      -4.6391      0.76481       -6.0657     2.1983e-08


Number of observations: 115, Error degrees of freedom: 103
Root Mean Squared Error: 0.071
R-squared: 0.61,  Adjusted R-Squared 0.569
F-statistic vs. constant model: 14.7, p-value = 1.14e-16
```

Summing up the Sweden Banking Sector

According the credit series availability, as for Italy, there has been examined and reported seven different credit-related variables, namely, the total bank credit to the PNFS both in absolute and in percentage terms, the total credit (granted from all sector and not only commercial banks) to PNFS again in absolute and percentage terms, the three Credit-to-GDP variants (Credit-to-GDP ratio, Credit-to-GDP trend and Credit-to-GDP gap). Indeed, besides the above variables four further BIS statistics have been tested, i.e. the credit granted to NFCs but with very bad results thus not reported, the DSRs which revealed significant but not much informative and the credit to households and NPISHs (in absolute and percentage terms) along with the residential property prices (RPPs) which instead turned out to be best predictors of the Swedish Banking Sector.
Comin back to the 'decent' explaining regressors, on one hand, the *bank credit* growth rate revealed, as expected, one of the most important predictor of banking stress/(in)stability performing better than the credit from all sector. On the other hand, the most powerful predictor of the Swedish Banking Index (SweBI) turned out to be, in order, the RPPs and the credit (from all sectors) granted to HHs and NPISHs especially together as illustrates the baseline model (5). The last observation concerns the role of the bank financial system's depth proxied by a 3 or 5 years' MA. Note that their 3-5 years MA history does not ameliorate the model. The results get better, instead, if a one year aggregation of bank or financial depth is taken with the former better than the latter.

A quick look to the EU countries more affected by the 2007-08 financial crisis

For the sake of brevity, following, some of the EU countries that have been affected more by the last global financial crisis are going to be analyzed. 'Affected more' means countries that, according the crisis dataset based on the CMAX tool, showed a red code with a price decline to through equal or higher than the 90%. Naturally, keeping into account the data availability as well. For this scope, only the most significant models belonging to the best baseline version, normally baseline model (3) and/or (4), are illustrated.

Belgium

Broadly speaking, for this country, there is no variable that shines in terms of performance. The bank credit variables, with respect to the other variables, perform quite well in predicting the BelBI. However, surprisingly, the best predictor for the Belgium is the Credit to HHs and NPISHs-to-GDP. Following, the table 4.47 shows, in order, the best baseline (4) S1 models. It is worth to notice the bad performance of credit (from all sectors) to GDP variables.

Table 4.37 – Baseline model (4) with the best BelBI predictors.

```
Linear regression model:
    MA_D_log(BelBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                                  Estimate         SE         tStat       pValue  
                                                 ___________    _________    _________    __________

    (Intercept)                                  -0.00022948    0.0083066    -0.027626       0.97801
    L4_Aggr_D_log(Credit to HHs&NPISHs/GDP)           1.0294      0.98806       1.0418       0.29981
    L8_Aggr_D_log(Credit to HHs&NPISHs/GDP)        -0.028816       1.0515    -0.027405       0.97819
    L12_Aggr_D_log(Credit to HHs&NPISHs/GDP)         -4.1515       1.0403      -3.9908    0.00011967
    L16_Aggr_D_log(Credit to HHs&NPISHs/GDP)         -1.3551       1.0577      -1.2813       0.20281
    L20_Aggr_D_log(Credit to HHs&NPISHs/GDP)          2.3858      0.99869       2.3889      0.018615


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0877
R-squared: 0.198,  Adjusted R-Squared 0.161
F-statistic vs. constant model: 5.38, p-value = 0.000183
```

```
Linear regression model:
    MA_D_log(BelBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                                 Estimate        SE         tStat       pValue  
                                                __________    ________    ________    _________

    (Intercept)                                 -0.0028143    0.008447    -0.33317      0.73965
    L4_Aggr_D_log(Bank credit to PNFS/CPI)         -2.4506     0.72869      -3.363    0.0010645
    L8_Aggr_D_log(Bank credit to PNFS/CPI)         -1.6604     0.75374     -2.2029      0.02971
    L12_Aggr_D_log(Bank credit to PNFS/CPI)       -0.82458     0.80135      -1.029      0.30576
    L16_Aggr_D_log(Bank credit to PNFS/CPI)         -1.487     0.79436     -1.8719     0.063902
    L20_Aggr_D_log(Bank credit to PNFS/CPI)          -1.89     0.82135      -2.301     0.023291


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0902
R-squared: 0.152,  Adjusted R-Squared 0.113
F-statistic vs. constant model: 3.91, p-value = 0.00269
```

Table 4.38 – Baseline model (5) with the best BelBI predictors and the bank/ financial depth proxied by the respective credit to GDP.

```
Linear regression model:
    MA_D_log(BelBI_QLP/CPI) ~ [Linear formula with 12 terms in 11 predictors]

Estimated Coefficients:
                                                 Estimate        SE         tStat       pValue
                                                _________    _________    ________    _________

    (Intercept)                                 -0.003458    0.0075342    -0.45898      0.64721
    L4_Aggr_D_log(Credit to HHs&NPISHs/GDP)        1.5597      0.93873      1.6615     0.099648
    L8_Aggr_D_log(Credit to HHs&NPISHs/GDP)       0.37716       1.0382     0.36328      0.71714
    L12_Aggr_D_log(Credit to HHs&NPISHs/GDP)      -2.7372       1.1133     -2.4586     0.015615
    L16_Aggr_D_log(Credit to HHs&NPISHs/GDP)      0.22509       1.1482     0.19604      0.84496
    L20_Aggr_D_log(Credit to HHs&NPISHs/GDP)       3.1807       1.0377       3.065    0.0027789
    L4_Aggr_D_log(Bank credit to PNFS/CPI)         -1.117      0.72274     -1.5456      0.12528
    L8_Aggr_D_log(Bank credit to PNFS/CPI)       -0.42933      0.76154    -0.56377      0.57413
    L12_Aggr_D_log(Bank credit to PNFS/CPI)      -0.12062      0.83144    -0.14507      0.88494
    L16_Aggr_D_log(Bank credit to PNFS/CPI)       -1.3026      0.76978     -1.6922     0.093639
    L20_Aggr_D_log(Bank credit to PNFS/CPI)      -0.86996      0.80403      -1.082      0.28178
    Aggr_D_log(Bank credit/GDP)                    2.9607      0.63429      4.6677   9.2063e-06


Number of observations: 115, Error degrees of freedom: 103
Root Mean Squared Error: 0.0776
R-squared: 0.407,  Adjusted R-Squared 0.344
F-statistic vs. constant model: 6.42, p-value = 5.01e-08
```

```
Linear regression model:
    MA_D_log(BelBI_QLP/CPI) ~ [Linear formula with 12 terms in 11 predictors]

Estimated Coefficients:
                                                 Estimate         SE         tStat       pValue
                                                __________    _________    ________    _________

    (Intercept)                                 -0.0016473    0.0079736     -0.2066      0.83673
    L4_Aggr_D_log(Credit to HHs&NPISHs/GDP)        0.84061        1.016      0.8274      0.40992
    L8_Aggr_D_log(Credit to HHs&NPISHs/GDP)       0.085222       1.1058     0.07707      0.93872
    L12_Aggr_D_log(Credit to HHs&NPISHs/GDP)       -2.9819       1.1777      -2.532      0.01285
    L16_Aggr_D_log(Credit to HHs&NPISHs/GDP)       -1.0579       1.2079    -0.87587      0.38314
    L20_Aggr_D_log(Credit to HHs&NPISHs/GDP)         2.435       1.0881      2.2378     0.027387
    L4_Aggr_D_log(Bank credit to PNFS/CPI)        -0.88483      0.80711     -1.0963      0.27551
    L8_Aggr_D_log(Bank credit to PNFS/CPI)        -0.40843      0.81963    -0.49832      0.61932
    L12_Aggr_D_log(Bank credit to PNFS/CPI)       -0.96939      0.88083     -1.1005      0.27367
    L16_Aggr_D_log(Bank credit to PNFS/CPI)       -0.44488       0.8431    -0.52767      0.59887
    L20_Aggr_D_log(Bank credit to PNFS/CPI)        -2.0908      0.81486     -2.5659     0.011731
    Aggr_D_log(Credit/GDP)                         -1.9314      0.65772     -2.9364    0.0040957


Number of observations: 115, Error degrees of freedom: 103
Root Mean Squared Error: 0.0821
R-squared: 0.337,  Adjusted R-Squared 0.266
F-statistic vs. constant model: 4.76, p-value = 6.99e-06
```

The overall performance of the model improves in an increasing way when including the financial and then the banking sector proxied by the respectively credit to GDP ratios. Note that while the BelBI is aggregated, as usual, over a moving window of one year and half (n = 6), the best aggregation length for the two best credit predictors equals to one year (n = 4) whereas for both the bank and financial sector the best aggregation window is equal to three quarters (n = 3).

Greece

For this country, it is worth to highlight the bad performance of essentially all the credit-related variables. The good news is that there is one indicator which performs quite well. It is the Credit to General Government both in absolute terms and in percentage of GDP. This is in line with the dynamics that featured the Greece as the most indebted state in the EU which make it suffer most the 2007-08 financial crisis. Also, it is worth to say that data availability on the credit series for this country is quite poor, with the best predictor starting from the last quarter of 1997. Table 4.53 shows the results for the baseline model (4).

Table 4.39 – Baseline model (4) with the best GreBI predictors.

Linear regression model:
MA_D_log(GreBI_QLP/CPI) ~ [Linear formula with 4 terms in 3 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.032694	0.01384	-2.3624	0.021419
L4_Aggr_D_log(Credit to GG/CPI)	-0.2196	0.36294	-0.60504	0.54743
L8_Aggr_D_log(Credit to GG/CPI)	-0.59333	0.39851	-1.4889	0.14176
L12_Aggr_D_log(Credit to GG/CPI)	-2.2057	0.39889	-5.5295	7.3839e-07

Number of observations: 64, Error degrees of freedom: 60
Root Mean Squared Error: 0.11
R-squared: 0.384, Adjusted R-Squared 0.354
F-statistic vs. constant model: 12.5, p-value = 1.91e-06

Linear regression model:
MA_D_log(GreBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.031609	0.013623	-2.3204	0.023924
L2_Aggr_D_log(Credit to GG/CPI)	-0.3157	0.43808	-0.72065	0.47407
L4_Aggr_D_log(Credit to GG/CPI)	-0.40762	0.48449	-0.84134	0.40367
L6_Aggr_D_log(Credit to GG/CPI)	0.43768	0.56225	0.77844	0.43953
L8_Aggr_D_log(Credit to GG/CPI)	-0.84188	0.56455	-1.4912	0.14141
L10_Aggr_D_log(Credit to GG/CPI)	-0.20576	0.50871	-0.40447	0.68738
L12_Aggr_D_log(Credit to GG/CPI)	-2.3796	0.48577	-4.8986	8.3452e-06

Number of observations: 64, Error degrees of freedom: 57
Root Mean Squared Error: 0.108
R-squared: 0.436, Adjusted R-Squared 0.377
F-statistic vs. constant model: 7.34, p-value = 7.62e-06

```
Linear regression model:
    MA_D_log(GreBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.027908	0.014919	-1.8707	0.066439
L4_Aggr_D_log(Credit to GG/GDP)	-0.30208	0.56267	-0.53687	0.59341
L8_Aggr_D_log(Credit to GG/GDP)	-0.69166	0.86512	-0.7995	0.42726
L12_Aggr_D_log(Credit to GG/GDP)	-2.3016	1.1304	-2.0361	0.046315
L16_Aggr_D_log(Credit to GG/GDP)	0.60514	1.2563	0.48169	0.63184
L20_Aggr_D_log(Credit to GG/GDP)	1.2	0.99491	1.2062	0.23266

```
Number of observations: 64, Error degrees of freedom: 58
Root Mean Squared Error: 0.109
R-squared: 0.415,  Adjusted R-Squared 0.365
F-statistic vs. constant model: 8.23, p-value = 6.32e-06
```

```
Linear regression model:
    MA_D_log(GreBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.024199	0.014385	-1.6822	0.098407
L2_Aggr_D_log(Credit to GG/GDP)	-0.95425	0.53144	-1.7956	0.078261
L4_Aggr_D_log(Credit to GG/GDP)	0.22759	0.60157	0.37833	0.7067
L6_Aggr_D_log(Credit to GG/GDP)	-0.58368	0.8783	-0.66455	0.50922
L8_Aggr_D_log(Credit to GG/GDP)	0.64379	0.94495	0.6813	0.49865
L10_Aggr_D_log(Credit to GG/GDP)	-2.0658	1.1318	-1.8252	0.073611
L12_Aggr_D_log(Credit to GG/GDP)	-0.36935	1.1635	-0.31744	0.75215
L14_Aggr_D_log(Credit to GG/GDP)	-1.9015	1.0528	-1.8062	0.076565
L16_Aggr_D_log(Credit to GG/GDP)	2.6436	1.1095	2.3826	0.020811
L18_Aggr_D_log(Credit to GG/GDP)	-1.2172	0.83352	-1.4603	0.15011
L20_Aggr_D_log(Credit to GG/GDP)	0.95656	0.8364	1.1437	0.2579

```
Number of observations: 64, Error degrees of freedom: 53
Root Mean Squared Error: 0.103
R-squared: 0.522,  Adjusted R-Squared 0.432
F-statistic vs. constant model: 5.79, p-value = 8.02e-06
```

While the criteria select the S1 and S2 for the 3/year window and always S2 for the longest horizon, I report both specification for the best variable. The results improve when moving from the growth rate of credit to the GG to the same variable in percentage of GDP. However, the story does not change too much, with the third lag significant and informative. This can be appreciated in both horizons but more in the shortest one with a tStat of about -5.53.

Ireland

Ireland is another particular EU country as, along with the Greece, it has been affected to a greater extent by the last global financial crisis. However, while for the latter problems seemed to derive basically from the growth of the General Government's debt, the framework for the former is different.

First, it has to be noted that, roughly, almost all the credit-related (and not only) variables belonging to the set tested are more or less informative which may be symptomatic of a multitude of causes at the roots of the Ireland's instability. However, some predictors are sharply more informative.

The bank credit variables, with respect to the other variables, perform quite well in predicting the IriBI but, as for the Belgium and Greece, the credit granted from banks to the PNFS is not the best predictor. Indeed, the Irish Banking Sector's movements seem to be well explained by the Credit to the NFCs, both in absolute terms and in percentage of GDP. While for both series the best aggregation lengths are 4, 3 and 4 quarters for S1, S2 and S3 respectively and in both horizons the best model selection changes. For the former, S2 is always preferred in the 3-year horizon whereas for the 5-year window the two criteria choose S2 and S3. When considering the latter, instead, the criteria agree along the two time windows as they select always S2 and S3 as the best models.

The second most informative predictor is the Credit to HHs and NPISHs. Indeed, the Credit to NFS is slightly more informative than the Credit to HHs and NPISHs but the former is a broader variable that includes the Credit to NFCs and since this is much more informative than the Credit to NFS, it is clear that the important portion of credit is the flow to the NFCs, making redundant the inclusion of the Credit to NFS.

Coming back to the Credit to HHs and NPISHs, the best aggregation lengths are 3, 2 and 3 quarters for S1, S2 and S3 respectively in the 3-year horizon and 3, 3 and 4 quarters for the 5-year window. In terms of code selection, the criteria agree by selecting S1 and S3 in both horizons. If we consider the Credit to HHs and NPISHs to GDP, while the best aggregation length of the predictor is the same for the two horizons, i.e. 3, 3 and 4 quarters for S1, S2 and S3 respectively, the two criteria agree solely for the 3-year horizon by choosing always S2 whereas for the 5-year window the code selects S2 and S3. However, for the sake of brevity and comparison purposes, I always report the first specification. Table 4.54 and 4.55 illustrate the results for the best predictors. A remark has to be done before commenting the result. Unfortunately, several credit time series for this country are not complete and, among others, for the two best predictors the credit time series start from the 2000.

Table 4.40 – Baseline model (4) with the best IreBI predictor, i.e. the Credit to NFCs.

```
Linear regression model:
    MA_D_log(IriBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	0.0010493	0.0095082	0.11036	0.91233
L4_Aggr_D_log(Credit to NFCs/CPI)	-0.28079	0.45333	-0.61939	0.53695
L8_Aggr_D_log(Credit to NFCs/CPI)	-3.2681	0.64267	-5.0852	1.5381e-06
L12_Aggr_D_log(Credit to NFCs/CPI)	-4.4911	0.66593	-6.7442	7.6638e-10
L16_Aggr_D_log(Credit to NFCs/CPI)	1.5563	0.68731	2.2643	0.025534
L20_Aggr_D_log(Credit to NFCs/CPI)	-1.772	0.7183	-2.4669	0.015185

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.101
R-squared: 0.476,  Adjusted R-Squared 0.452
F-statistic vs. constant model: 19.8, p-value = 5.42e-14
```

```
Linear regression model:
    MA_D_log(IriBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	0.00085315	0.009325	0.09149	0.92727
L4_Aggr_D_log(Credit to NFCs/GDP)	-0.032618	0.43885	-0.074325	0.94089
L8_Aggr_D_log(Credit to NFCs/GDP)	-3.2427	0.57559	-5.6336	1.3946e-07
L12_Aggr_D_log(Credit to NFCs/GDP)	-4.0718	0.58972	-6.9046	3.5038e-10
L16_Aggr_D_log(Credit to NFCs/GDP)	2.4017	0.60999	3.9372	0.00014558
L20_Aggr_D_log(Credit to NFCs/GDP)	-0.30139	0.60593	-0.4974	0.61991

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0984
R-squared: 0.503,  Adjusted R-Squared 0.48
F-statistic vs. constant model: 22, p-value = 3.32e-15
```

Table 4.41 – Baseline model (4) with the second best IreBI predictor, i.e. the Credit to HHs and NPISHs.

```
Linear regression model:
    MA_D_log(IriBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                                Estimate      SE        tStat       pValue
                                               __________  ________  ________  __________

    (Intercept)                                -0.0045082  0.010701  -0.42127     0.67439
    L4_Aggr_D_log(Credit to HHs&NPISHs/CPI)        7.4172    1.1722    6.3274  5.6612e-09
    L8_Aggr_D_log(Credit to HHs&NPISHs/CPI)       -3.1369    1.1889   -2.6386   0.0095442
    L12_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -3.9574    1.1912   -3.3221   0.0012166
    L16_Aggr_D_log(Credit to HHs&NPISHs/CPI)      0.96198    1.2083   0.79616     0.42767
    L20_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -3.8005    1.1975   -3.1736   0.0019571


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.111
R-squared: 0.372,  Adjusted R-Squared 0.343
F-statistic vs. constant model: 12.9, p-value = 7.08e-10
```

```
Linear regression model:
    MA_D_log(IriBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                                Estimate      SE        tStat       pValue
                                               __________  ________  ________  __________

    (Intercept)                                -0.0017313  0.010593  -0.16343     0.87048
    L4_Aggr_D_log(Credit to HHs&NPISHs/GDP)        4.4902    1.0574    4.2464   4.588e-05
    L8_Aggr_D_log(Credit to HHs&NPISHs/GDP)      -0.72323    1.0938  -0.66119     0.50989
    L12_Aggr_D_log(Credit to HHs&NPISHs/GDP)       -6.493    1.0848   -5.9856  2.8035e-08
    L16_Aggr_D_log(Credit to HHs&NPISHs/GDP)       1.8824     1.102    1.7081    0.090462
    L20_Aggr_D_log(Credit to HHs&NPISHs/GDP)      -4.6067    1.1879   -3.8779  0.00018056


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.111
R-squared: 0.367,  Adjusted R-Squared 0.338
F-statistic vs. constant model: 12.6, p-value = 1.1e-09
```

The first observation is that the two best variables perform better when taken in absolute terms with respect to the percentage of GDP. Also, the story does not change as revealed by the CEs signs.

Let us check, as the final exercise for the country examined, what happen when including the best predictors in the same regression and accounting for the bank/financial depth, namely the baseline model (5).

Table 4.42 – Baseline model (5) with the best IriBI predictors and the bank/ financial depth proxied by the respective credit to GDP.

