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Lobbies Influence in Banking Regulation: A Machine Learning Approach to the Consultation Process

A Case Study on G-SIB Policy Evolution Through Natural Language Processing

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1 Introduction

In an increasingly interconnected world, systemic vulnerability in the global financial sector can no longer be ignored, as far as we are able to manage and contain global shocks, we have a duty to mantein a resilient and stable financial system.

While full control could not always be possible, especially in case of unpredictable shock, proactive regulation and risk mitigation remain essential to preventing systemic damage and averting financial contagion.

Specifically, a single crisis revealed not just the failure of specific bank but a systemic vulnerability whereby the strain on a single institution would engender failure cascades on a global scale. All this, essentially shifted our focus on financial regulation from safety on the individual bank level to stability on the system level.

But, who shapes the rules that govern the world's largest banks?

In 2011, the Basel Committee on Banking Supervision launched the Global Systemically Important Banks (G-SIB) model with the intention of creating a new paradigm for identifying and regulating institutions whose failure could threaten global financial stability. Behind the technical complexity of framework, there is a more fundamental issue: how the rules are written, debated, and agreed.

This thesis examines the dynamics of G-SIB standard regulatory influence employing Natural Language Processing techniques to find consultation documents' latent patterns.

The standard techniques for investigating the influence of regulation have applied proxies, numbers of meetings, personnel changes, or economic contributions. Here, we take a different path: the direct measurement of the stakeholder positions from the stakeholders' own words and a tracing of the combination of technical argumentation, emotional appeal, and institutional weight that comes together to shape the regulatory outcome.

Our findings challenge simplistic narratives of regulatory capture, rather than a usually dominance of powerful banks, we discover a more nuanced world in which influence comes through diverse channels. Private institutions exert greater influence than their public counterparts, but this influence is neither

absolute nor uniform. Instead, it reflects what we term "soft capture", a subtle alignment of regulatory outcomes with industry preferences that stops short of complete control.

Moreover, this methodological journey testifies the challenges of the application of machine intelligence to regulative documents: from the failed attempts in topic modeling with standard LDA methods to the successful application of transformer models and Natural Language Inference, we learned that regulative language demands specialized treatment. The documents' technical, formal nature defies the standard NLP solutions, requiring for unique solutions.

Building a Composite Influence Index, we present a unique quantitative framework for the calculation of multidimensional regulatory influence, an index that captures not just the alignment of stakeholders' preferences with outcomes but also the manner in which technical sophistication, engagement intensity, and convergence of opinion complement each other to generate possible influence.

The results describes pluralistic and not oligopolistic influence, a finding that testifies the success of the Basel Committee in obtaining some measure of regulatory autonomy while incorporating industry input.

The implications extend beyond the single consultation: as financial regulation increasingly relies on technical expertise and stakeholder input, understanding the mechanisms of influence becomes crucial for maintaining the delicate balance between industry knowledge and public utility. For this reason, the research aims to clarify the dynamic nature of international financial governance, where Basel Committee lacks of formal legal authority, yet its standards shape worldwide banking regulation, and understand how influence operates within this soft law framework, to evaluate the legitimacy and effectiveness of the instituion.

Here we find geographic and institutional variables matter, European banks demonstrate more critical engagement, American institutions show moderated negativity, while Asian stakeholders adopt more neutral tones, reflecting different regulatory cultures and strategic approaches.

Considering these premises, the central questions guiding this study are:

In which measure has lobbying impacted the development and evolution of the GSIB policy framework?

Specifically, to what degree do banks and other interest groups' arguments and representations expressed in public consultation process correspond to the final regulatory outcomes in the G-SIB framework?

These questions can be summarized in four hypothesis:

- **H1**: Negative sentiment in stakeholder submissions is associated with a higher likelihood of regulatory adjustment in the corresponding topic.
- **H2**: Private financial institutions exert a greater influence on final regulatory outcomes than public or academic stakeholders.
- **H3**: Financial institutions designated as GSIBs by the FSB following consultation rounds demonstrate higher regulatory influence and/or more negative sentiment than non-designated institutions during the consultation process.

Between standard regulatory analysis and computational method, this work reveals both possibility and limits of using AI to policy research. In particular, Natural Language Processing possesses the capability of revealing the patterns not perceivable by standard approach, of quantifying the qualitative judgments once dominant and usually prevailing, and of handling the vast amount of text information.