```
Linear regression model:
    MA_D_log(IriBI_QLP/CPI) ~ [Linear formula with 10 terms in 9 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	0.010483	0.0085081	1.2322	0.22064
L4_Aggr_D_log(Credit to NFCs/CPI)	-0.59775	0.46904	-1.2744	0.20533
L8_Aggr_D_log(Credit to NFCs/CPI)	-3.3998	0.71651	-4.7449	6.6109e-06
L12_Aggr_D_log(Credit to NFCs/CPI)	-3.2372	0.66403	-4.875	3.879e-06
L16_Aggr_D_log(Credit to NFCs/CPI)	1.3536	0.89098	1.5193	0.1317
L20_Aggr_D_log(Credit to NFCs/CPI)	-2.7231	0.78797	-3.4558	0.00079293
L4_Aggr_D_log(Credit to HHsandNPISHs/CPI)	4.2338	1.0504	4.0309	0.00010548
L8_Aggr_D_log(Credit to HHsandNPISHs/CPI)	1.898	1.2586	1.5081	0.13454
L4_Aggr_D_log(RPP/CPI)	-0.2117	0.60144	-0.35199	0.72555
L8_Aggr_D_log(RPP/CPI)	-2.8808	0.60674	-4.7479	6.5306e-06

```
Number of observations: 115, Error degrees of freedom: 105
Root Mean Squared Error: 0.0873
R-squared: 0.623,  Adjusted R-Squared 0.591
F-statistic vs. constant model: 19.3, p-value = 1.17e-18
```

```
Linear regression model:
    MA_D_log(IriBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	0.013692	0.0087035	1.5731	0.11892
L4_Aggr_D_log(Credit to NFCs/CPI)	-0.19591	0.49141	-0.39868	0.691
L8_Aggr_D_log(Credit to NFCs/CPI)	-3.2421	0.71233	-4.5514	1.5314e-05
L12_Aggr_D_log(Credit to NFCs/CPI)	-3.6395	0.67453	-5.3955	4.7498e-07
L16_Aggr_D_log(Credit to NFCs/CPI)	0.59591	0.92794	0.64218	0.52225
L20_Aggr_D_log(Credit to NFCs/CPI)	-3.274	0.80722	-4.0559	0.00010031
L4_Aggr_D_log(Credit to HHsandNPISHs/CPI)	2.2544	1.2972	1.7379	0.085362
L8_Aggr_D_log(Credit to HHsandNPISHs/CPI)	0.38208	1.3886	0.27516	0.78377
L4_Aggr_D_log(RPP/CPI)	-0.57595	0.61447	-0.93732	0.3509
L8_Aggr_D_log(RPP/CPI)	-3.0489	0.60419	-5.0462	2.0759e-06
3YMA_D_log(Bank credit/GDP)	2.9169	1.1309	2.5792	0.01139

```
Number of observations: 109, Error degrees of freedom: 98
Root Mean Squared Error: 0.0864
R-squared: 0.653,  Adjusted R-Squared 0.617
F-statistic vs. constant model: 18.4, p-value = 1.71e-18
```

```
Linear regression model:
    MA_D_log(IriBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                                 Estimate       SE         tStat       pValue
                                                 ________    _________    _______    __________

    (Intercept)                                  0.016329    0.0089953     1.8153      0.072805
    L4_Aggr_D_log(Credit to NFCs/CPI)             -1.2027      0.49664    -2.4216      0.017457
    L8_Aggr_D_log(Credit to NFCs/CPI)             -3.3859      0.70746     -4.786    6.6348e-06
    L12_Aggr_D_log(Credit to NFCs/CPI)            -1.5589      0.82556    -1.8883      0.062207
    L16_Aggr_D_log(Credit to NFCs/CPI)             3.4167       1.0835     3.1534     0.0021938
    L20_Aggr_D_log(Credit to NFCs/CPI)            -2.7635      0.78326    -3.5282    0.00066109
    L4_Aggr_D_log(Credit to HHsandNPISHs/CPI)      4.7427       1.0442     4.5418    1.7247e-05
    L8_Aggr_D_log(Credit to HHsandNPISHs/CPI)      3.9041       1.3723     2.8449     0.0055003
    L4_Aggr_D_log(RPP/CPI)                        0.06473      0.62448    0.10365       0.91767
    L8_Aggr_D_log(RPP/CPI)                        -2.4078      0.64271    -3.7464    0.00031628
    5YMA_D_log(Credit/GDP)                        -7.1388       2.1424    -3.3321      0.001252


Number of observations: 101, Error degrees of freedom: 90
Root Mean Squared Error: 0.0858
R-squared: 0.679,  Adjusted R-Squared 0.643
F-statistic vs. constant model: 19, p-value = 2.88e-18
```

Several observations worth to be cited for the baseline (5).
First, besides the two best predictors, the RPPs indicator has been added since it gives its contribute in explaining the IriBI movements. The results improve with respect to the model in which only a single predictor is used.
Second, the bank and the financial depth seem to affect and contribute to explain the IriBI as the significance of their CEs demonstrates and the higher goodness-of-fit reveals even though the F-statistic slightly weakens, especially with the Bank depth. Note that to keep the regression structure reasonable a MA of the bank/financial sector is taken instead of the annual lags. Also, note that while for the bank depth the best aggregation window is three years, for the financial depth the 5-year history is more informative in explaining the IriBI. Interestingly, the former has a positive relationship with the Irish Banking Sector whereas the latter a negative one. This make sense and may be pointing out that while an increase in the credit granted from the Irish banking sector to the PNFS in percentage of GDP, over three last years, corroborates the banking sector itself, the same increase of the financial depth, i.e. the Credit to GDP ratio, over the last five years, weakens the banking sector by amplifying the effects of the best predictors.

Netherland

For this country, the Credit to GDP variables perform well relative to the other variables. The bank credit granted to the PNFS does not contribute in explaining the Dutch Banking Index even though the results improve when considering the variable in percentage of GDP. The best predictor seems to be the portion of Credit from all sector granted to NFCs, especially in percentage of GDP. This is corroborated by the good performance of the DSR of NFCs. However, surprisingly, the best DSR is the one of HHs and NPISHs with a really good performance followed by the DSR of PNFS. Another important predictor is the Credit to GG. Finally, some information is given by the Credit to HHs and NPISHs and the RPPs as well.

Let us start with the best DutBI predictor, namely the DSR of HHs and NPISHs. This is surprising as the Credit to NFCs performs sharply better than the flow of Credit to HHs and NPISHs. This corroborates the quality of the DSRs variables as EWIs. However, the best aggregation length is always the same for all specifications and both horizons, i.e. one year (*n =4*). Regarding the best model selection, the code select always S2 and S3 in both time windows. Table 4.57 shows the results. As usual only the S1 is reported.

Table 4.43 – Baseline model (4) with the best DSR predictor for the DutBI, i.e. the DSR of HHs and NPISHs.

```
Linear regression model:
    MA_D_log(DutBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0035073	0.01276	-0.27487	0.78449
L4_Aggr_D_log(DSR of HHs&NPISHs)	6.1673	1.1562	5.3342	2.0261e-06
L8_Aggr_D_log(DSR of HHs&NPISHs)	0.5572	1.2607	0.44197	0.66031
L12_Aggr_D_log(DSR of HHs&NPISHs)	-5.8275	1.2781	-4.5595	3.0625e-05
L16_Aggr_D_log(DSR of HHs&NPISHs)	-2.7272	1.2655	-2.1549	0.03573
L20_Aggr_D_log(DSR of HHs&NPISHs)	0.31544	1.207	0.26134	0.79484

```
Number of observations: 59, Error degrees of freedom: 53
Root Mean Squared Error: 0.0785
R-squared: 0.547,  Adjusted R-Squared 0.504
F-statistic vs. constant model: 12.8, p-value = 3.66e-08
```

Let's see now the Credit to GDP variables. The first that is going to be analyzed is the Credit to GDP ratio. The best aggregation length is always 3 quarters for the 3-years and 3, 2, 3 quarters for the 5-years whereas as the best specifications the code selects S1 and S2 for the 3-year horizon and S1 and S3 for the 5-year window.

For the Credit to GDP trend the best *n* remains unchanged for all specifications and both the time windows at one year whereas the best models as the criteria prefer are always S2 in both horizons. Finally, the Credit to GDP gap, the best aggregation length is 3, 3, 4 quarters for the 3-years and always 3 quarters for the 5-years. About the models preferred by the two criteria, the S1 is always chosen in the shortest horizon whereas S1 and S3 are selected in the longest window. Table 4.57 illustrates the results.

Table 4.44 – Baseline model (4) with the Credit to GDP variables as DutBI predictors.

```
Linear regression model:
    MA_D_log(DutBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	0.00073631	0.0071524	0.10295	0.9182
L4_Aggr_D_log(Credit/GDP)	2.9398	0.90079	3.2636	0.0014698
L8_Aggr_D_log(Credit/GDP)	-1.8166	1.0545	-1.7228	0.087754
L12_Aggr_D_log(Credit/GDP)	-4.1115	1.0704	-3.8413	0.00020595
L16_Aggr_D_log(Credit/GDP)	0.11951	1.0694	0.11175	0.91122
L20_Aggr_D_log(Credit/GDP)	2.8199	0.94706	2.9775	0.0035814

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0767
R-squared: 0.29,  Adjusted R-Squared 0.258
F-statistic vs. constant model: 8.92, p-value = 3.97e-07
```

```
Linear regression model:
    MA_D_log(DutBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.00077612	0.0073363	-0.10579	0.91594
L2_Aggr_D_log(Credit-to-GDP trend)	17.179	12.91	1.3307	0.18609
L4_Aggr_D_log(Credit-to-GDP trend)	10.961	23.794	0.46066	0.64597
L6_Aggr_D_log(Credit-to-GDP trend)	-49.856	29.968	-1.6636	0.099084
L8_Aggr_D_log(Credit-to-GDP trend)	23.96	30.043	0.79755	0.42688
L10_Aggr_D_log(Credit-to-GDP trend)	-52.238	24.411	-2.1399	0.03461
L12_Aggr_D_log(Credit-to-GDP trend)	45.174	13.634	3.3134	0.0012547

```
Number of observations: 115, Error degrees of freedom: 108
Root Mean Squared Error: 0.0771
R-squared: 0.29,  Adjusted R-Squared 0.25
F-statistic vs. constant model: 7.34, p-value = 1.34e-06
```

```
Linear regression model:
    MA_D_log(DutBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	2.3447e-05	0.0071306	0.0032883	0.99738
L4_Aggr_D_log(Credit-to-GDP gap)	0.45851	0.13384	3.4258	0.00086537
L8_Aggr_D_log(Credit-to-GDP gap)	-0.23329	0.17796	-1.3109	0.19263
L12_Aggr_D_log(Credit-to-GDP gap)	-0.58396	0.19423	-3.0066	0.0032798
L16_Aggr_D_log(Credit-to-GDP gap)	-0.0059153	0.18817	-0.031436	0.97498
L20_Aggr_D_log(Credit-to-GDP gap)	0.51633	0.16672	3.0971	0.0024855

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0763
R-squared: 0.296,  Adjusted R-Squared 0.264
F-statistic vs. constant model: 9.18, p-value = 2.6e-07
```

Coming to the Credit to NFCs, the best aggregation length is 4, 4, 3 for the 3-years and 4, 2, 3 for the 5-years. About the best specification, the two criteria agree by always selecting the S1 in both time windows. The results get better when considering the variable in percentage of GDP, where the best *n* is always equal to one year while the best specification is S1 for both criteria in the shortest horizon and S2 and S3 in the longest one. Table 4.58 shows the results.

Table 4.45 – Baseline model (4) with the best DutBI predictor, i.e. the Credit to NFCs.

```
Linear regression model:
    Aggr_D_log(DutBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                              Estimate        SE         tStat        pValue
                                             __________    ________    ________    __________

    (Intercept)                              -0.0028583    0.007222    -0.39577       0.69305
    L4_Aggr_D_log(Credit to NFCs/CPI)           0.38853     0.89843     0.43245       0.66627
    L8_Aggr_D_log(Credit to NFCs/CPI)            -4.862     0.93619     -5.1934    9.6768e-07
    L12_Aggr_D_log(Credit to NFCs/CPI)          -3.2588     0.92008     -3.5418    0.00058602
    L16_Aggr_D_log(Credit to NFCs/CPI)           0.2328     0.96538     0.24115       0.80989
    L20_Aggr_D_log(Credit to NFCs/CPI)           1.3331      1.0046      1.3271       0.18726


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0765
R-squared: 0.294,  Adjusted R-Squared 0.261
F-statistic vs. constant model: 9.07, p-value = 3.12e-07
```

```
Linear regression model:
    MA_D_log(DutBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                              Estimate         SE          tStat        pValue
                                             ___________    _________    _________    __________

    (Intercept)                              -0.00011752    0.0066428    -0.017691       0.98592
    L4_Aggr_D_log(Credit to NFCs/GDP)             2.5745      0.90136       2.8563     0.0051339
    L8_Aggr_D_log(Credit to NFCs/GDP)            -3.5998       1.0032      -3.5884    0.00049986
    L12_Aggr_D_log(Credit to NFCs/GDP)           -3.9986      0.99296      -4.0269    0.00010474
    L16_Aggr_D_log(Credit to NFCs/GDP)             1.562        1.012       1.5435        0.1256
    L20_Aggr_D_log(Credit to NFCs/GDP)             4.409      0.99324        4.439    2.1736e-05


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.071
R-squared: 0.392,  Adjusted R-Squared 0.364
F-statistic vs. constant model: 14.1, p-value = 1.32e-10
```

Finally, the baseline model (5). Here, I report the best predictors in explaining the aggregate-as-usual DutBI movements. Note that is DSR of HHs and NPISHs does not appear. This because while alone is capable of giving information about the Dutch Banking Sector, when it is included with the other regressors only the first two lags are informative but the overall performance get worse. Also, note that the bank and financial history, in particular the last 3-years, ameliorate the model with the former slightly better than the latter.

Table 4.46 – Baseline model (5) with the best DutBI predictors and the bank/ financial depth proxied by the respective credit to GDP.

```
Linear regression model:
    MA_D_log(DutBI_QLP/CPI) ~ [Linear formula with 11 terms in 10 predictors]

Estimated Coefficients:
                                        Estimate       SE        tStat       pValue
                                       __________   _________   ________   __________

    (Intercept)                         -0.010176   0.0064417    -1.5797      0.11722
    L4_Aggr_D_log(Credit to NFCs/GDP)      2.4668     0.86049     2.8667    0.0050211
    L8_Aggr_D_log(Credit to NFCs/GDP)     -2.7045      0.9722    -2.7818    0.0064193
    L12_Aggr_D_log(Credit to NFCs/GDP)     -3.233     0.96318    -3.3565    0.0011031
    L16_Aggr_D_log(Credit to NFCs/GDP)    0.40213      1.0312    0.38997      0.69736
    L20_Aggr_D_log(Credit to NFCs/GDP)     3.8077        1.02     3.7331   0.00030879
    L4_Aggr_D_log(Credit to GG/GDP)         1.504     0.37189     4.0441   0.00010101
    L8_Aggr_D_log(Credit to GG/GDP)        1.6128     0.43091     3.7427   0.00029862
    L12_Aggr_D_log(Credit to GG/GDP)       1.2399     0.44581     2.7812    0.0064316
    L16_Aggr_D_log(Credit to GG/GDP)      0.91283     0.41502     2.1995     0.030055
    L20_Aggr_D_log(Credit to GG/GDP)       1.2866     0.37738     3.4093   0.00092788


Number of observations: 115, Error degrees of freedom: 104
Root Mean Squared Error: 0.0646
R-squared: 0.519,  Adjusted R-Squared 0.473
F-statistic vs. constant model: 11.2, p-value = 8.33e-13
```

```
Linear regression model:
    MA_D_log(DutBI_QLP/CPI) ~ [Linear formula with 12 terms in 11 predictors]

Estimated Coefficients:
                                        Estimate        SE         tStat       pValue
                                       __________   _________   ________   __________

    (Intercept)                        -0.0020484   0.0067928   -0.30155      0.76364
    L4_Aggr_D_log(Credit to NFCs/GDP)      2.0032     0.84207     2.3789     0.019325
    L8_Aggr_D_log(Credit to NFCs/GDP)     -3.1599     0.94776    -3.3341    0.0012129
    L12_Aggr_D_log(Credit to NFCs/GDP)    -2.5454     0.95286    -2.6713    0.0088616
    L16_Aggr_D_log(Credit to NFCs/GDP)     1.1391      1.0197      1.117      0.26673
    L20_Aggr_D_log(Credit to NFCs/GDP)     4.0994     0.98678     4.1544   7.0267e-05
    L4_Aggr_D_log(Credit to GG/GDP)       0.88586     0.40655      2.179     0.031756
    L8_Aggr_D_log(Credit to GG/GDP)        1.0249     0.45337     2.2607     0.026015
    L12_Aggr_D_log(Credit to GG/GDP)      0.72492     0.45816     1.5822      0.11685
    L16_Aggr_D_log(Credit to GG/GDP)      0.66279     0.40738     1.6269      0.10699
    L20_Aggr_D_log(Credit to GG/GDP)       1.5855       0.377     4.2056   5.8067e-05
    3YMA_D_log(Bank depth)                 6.8963      2.1707      3.177    0.0019962


Number of observations: 109, Error degrees of freedom: 97
Root Mean Squared Error: 0.0622
R-squared: 0.573,  Adjusted R-Squared 0.525
F-statistic vs. constant model: 11.9, p-value = 9.44e-14
```

```
Linear regression model:
    MA_D_log(DutBI_QLP/CPI) ~ [Linear formula with 12 terms in 11 predictors]

Estimated Coefficients:
                                          Estimate       SE          tStat        pValue
                                          ________    _________    _______    __________

    (Intercept)                           -0.00661    0.0065752    -1.0053       0.31725
    L4_Aggr_D_log(Credit to NFCs/GDP)       2.2196        0.847     2.6206      0.010191
    L8_Aggr_D_log(Credit to NFCs/GDP)      -3.5962       1.0099    -3.5609    0.00057463
    L12_Aggr_D_log(Credit to NFCs/GDP)     -2.2087       1.0192     -2.167      0.032684
    L16_Aggr_D_log(Credit to NFCs/GDP)      1.5719        1.101     1.4276       0.15661
    L20_Aggr_D_log(Credit to NFCs/GDP)      4.2671       1.0123     4.2154    5.5981e-05
    L4_Aggr_D_log(Credit to GG/GDP)         1.2232      0.37837     3.2327     0.0016759
    L8_Aggr_D_log(Credit to GG/GDP)         1.6091      0.42225     3.8107     0.0002433
    L12_Aggr_D_log(Credit to GG/GDP)        1.4139      0.44309     3.1909     0.0019111
    L16_Aggr_D_log(Credit to GG/GDP)        1.2499      0.42784     2.9214     0.0043341
    L20_Aggr_D_log(Credit to GG/GDP)        1.6583      0.39726     4.1744    6.5222e-05
    3YMA_D_log(Financial depth)               7.87       2.9896     2.6325     0.0098642


Number of observations: 109, Error degrees of freedom: 97
Root Mean Squared Error: 0.0632
R-squared: 0.56,  Adjusted R-Squared 0.511
F-statistic vs. constant model: 11.2, p-value = 3.66e-13
```

Summing up the Banking Sector of Belgium, Greece, Ireland and Netherland

The second group of countries analyzed in the Eurozone is composed by

As anticipated before, broadly speaking, there is no variable that shines in terms of performance in explaining the Belgium Banking Index. However, while the best predictor for the Belgium is the Credit to HHs and NPISHs in percentage of GDP, the bank credit variables, with respect to the other variables, perform quite well in predicting the BelBI. It is noteworthy to notice the bad performance of credit (from all sectors) to GDP variables.

About the Greek case, unfortunately, almost all the credit-related variables have a poor performance. There is one indicator which performs quite well. It is the Credit to General Government both in absolute terms and in percentage of GDP. This is in line with the dynamics that featured Greece as the most indebted state in the EU which made it suffer most the 2007-08 financial crisis.

Ireland, along with the Greece, represents the EU country that has been affected to a greater extent by the last global financial crisis. However, unlike the latter, almost all the variables belonging to the set tested are, more or less, informative which may be symptomatic of a multitude of causes at the roots of the Ireland's instability. The best predictors, in order of performance, are the Credit to the NFCs and the Credit to HHs and NPISHs both in absolute terms and in percentage of GDP. Also, the residential property prices (RPPs) give a contribute in explaining the Irish Banking Sector but only the second lag. Note, the inclusion of the bank and financial depth history (3YMA and

5YMA respectively) that ameliorate the model with the latter being preferred to the former.

Finally, the Netherland. Even for this country almost all the variables tested are, more or less, informative pointing out a multitude of causes at the roots of the Netherland's instability. However, some variables perform clearly better than the others. Beside the Credit to GDP variables that remain important, once again the DSRs reveal a good EWI. The best ones are the DSR of HHs and NPISHs followed by the DSR of PNFS. This is quite surprising since the second-best predictor is the flow of Credit to NFCs. In addition, the Credit to the general government is still important in explaining the Dutch Banking Sector. In fact, the baseline (5) is constituted by the Credit to NFCs and Credit to GG with the bank and financial depth amplifying the best predictors' effect.

What about France, Germany, Spain and UK?

Finally, let’s have a look at the four remaining most important countries in Europe: France, Germany, Spain and UK. Even though their price decline to through does not reach and overcame the 90% of loss and although they have not experienced a well-known banking crisis during the period covered by the indices’ time series, they still suffered the latest global financial crisis. In addition, their role and importance in the Eurozone is crucial, thus they deserve at least a quick analysis. As usual, only the most interesting model will be illustrated, namely the baseline model (4).

France

For this country two important observations are worth to be mentioned.
First, broadly speaking, the Credit to GDP variables perform quite well and seem to be the best predictors of the FreBI movements.
Second, the bank credit granted to the PNFS performs bad. While some improvement is reached when the variable is taken as a percentage of GDP, the results are still scarce.
Third, among the remainder variables, only the Credit to the general government (GG) and the debt-service ratio (DSR) for the credit to NFCs are noteworthy.
Let us start with the Credit to GDP variables.
The first that is going to be examined is the Credit to GDP ratio. The best aggregation length for this variable is always equal to four (*n = 4*) for both time window and for all the specifications. About the best specifications, while for the 3-year horizon the two criteria agree on the S1, for the 5-year window the code select S1 and S2.
For the Credit to GDP trend the best aggregation length remains one year (*n = 4*) for all the 3-year horizon’s specifications, whereas for the 5-year window the code prefers *n = 4* for S1 and S2, and *n = 3* for S3. Regarding the best models, the criteria are consistent along the two horizons by selecting always S1 and S2.
Finally, for the Credit to GDP gap the usual special treatment has been adopted, i.e. the series has been made positive by adding its minimum value plus a constant which I set to 10. The best aggregation length for this variable is always equal to four (*n = 4*) for both time window and for all the specifications. About the best specifications, while for the 3-year horizon the two criteria agree on the S1, for the 5-year window the code select S1 and S2. Table 4.59 shows the 5YS1 of the three Credit to GDP variables. While the credit to GDP trend seems to explain better the FreBI as the goodness-of-fit and the F-statistic significance illustrate, the prediction accuracy is really poor with SE extremely high.

Table 4.47 – Baseline model (4) with the best FreBI predictor, i.e. the Credit to GDP variables.

```
Linear regression model:
    MA_D_log(FreBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0053156	0.0075097	-0.70783	0.48056
L4_Aggr_D_log(Credit/GDP)	4.7544	1.417	3.3553	0.0010917
L8_Aggr_D_log(Credit/GDP)	0.75076	1.4938	0.5026	0.61626
L12_Aggr_D_log(Credit/GDP)	-3.8966	1.5747	-2.4745	0.014885
L16_Aggr_D_log(Credit/GDP)	1.2509	1.5365	0.81413	0.41735
L20_Aggr_D_log(Credit/GDP)	4.6816	1.5123	3.0956	0.0024965

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0802
R-squared: 0.268,  Adjusted R-Squared 0.234
F-statistic vs. constant model: 7.97, p-value = 1.96e-06
```

```
Linear regression model:
    MA_D_log(FreBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.00639	0.0078327	-0.81582	0.41638
L4_Aggr_D_log(Credit-to-GDP trend)	23.975	8.2671	2.9	0.0045139
L8_Aggr_D_log(Credit-to-GDP trend)	-29.523	9.0699	-3.2551	0.0015106
L12_Aggr_D_log(Credit-to-GDP trend)	-12.438	9.415	-1.321	0.18925
L16_Aggr_D_log(Credit-to-GDP trend)	46.615	9.7471	4.7825	5.4587e-06
L20_Aggr_D_log(Credit-to-GDP trend)	-17.453	8.887	-1.9638	0.052095

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0796
R-squared: 0.279,  Adjusted R-Squared 0.246
F-statistic vs. constant model: 8.43, p-value = 8.96e-07
```

```
Linear regression model:
    MA_D_log(FreBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0041221	0.0076546	-0.53851	0.59132
L4_Aggr_D_log(Credit-to-GDP gap)	0.49622	0.2008	2.4712	0.015013
L8_Aggr_D_log(Credit-to-GDP gap)	0.12673	0.21764	0.58228	0.56158
L12_Aggr_D_log(Credit-to-GDP gap)	-0.60318	0.22865	-2.6381	0.0095581
L16_Aggr_D_log(Credit-to-GDP gap)	0.091409	0.22232	0.41116	0.68176
L20_Aggr_D_log(Credit-to-GDP gap)	0.56568	0.21412	2.6419	0.0094575

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.082
R-squared: 0.236,  Adjusted R-Squared 0.201
F-statistic vs. constant model: 6.72, p-value = 1.71e-05
```

Let us see now the other two predictors.
For what concerns the Credit to GG, the best aggregation length is 4, 3 and 3 quarters for the 3-year horizon, in which the code select always the S1, and always 3 quarters for the 5-year window in which the criteria prefer always S2.
When considering the Credit to GG in percentage of GDP, the best aggregation length is always the same for the three specifications and among the two horizons with always $n = 3$ quarters. Regarding the best models, instead, the two criteria agree among themselves in the 3-year horizon by always selecting S1 whereas they choose S1 and S2 in the 5-year window.
The last predictor illustrated for this country is the DSR on the Credit granted to the NFCs. Note that the other two DSR's series, i.e. on the credit to the HHs and NPISHs and to the PNFS, are not informative and significant for the FreBI movements. For this predictor, the best aggregation length remains the same, i.e. one year ($n = 4$) over both horizons and for all the specifications. About the best models, the code selects always S2 for the 3-year horizon whereas S1 and S2 for the 5-year window. Tables 4.48 and 4.49 show the results for both predictors. For the Credit to GG, while the absolute version gives already good results, these clearly improve when taking the variable as a percentage of GDP. Regarding the DSR of the NFCs, it is worth to notice the second and fourth lags (L8 and L16) that are completely uninformative.

Table 4.48 – Baseline model (4) with the Credit to GG as predictor.

```
Linear regression model:
    MA_D_log(FreBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                  Estimate        SE        tStat       pValue
                                 _________    _________    _______    _________

    (Intercept)                  -0.024498    0.0096324    -2.5433     0.013935
    L4_Aggr_D_log(Credit to GG/CPI)     3.5616      0.60562     5.8809   2.7991e-07
    L8_Aggr_D_log(Credit to GG/CPI)     2.1671       0.6768      3.202    0.0023087
    L12_Aggr_D_log(Credit to GG/CPI)   0.34267      0.67921    0.50451        0.616
    L16_Aggr_D_log(Credit to GG/CPI)    2.2628       0.6863      3.297    0.0017485
    L20_Aggr_D_log(Credit to GG/CPI)    2.9644      0.68167     4.3487   6.2527e-05


Number of observations: 59, Error degrees of freedom: 53
Root Mean Squared Error: 0.0659
R-squared: 0.47,  Adjusted R-Squared 0.42
F-statistic vs. constant model: 9.41, p-value = 1.83e-06
```

```
Linear regression model:
    MA_D_log(FreBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                       Estimate       SE        tStat       pValue
                                      __________    _________   ________    __________

    (Intercept)                        -0.027636    0.0082407   -3.3536      0.0014788
    L4_Aggr_D_log(Credit to GG/GDP)       3.5653      0.45591    7.8201     2.1702e-10
    L8_Aggr_D_log(Credit to GG/GDP)       2.0745      0.48736    4.2566     8.5058e-05
    L12_Aggr_D_log(Credit to GG/GDP)     0.66176      0.50527    1.3097        0.19594
    L16_Aggr_D_log(Credit to GG/GDP)      2.2847       0.4928    4.6362     2.3552e-05
    L20_Aggr_D_log(Credit to GG/GDP)       2.858      0.51219      5.58     8.3621e-07


Number of observations: 59, Error degrees of freedom: 53
Root Mean Squared Error: 0.0564
R-squared: 0.611,  Adjusted R-Squared 0.574
F-statistic vs. constant model: 16.6, p-value = 7.41e-10
```

Table 4.49 – Baseline model (4) with the DSR on the Credit to NFCs as predictor.

```
Linear regression model:
    MA_D_log(FreBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                   Estimate         SE         tStat        pValue
                                 ___________    ________    ________    __________

    (Intercept)                  -0.00092205    0.008709    -0.10587       0.91608
    L4_Aggr_D_log(DSR of NFCs)        1.8706     0.89204       2.097      0.040779
    L8_Aggr_D_log(DSR of NFCs)       0.83158     0.91705     0.90679       0.36862
    L12_Aggr_D_log(DSR of NFCs)      -1.4491      1.0147     -1.4281       0.15914
    L16_Aggr_D_log(DSR of NFCs)      0.50285      1.0193     0.49332       0.62382
    L20_Aggr_D_log(DSR of NFCs)       5.0851      1.0479      4.8525    1.1136e-05


Number of observations: 59, Error degrees of freedom: 53
Root Mean Squared Error: 0.0661
R-squared: 0.466,  Adjusted R-Squared 0.415
F-statistic vs. constant model: 9.23, p-value = 2.29e-06
```

As usual the baseline model (5) with the best predictors in the same regression is going to be illustrated in table 4.50.

Table 4.50 – Baseline model (5) with the best FreBI predictors.

```
Linear regression model:
    MA_D_log(FreBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
                                         Estimate        SE        tStat       pValue
                                        _________    _________    ________    __________

    (Intercept)                         -0.026501    0.0079422    -3.3368      0.0015705
    L4_Aggr_D_log(Credit to GG/GDP)        3.3643      0.44719     7.5231      7.262e-10
    L8_Aggr_D_log(Credit to GG/GDP)         2.436      0.49449     4.9263     8.9095e-06
    L12_Aggr_D_log(Credit to GG/GDP)      0.90241      0.49718     1.8151       0.075284
    L16_Aggr_D_log(Credit to GG/GDP)       1.8303      0.51362     3.5635     0.00079399
    L20_Aggr_D_log(Credit to GG/GDP)       2.8154      0.49304     5.7103     5.4993e-07
    L4_Aggr_D_log(DSR of NFCs)             1.9764      0.86014     2.2978       0.025626


Number of observations: 59, Error degrees of freedom: 52
Root Mean Squared Error: 0.0543
R-squared: 0.647,  Adjusted R-Squared 0.606
F-statistic vs. constant model: 15.9, p-value = 2.91e-10
```

While for the Credit to GG in percentage of the GDP all lags are informative, for the DSR only the first lag seems to contribute in explaining the FreBI. Note that the bank/financial depth history, proxied by a 5-year MA of the respective Credit to GDP ratio does not appear for two reasons. First, it does not make much sense to include them since the main predictor is already in percentage of GDP. Second, the results get worse with their inclusion.

Germany

As for the France, even for this country the Credit to GDP variables perform quite well and better than the other predictors. However, among the flows of credit granted to the PNFS, the best predictor is the bank credit granted to the PNFS but in percentage of GDP. In addition, similarities with the France occur even for some other predictor. For instance, among the others, the Credit to GG seems to be the best informative predictor. Other variables that gives a contribution in explaining the GerBI and thus are worth to mentioned are the Credit to HHs and NPISHs and the DSR of HHs and NPISHs and of NFCs but only the first two lags. The performance improves when considering the predictors in percentage of GDP.

Let us start with the Credit to GDP variables.

The best variable seems to be the bank credit granted to the PNFS in percentage of GDP. The best aggregation length is always equal to one year (*n = 4*) for both horizons and all specifications whereas the two criteria select both the S2 for the 3-year horizon and the S1 for the 5-year window. Similarly, when considering the Credit to GDP. The only difference is that while the two criteria select the same S2 for the 3-year horizon, for the 5-year window the specification preferred are S1 and S2. For the Credit to GDP trend, instead, there are some differences. The best aggregation length is always 3 and 1 quarters (*n = 3*, *n = 1*) for the 3-year and 5-year window respectively whereas on the best model selection the two criteria agree by choosing S1 and S2 in both horizons. Finally, for the Credit to GDP gap, the best *n* is 4, 4 and 1 quarters for S1, S2 and S3 in the 3-year window, whereas always one year for the all the specifications in the 5-year horizon. Regarding the model selection, the criteria choose S1 and S2 in the shortest time window and always S1 in longest horizon.

Table 4.51 – Baseline model (4) with the GerBI credit to GDP predictors, i.e. the bank credit to GDP and the Credit to GDP variables.

```
Linear regression model:
    MA_D_log(GerBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                          Estimate        SE         tStat        pValue
                                         __________    _________   _________   ___________

    (Intercept)                          -0.0021417    0.0066159    -0.32372        0.74677
    L4_Aggr_D_log(Bank credit/GDP)           5.1974       1.1192      4.6438     9.6061e-06
    L8_Aggr_D_log(Bank credit/GDP)          -0.3585       1.2163    -0.29474        0.76875
    L12_Aggr_D_log(Bank credit/GDP)         -3.7972       1.2829     -2.9598      0.0037768
    L16_Aggr_D_log(Bank credit/GDP)          1.3538       1.2382      1.0933        0.27666
    L20_Aggr_D_log(Bank credit/GDP)         -1.8661       1.1509     -1.6214        0.10782


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0697
R-squared: 0.349,  Adjusted R-Squared 0.319
F-statistic vs. constant model: 11.7, p-value = 4.88e-09
```

Linear regression model:
MA_D_log(GerBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.0013472	0.0068673	-0.19617	0.84484
L4_Aggr_D_log(Credit/GDP)	3.9563	1.1902	3.324	0.001209
L8_Aggr_D_log(Credit/GDP)	0.4024	1.3818	0.29121	0.77145
L12_Aggr_D_log(Credit/GDP)	-1.6472	1.592	-1.0347	0.30312
L16_Aggr_D_log(Credit/GDP)	2.7299	1.5111	1.8066	0.073591
L20_Aggr_D_log(Credit/GDP)	-1.909	1.3723	-1.3911	0.16702

Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.073
R-squared: 0.286, Adjusted R-Squared 0.253
F-statistic vs. constant model: 8.71, p-value = 5.63e-07

Linear regression model:
MA_D_log(GerBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-6.7557e-05	0.0072676	-0.0092956	0.9926
L4_Aggr_D_log(Credit-to-GDP trend)	18.51	5.4608	3.3895	0.00097556
L8_Aggr_D_log(Credit-to-GDP trend)	-17.259	5.654	-3.0525	0.0028511
L12_Aggr_D_log(Credit-to-GDP trend)	-3.4216	5.5656	-0.61478	0.53998
L16_Aggr_D_log(Credit-to-GDP trend)	18.365	5.8307	3.1497	0.0021097
L20_Aggr_D_log(Credit-to-GDP trend)	-11.815	5.8464	-2.021	0.045734

Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0728
R-squared: 0.29, Adjusted R-Squared 0.258
F-statistic vs. constant model: 8.92, p-value = 3.95e-07

Linear regression model:
MA_D_log(GerBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.0032651	0.0070142	-0.46549	0.64251
L4_Aggr_D_log(Credit-to-GDP gap)	0.68006	0.19042	3.5713	0.00053013
L8_Aggr_D_log(Credit-to-GDP gap)	0.29517	0.22862	1.2911	0.1994
L12_Aggr_D_log(Credit-to-GDP gap)	-0.13436	0.28908	-0.4648	0.643
L16_Aggr_D_log(Credit-to-GDP gap)	0.31446	0.26203	1.2001	0.2327
L20_Aggr_D_log(Credit-to-GDP gap)	-0.33582	0.25062	-1.3399	0.18306

Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0746
R-squared: 0.255, Adjusted R-Squared 0.221
F-statistic vs. constant model: 7.47, p-value = 4.63e-06

Let us move to the best predictor, namely, Credit to GG. The best aggregation length is 4, 3 and 2 quarters for the 3-year window, in which the code select S1 and S2 whereas always one year in the 5-year horizon in which the two criteria agree by always selecting S2.
The results sharply improve when considering this variable in percentage of GDP where the best aggregation length is 4, 3 and 3 quarters for the three specifications in the 3-year horizon and always one year ($n = 4$) over the 5-year window.

Table 4.52 – Baseline model (4) with the Credit to GG as predictor.

```
Linear regression model:
    MA_D_log(GerBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                       Estimate      SE         tStat       pValue
                                       ________    _________    _______    __________

    (Intercept)                        -0.021216    0.0099738    -2.1271      0.037992
    L4_Aggr_D_log(Credit to GG/CPI)       5.6089      0.95432     5.8774    2.6793e-07
    L8_Aggr_D_log(Credit to GG/CPI)       3.5584      0.93751     3.7956    0.00037459
    L12_Aggr_D_log(Credit to GG/CPI)     0.79243      0.88929    0.89108       0.37684
    L16_Aggr_D_log(Credit to GG/CPI)      4.9274       1.1466     4.2975    7.2572e-05
    L20_Aggr_D_log(Credit to GG/CPI)      5.5374       1.2769     4.3364    6.3678e-05


Number of observations: 60, Error degrees of freedom: 54
Root Mean Squared Error: 0.0737
R-squared: 0.416,  Adjusted R-Squared 0.362
F-statistic vs. constant model: 7.7, p-value = 1.61e-05
```

```
Linear regression model:
    MA_D_log(GerBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                       Estimate      SE         tStat       pValue
                                       ________    _________    _______    __________

    (Intercept)                        -0.013496    0.0082406    -1.6377        0.1073
    L4_Aggr_D_log(Credit to GG/GDP)       5.4421      0.67639     8.0459    8.3194e-11
    L8_Aggr_D_log(Credit to GG/GDP)       2.6085      0.65038     4.0108    0.00018739
    L12_Aggr_D_log(Credit to GG/GDP)     0.92506      0.69924     1.3229       0.19143
    L16_Aggr_D_log(Credit to GG/GDP)      3.1626       0.7134     4.4331    4.5916e-05
    L20_Aggr_D_log(Credit to GG/GDP)      3.9172      0.82826     4.7294    1.6572e-05


Number of observations: 60, Error degrees of freedom: 54
Root Mean Squared Error: 0.0629
R-squared: 0.575,  Adjusted R-Squared 0.536
F-statistic vs. constant model: 14.6, p-value = 4.62e-09
```

Finally let us check the baseline model (5). The results are illustrated in table 4.53. The above analysis suggests a strong influence of the variable in percentage of GDP, thus the best variable, i.e. the Credit to GG is taken in percentage of GDP. The same for the other variable, the Credit to HHs and NPISHs but only the first lag as the others are not informative.

Table 4.53 – Baseline model (5) with the best GerBI predictors.

```
Linear regression model:
    MA_D_log(GerBI_QLP/CPI) ~ [Linear formula with 7 terms in 6 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.0089886	0.0071698	-1.2537	0.21557
L4_Aggr_D_log(Credit to GG/GDP)	1.6832	0.7692	2.1883	0.033165
L8_Aggr_D_log(Credit to GG/GDP)	1.4779	0.52506	2.8148	0.0068778
L12_Aggr_D_log(Credit to GG/GDP)	2.0774	0.60058	3.459	0.0010904
L16_Aggr_D_log(Credit to GG/GDP)	1.9278	0.60119	3.2066	0.0022989
L20_Aggr_D_log(Credit to GG/GDP)	1.4131	0.75516	1.8712	0.066941
L4_Aggr_D_log(Credit to HHs&NPISHs/GDP)	6.8625	1.1156	6.1512	1.1102e-07

```
Number of observations: 59, Error degrees of freedom: 52
Root Mean Squared Error: 0.051
R-squared: 0.727,  Adjusted R-Squared 0.696
F-statistic vs. constant model: 23.1, p-value = 4.33e-13
```

Note that the bank and/or financial depth proxied by the respective MA does not appear. This because of two reasons. First, it does not make much sense to include them since the predictors are already in percentage of GDP. Second, the results get worse with their inclusion.

Spain

For the Spain, unlike France and Germany, while the Credit to GDP variables are still informative, they do not emerge among the other predictors. The DSRs, instead, perform well relative the other predictors with the DSR of NFCs and of PNFS being the best ones. Here, the flow of informative credit comes, mainly, from the NFCs since its DSR performs better than the DSR of the PNFS and considering also the relatively good performance of the Credit to NFCs. Some information flows from the public sector as well as pointed out by the good performance of the Credit to GG.

Let's start with the best DSR, namely, the DSR of NFCs. The best aggregation length changes across the two time windows. It is equal to 4, 2 and 3 quarters for the shortest horizon and always one year (*n = 4*) for the longest time window. The two criteria instead remain consistent by selecting always S2 and S3. However, as usual I report the S1 in table 4.54.

Table 4.54 – Baseline model (4) with the best predictor, i.e. the DSR of NFCs.

```
Linear regression model:
    MA_D_log(SpaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.033273	0.0069049	-4.8188	1.2524e-05
L4_Aggr_D_log(DSR of NFCs)	-3.2658	0.40156	-8.1328	6.8704e-11
L8_Aggr_D_log(DSR of NFCs)	-1.4414	0.37985	-3.7948	0.00038128
L12_Aggr_D_log(DSR of NFCs)	-1.6838	0.50018	-3.3664	0.0014235
L16_Aggr_D_log(DSR of NFCs)	-1.8093	0.40223	-4.4981	3.7751e-05
L20_Aggr_D_log(DSR of NFCs)	-2.4055	0.44516	-5.4037	1.579e-06

```
Number of observations: 59, Error degrees of freedom: 53
Root Mean Squared Error: 0.0439
R-squared: 0.642,  Adjusted R-Squared 0.608
F-statistic vs. constant model: 19, p-value = 8.88e-11
```

The Credit to GG is the other predictor that is worth to be mentioned. The best aggregation length is 3, 3 and 4 quarters over the 3-years and always one year (*n = 4*) for the 5-year horizon. About the selection of the best model the two criteria agree among themselves and along the two time windows by selecting always S1.

When considering the Credit to GG in percentage of GDP the best aggregation length is always three quarters for the 3-year window and 3, 3 and 4 quarters for the 5-year horizon. Regarding the best model selection, the S1 remains the preferred one.

Table 4.55 – Baseline model (4) with the GG as predictor.

```
Linear regression model:
    MA_D_log(SpaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                        Estimate        SE        tStat       pValue
                                       _________    ________    _______    __________

    (Intercept)                        -0.010286    0.007053    -1.4584       0.14926
    L4_Aggr_D_log(Credit to GG/CPI)       1.3026     0.32369     4.0243    0.00014435
    L8_Aggr_D_log(Credit to GG/CPI)      0.35842     0.35195     1.0184       0.31205
    L12_Aggr_D_log(Credit to GG/CPI)     0.15546     0.35846    0.43369       0.66586
    L16_Aggr_D_log(Credit to GG/CPI)       0.561     0.35861     1.5644        0.1223
    L20_Aggr_D_log(Credit to GG/CPI)     0.99541     0.33498     2.9716     0.0040756


Number of observations: 75, Error degrees of freedom: 69
Root Mean Squared Error: 0.0608
R-squared: 0.33,  Adjusted R-Squared 0.282
F-statistic vs. constant model: 6.81, p-value = 3.24e-05
```

```
Linear regression model:
    MA_D_log(SpaBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                        Estimate        SE         tStat       pValue
                                       _________    _________    _______    __________

    (Intercept)                        -0.010991    0.0068965    -1.5937       0.11558
    L4_Aggr_D_log(Credit to GG/GDP)       1.1866      0.26558     4.4682    3.0103e-05
    L8_Aggr_D_log(Credit to GG/GDP)      0.48485      0.27567     1.7588      0.083045
    L12_Aggr_D_log(Credit to GG/GDP)     0.11729      0.28425    0.41264       0.68115
    L16_Aggr_D_log(Credit to GG/GDP)     0.31975       0.2841     1.1255       0.26428
    L20_Aggr_D_log(Credit to GG/GDP)     0.82412      0.27864     2.9577     0.0042419


Number of observations: 75, Error degrees of freedom: 69
Root Mean Squared Error: 0.0592
R-squared: 0.365,  Adjusted R-Squared 0.319
F-statistic vs. constant model: 7.92, p-value = 6.1e-06
```

As it is clear from the above results, the performance of the variable improves when it is considered in percentage of GDP. However, the Credit to the GG confirms again to be one of the protagonist of the banking index movements.

Table 4.56 – Baseline model (5) with the best SpaBI predictors.

```
Linear regression model:
    MA_D_log(SpaBI_QLP/CPI) ~ [Linear formula with 9 terms in 8 predictors]

Estimated Coefficients:
                                         Estimate       SE        tStat       pValue   
                                        _________    _________    _______    __________

    (Intercept)                         -0.029084    0.0064195    -4.5305    3.6767e-05
    L4_Aggr_D_log(DSR of NFCs)            -3.2225      0.36141    -8.9164    6.5839e-12
    L8_Aggr_D_log(DSR of NFCs)            -2.4618      0.44508    -5.5311    1.1607e-06
    L12_Aggr_D_log(DSR of NFCs)           -2.8347      0.61223    -4.6301    2.6303e-05
    L16_Aggr_D_log(DSR of NFCs)            -2.753      0.52131     -5.281    2.7978e-06
    L20_Aggr_D_log(DSR of NFCs)            -2.978      0.42664    -6.9802    6.4442e-09
    L8_Aggr_D_log(Credit to GG/GDP)        -1.129      0.31512    -3.5828    0.00076928
    L12_Aggr_D_log(Credit to GG/GDP)     -0.91176      0.37605    -2.4246      0.018983
    L16_Aggr_D_log(Credit to GG/GDP)     -0.82786      0.33001    -2.5086      0.015409


Number of observations: 59, Error degrees of freedom: 50
Root Mean Squared Error: 0.0395
R-squared: 0.727,  Adjusted R-Squared 0.683
F-statistic vs. constant model: 16.6, p-value = 1.06e-11
```

The best model is the above, in table 4.56, in which the DSR of the NFCs is taken with all its lag structure whereas for the Credit to GG the second, third and fourth lags are taken (L8, L12, L16). Note the change of the CEs significance of the Credit to GG when moving from baseline (4) to baseline (5). In the former, the first and last lags are the most informative one whereas in the latter the opposite occurs.

UK

Even for the UK, like the Spain, the Credit to GDP variables are informative but they do not emerge among the other predictors. The best variable seems to be the growth rate of the Credit to HHs and NPISHs but not in percentage of GDP. Again, the DSRs reveals a good predictor by performing well relative the other variables with the DSR of HHs and NPISHs and of NFCs being the best ones. Here, the flow of informative credit comes, mainly, from the HHs and NPISHs since its DSR performs better than the DSR of the NFS and considering also the good performance of the Credit to HHs and NPISHs. Some information flows from the public sector as well as pointed out by the discrete performance of the Credit to GG in percentage of GDP.

Let's start with the Credit to HHs and NPISHs. The best aggregation length founded by the code by means of the AIC criterion changes across the two time horizons. For the 3-year window it is equal to 3,4 and 4 quarters for S1, S2 and S3 respectively whereas for the 5-year horizon the best *n* is equal to 4, 4 and 2. About the best models the criteria choose always S1 for the shortest time window and S2 and S3 for the longest one.

When taking the variable in percentage of GDP, the best *n* is equal to 4, 3, 3 for all the specifications and for both the time windows. The code selects as the best model always S1 in the 3-years and S1 and S2 in the 5-years. However, I report only S1 as usual. Table 4.57 shows the results.

Table 4.57 – Baseline model (4) with the best predictor, i.e. the Credit to HHs and NPISHs.