The scenario that emerges is neither one of pure capture or perfect independence, but rather a complex negotiation where multiple forces shape outcomes as they can.

In an era where the stability of the global financial system depends on getting the right regulations, where a minimum variation could affected the all system, make these dynamics visible and measurable is essential to understand who influences them and how.

2 Conceptualizing Systemic Risk in Finance

Historically the recognition of systemic risk has derived from the lessons learned during various financial crises, in relatively recent times the collapse of Lehman Brothers bank demonstrated how the failure of a single institution could trigger a global financial meltdown that could persist for years. Within few weeks AIG (American International Group), one of the biggest insurance company, required a 182 billion dollar bailout, Washington Mutual collapsed in the largest bank failure in US history, and credit markets froze globally, demonstrating how interconnectedness amplifies individual failures.

Also the Great Depression highlighted how failures among internationally engaged financial institutions can precipitate contagion effects that reverberate throughout the global economy.

These events emphasized the importance of systemic risk, a concept that despite its relevance still lacks of an universally accepted regulatory definition, however, a widespread formulation jointly promulgated by the IMF, BIS, and FSB defines systemic risk as *"a risk of disruption to financial services that is caused by an impairment of all or part of the financial system and has the potential to have serious negative consequences for the real economy"* (IMF, BIS, FSB, 2009).

Until 2008, the focus of regulation had been more on the safety of individual banks rather than on system stability overall, but 2008's shock triggered a paradigm shift towards macro-prudential regulation and other improvements included tighter consumer and investor protections, consolidated oversight structures, and enhanced financial stability surveillance.

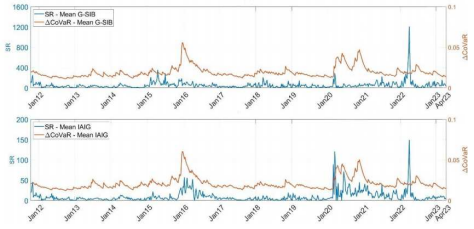
Governments and international authorities intensified the search for "too big to fail" institutions and the reduction of the adverse externalities their distress would bring, that is, regulators realized individual companies maximizing their own profits and do not take on the system costs of their possible failure. Without regulation, this tragedy of the commons[1] can end up producing socially suboptimal results.

[1]Risks to the commons financial system, are underestimated by the individual actors

2.1 Literature review

After these crises, there was a significant increase of academic studies focused on developing metrics that could capture what regulators had missed.
Recent systemic risk research on banks and insurers encompasses two primary areas: developing quantitative metrics to identify institutions which failure could threaten financial stability, and empirically examining the variables that drive systemic risk.
Within the first area, Benoit et al. (2015) and Ellis et al. (2022) focused on measures that aim to detect institutions' individual vulnerability (e.g.: Marginal Expected Shortfall-MES), contagion potential (e.g.: Conditional Value at Risk-CoVaR), and system-wide distress, noting that most existing tools emphasize firm-level rather than holistic system health. Aldasoro et al. (2018) extend this by offering macroprudential early warning indicators, demonstrating that granular credit metrics, such as household debt service ratios and foreign currency exposures, improve predictions of banking crises beyond conventional credit-GDP gaps.
Studies on return and volatility spillovers demonstrate how shocks propagate across sectors: Billio et al. (2012) employ Granger-causality networks to show that banks, insurers, hedge funds, and broker-dealers were increasingly interlinked before the 2008 crisis, amplifying systemic vulnerability, while for extreme-event analysis, Härdle et al. (2016) propose a tail event driven network model (TENET) that identifies key risk emitters and receivers by focusing on co-movements in the tails of loss distributions.
Building on this, Chen, Sun (2020) construct tail risk networks for global insurers, confirming that designated global systemically important insurers (G-SIIs) rank highest in systemic impact, though some non-designated firms occasionally exceed these levels. Finally, Sun (2023) further links insurers' systemic contributions to their positions within global value chains, underscoring how insurance firms' interconnectedness can transmit shocks across borders and sector.