```
Linear regression model:
    MA_D_log(UKBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.009345	0.0054279	-1.7217	0.087967
L4_Aggr_D_log(Credit to HHs&NPISHs/CPI)	-2.6235	0.74394	-3.5265	0.00061736
L8_Aggr_D_log(Credit to HHs&NPISHs/CPI)	-1.7534	0.75498	-2.3224	0.02207
L12_Aggr_D_log(Credit to HHs&NPISHs/CPI)	3.568	0.75593	4.72	7.0495e-06
L16_Aggr_D_log(Credit to HHs&NPISHs/CPI)	-2.7128	0.77434	-3.5033	0.00066759
L20_Aggr_D_log(Credit to HHs&NPISHs/CPI)	-2.9575	0.7732	-3.825	0.00021829

```
Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0556
R-squared: 0.361,  Adjusted R-Squared 0.331
F-statistic vs. constant model: 12.3, p-value = 1.85e-09
```

```
Linear regression model:
    MA_D_log(UKBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                              Estimate       SE         tStat       pValue
                                              _________    _________    ________    __________

    (Intercept)                               -0.0051135   0.0059042    -0.86608       0.38835
    L4_Aggr_D_log(Credit to HHs&NPISHs/GDP)      -1.6933     0.99939     -1.6943      0.093061
    L8_Aggr_D_log(Credit to HHs&NPISHs/GDP)       -1.563     0.97899     -1.5966       0.11325
    L12_Aggr_D_log(Credit to HHs&NPISHs/GDP)      2.9138     0.98044       2.972     0.0036418
    L16_Aggr_D_log(Credit to HHs&NPISHs/GDP)     -1.3599     0.98332      -1.383       0.16949
    L20_Aggr_D_log(Credit to HHs&NPISHs/GDP)     -3.4139     0.99146     -3.4432    0.00081651


Number of observations: 115, Error degrees of freedom: 109
Root Mean Squared Error: 0.0622
R-squared: 0.201,  Adjusted R-Squared 0.165
F-statistic vs. constant model: 5.49, p-value = 0.00015
```

The next variable which worth to be illustrated is the DSR of HHs and NPISHs (table 4.58). The best aggregation length is 3, 4, 4 quarters over the 3-years and always one year (*n = 4*) over the 5-years. The two criteria agree among themselves and between the two horizons by always selecting the S1.

Table 4.58 – Baseline model (4) with the best DSR as predictor, i.e. of HHs and NPISHs.

```
Linear regression model:
    MA_D_log(UKBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                      Estimate       SE         tStat        pValue
                                      _________    _________    ________    __________

    (Intercept)                       -0.013176    0.0080796     -1.6308       0.10886
    L4_Aggr_D_log(DSR of HHs&NPISHs)     -2.136      0.57803     -3.6952    0.00052138
    L8_Aggr_D_log(DSR of HHs&NPISHs)   -0.40639      0.59237    -0.68604       0.49568
    L12_Aggr_D_log(DSR of HHs&NPISHs)   0.21975      0.60945     0.36058       0.71985
    L16_Aggr_D_log(DSR of HHs&NPISHs)   -3.7005      0.59706     -6.1978    8.7573e-08
    L20_Aggr_D_log(DSR of HHs&NPISHs)   -1.5367      0.59305     -2.5911      0.012331


Number of observations: 59, Error degrees of freedom: 53
Root Mean Squared Error: 0.0589
R-squared: 0.524,  Adjusted R-Squared 0.479
F-statistic vs. constant model: 11.7, p-value = 1.26e-07
```

The last variable illustrated for UK is the Credit to GG (table 4.59). As anticipated before, if considered in absolute terms, the performance is not so exciting. However, the best aggregation length for the three specifications is 4, 3, 3 for the 3-year window and 4, 3, 1 for the 5-year horizon. The criteria agree by always selecting S2 as the best specification. When considering the Credit to GG in percentage of GDP, the best aggregation length remains unchanged across the two time windows, i.e. 4, 3 and 3 quarters. The code selects S2 and S3 for the shortest horizon and S1 and S3 for the longest one.

Table 4.59 – Baseline model (4) with the GG as predictor.

```
Linear regression model:
    MA_D_log(UKBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                        Estimate       SE         tStat       pValue
                                        _________    _______     _______    _________

    (Intercept)                         -0.017768    0.011174    -1.5902      0.11775
    L4_Aggr_D_log(Credit to GG/CPI)        2.0937     0.55362     3.7818    0.0003973
    L8_Aggr_D_log(Credit to GG/CPI)        1.0219     0.52963     1.9294      0.05904
    L12_Aggr_D_log(Credit to GG/CPI)      0.39875     0.64978    0.61368      0.54205
    L16_Aggr_D_log(Credit to GG/CPI)      0.94862     0.58924     1.6099      0.11336
    L20_Aggr_D_log(Credit to GG/CPI)       1.3939     0.74782     1.8639     0.067876


Number of observations: 59, Error degrees of freedom: 53
Root Mean Squared Error: 0.0735
R-squared: 0.258,  Adjusted R-Squared 0.188
F-statistic vs. constant model: 3.68, p-value = 0.00621
```

```
Linear regression model:
    MA_D_log(UKBI_QLP/CPI) ~ [Linear formula with 6 terms in 5 predictors]

Estimated Coefficients:
                                        Estimate       SE         tStat       pValue
                                        _________    _______     _______    __________

    (Intercept)                         -0.021949    0.010194    -2.1531      0.035885
    L4_Aggr_D_log(Credit to GG/GDP)        2.3629     0.46231     5.1111    4.4859e-06
    L8_Aggr_D_log(Credit to GG/GDP)       0.61954     0.42005     1.4749       0.14615
    L12_Aggr_D_log(Credit to GG/GDP)       0.7166     0.53549     1.3382       0.18654
    L16_Aggr_D_log(Credit to GG/GDP)      0.88613     0.46481     1.9064      0.062021
    L20_Aggr_D_log(Credit to GG/GDP)       1.6736      0.6045     2.7686     0.0077391


Number of observations: 59, Error degrees of freedom: 53
Root Mean Squared Error: 0.0677
R-squared: 0.371,  Adjusted R-Squared 0.312
F-statistic vs. constant model: 6.26, p-value = 0.000125
```

Lastly, the baseline model (5) for UK (table 4.60).
As one may notice while for the Credit to HHs and NPISHs all lags are informative, for the Credit to GG in percentage of GDP only the first lag seems to contribute in explaining the UKBI. Note also that the financial depth is added proxied by the 5YMA. While it slightly increases the prediction error both the CEs and the goodness-of-fit ameliorate.

Table 4.60 – Baseline model (5) with the best UKBI predictors.

```
Linear regression model:
    MA_D_log(UKBI_QLP/CPI) ~ [Linear formula with 8 terms in 7 predictors]

Estimated Coefficients:
                                                Estimate        SE          tStat       pValue
                                               _________    _________    _______    __________

    (Intercept)                                -0.013348    0.0058405    -2.2855      0.024557
    L4_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -1.8144      0.81067    -2.2382      0.027596
    L8_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -1.2873      0.88703    -1.4513       0.15007
    L12_Aggr_D_log(Credit to HHs&NPISHs/CPI)       3.297      0.86774     3.7995    0.00025861
    L16_Aggr_D_log(Credit to HHs&NPISHs/CPI)     -2.3864      0.79547         -3     0.0034647
    L20_Aggr_D_log(Credit to HHs&NPISHs/CPI)      -2.026      0.85551    -2.3681      0.019948
    L4_Aggr_D_log(Credit to GG/GDP)               1.0928      0.34233     3.1922     0.0019264
    5YMA_D_log(Credit/GDP)                       -4.2291       2.3811    -1.7761      0.078982


Number of observations: 101, Error degrees of freedom: 93
Root Mean Squared Error: 0.0539
R-squared: 0.464,  Adjusted R-Squared 0.423
F-statistic vs. constant model: 11.5, p-value = 1.96e-10
```

<u>Summing up the Banking Sector of France, Germany, Spain and UK</u>

The last group of EU countries examined is represented by France, Germany, Spain and UK. As previously said, even though they have not experienced a well-known banking crisis during the period covered by the indices' time series and although their price decline to through does not reach and overcame the 90% of loss, they still suffered the latest global financial crisis.
Let's start from the French Banking Sector. The Credit to GDP variables perform quite well and along with the Credit to GG (especially in percentage of GDP) and the DSR of NFCs (in particular the first and last lags) are the best predictors of the FreBI movements.
For Germany, as for France, the Credit to GDP variables perform well but unlike the latter in which the bank credit reveals a bad performer in explaining the French Banking Sector's movements, for the former, among the flows of credit granted to the PNFS, the best predictor is the bank credit granted to the PNFS but in percentage of GDP. Again, the history of Credit to GG exercises a predominant role in explaining the banking sector. Other informative variables that are worth to be mentioned are the Credit to HHs and NPISHs and the DSR of HHs and NPISHs and of NFCs but only the first two lags. Even in this case the performance improves when considering the predictors in percentage of GDP. In fact, the bank and/or financial depth, proxied by the respective MA, does not appear in the final model as it is already accounted for by the best predictors expressed in percentage to the GDP.

The Spanish and UK framework slightly change. Unlike France and Germany, the Credit to GDP variables are still informative but they do not emerge among the other predictors. For the SpaBI the DSRs perform well relative the other predictors with the DSR of NFCs and of PNFS being the best ones. However, the flow of informative credit comes from the NFCs as its DSR performs better than the DSR of the PNFS and considering also the relatively good performance of the Credit to NFCs. The history of Credit to the general government maintains its importance as pointed out by the good performance of the Credit to GG.

Last, but not least the UK. The best variable is the growth rate of the Credit to HHs and NPISHs but not in percentage of GDP. The DSRs reveals, once again, a good predictor with the DSR of HHs and NPISHs and of NFCs being the best ones. However, the flow of informative credit comes from the HHs and NPISHs since its DSR performs better than the DSR of the NFS and considering also the good performance of the Credit to HHs and NPISHs. Some information flows from the public sector as well as pointed out by the discrete performance of the Credit to GG in percentage of GDP.

Chapter 5

POLICY IMPLICATIONS

Let us try, now, to extrapolate some implications, mainly of policy nature, deriving from the analysis and the empirical results reported in the previous chapter. This is, therefore, the conclusive chapter.

In order to grasp the main empirical findings, a brief refresh of the EU countries' analysis and results is necessary.

First, it is worth to recall that, due to the elevated number of EU countries examinable, a skimming turned out essential. This step has been carried out by means of two main criteria, more or less objective.

The first criteria needful as well as physio-logical is the bound of data availability. This is especially true for the dependent variable, i.e. the appropriately constructed banking indices, rather than the BIS statistics which go enough back in time apart some cases. However, even though twenty-three banking indices have been constructed, some of them is not employable as dependent variable in the FDL model as their history is too short. A clear example is the BulBI with only fifteen years of data.

The second criterion is represented by the interest.

Since I am studying the financial (in)stability but I am principally interested in the *banking* stress/(in)stability the attention turned first on EU countries that, during the period covered by the indices, experience well-known banking crisis, i.e. well-recognized by the most important crisis datasets. Unfortunately, from the inception of 1985 until the mid of 2016 there are only two countries in the Eurozone that result positive to the above issue, namely the Finnish and Sweden banking crisis of 90-91's. For the reasons explained at the time, on the difficulties tied to the FinBI's construction, only the Sweden Banking Sector has been analyzed. Subsequently, I tried to report the most interesting cases, thus focusing, firstly, on the EU countries that suffered most the 2007-08 financial crisis, i.e. whose price decline-to-though reached and/or surpass the 90% threshold. To this group take part Belgium, Greece, Ireland and Netherland. Secondly, I gone through the main EU countries among the remainders, that is France, Germany, Spain and UK. Given the personal interest, the first country that has been examined is Italy. The Italian banking sector along with the Swedish one are the countries for which all the models are illustrated even the baseline model (1) and (2) that usually perform bad. This to make the reader understanding the various models and specifications designed. Subsequently, only the most important are shown. The bad news is that, broadly speaking, the baseline model (1) and almost always the baseline (2), are completely meaningless. The god news is that the results improve when passing from it to the FDL model with aggregated variables.

For the Italian banking sector, while the credit to households and NPISHs (in absolute and percentage terms) and the DSR perform really bad, the *bank credit* growth rate revealed, as expected, one of the most important predictor of the banking stress. Surprisingly, the most powerful predictor of the Italian Banking Index (ItaBI) turned out to be the *credit (from all sectors) granted to NFCs*.

For the Sweden case, while the *bank credit* to the PNFS revealed, as expected, one of the most important predictor of the banking stress the best predictor is represented by the *RPPs* with some information floating from the *Credit to HHs and NPISHs*. The two indicators work well together as the table 4.36 shows. Note the bad performance of the flow of credit granted to NFCs.

Let us see now the first group of countries, i.e. the one affected more by the 2007-08 financial crisis.

In order, the Belgium is the first analyzed. Broadly speaking, there is no variable that shines in terms of performance in explaining the Belgium Banking Index. The best predictor is the *Credit to HHs and NPISHs in percentage of GDP* and the *bank credit variables*, with respect to the other variables, perform quite well in predicting the BelBI. Note the bad performance of credit (from all sectors) to GDP variables.

Greece along with the Ireland, represents the EU country that has been affected to a greater extent by the last global financial crisis. For the Greek case, unfortunately, almost all the credit-related variables have a poor performance. The best indicator is the *Credit to General Government* (GG) both in absolute terms and in percentage of GDP. This is in line with the dynamics that featured Greece as the most indebted country in the EU which probably made it suffer most the 2007-08 financial crisis.

The Irish case is different from the Greek one. Unlike the latter, almost all the variables tested are, more or less, informative which may be symptomatic of a multitude of causes at the roots of the Ireland's instability. The best predictors, in order of performance, are the *Credit to the NFCs* and the *Credit to HHs and NPISHs* both in absolute terms and in percentage of GDP. Also, the residential property prices (RPPs) give a contribute in explaining the Irish Banking Sector but only the second lag. Note, the inclusion of the bank and financial depth history (3YMA and 5YMA respectively) that ameliorate the model with the latter being preferred to the former.

Last, but not least the Netherland. Even for this country a multitude of causes seems to be at the roots of the Netherland's instability. Besides the Credit to GDP variables that remain important, the DSRs reveal a good EWI. The best ones are the DSR of HHs and NPISHs followed by the DSR of PNFS. This is quite surprising since the second-best predictor is the flow of Credit to NFCs. The Credit to the general government is still important in explaining the Dutch Banking Sector. The final baseline (5) in table 4.46 is, in fact, constituted by the *Credit to NFCs* and *Credit to GG* with the bank and financial depth amplifying the best predictors' effect.

Let's see now the last group examined, namely France, Germany, Spain and UK.

In explaining the French Banking Sector, the *Credit to GDP variables* perform quite well and along with the *Credit to GG* (especially in percentage of GDP) and the *DSR of NFCs* (in particular the first and last lags) are the best predictors of the FreBI movements.

For Germany, as for France, the Credit to GDP variables are still important but unlike France for which the bank credit has a bad performance, for Germany, among the flows of credit granted to the PNFS, the best predictor is the *bank credit granted to the PNFS* but *in percentage of GDP*. Once again, the *Credit to GG* exercises a predominant role in explaining the banking sector. Also, the *Credit to HHs and NPISHs* and the DSR of HHs and NPISHs and of NFCs (but only the first two lags) are informative. The performance improves when considering the predictors in percentage of GDP.

For Spain and UK the framework changes. The Credit to GDP variables are still informative but they do not emerge among the other predictors. In more details, the SpaBI is well explained by the DSRs with the DSR of NFCs and of PNFS being the best ones. However, the great portion of the SpaBI movements is explained by the NFCs. This for two reasons. First, its DSR performs better than the DSR of the PNFS and second the *Credit to NFCs* performs. The history of Credit to the general government maintains its importance as pointed out by the good performance of the *Credit to GG*.

Finally, the UK. The best variable is the *Credit to HHs and NPISHs* but *only in absolute terms*. Once again, the DSRs turns out to be a good predictor with the DSR of HHs and NPISHs and of NFCs being the best ones. The flow of informative credit comes from the

HHs and NPISHs since its DSR performs better than the DSR of the NFS and considering also the good performance of the Credit to HHs and NPISHs. The General Government gives its own contribution in explaining the UKBI as pointed out by the performance of the *Credit to GG in percentage of GDP*.

The above summary has a twofold function. First, it allows the reader to have a clearer and almost contemporary picture of the situation of all the EU countries examined. This permits to better capture similarities and divergences. Second, it brings out several observations. At a first glance, it is clear that while some predictors recur among the various countries, finding a "universal" EWI of banking stress is a really hard job. This depends upon a multitude of factors. Even though the countries analyzed belongs all the Eurozone, differences are not lacking. However, with some effort something interesting can be pulled out.

First, the Credit to GDP variable are, broadly speaking, a good indicator apart from some sporadic case, such as the Belgium, in which, they appear completely meaningless but here the *bank credit variables* (along with the *Credit to HHs and NPISHs in percentage of GDP*) are the best predictors. The *bank credit granted to the PNFS* but *in percentage of GDP* turns out to be fundamental for the Germany as well. Thus, the bank/financial depth remain an indicator that absolutely is worth monitoring. If we enter in more detail, two indicators that recurs often among the EU countries examined are the history of *Credit to NFCs* and the *Credit to GG*. The former is important in explaining the banking sector of Italy, Ireland, Netherland and Spain, whereas the latter is important for various EU countries, such as France, Germany, Netherland, Spain, UK and is crucial for the Greece.

When it comes to examine a banking crisis, such as the Swedish banking sector in the 90's the best EWI is represented by the *RPPs* accompanied by the *Credit to HHs and NPISHs*. This is in line with the findings of Reinhart and Rogoff (2008)[156] which analyzes the five, big banking crisis after the WWII, i.e. the Spain (1977), the Norway (1987), the Finland and Sweden (1991) and the Japan (1992) and demonstrate that all the five episodes are preceded by a strong increase of real estate market.

A final remark for the DSR, the most recent discovered EWI. It achieves good performances among the EU countries examined. In particular, for Germany DSR of HHs & NPISHs and of NFCs, for France the DSR of NFCs, for Netherland the DSR of HHs & NPISHs followed by the DSR of PNFS in terms of importance, for Spain the DSR of NFCs and of PNFS and for the UK the DSR of HHs & NPISHs and of NFCs.

[156] See "Is the 2007 US Sub-Prime Financial Crisis so different? An International Historical Comparison".

CONCLUSIONS

Financial (In)stability, as abundantly illustrated in the first chapters, remains the Achilles heel of the financial system. While a financial system is vital for the economy, the opposite is true as well. They are complementary. This implies that all the agents and institutions responsible for maintaining the financial stability 'must' avoid that the financial system's cons, that are collateral to the benefits, destroy the economy. With the awareness that the task is massive this work try to give a small contribution to the existing theoretical and empirical literature. In more details, by focusing primarily on the identification and prediction of banking stress/(in)stability, the credit aggregates have been studied in all their facets. The results give a response to the starting questions that triggered the work and, answering affirmatively to the issues posed at the inception, point out that a discrimination of the flow of credit in its main components turns out to be indispensable for the proper execution of the task which, of course, does not guarantee the success.

APPENDIX

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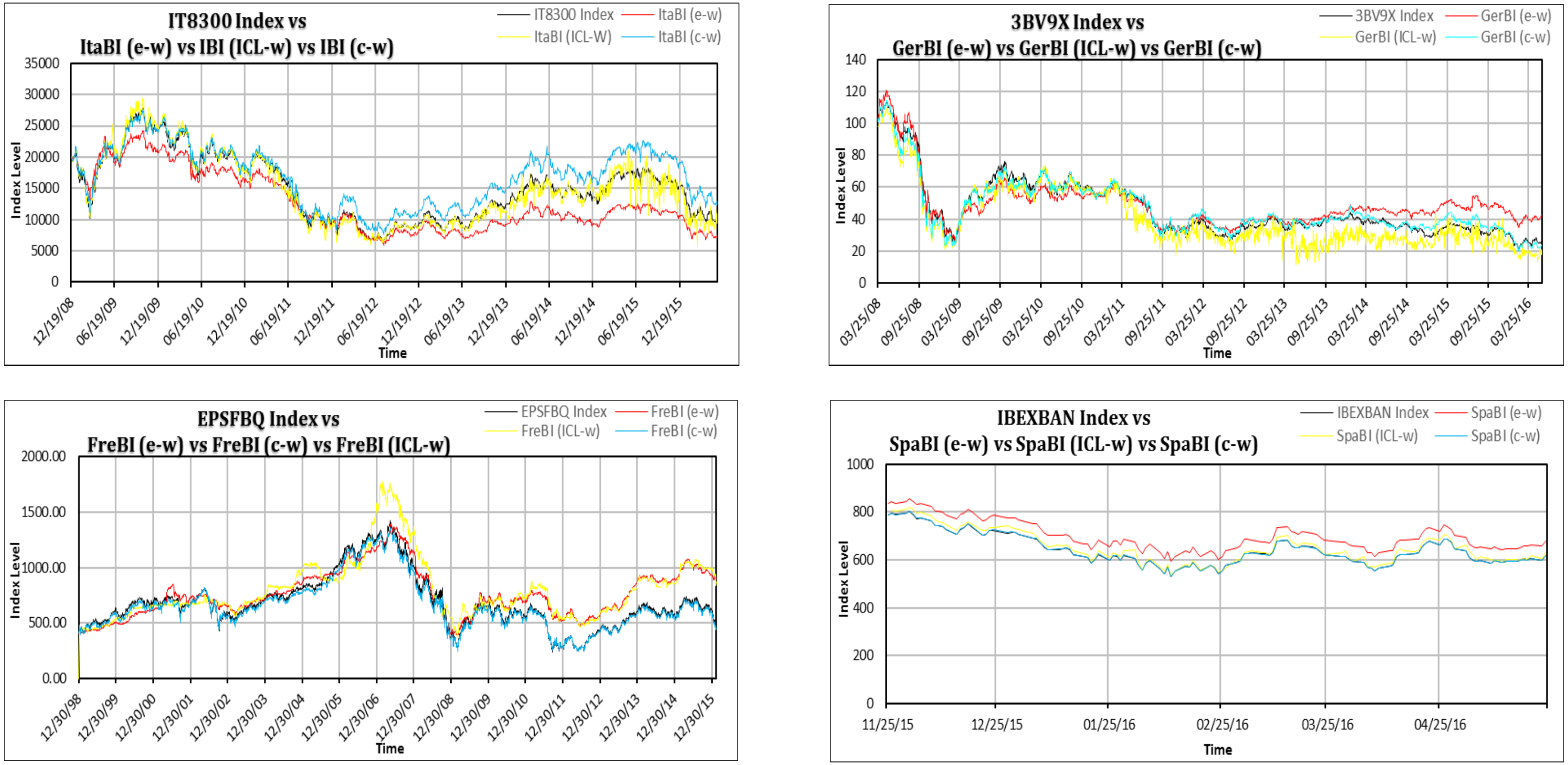
Figure 3.1 – Comparing and constructing Banking Indices: the Italian IT8300, the French EPSFBQ, the German 3VB9X and the Spanish IBEXBAN compared to the respectively three techniques, i.e. equally-weighted, ICL-weighted and cap-weighted[157].



157

CRITERIA	IT8300 Index vs IBI (e-w)	IT8300 Index vs IBI (c-w)	IT8300 Index vs IBI (ICL-w)
CORRr	0.93621	**0.97311**	0.45215

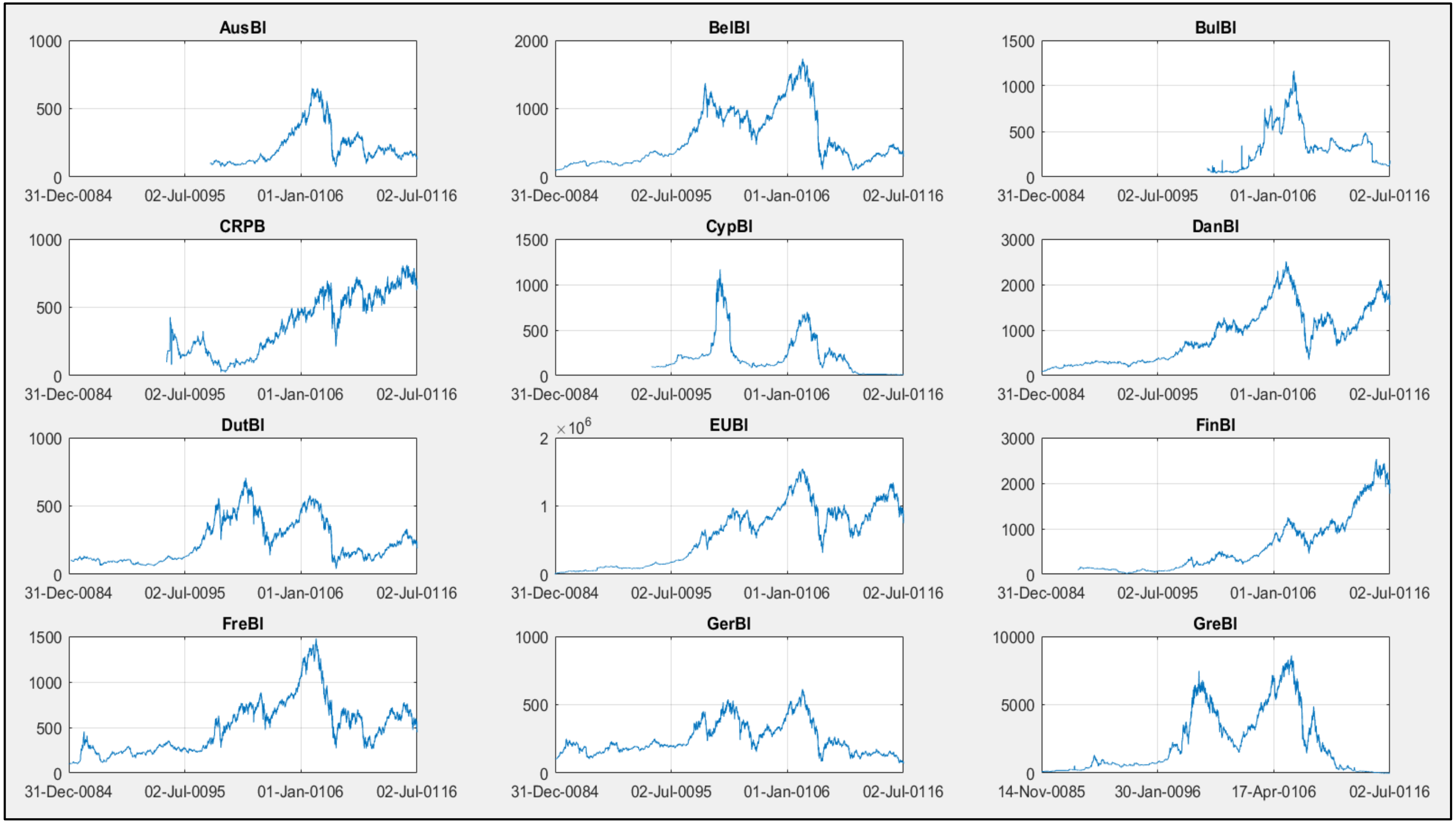
CRITERIA	EPSFBQ Index vs FBI (e-w)	EPSFBQ Index vs FBI (c-w)	EPSFBQ Index vs FBI (ICL-w)
CORRr	0.68634	**0.98918**	0.31526

CRITERIA	3BV9X Index vs GBI (e-w)	3BV9X Index vs GBI (c-w)	3BV9X Index vs GBI (ICL-w)
CORRr	0.87304	**0.88947**	0.23567

CRITERIA	IBEXBAN Index vs SBI (e-w)	IBEXBAN Index vs SBI (c-w)	IBEXBAN Index vs SBI (ICL-w)
CORRr	0.99317	**0.99979**	0.91067

Figure 3.2 – EU country-specific banking indices from January 1, 1985 for the longest banking indices and at the earliest available date for the rest until the 2016 Q1.

(a)



(b)

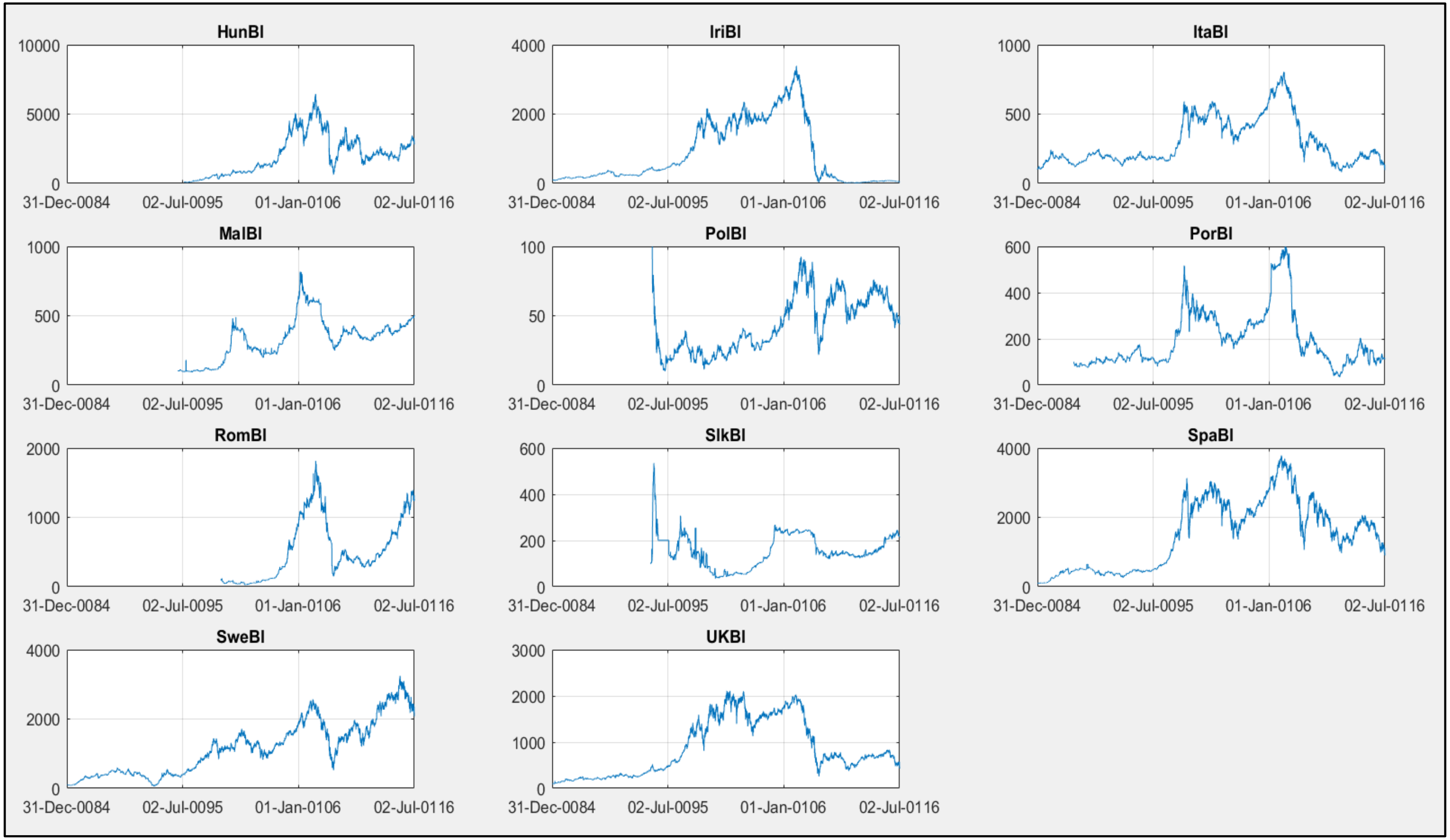
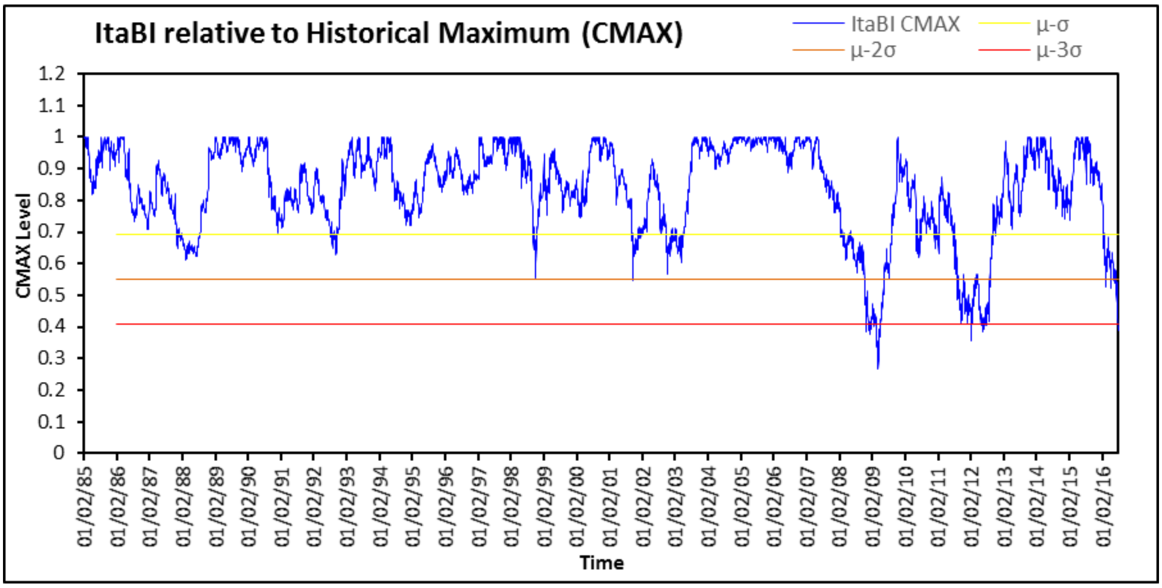
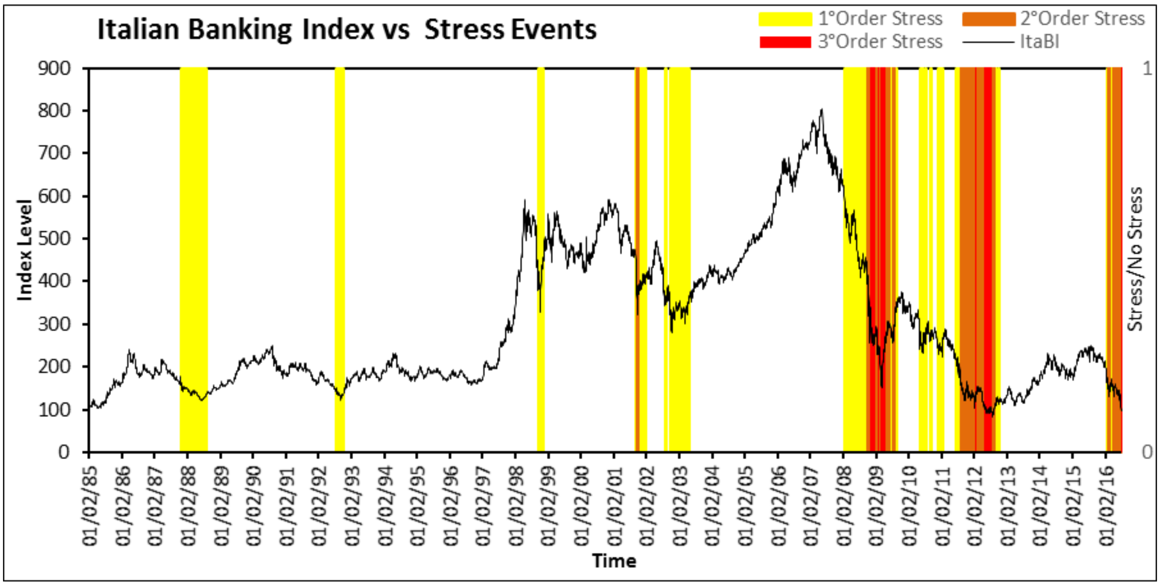

HunBI
10000
5000
0
IriBI
4000
2000
0
ItaBI
1000
500
0
MalBI
1000
500
0
PolBI
100
50
0
PorBI
600
400
200
0
RomBI
2000
1000
0
SlkBI
600
400
200
0
SpaBI
4000
2000
0
SweBI
4000
2000
0
UKBI
3000
2000
1000
0
31-Dec-0084
02-Jul-0095
01-Jan-0106
02-Jul-0116

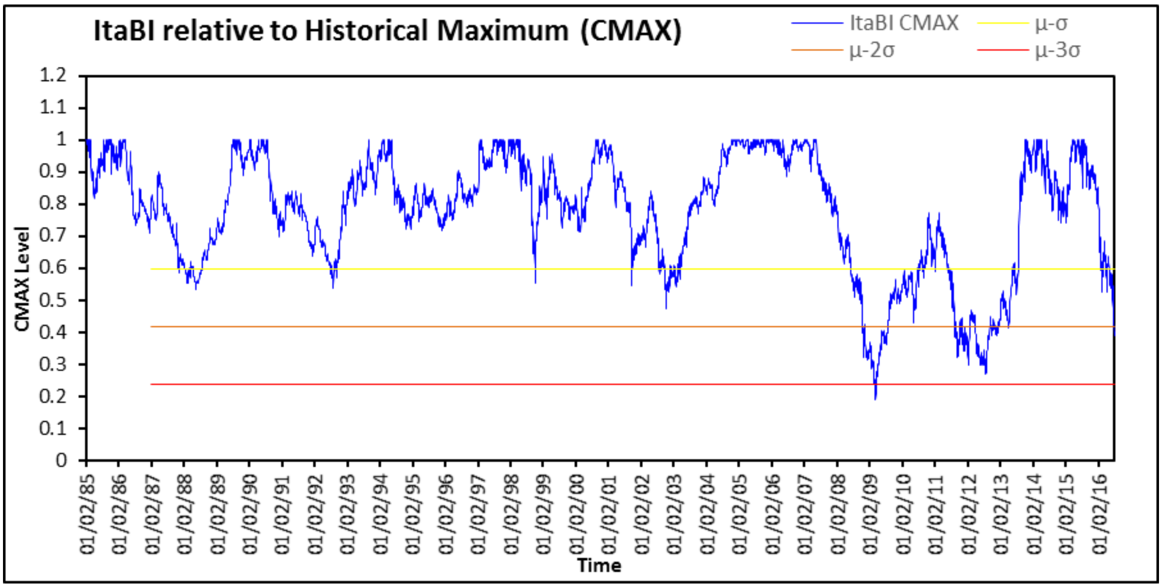
Figure 4.1 (a) – CMAX with moving windows of 12 months, the Italian Banking Index vs stress periods and the number of stress events identified with the relative depth.

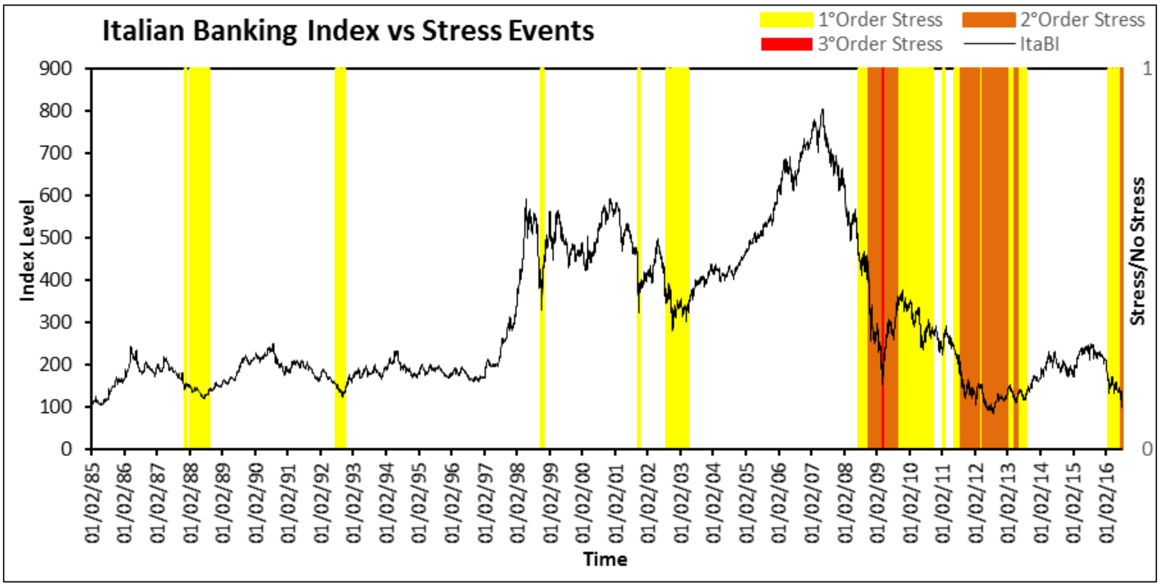




Alarm Code	Mean dispersion	Threshold	Stress Events
1	μ-σ	0.69385723	4
2	μ-2σ	0.55051749	1
3	μ-3σ	0.40717775	3

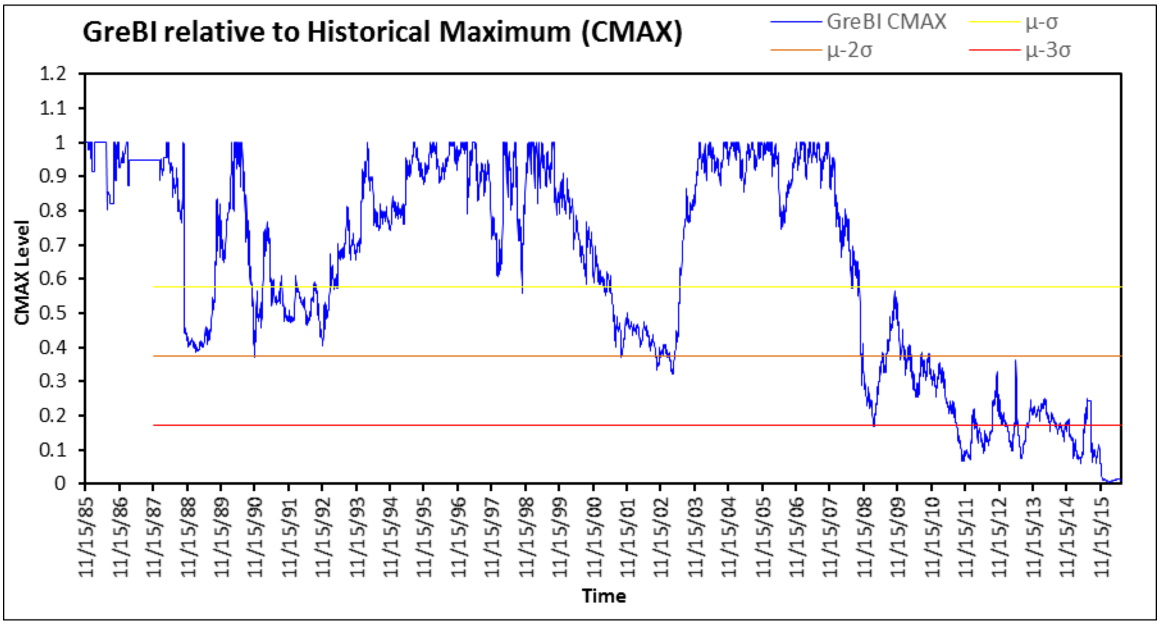
Figure 4.1 (b) – CMAX with moving windows of 24 months, the Italian Banking Index vs stress periods and the number of stress events identified with the relative depth.

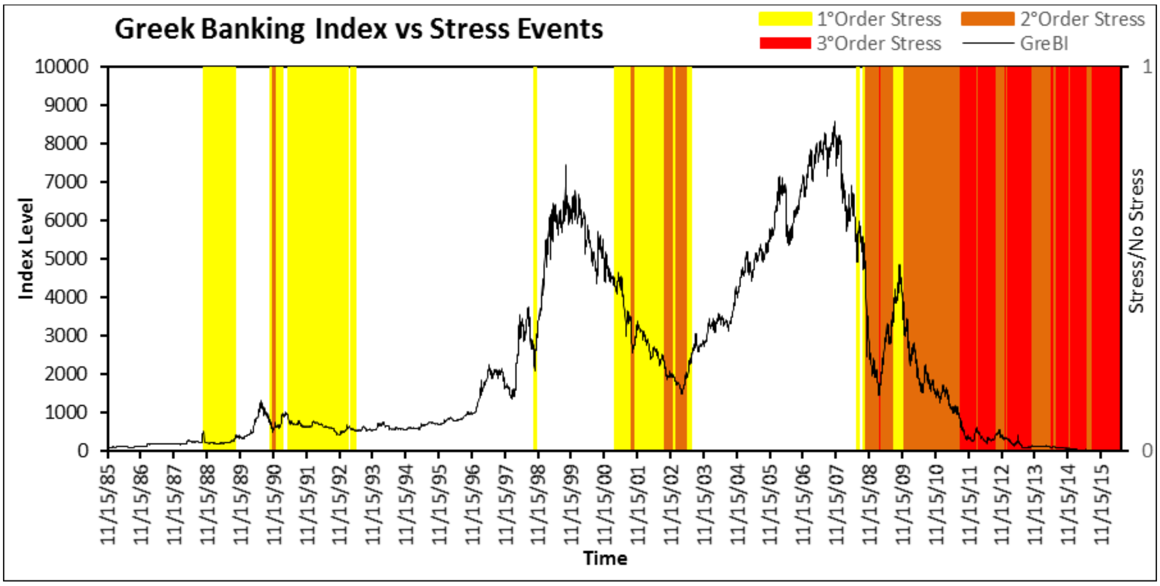




Alarm Code	Mean dispersion	Threshold	Stress Events
1	μ-σ	0.596742029	4
2	μ-2σ	0.415890612	1
3	μ-3σ	0.235039196	1

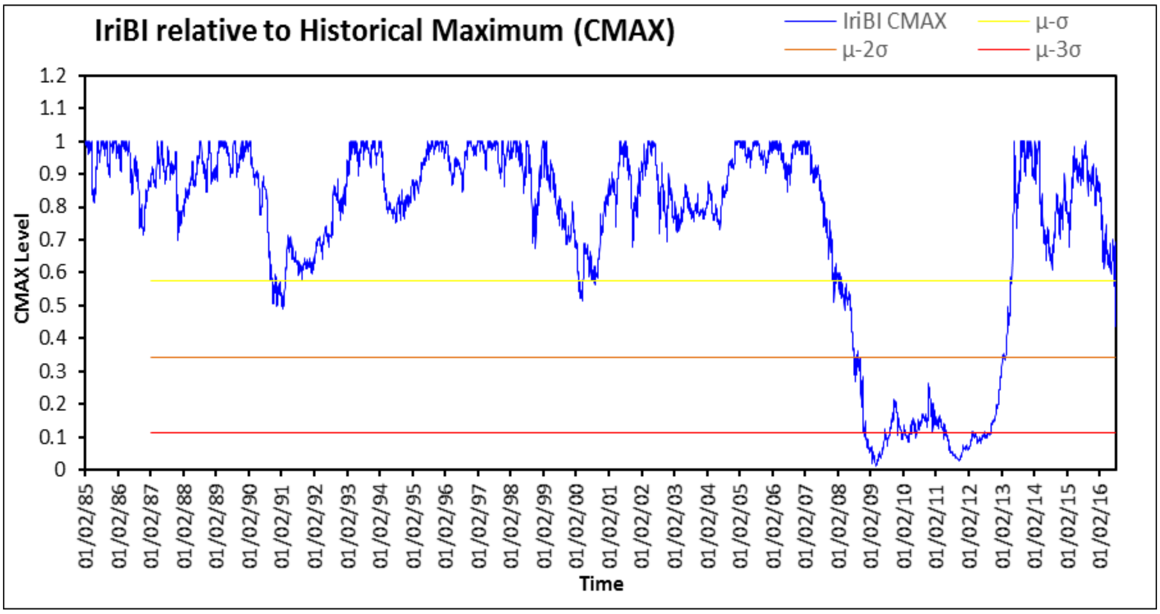
Figure 4.2 (a) – CMAX vs stress periods and the number of stress events identified with the relative depth for Greece.

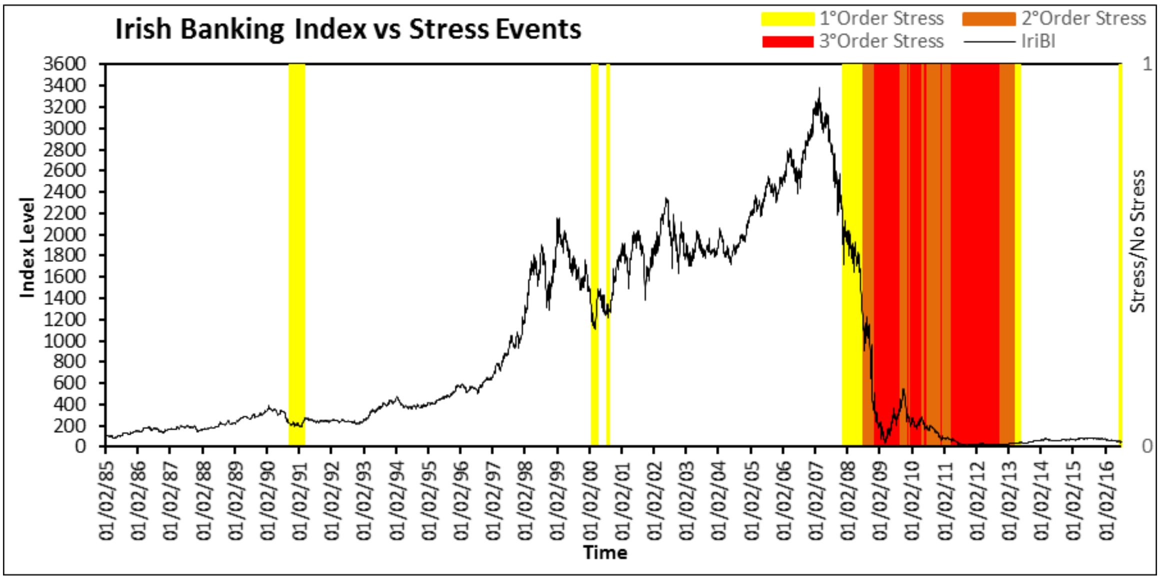




Alarm Code	Mean dispersion	Threshold	Stress Events
1	μ-σ	0.577283559	2
2	μ-2σ	0.374435942	2
3	μ-3σ	0.171588326	1

Figure 4.2 (b) – CMAX vs stress periods and the number of stress events identified with the relative depth for Ireland.





Alarm Code	Mean dispersion	Threshold	Stress Events
1	μ-σ	0.57318088	3
2	μ-2σ	0.34271580	0
3	μ-3σ	0.112250721	1

Figure 4.3 – Chronology of stress events in Italy, France, Germany and Spain[158].

A Chronology of Stress Events in the Eurozone: Italy

Alarm Code (Gravity)	Beginning of Stress/Crisis	Beginning of Crash	Date of Trough	Date of Recovery	Smooth period (from Recovery up to the next stress)	Months to Trough (Days)	Months to Recovery (Days)	Price decline to Trough	Annual Returns before Stress/Crisis			Cumulative Return before Stress/Crisis	Annual Returns after Stress/Crisis			Cumulative Return before Stress/Crisis
									One Year	Two Years	Three Years	Over Three Years	One Year	Two Years	Three Years	Over Three Years
1	03/20/86	11/06/87	05/19/88	07/26/88	24 (6)	25 (29)	28 (6)	-49%	121%	9%*	NA	141%*	-10%	-33%	10%	-34%
1	08/01/90	06/29/92	07/30/92	09/14/92	67 (7)	23 (29)	25 (13)	-45%	20%	49%	-24%	35%	-17%	-34%	33%	-27%
1	04/21/98	10/02/98	10/05/98	10/09/98	24 (23)	5 (14)	5 (18)	-44%	196%	4%	3%	218%	-8%	-16%	12%	-13%
1	11/02/00	09/20/01	10/09/02	03/14/03	49 (26)	23 (7)	28 (12)	-52%	28%	3%	53%	102%	-35%	-16%	27%	-30%
3	05/10/07	06/06/08	03/09/09	07/19/13	24 (2)	21 (27)	74 (9)	-81%	16%	38%	26%	101%	-32%	-44%	-6%	-65%
2	07/21/15	02/03/16	06/30/16	NA	NA	11 (9)	NA	-59%	29%	50%	47%	184%	-59%	NA	NA	NA

A Chronology of Stress Events in the Eurozone: France

Alarm Code (Gravity)	Beginning of Stress/Crisis	Beginning of Crash	Date of Trough	Date of Recovery	Smooth period (from Recovery up to the next stress)	Months to Trough (Days)	Months to Recovery (Days)	Price decline to Trough	Annual Returns before Stress/Crisis			Cumulative Return before Stress/Crisis	Annual Returns after Stress/Crisis			Cumulative Return before Stress/Crisis
									One Year	Two Years	Three Years	Over Three Years	One Year	Two Years	Three Years	Over Three Years
2	05/21/86	10/20/86	05/19/88	09/29/88	20 (2)	23 (28)	28 (8)	-72%	276%	18%	NA	NA	-51%	-43%	69%	-53%
1	05/31/90	10/09/90	01/14/91	01/17/91	90 (4)	7 (14)	7 (17)	-44%	36%	63%	-45%	23%	-24%	10%	25%	3%
1	07/21/98	09/11/98	10/05/98	11/20/98	41 (25)	2 (14)	4	-55%	103%	33%	-11%	139%	-18%	40%	0%	14%
1	05/15/02	09/24/02	10/09/02	03/14/03	50	4 (24)	9 (27)	-46%	18%	8%	30%	65%	-28%	17%	12%	-5%
3	05/14/07	01/21/08	03/09/09	06/09/10	8 (9)	21 (23)	36 (25)	-81%	19%	46%	12%	94%	-38%	-46%	13%	-62%
2	02/18/11	08/08/11	06/01/12	11/21/12	29 (7)	15 (13)	21 (3)	-62%	18%	84%	-62%	-17%	-45%	27%	41%	-1%
1	04/28/15	06/27/16	06/27/16	06/29/16	SO FAR	13 (29)	14 (1)	-42%	15%	45%	43%	140%	-23%	NA	NA	NA

A Chronology of Stress Events in the Eurozone: Germany

Alarm Code (Gravity)	Beginning of Stress/Crisis	Beginning of Crash	Date of Trough	Date of Recovery	Smooth period (from Recovery up to the next stress)	Months to Trough (Days)	Months to Recovery (Days)	Price decline to Trough	Annual Returns before Stress/Crisis			Cumulative Return before Stress/Crisis	Annual Returns after Stress/Crisis			Cumulative Return before Stress/Crisis
									One Year	Two Years	Three Years	Over Three Years	One Year	Two Years	Three Years	Over Three Years
1	12/31/85	03/10/87	02/01/88	09/13/88	114 (13)	37	42 (12)	-59%	149%	NA	NA	NA	-12%	-49%	37%	-39%
1	05/26/98	10/01/98	10/05/98	10/14/98	22 (4)	4 (9)	4 (18)	-48%	58%	38%	5%	129%	-32%	49%	6%	8%
2	08/18/00	09/12/01	03/13/03	06/25/03	46 (20)	30 (24)	34 (7)	-71%	44%	-3%	11%	54%	-24%	-30%	-4%	-49%
3	05/15/07	03/05/08	01/26/09	06/02/10	8 (16)	20 (11)	36 (17)	-86%	20%	66%	0%	97%	-35%	-56%	32%	-62%
2	02/18/11	08/09/11	09/13/11	04/24/13	8 (24)	6 (26)	26 (6)	-56%	12%	122%	-74%	-36%	-36%	-1%	8%	-31%
1	01/17/14	01/15/16	06/30/16	NA	NA	29 (13)	NA	-60%	12%	22%	-41%	-19%	-28%	-22%	NA	-60% *

A Chronology of Stress Events in the Eurozone: Spain

Alarm Code (Gravity)	Beginning of Stress/Crisis	Beginning of Crash	Date of Trough	Date of Recovery	Smooth period (from Recovery up to the next stress)	Months to Trough (Days)	Months to Recovery (Days)	Price decline to Trough	Annual Returns before Stress/Crisis			Cumulative Return before Stress/Crisis	Annual Returns after Stress/Crisis			Cumulative Return after Stress/Crisis
									One Year	Two Years	Three Years	Over Three Years	One Year	Two Years	Three Years	Over Three Years
2	08/01/89	03/06/90	01/14/91	11/12/92	67 (9)	17 (13)	39 (11)	-40%	5%	-4%	89%	91%	-14%	-8%	-26%	-41%
2	07/20/98	08/28/98	10/02/98	01/15/99	20 (3)	2 (12)	5 (26)	-54%	107%	117%	38%	520%	-21%	13%	-10%	-20%
2	09/18/00	09/14/01	10/01/02	07/02/03	43 (13)	24 (13)	33 (14)	-53%	25%	56%	-3%	89%	-32%	-20%	20%	-34%
3	02/15/07	07/11/08	03/09/09	07/23/13	10 (18)	24 (22)	77 (8)	-72%	25%	21%	12%	70%	-27%	-49%	55%	-42%
2	06/10/14	09/24/15	06/27/16	NA	NA	24 (17)	NA	-56%	57%	15%	-39%	10%	-12%	-42%	NA	NA

[158] The symbol * points out that the index return is computed on a time window shorter than indicated.

Figure 4.4 – A Chronology of Crisis Episodes in the Eurozone.

A Chronology of Crisis Events in the Eurozone: All Countries																
Country	*Alarm Code (Gravity)*	*Beginning of Stress/Crisis*	*Beginning of Crash*	*Date of Trough*	*Date of Recovery*	*Months to Trough (Days)*	*Months to Recovery (Days)*	*Price decline to Trough*	*Annual Returns before Stress/Crisis*			*Cumulative Return before Stress/Crisis*	*Annual Returns after Stress/Crisis*			*Cumulative Return after Stress/Crisis*
									One Year	*Two Years*	*Three Years*	*Over Three Years*	*One Year*	*Two Years*	*Three Years*	*Over Three Years*
Austria:																
	3	01/04/07	09/16/08	02/17/09	08/13/10	25 (13)	43 (9)	-89%	59%	24%	56%	210%	-23%	-73%	84%	-61%
	2	02/17/11	09/09/11	11/23/11	07/11/13	9 (6)	28 (24)	-71%	29%	251%	-83%	-22%	-48%	20%	14%	-29%
Belgium:																
	3	05/21/07	06/23/08	03/06/09	04/10/13	21 (13)	70 (20)	-94%	26%	20%	33%	101%	-29%	-74%	32%	-76%
Cyprus:																
	2	11/30/99	07/25/00	04/04/01	10/15/01	16 (5)	22 (15)	-84%	392%	22%	-3%	479%	-77%	-40%	-18%	-89%
	3	10/12/07	02/28/08	03/06/09	04/29/09	16 (22)	18 (17)	-88%	60%	120%	78%	534%	-61%	13%	-27%	-68%
	3	10/26/10	05/19/11	12/16/11	04/26/13	13 (21)	30	-88%	-22%	58%	-72%	-65%	-71%	-65%	-42%	-94%
Czech Republic:																
	2	03/04/94	04/11/94	04/18/94	01/15/96	1 (14)	22 (11)	-81%	326%	NA	NA	NA	-67%	50%	30%	-36%
	3	02/24/97	05/19/97	10/06/98	01/05/00	19 (12)	34 (12)	-92%	55%	58%	-27%	77%	-69%	-72%	295%	-66%
	2	05/21/08	10/17/08	02/25/09	07/09/09	9 (4)	13 (18)	-68%	18%	29%	14%	73%	-39%	26%	30%	0%
Denmark:																
	3	02/08/07	11/22/07	03/06/09	05/26/10	24 (26)	39 (18)	-86%	26%	33%	19%	99%	-35%	-68%	120%	-54%
	2	11/05/10	06/15/11	09/12/11	01/07/13	10 (7)	26 (2)	-53%	27%	15%	-54%	-33%	-48%	30%	39%	-6%
EU:																
	2	05/15/02	07/22/02	03/12/03	06/10/03	9 (26)	12 (26)	-45%	-1%	14%	7%	21%	-31%	19%	13%	-7%
	3	02/08/07	01/21/08	03/09/09	09/01/10	25 (1)	35 (1)	-82%	20%	21%	13%	63%	-33%	-59%	41%	-61%
	2	02/18/11	07/18/11	11/23/11	12/18/12	9 (5)	22	-51%	12%	78%	-66%	-32%	-33%	12%	22%	-8%
Finland:																
	3	07/01/88	11/21/91	09/16/92	08/04/93	50 (15)	61 (3)	-92%	61%	NA	NA	NA	-12%	-12%	-10%	-31%
	2	07/24/98	09/01/98	10/09/98	02/23/00	2 (15)	19	-62%	120%	113%	13%	429%	-46%	58%	34%	13%
	2	04/13/07	10/06/08	03/09/09	07/15/09	22 (24)	27 (2)	-62%	37%	52%	38%	186%	-21%	-36%	68%	-16%
France:																
	2	05/21/86	10/20/86	05/19/88	09/29/88	23 (28)	28 (8)	-72%	276%	18%	NA	NA	-51%	-43%	69%	-53%
	3	05/14/07	01/21/08	03/09/09	06/09/10	21 (23)	36 (25)	-81%	19%	46%	12%	94%	-38%	-46%	13%	-62%
	2	02/18/11	08/08/11	06/01/12	11/21/12	15 (13)	21 (3)	-62%	18%	84%	-62%	-17%	-45%	27%	41%	-1%
Germany:																
	2	08/18/00	09/12/01	03/13/03	06/25/03	30 (24)	34 (7)	-71%	44%	-3%	11%	54%	-24%	-30%	-4%	-49%
	3	05/15/07	03/05/08	01/26/09	06/02/10	20 (11)	36 (17)	-86%	20%	66%	0%	97%	-35%	-56%	32%	-62%
	2	02/18/11	08/09/11	09/13/11	04/24/13	6 (26)	26 (6)	-56%	12%	122%	-74%	-36%	-36%	-1%	8%	-31%
Greece:																
	2	07/05/90	10/15/90	11/12/90	04/29/93	4 (7)	33 (22)	-62%	466%	-6%	31%	594%	-47%	-9%	-15%	-59%
	2	09/21/99	03/14/01	04/01/03	06/12/03	42 (11)	44 (21)	-79%	166%	33%	106%	630%	-26%	-51%	-15%	-69%
	3	11/07/07	07/02/08	02/11/16	NA	99 (4)	NA	-99.99%	24%	27%	31%	106%	-62%	37%	-64%	-81%
Hungary:																
	3	07/24/07	02/07/08	03/05/09	09/17/10	19 (9)	37 (24)	-90%	93%	-27%	82%	157%	-32%	-54%	28%	-60%
	2	04/29/11	08/08/11	11/10/11	04/08/13	6 (11)	23 (10)	-62%	-12%	184%	-65%	-11%	-44%	15%	-10%	-43%
Ireland:																
	3	02/22/07	11/14/07	03/05/09	04/23/13	24 (11)	74 (1)	-99%	20%	19%	19%	71%	-46%	-96%	178%	-94%
Italy:																
	3	05/10/07	06/06/08	03/09/09	07/19/13	21 (27)	74 (9)	-81%	16%	38%	26%	101%	-32%	-44%	-6%	-65%
	2	07/21/15	02/03/16	06/30/16	NA	11 (9)	NA	-59%	29%	50%	47%	184%	-59%	NA	NA	NA
Malta:																
	2	02/22/06	01/11/08	04/13/09	01/08/10	37 (22)	46 (17)	-69%	100%	47%	19%	250%	-25%	-23%	-42%	-67%
Netherlands:																
	2	01/05/01	09/20/01	03/12/03	04/01/04	26 (7)	38 (27)	-80%	49%	2%	38%	110%	-35%	-41%	14%	-56%
	3	10/20/06	02/08/08	03/06/09	10/06/10	28 (14)	47 (16)	-93%	50%	18%	13%	101%	-12%	-70%	28%	-66%
Poland:																
	3	01/26/94	03/31/94	03/28/95	06/04/96	14 (2)	28 (8)	-90%	NA	NA	NA	NA	-88%	99%	50%	-63%
	2	01/22/97	07/14/97	10/09/98	04/30/99	20 (17)	27 (8)	-70%	81%	55%	-86%	-62%	-54%	-9%	76%	-27%
	2	07/24/07	10/16/08	03/02/09	10/16/09	19 (6)	26 (22)	-76%	57%	50%	24%	192%	-11%	-48%	48%	-31%
Portugal:																
	2	07/05/07	01/28/08	11/10/11	09/27/12	52 (5)	62 (22)	-93%	15%	86%	6%	126%	-64%	-22%	-16%	-77%
Slovakia:																
	3	03/23/94	05/27/94	03/06/96	06/25/96	23 (11)	27 (2)	-78%	430%	NA	NA	NA	-62%	-30%	60%	-58%
	3	08/21/96	04/25/97	10/22/99	06/07/01	38 (1)	57 (17)	-87%	107%	-32%	101%	182%	-48%	-18%	-58%	-82%
Spain:																
	2	08/01/89	03/06/90	01/14/91	11/12/92	17 (13)	39 (11)	-40%	5%	-4%	89%	91%	-14%	-8%	-26%	-41%
	2	07/20/98	08/28/98	10/02/98	01/15/99	2 (12)	5 (26)	-54%	107%	117%	38%	520%	-21%	13%	-10%	-20%
	2	09/18/00	09/14/01	10/01/02	07/02/03	24 (13)	33 (14)	-53%	25%	56%	-3%	89%	-32%	-20%	20%	-34%
	3	02/15/07	07/11/08	03/09/09	07/23/13	24 (22)	77 (8)	-72%	25%	21%	12%	70%	-27%	-49%	55%	-42%
	2	06/10/14	09/24/15	06/27/16	NA	24 (17)	NA	-56%	57%	15%	-39%	10%	-12%	-42%	NA	NA
Sweden:																
	3	08/01/89	11/21/90	11/19/92	07/26/93	39 (18)	47 (25)	-90%	42%	11%	15%	83%	-5%	-19%	-57%	-66%
	3	04/23/07	06/11/08	03/06/09	11/04/09	22 (11)	30 (12)	-79%	18%	32%	23%	92%	-25%	-46%	52%	-39%
United Kingdom:																
	3	01/25/07	01/04/08	03/09/09	10/06/10	25 (12)	44 (11)	-87%	17%	4%	5%	27%	-37%	-72%	74%	-69%
	2	02/18/11	08/04/11	11/23/11	09/06/12	9 (5)	18 (19)	-51%	21%	73%	-70%	-36%	-30%	25%	6%	-6%

Table 4.5 (a, b) – Belsley collinearity diagnostics for assessing the strength and sources of collinearity among lagged regressor variables. The results refer to the 5-year specification model in table 4.3. From the top to the bottom, the collinearity diagnostics for the 5YS1 and 5YS2 models.

(a)

Variance Decomposition

sValue	condIdx	var1	var2	var3	var4	var5
1.1606	1	0.1161	0.1944	0.0000	0.1811	0.2097
1.0908	1.0639	0.2364	0.0556	0.3883	0.0326	0.0858
0.9443	1.2290	0.0133	0.2847	0.3219	0.4220	0.0290
0.9300	1.2479	0.2771	0.2271	0.0378	0.2686	0.2818
0.8405	1.3807	0.3570	0.2382	0.2520	0.0957	0.3937

Variance Decomposition

sValue	condIdx	var1	var2	var3	var4	var5	var6	var7	var8	var9	var10
1.5157	1	0.0169	0.0003	0.0062	0.0116	0.0021	0.0028	0.0098	0.0028	0.0045	0.0294
1.4916	1.0162	0.0123	0.0193	0.0071	0.0003	0.0093	0.0076	0.0000	0.0067	0.0105	0.0003
1.3223	1.1463	0.0001	0.0008	0.0033	0.0062	0.0082	0.0114	0.0145	0.0155	0.0114	0.0040
1.2841	1.1804	0.0334	0.0214	0.0110	0.0056	0.0036	0.0013	0.0003	0.0076	0.0226	0.0266
0.9517	1.5927	0.1223	0.0090	0.0123	0.0067	0.0043	0.0061	0.0028	0.0102	0.0121	0.1472
0.7463	2.0308	0.1249	0.0162	0.0281	0.0164	0.0192	0.0138	0.0185	0.0223	0.0223	0.1286
0.5464	2.7738	0.1782	0.0595	0.0019	0.0723	0.0211	0.0323	0.0663	0.0000	0.0822	0.1974
0.4413	3.4348	0.1218	0.1589	0.0464	0.0109	0.1087	0.0908	0.0012	0.0744	0.1752	0.1131
0.3181	4.7642	0.1964	0.2769	0.2664	0.1222	0.0098	0.0213	0.1383	0.2548	0.2223	0.1567
0.1530	9.9072	0.1937	0.4378	0.6172	0.7478	0.8137	0.8126	0.7483	0.6056	0.4367	0.1968

(b)

Variance Decomposition

sValue	condIdx	var1	var2	var3	var4	var5	var6	var7	var8	var9	var10	var11	var12	var13	var14	var15	var16	var17	var18	var19	var20
2.0882	1	0.0012	0.0002	0.0000	0.0004	0.0010	0.0013	0.0014	0.0010	0.0003	0.0000	0.0003	0.0009	0.0013	0.0010	0.0004	0.0000	0.0003	0.0012	0.0016	0.0025
2.0684	1.0096	0.0014	0.0016	0.0022	0.0021	0.0008	0.0001	0.0001	0.0006	0.0012	0.0012	0.0008	0.0003	0.0000	0.0002	0.0007	0.0012	0.0012	0.0005	0.0000	0.0003
1.8675	1.1182	0.0001	0.0000	0.0000	0.0001	0.0002	0.0004	0.0005	0.0007	0.0008	0.0008	0.0010	0.0012	0.0015	0.0016	0.0017	0.0020	0.0021	0.0013	0.0006	0.0004
1.8065	1.1559	0.0036	0.0023	0.0027	0.0026	0.0015	0.0009	0.0006	0.0005	0.0004	0.0004	0.0003	0.0002	0.0000	0.0000	0.0003	0.0010	0.0023	0.0026	0.0022	0.0027
1.2777	1.6344	0.0155	0.0068	0.0029	0.0001	0.0009	0.0018	0.0014	0.0002	0.0002	0.0009	0.0010	0.0003	0.0000	0.0008	0.0014	0.0007	0.0001	0.0037	0.0086	0.0186
0.9717	2.1491	0.0304	0.0032	0.0006	0.0056	0.0059	0.0007	0.0007	0.0036	0.0035	0.0006	0.0003	0.0029	0.0032	0.0009	0.0004	0.0053	0.0060	0.0009	0.0032	0.0340
0.6401	3.2625	0.0616	0.0018	0.0032	0.0142	0.0041	0.0021	0.0095	0.0074	0.0002	0.0082	0.0093	0.0006	0.0058	0.0100	0.0035	0.0037	0.0148	0.0049	0.0017	0.0719
0.5470	3.8177	0.0499	0.0010	0.0227	0.0043	0.0000	0.0163	0.0099	0.0046	0.0180	0.0045	0.0032	0.0177	0.0070	0.0083	0.0158	0.0009	0.0029	0.0306	0.0010	0.0498
0.4881	4.2787	0.0533	0.0517	0.0106	0.0016	0.0001	0.0193	0.0132	0.0005	0.0003	0.0027	0.0004	0.0002	0.0012	0.0195	0.0316	0.0023	0.0003	0.0118	0.0828	0.0791
0.4577	4.5628	0.0037	0.0000	0.0012	0.0001	0.0065	0.0191	0.0007	0.0140	0.0244	0.0260	0.0084	0.0110	0.0511	0.0242	0.0035	0.0025	0.0483	0.0290	0.0007	0.0112
0.4546	4.5935	0.0053	0.0052	0.0040	0.0068	0.0003	0.0146	0.0363	0.0234	0.0033	0.0079	0.0444	0.0395	0.0049	0.0031	0.0205	0.0298	0.0055	0.0025	0.0026	0.0000
0.4408	4.7376	0.0148	0.0270	0.0042	0.1122	0.0457	0.0032	0.0001	0.0147	0.0331	0.0013	0.0010	0.0030	0.0024	0.0002	0.0001	0.0081	0.0907	0.0253	0.0099	0.0175
0.4340	4.8117	0.0696	0.0004	0.1054	0.0052	0.0267	0.0000	0.0026	0.0254	0.0053	0.0231	0.0039	0.0052	0.0069	0.0015	0.0021	0.0461	0.0031	0.0649	0.0037	0.0456
0.2952	7.0739	0.1971	0.2220	0.0400	0.0102	0.0225	0.0002	0.0171	0.0006	0.0002	0.0244	0.0283	0.0031	0.0038	0.0140	0.0008	0.0253	0.0078	0.0500	0.2669	0.2257
0.2467	8.4656	0.0228	0.0231	0.1999	0.0015	0.2248	0.0136	0.0612	0.0106	0.0151	0.0151	0.0115	0.0014	0.0386	0.0378	0.0444	0.1042	0.0749	0.2572	0.0002	0.0657
0.2424	8.6149	0.0847	0.0681	0.0601	0.3495	0.0161	0.0523	0.0053	0.0343	0.0337	0.0042	0.0064	0.0546	0.0154	0.0387	0.0171	0.1332	0.2693	0.0000	0.0663	0.0176
0.1764	11.8356	0.0939	0.2206	0.2269	0.1013	0.0791	0.1428	0.1832	0.0618	0.0000	0.0038	0.0007	0.0004	0.0508	0.2169	0.1902	0.0910	0.0999	0.2317	0.2182	0.0860
0.1459	14.3100	0.0038	0.0841	0.0333	0.1798	0.0786	0.1497	0.0713	0.3252	0.2684	0.1193	0.1512	0.2230	0.3895	0.0391	0.1529	0.0641	0.1958	0.0207	0.0825	0.0048
0.1334	15.6585	0.2229	0.1032	0.0868	0.0781	0.2962	0.1951	0.1536	0.1616	0.2390	0.2153	0.2013	0.3037	0.1107	0.1604	0.1763	0.3127	0.0531	0.0797	0.0949	0.2155
0.1015	20.5822	0.0646	0.1778	0.1932	0.1242	0.1889	0.3667	0.4312	0.3094	0.3527	0.5402	0.5263	0.3309	0.3061	0.4216	0.3365	0.1659	0.1215	0.1816	0.1522	0.0510

REFERENCES

Abbas, S. M. Ali, Nazim Belhocine, Asmaa ElGanainy and Mark Horton. 2011. "Historical Patterns and Dynamics of Public Debt - Evidence From a New Database". *International Monetary Fund Economic Review,* **59**: 717-742.

Abiad, Abdul D. 2003. "Early Warning Systems; A Survey and a Regime-Switching Approach". IMF Working Papers **03/32**.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith and Peter Howitt. 2005. "Competition And Innovation: An Inverted-U Relationship". *Quarterly Journal of Economics*, **120**: 701-728.

Aghion, Philippe, Eve Caroli and Cecilia García-Peñalosa. 1999. "Inequality and Economic Growth: The Perspective of the New Growth Theories". *Journal of Economic Literature,* **37** (4): 1615–1660.

Alessi, Lucia & Detken, Carsten. 2009. "Real time'early warning indicators for costly asset price boom/bust cycles: a role for global liquidity". European Central Bank, Working Paper Series **1039**.

Allen, F., and D. Gale. 2000b. "Financial Contagion". *Journal of Political Economy,* **108**: 1–33.

Allen, Franklin and Douglas Gale. 2004. "Financial Intermediaries and Markets". *Econometrica*, **72**(4): 1023-1061.

Allen, William A. and Geoffrey Wood. 2005. "Defining and achieving financial stability". *Cass Business School, City University*, (160).

Allen, F. 1989. "The Changing Nature of Debt and Equity: A Financial Perspective". R. Kopcke and E. Rosengren. *Are the distinctions between Debt and Equity Disappearing?. Federal Reserve Bank of Boston Conference Series*, **33**: 12-38.

Almarzoqi, Raja, Sami Ben Naceur and Akshay Kotak. 2015. "What Matters for Financial Development and Stability?". International Monetary Fund, IMF Working Papers: **15/173**.

Apoteker, Thierry and Sylvain Barthelemy. 2000. "Genetic Algorithms and Financial Crises in Emerging Markets". AFFI International Conference in Finance Processing.

Arcand, Jean-Louis, Enrico Berkes and Ugo Panizza. 2012. "Too Much Finance?". International Monetary Fund, IMF Working Papers: **12/161.**

Asako, K. 1991. "The Land Price Bubble in Japan". *Ricerche Economiche*, **45**(2-3): 167-184.

Aziz, Jahangir, Francesco Caramazza and Ranil Salgado. 2000. " Currency Crises: In Search of Common Elements". T. Bayoumi, F. Caramazza, and D. Robinson. Africa, Asia and pacific, and Research Departments. International Monetary Fund, IMF Working Papers: WP **00/67.**

Bagehot, Walter. 1873. *Lombard Street: A Description of the Money Market.* London: Henry S. King and Co. E. Johnstone; Hartley Withers, eds.

Basel III: *A Global Regulatory Framework for More Resilient Banks and Banking Systems*. 2010. Bank for International Settlements.

Beck, Thorsten, Hans Degryse and Christiane Kneer. 2012. *Is more finance better? Disentangling intermediation and size effects of financial systems*. Tilburg University mimeo.

Becker, Torbjörn and Paolo Mauro. 2006. "Output Drops and the Shocks That Matter". International Monetary Fund, IMF Working Papers: **06/172.**

Bell, T. B.,G. S. Ribar and J. Verchio. 1990. "Neural Nets versus Logistic Regression: A Comparison of Each Model's Ability to Predict Commercial Bank Failures". Srivatsava: R.P. (Ed.), *Proceedings of the 1990 Deloitte and Touch/University of Kansas Symposium of Auditing Problems*, 29-58.

Belsley, D. A., E. Kuh, and R. E. Welsch. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. Hoboken, NJ: John Wiley & Sons.

Berg A and Pattillo C. 2000. "The challenges of predicting economic crisis". IMF Economic, **22**.

Berg, Andrew and Carol Pattillo. 1999a."Are Currency Crises Predictable? A Test". *IMF Staff Papers* **46**(2).

Berg, Andrew and Carol Pattillo. 1999b. "Predicting currency crises: The indicators approach and an alternative". Journal of International Money and Finance, **18**: 561-586.

Bencivenga, V. R., and Smith, B.D. 1991. "Financial Intermediation and Endogenous Growth". *Review of Economic Studies*, **58**(2):195-209.

Bentham, Jeremy. 1952–54. *Jeremy Bentham's Economic Writings*. Stark, London: George Allen & Unwin.

Bernanke, Ben S., Thomas Laubach, Frederic S. Mishkin and Adam Posen. 1999. *Inflation targeting: Lessons from the International Experience*. Princeton NJ: Princeton University Press.

Bernanke, B. and Mark Gertler. 1995. "Inside the Black Box: The Credit Channel of Monetary Policy Transmission". *Journal of Economic Perspectives,* **9**(4): 27-48.

Bernanke, B. and Mark Gertler. 1990. "Financial Fragility and Economic Performance". *The Quarterly Journal of Economics.* **105**: 87-114.

Bernanke, Ben. 1983. "Nonmonetary effects of the financial crisis in the propagation of the Great Depression". *American Economic Review* **73**: 257-263.

BIS Statistical Bulletin. 2016. "Credit to the non-financial sector". *Bank for International Settlements.*

Blanchard, Olivier J. and Stanley Fischer. 1989. *Lectures on Macroeconomics.* MIT Press.

Blejer, M. I. and L. Schumacher. 1998. "Central bank vulnerability and the credibility of commitments: A value-at risk approach to currency crises". IMF Working Paper.

Bordo, M.D. and A.P. Murshid. 2001. " Are Financial Crises Becoming More Contagious?". chapter 14 in International Financial Contagion(eds) Stijn Claessens and Kristin I. Forbes. Boston: Kluwer Academic Publishers: 367-403.

Bordo, M.D. , B. Eichengreen, D. Klingebiel, and M.S. Martinez-Peria. 2001. " Is the Crisis
Problem Growing More Severe?". Economic Policy April.

Bordo, Michael D. and Olivier Jeanne. 2002. "Monetary Policy and Asset Prices: Does "Benign Neglect" Make Sense?". International Monetary Fund IMF, Working Papers. **02/225**.

Borio, C. and M. Drehmann. 2009. "Assessing the Risk of Banking Crisis-revisited". *BIS Quarterly Review,* 29-46.

Borio, C. 2008. "The financial turmoil of 2007-?: a preliminary assessment and some policy considerations". Bank for International Settlements. BIS Working Papers **251**.

Borio, C and P Lowe. 2004. "Securing sustainable price stability: Should credit come back from the wilderness". BIS Working Papers **157**.

Borio, C and P Lowe. 2002a. "Asset prices, financial and monetary stability: exploring the nexus". BIS Working Papers **114.**

Borio, C and P Lowe. 2002b. "Assessing the risk of banking crises". *BIS Quarterly Review,* 43–54.

Box, G. E. P., G. M. Jenkins, and G. C. Reinsel. 1994. *Time Series Analysis: Forecasting and Control*. 3rd ed. NJ: Prentice Hall. Englewood Cliffs.

Box, G. E. P. and D. R. Cox. 1964. “An analysis of Transformation”. *Journal of the Royal Statistical Society. Series B (Methodological),* **26**(2): 211-252.

Bryant, John. 1980. “A model of reserves, bank runs, and deposit insurance”. *Journal of Banking & Finance*, **4**: 335-344.

Bullow, Jeremy and Kenneth Rogoff. 1989. “Sovereign debt: Is to forgive t forget?”. *American Economic Review,* **79**: 43-50.

Bunn, A. G., S. J. Goetz, and G. J. Fiske. 2005. “Observed and predicted responses of plant growth to climate across Canada, Geophys”. *Geophysical Research Letters,* **32**(16).

Burns, Arthur F. and Wesley C. Mitchell. 1946. “ Measuring Business Cycles”. *National Bureau of Economic Research*, NBER Book Series Studies in Business Cycles.

Burkart, Olivier and Virginie Coudert. 2000. “Leading Indicators of Currency Crises In Emerging Economies”. Banque De France. Working Papers **74**.

Bussière, Matthieu & Fratzscher, Marcel. 2002. "Towards a new early warning system of financial crises" . European Central Bank. Working Paper Series **0145**.

Charles W. Calomiris & Gary Gorton, 1991. "The Origins of Banking Panics: Models, Facts, and Bank Regulation". National Bureau of Economic Research. NBER Chapters, Financial Markets and Financial Crises, 109-174.

Calvo, Guillermo, Alejandro Izquierdo, and Luis-Fernando Mejía. 2008. “Systemic Sudden Stops: The Relevance of Balance-Sheet Effects and Financial Integration.” NBER Working Paper **14026**.

Calvo, Guillermo A. , Alejandro Izquierdo and Ernesto Talvi. 2006. "Sudden Stops and Phoenix Miracles in Emerging Markets". *American Economic Review, American Economic Association,* **96(2)**: 405-410.

Calvo, Guillermo A., Alejandro Izquierdo and Ernesto Talvi. 2003. “Sudden Stops, the Real Exchange Rate, and Fiscal Sustainability: Argentina’s Lessons”. Cambridge, MA: National Bureau of Economic Research. NBER, Working Paper **9828**.

Calvo, Guillermo A. 1998. “Capital Flows and Capital Market Crises: The Simple Economics of Sudden Stops”. *Journal of Applied Economics*. CEMA, Argentina: **1**:35-54.

Caprio, Gerard, and Daniela Klingebiel. 1996. “Bank Insolvencies: Cross-Country Experience.” Washington, D.C.: World Bank, Policy Research. Working Paper **1620**.

Cecchetti,S.G. P. Lam and N. C. Mark.1990. “Mean reversion in equilibrium asset prices”. *American Economic Review,* **80**: 398-418.

Cerra, Valerie and Sweta Chaman Saxena. 2008. "Growth Dynamics: The Myth of Economic Recovery." *American Economic Review,* **98**(1): 439-57.

Cerra, Valerie and Sweta Chaman Saxena. 2001. "What Caused the 1991 Currency Crisis in India?". International Monetary Fund. IMF Working Papers **00/157**.

Chang, Roberto and Andrés Velasco. 2000. “Liquidity Crises in Emerging Markets: Theory and Policy”. MIT Working Papers:**14**: 11-78.

Chari, V. V. and Ravi Jagannathan. 1988. “Banking Panics, Information, and Rational Expectation Equilibrium”. *The Journal of Finance,* **43**(3): 749-61.

Chui, M. and P. Gai. 2005. *Private Sector Involvement and International Financial Crises*. Oxford and New York: Oxford University Press.

Cifuentes, R., G. Ferrucci, and H.S. Shin. 2005. "Liquidity risk and contagion." *Journal of the European Economic Association,* **3**: 556-566.

Cihak, Martin. 2007. *"*Systemic Loss: A Measure of Financial Stability (in English*)".* *Journal of Economics and Finance (Finance a uver).* Charles University Prague, Faculty of Social Sciences, **57**(1-2):5-26.

Clements, M.P. and D.F. Hendry. 1998. “Forecasting Economic processes”. *International Journal of Forecasting,* **14**: 111–131.

Collins, Hugh. 2003. “Discrimination, Equality and Social Inclusion”. *The Modern Law Review,* **66**: 16–43.

Corsetti, Giancarlo, Paolo Pesenti and Nouriel Roubini. 1998. “What Caused the Asian Currency and Financial Crisis? Part II: The Policy Debate”. *NBER* Working Paper: **6843.**

Corsi, Fulvio. 2008. “A Simple Approximate Long-Memory Model of Realized Volatility”. *Journal of Financial Econometrics,* **7**:174-196.

Coudert, V. and M. Gex. 2006. “Can risk aversion indicators anticipate financial crises?”. *Banque de France Financial Stability Review,* **9**: 67–87.

Claessens, Stijn and M. Ayhan Kose. 2013. “Financial Crises: Explanations, Types, and Implications”. IMF Working Paper: **13/28.**

Claessens, Stij, M. Aythan Kose and Marco Terrones. 2012. “How Do Business and Financial Cycles Interact?”. *Journal of International Economics,* **87**: 178-190.

Crockett, Andrew. 1997. "The Theory and Practice of Financial Stability". United Kingdom: Gonville and Caius College Cambridge. GEI Newsletter Issue **6**: 11-12.

Davis, E. and Dilruba Karim. 2008. "Comparing early warning systems for banking crises". *Journal of Financial Stability*, **4**(2): 89-120.

Demirguc-Kunt, Asli, E. Kane and Luc Laeven. 2008. "Deposit insurance around the world: issues of design and implementation". Cambridge: MIT Press, MA.

Demirguc-Kunt, Asli and Enrica Detragiache. 1998. "Financial Liberalization and Financial Fragility". International Monetary Fund. Working Paper: **98/83.**

Deutsche Bundesbank. 2003. "Report on the Stability of the German Financial System". Frankfurt. Monthly Report, December.

Diamond, Douglas W. and Raghuram G. Rajan. 2001. "Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking". *The Journal of Political Economy*, **109**(2): 287-327.

Diamond, Douglas W. and Philip H. Dybvig. 1983. "Bank Runs, Deposit Insurance, and Liquidity". *The Journal of Political Economy*, **91**(3): 401-419.

Diebold, F.X. J. Gardeazabal, and K.Yilmaz. 1994. "On cointegration and exchange rate dynamics". *Journal of Finance*, **49:** 727-735.

Dokko, Y., Edelstein, R.H. and Urdang. 1990. "Does credit rationing affect residential investment? Déjà vu all over again". *The Journal of Real Estate Finance and Economics*, **3**(4): 357–371.

Dornbusch, Rudiger, Goldfajn Ilan and Valdés Rodrigo. "Currency Crises and Collapses". Brookings Papers on Economic Activity, **2**: 219-95.

Drehmann, Mathias and Juselius, Mikael. 2012. "Do Debt Service Costs Affect Macroeconomic and Financial Stability?". *BIS Quarterly Review September.*

Eaton,Jonathan and Mark Gersovitz. 1981. " Debt with potential repudiation: Theoretical and empirical analysis". *Review of Economic Studies*, **48:** 289-309.

Edwards, S., Santaella, J.A.1993. "Devaluation Controversies in the Developing Countries: lessons from the Bretton Woods Era". In Bordo, M.D., B. Eichengreen (Eds.), A Retrospective on the Bretton Woods System, Chicago: University of Chicago Press.

Edwards S. 1989. "Real Exchange Rates, Devaluation, and Adjustment: Exchange Rate Policy in Developing Countries". MIT, Cambridge, MA.

Edwards S. and P. Montiel. 1989. “Devaluation Crises and the Macroeconomic Consequences of Postponed Adjustment in Developing Countries”.IMF Staff Papers, **36**(4): 875-903.

Eichengreen, Barry, Rose Andrew K. and Wyplosz Charles. 1996a. “Exchange Market Mayhem: the Antecedents and Aftermath of Speculative Attacks”. *Economic Policy,* **21**: 249-312.

Eichengreen, Barry, Rose Andrew K. and Wyplosz Charles.1996b. “Contagious Currency Crises”. CEPR Discussion Paper **1453**.

Elsinger, H., Lehar, A., and Summer, M. 2006. “Risk Assessment for Banking Systems”. Management Science, **52**(9):1301–1314.

Eliasson, A.-C. and C. Kreuter. 2002. “On Currency Crisis Models: A Continuous Crisis Definition”. *Deutsche Bank, Research paper*. Frankfurt am Main.

Engel, C and JD Hamilton. 1990. “Long swings in the dollar: Are they in the data and do markets know it?”. *The American Economic Review*, 689-713.

Esquivel, Gerardo and Felipe Larrain. 1998. “Explaining Currency Crises”. Mimeo, *Harvard Institute for International Development* (June).

European Central Bank. 2005. “Assessing Financial Stability: Conceptual Boundaries and Challenges”. European Central Bank. Financial Stability Review, June: 117-125.

Ferguson, R. W., 2002. “Should Financial Stability Be An Explicit Central Bank Objective?”. Washington: Federal Reserve Board.

Filardo, Andrew J. 1993-1994. "Business-Cycle Phases and Their Transitional Dynamics". Journal of Business & Economic Statistics, *American Statistical Association,* **12**(3): 299-308.

Fisher, Irving. 1933. “The Debt-Deflation Theory of Great Depressions”. *Econometrica* **1**:337-57.

Fisher, Irving. 1911. The Purchasing Power of Money. Its Determination and Relation to Credit, Interest, and Crises. New York: The Macmillan Co.

Flood, Robert, and Peter Garber. 1984a. “Collapsing Exchange Rate Regimes: Some Linear Examples”. *Journal of International Economics*, **17**:1-13.

Flood, Robert and Peter Garber. 1984b. “Gold Monetization and Gold Discipline”. *Journal of Political Economy,* **92**: 90-107.

Foot, Michael. 2003. “What is ‘Financial stability’ and How Do We Get It?”. The Roy Bridge Memorial Lecture. United Kingdom: Financial Services Authority.

Forbes, Kristin J. and Francis E. Warnock. 2012.“Capital Flow Waves: Surges, Stops, Flight and Retrenchment”. *Journal of International Economics* **88** (2):235-251.

Frankel, Jeffrey and George Saravelos. 2012. “Are Leading Indicators of Financial Crises Useful for Assessing Country Vulnerability? Evidence from the 2008-09 Global Crisis”. *Journal of International Economics, **87***: 216.

Frankel, Jeffrey and SJ Wei. 2004. “Managing macroeconomic crises” *National Bureau of Economic Research*.

Frankel, Jeffrey and Andrew K. Rose. 1996. “Exchange Rate Crises in Emerging Markets”. *Journal of International Economics,* **41**: 351-68.

Fratzscher, M. 1999. "What Causes Currency Crises: Sunspots, Contagion or Fundamentals?". European University Institute. Economics Working Papers eco **99/39**.

French, Kenneth R. and James M. Poterba. 1991. "Investor Diversification And International Equity Markets". *American Economic Review*, **81**(2): 222-226.

Freixas, X., and B. Parigi. 1998. “Contagion and Efficiency in Gross and Net Interbank Payment Systems”. *Journal of Financial Intermediation,* **7**: 3–31.

Freixas, X. and Jean-Charles Rochet. 1997. *Microeconomics of Banking*. Institute of Technology.

Friedman, M. 1992. *Money mischief: Episodes in monetary history.* A Harvest Book, Harcourt Brace & Company.

Friedman, M. 1990. *Critical Assessments*. John C. Wood, Ronald N. Woods. Psychology Press.

Friedman, Milton, and Anna Jacobson Schwartz. 1963. *A Monetary History of the United States, 1867-1960*. Princeton: Princeton University Press.

Friedman, M. 1956. “The quantity theory of money–A restatement”. Studies in the quantity theory of money. *University of Chicago Press*. Chicago, 3-21.

Galbrait, John K. 1975. “*Money: Whence It Came, Where It Went”.* Boston: Houghton Mifflin.

Gerdrup, Karsten R. 2003. “Three episodes of financial fragility in Norway since the 1890s”. Bank for International Settlements.BIS Working Papers **142**.

Gertler, Mark . 1988. “Financial Structure and Aggregate Economic Activity: An Overview”. *Journal of Money, Credit and Banking*: Recent Developments in Macroeconomics, **20** (3) Part 2: 559-588.

Ghosh, S. and Ghosh, A.R. 2002. “Structural vulnerabilities and currency crises”. International Monetary Fund, IMF Working Paper **02/9**.

Glick, R and M. Hutchison. 2011. “Currency Crises” . Federal Reserve Bank of San Francisco Working Paper Series.Working Paper **2011-22**.

Goldsmith, Raymond W. 1969. *Financial structure and development*. New Haven, CT: Yale University Press.

Goldfajn, I., Valdes, R.O. 1997. “ Capital flows and the twin crises: the role of liquidity”. International Monetary Fund Working Paper **1997/1987**.

Golfield, S. and Quandt R. 1976. Techniques for estimating switching regressions. Studies in Nonlinear Estimation. Cambridge, Massachusetts: Ballinger.

Goldfeld, Stephen M. and Richard E. Quandt. 1973.” A Markov model for switching regressions”. *Journal of Econometrics*, **1**(1): 3-15.

Goodhart, C.A.E. 2006. “A framework for assessing financial stability?” *Journal of Banking & Finance*, **30**(12): 3415–22.

Gorton, Gary. 1988. “Banking Panics and Business Cycles”. *Oxford Economic Papers.* Oxford: Oxford University Press. New Series, **40**(4): 751-781.

Gourinchas, Pierre-Olivier, Rodrigo Valdes and Oscar Landerretche. 2001. “Lending Booms: Latin America and the World”. NBER, Working Papers **82/49**.

Graupe, Daniel. 2007. *Principles of artificial neural networks*. World Scientific Publishing Co. Pte. Ltd.

Hamilton, James D. 1990. “Analysis of time series subject to changes in regime”. *Journal of econometrics*, **45** (1), 39-70.

Hamilton, James D. 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle". *Econometrica ,Econometric Society*, **57**(2): 357-384.

Hamilton, James D. 1988. "A Neoclassical Model of Unemployment and the Business Cycle". *Journal of Political Economy,* **96**: 593-617.

Haykin, Simon. 1999. “ Neural Networks”. *A comprehensive Foundation*. Singapore: Pearson Education.

Hetzel, R. L. 1984. "The Formulation of Monetary Policy in a Democracy". Unpublished manuscript, *Federal Reserve Bank of Richmond*.

Holland, J. H. 1975. *Adaptation in Natural and Artificial Systems*. Cambridge, MA: University of Michigan Press.

Hardy, Daniel and Pazarbazioglu, Ceyla.1999. "Determinants and Leading Indicators of Banking Crises". IMF Staff Paper **46(3)**.

Hamilton, James and Oscar Jorda. 2002. "A Model of The Federal Funds Rate Target". *Journal of Political Economy*, **110**(5): 1135-1167.

Hossein, Jalilian and Colin Kirkpatrick. 2002. "Financial Development and Poverty Reduction in Developing Countries." *International Journal of Finance and Economics* **7 (**2): 97-108.

Hossein, Jalilian and Colin Kirkpatrick. 2005. "Does Financial Development Contribute to Poverty Reduction?". *The Journal of Development Studies,* **41** (4): 636-656.

Hume, Michael & Sentance, Andrew. 2009. "The global credit boom: Challenges for macroeconomics and policy". *Journal of International Money and Finance*, Elsevier, **28**(8): 1426-1461.

IMF International Monetary Fund. 2005. World Economic Outlook, April 2005. Washington.
D.C.: International Monetary Fund.

IMF Working Paper. 1998. "Financial Crisis and Credit Crunch as a Result of Inefficient Financial Intermediation-with Reference to the Asian Financial Crisis". Research Department, WP **98/127**.

Jeanne, Olivier & Masson, Paul R. 1998. "Currency Crises, Sunspots and Markov-Switching Regimes". C.E.P.R. Discussion Papers **1990**.

Jeanne, Olivier. 2009. "Debt Maturity and the International Financial Architecture". *American Economic Review*, **99** (5): 2135-48.

Jeanneney, Sylviane G. and Kangni Kpodar. 2011. *"*Financial Development, Financial Instability and Poverty.*"* Humanities and Social Sciences / Economies and finances, Working Paper. CERDI, Etudes et Documents, E.2006.7

Jeanneney S.G., and K. Kpodar (2005), "Financial Development, Financial Instability and Poverty".CERDI-CNRS-University of Auvergne. CSAE WPS **05/09**.

Judd, John P. and John L. Scadding. 1981. "Liability Management, Bank Loans and Deposit Market Disequilibrium". Federal Reserve Bank of san Francisco. *Economic Review*: 21-44

Kamin S. 1988. “Devaluation, External Balance, and Macroeconomic Performance: A Look at the Numbers”. *Princeton Studies in International Finance*. International Economics Section, Princeton University, **62**.

Kaminsky, Graciela L. and Carmen M. Reinhart. 1999. “The Twin Crises: The Causes of Banking and Balance-of-Payments Problems”. *American Economic Review*, **89**(3): 473-500.

Kaminsky, Graciela L., Saul Lizondo and Carmen M. Reinhart. 1998. “Leading Indicators of Currency Crises”. *International Monetary Fund Quarterly Journal*, **45**(1).

Kindleberger, Charles P. 1978. *Manias, Panics, and Crashes: A History of Financial Crises*. New York: Basic Books.

Kindleberger, Charles P. 1996. *World Economic Primacy, 1500-1990*. New York: Oxford University Press.

King, Robert G. and Ross Levine. 1993. “Finance and Growth: Schumpeter Might be Right.”
The Quarterly Journal of Economics, **108** (3): 717-737.

Kiyotaki, Nobuhiro and John Moore. 1997. “Credit Cycles”. *The Journal of Political Economy,* **105**(2): 211-248. Chicago: University of Chicago Press.

Klein, M. and Marion, N. 1997. ”Explaining the duration of exchange-rate pegs”. *Journal of Development Economics,* **54**: 387-404.

Kruger, M., P.N. Osakwe and J. Page. 1998. “Fundamentals, Contagion and Currency Crises: An Empirical Analysis”. Bank of Canada Working Paper **10**.

Krugman, Paul. 1998. “What Happened in Asia,” *unpublished manuscript, MIT*.

Krugman, P. 1979. “Increasing returns, monopolistic competition, and international tradeí”. *Journal of International Economics*, **9** (4) :669-479.

Kumar, K., Subramaniam, R. & Yauger, C. 1998. “Examining the market -performance relationship: a context specific study”. *Journal of Management*, **24**(2): 201-234.

Kumar, Mohan, Uma Moorthy and William Perraudin. 2002-2003. "Predicting emerging market currency crashes". *Journal of Empirical Finance,* **10**(4): 427-454.

Kuan, C.-M. and H. White. 1994. “Artificial neural networks: An econometric perspective
(with discussions)”. *Econometric Reviews*, **13**: 1–91 and 139–143.

LeSage, JP. 1999. “Applied econometrics using MATLAB”.
Manuscript, Dept. of Economics, University of Toledo, **154-159**.

Law , J. 1720. *Money and trade considered; with a proposal for supplying the nation with money*. London .

Laeven, Luc, and Fabian Valencia. 2008. “Systemic Banking Crises: A New Database”. IMF
Working Paper **08/224**.

Leaven, Luc and Fabiàn Valencia. 2013. “Systemic Banking Crises Database: An Update”. *IMF Economic Review*, **61** (2) :225–270.

Lee, A. S.1991. "Integrating Positivist and Interpretive Approaches to Organizational Research". *Organization Science,* (2): 342-365.

Levine,Ross and Sara Zervos. 1998. Stock Markets, Banks, and Economic Growth.
The American Economic Review, **88 (**3): 537-558.

Lucas, Robert. 1988. "On the Mechanics of Economic Development". *Journal of Monetary Economics,* **22** (1): 3–42.

Macleod, Henry Dunning. 1855/56. *The Theory and Practice of Banking; with the elementary principles of currency, prices, credit and exchanges.* London: Longman.

Martinez Peria,Maria Soledad. 2002. "A regime-switching approach to the study of speculative attacks: A focus on EMS crises". *Empirical Economics,* Springer, **27**(2): 299-334.

McAndrews, James and William Roberds. 1995. “Banks, Payment, and Coordination”. *Journal of Financial Intermediation*, **4**(4): 305-327.

McKinnon R.I. 1973. *Money and Capital in Economic Development.* Washington: The Brooking Institution.

McKinnon, R., & Shaw, E. 1973. *Financial deepening in economic development.* Washington, Brookings Institution.

McKinnon, R.I. and Pill H. 1996. "Credible liberalizations and international capital
flows: the overborrowing syndrome" in T. Ito and A.O. Krueger, eds. *Financial Deregulation and Integration in East Asia*, Chicago: Chicago University Press.

Melvin, Michael. 1983. “Expected Inflation and Interest Rates: Reply”. *American Economic Review,* **73**(3): 503-06.

Mendoza, Enrique G. and Marco E. Terrones. 2008. “An Anatomy Of Credit Booms: Evidence From Macro Aggregates And Micro Data” . NBER Working Papers **14049**.

Merton, Robert C. 1994. “On The Pricing of Corporate Debt: The Risk Structure of Interest Rates”. *Journal of Finance,* **29**(2): 449-70.

Mill, John Stuart. 1848. *Principles of Political Economy with some of their Applications to Social Philosophy.* London; Longmans, Green and Co.

Miller, Merton H. 1998. "Financial Markets and Economic Growth," Journal of Applied Corporate Finance, Morgan Stanley, **11** (3): 8-15.

Miller, Merton H. 1986. *Financial innovation : the last twenty years and the next*. Chicago, Graduate School of Business, University of Chicago.

Minsky, Hyman P. 1992. “The Financial Instability Hypothesis”. The Jerome Levy Economics Institute of Bard College, Working paper **74**.

Mishkin, Frederick. 1999. “International Capital Movement, Financial Volatility and Financial Instability”. NBER, working paper **6390.**

Mishkin, Frederick and Eugene N. White. 2002. “U.S. Stock Market Crashes and their aftermath: implications for monetary policy”. NBER, Working Papers **8992**.

Mishkin, F. S. 1978. “Monetary Policy And Liquidity: Simulation Results”. *Economic Inquiry,* 16: 16–36.

Minsky, Hyman P. 1982. “Can IT Happen Again?”. Armonk, N.Y.: ME Sharpe.

Minsky, H.P. 1977. ‘A Theory of Systemic Fragility’ in Altman, E.I and A.W. Sametz. *Financial Crises: Institutions and Markets in a Fragile Environment*. New York: John Wiley and Son.

Modigliani, Franco and Merton Miller. 1958. “The Cost of Capital, Corporate Finance, and the Theory of Investment”. *American Economic Review,* **3**(48): 261-297.

Naceur, Sami B. and RuiXin Zhang. 2007. “Financial Development, Inequality and Poverty: Some International Evidence*”*. International Monetary Fund. IMF Working Papers **16/32.**

Nag, A. and A. Mitra. 1999. “Neural Networks and Early Warning Indicators of Currency Crises”. *Reserve Bank of India Occasional Papers,* ***20***(3): 183-222.

Newcom,Simon. 1885. *Principles of political economy*. New York: Harper & brothers.

Nelson, Richard. 2008. “What enables rapid economic progress: What are the needed institutions”. *Research Policy,* **37**(1): 1-11.

Niggle, Christopher J. 1989. “The Correct Conception of Capital: A Reply to Baldwin Ranson”. Journal of Economic Issues, **23** (1): 247-249.

Obstfeld, Maurice and Kenneth Rogoff. 1986. “Ruling out divergent speculative bubbles”. *Journal of Monetary Economics*, **17**: 349-362.

Obstfeld, Maurice and Alan M. Taylor. 2004. “Globalization in Historical Perspective”. National Bureau of Economic Research. The University of Chicago Press.

Oztemel, E. 2003. *Artificial Neural Network*. Papatya Publishing.

Patel, Sandeep A. and Asani Sarkar. 1998. “Crises in Developed and Emerging Stock Markets”. *Financial Analysts Journal*, **54**: 50-61.

Pesaran, H. , Pettenuzzo D and Timmerman A. 2006. “Learning, structural instability and present value calculations. *Discussion Paper*.

Pollexfen , J. 1697. *England and East-India inconsistent in their manufactures*. London.

Quandt, Richard E. 1958. “The examination of Parameters of a Linear Regression System Obeying Two Separate Regimes”. *Journal of the American Statistical Association*, **53**(284): 873-880.

Rajan, Raghuram G.2005. “ Has Financial Development Made the World Riskier?”. National Bureau of Economic Research, Working Paper **11728.**

Rajan, Raghuram G. and Luigi Zingales. 1998. “Financial Dependence and Growth.” *The American Economic Review*, **88 (**3): 559-586.

Reinhart, Carmen M. and Kenneth S. Rogoff. 2008b. “Banking Crises: An Equal Opportunity Menace”. NBER, Working Paper **14587**.

Reinhart, Carmen M. and Kenneth S. Rogoff. 2010. “Growth in a Time of Debt”. *American Economic Review*, **100** (2): 573–78.

Reinhart, Carmen & Reinhart, Vincent. 2009. "**When the North Last Headed South: Revisiting the 1930s**". University Library of Munich, Germany. MPRA Paper **22612**.

Reinhart, C.M. e K.S. Rogoff. 2009. *This Time is Different: Eight Centuries of Financial Folly*. Princeton and Oxford: Princeton University Press.

Rioja, Felix, and Neven Valev. 2004. “Finance and the Sources of Growth at Various Stages of Economic Development”. *Economic Inquiry*, **42** (1): 127-140.

Robinson, Joan. 1952. *The rate of interest and other essays.* London: MacMillan.

Rochet, J., and J. Tirole. 1996a. “Interbank Lending and Systemic Risk”. *Journal of Money,*
Credit, and Banking, **28**: 733–762.

Rochet, J., and J. Tirole. 1996b. “Controlling Risk in Payment Systems”. *Journal of Money,*
Credit, and Banking, **28**: 832–862.

Roley, V. Vance. 1985. ”Money Demand Predictability”. *Journal of Money, Credit, and Banking Vol. XVI*I, **4** (2): 611-641.

Ruppert, David. 2011. Statistics and Data Analysis for Financial Engineering. New York: Springer-Verlag.

S&P Dow Jones Indices: Index Methodology.

Schinasi, Garry J. 2004. “Defining financial Stability”. International Monetary Fund, IMF Working paper **04/187**.

Schinasi, Garry J. 2006. *Safeguarding Financial Stability: Theory and Practice*. International Monetary Fund.

Schularick, Moritz and Alan M. Taylor. 2012. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008." *American Economic Review,* **102(2)**:1029-61.

Schumpeter, J. A. 1954. *History of Economic Analysis* . London: Allen & Unwin.

Schumpeter, J. A. 1911. *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest and the Business Cycle*. Cambridge, MA: Harvard University Press.

Selden, R. T. 1956: “Monetary Velocity in the United States”, in M. Friedman ed. *Studies in the Quantity Theory of Money*. University of Chicago Press, 405-454.

Shaw, Edward. 1973. *Financial Deepening in Economic Development*. New York: Oxford
University Press.

Shin, Hyun Song. 2011. “Global Banking Glut and Loan Risk Premium”. IMF, *Economic Review,* **60**: 155-92.

Sims,Christopher A. 1980.“Macroeconomics and Reality”. Econometrica, *The Econometric Society,* **48**(1): 1-48.

Spindt, Paul A. 1985. “Money is what money does: Monetary aggregation and the equation of exchange”. *Journal of Political Economy,* **93**(February):175-204.

Stock, James, and Mark Watson. “Forecasting Inflation”. *Journal of Monetary Economics*, 293–335.

Stone, Courtenay C. and Daniel L. Thornton. “Solving the 1980s’ Velocity Puzzle: A Progress Report.” *Federal Reserve Bank of St. Louis Rex&xv 69* (August/September): S-23.

The Encyclopedia Britannica. 1911 . “*A dictionary of Arts, Sciences, Literature and General Information”.* Eleventh edition.

Thornton, Henry. 1802. *An Enquiry into the Nature and Effects of the Paper Credit of Great Britain.* Hatchard

Ueda, Kazuo. 1990. “Japanese capital outflows”. *Journal of Banking & Finance,* **14**(5): 1079-1101.

UK Central Statistical Office. 1968. CSO.

Vlaar P.2000. “Value at Risk Models for Dutch Bond Portfolios”. *Journal of Banking and Finance*, **24**: 1131-1154.

Werner, Richard A. 2012. "Towards a New Research Programme on ‘Banking and the Economy’- Implications of the Quantity Theory of Credit for the Prevention and Resolution of Banking and Debt Crises”. International Review of Financial Analysis, **25**: 94–105.

Werner, Richard A. 2005. *New paradigm in macroeconomics: Solving the Riddle of Japanese Macroeconomic Performance*. Palgrave Macmillan, Basingstoke.

Werner, Richard A..1997. "Towards a New Monetary Paradigm: A Quantity Theorem of Disaggregated Credit, with Evidence from Japan". *Berlin: Duncker & Humblot, Kredit und Kapital*, **30** (2): 276–309.

Werner, Richard A. 1994. ”Japanese Foreign Investment and the ‘Land Bubble’”. Review of International Economics, **2**: 166–178.

Werner, Richard A. 1992. "The Great Yen Illusion: Japanese Capital Flows and the Role of Land," Oxford Applied Economics Discussion Paper Series, Oxford: *Institute of Economics and Statistic*s, *University of Oxford*, N-129, December.

Wooldridge, Jeffrey M. 2008. *Introductory Econometrics: A modern approach, 4th Edition.* South-Western Cengage Learning.

World Bank. 2003. *World Development Indicators 2003*. Washington, DC .

Zhang, Kevin H. 2001. “How does foreign direct investment affect economic growth in China?”. *Economics of Transition,* **9**(3): 679-693.