Systemic Risk and CoVaR Trends for GSIBs and IAIGs



GSIBs and IAIGs' Systemic Risk with Major Financial Events

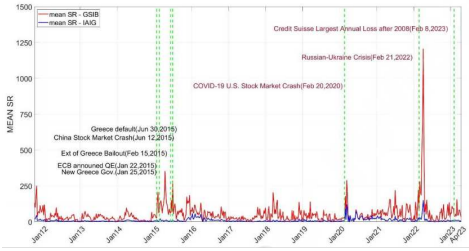


Figure 1: Source Sun T., "Systemic Risk of Systemically Important Financial Institutions in the Post-2008 Global Financial Crisis Era: A Tail Risk Network Approach", 2023.
Systemic Risk (SR) is a network-based metric derived using the Tail Event-driven Network model, this approach quantifies how much distress in one institution can potentially propagate to the rest of the system, focusing specifically on the risk of extreme (tail) events. It is calculated as the sum of two components
–SRE (Systemic Risk Emitting Index): how much systemic risk that institution conveys to others.
–SRR (Systemic Risk Receiving Index): how much systemic risk that institution receives from others.
The first figure presents the evolution of SR and CoVaR for Global Systemically Important Banks and Internationally Active Insurance Groups. Both indicators reveal distinct periods of increased risk, notably during the COVID-19 pandemic, the Russian-Ukrainian conflict, and other stress episodes, highlighting the synchronized vulnerabilities of banks and insurers.
The second figure compares the average SR for G-SIBs (in red) and IAIGs (in blue) over the same time period. These events include. The figure shows how SR responds dynamically to real-world events like the Greece default, the China Stock Market Crash, and the Credit Suisse crisis with banks and insurers often experiencing simultaneous surges in systemic risk, demonstrating the usefulness of the SR measure in capturing the time-varying and event-driven nature of financial system fragility.

The second research area strand empirically investigates systemic risk drivers and assesses macroprudential regulation outcomes, Weiß, Mühlnickel (2013) for instance, applied MES and CoVaR to U.S. banks and insurers, revealing that during the global financial crisis, large insurers engaging in bank-like activities showed similar vulnerability to systemic shocks as banks, primarily due to their size and involvement in non insurance operations.
Sun (2021) highlight that even some non Global Systemically Important Institutions can pose systemic threats comparable to G-SIIs, suggesting that regulatory designations may lag evolving risk profiles.
On the banking side, post-crisis reforms have reduced systemic risk: the International Monetary Fund (2018) and Adrian, Kiff, et al. (2018)

works observe benefits from improved capital, liquidity, and loss-absorbing capacities among banks, while Basel Committee on Banking Supervision (2022) finds that higher capital and lower leverage requirements under Basel III are correlate with reduced market-based systemic risk metrics, with the effect more pronounced for global systemically important banks (G-SIBs). Collectively, these studies converge on the view that *size, interconnectedness, substitutability, complexity, and correlatedness* are the key determinants. These correspond to the factors subsequently identified to recognize Global Systemically Important Banks (G-SIBs) under the Basel framework.

Network of major international banks before (a) and during (b) the peak of 2008 financial crisis

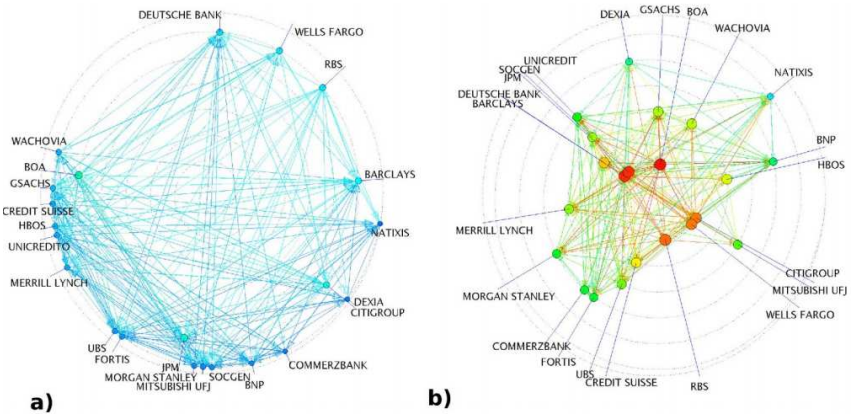


Figure 2: Source Battiston, S. et al., "DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk", 2012
Where each node identify a bank and the links represent credit exposures between them. In the early stage most banks have low systemic relevance and are located near the border, while during the crisis several banks become highly central (larger and redder nodes), meaning that a single default could trigger wide-reaching systemic consequences.

2.2 Evolution of the Basel G-SIB Regulatory Framework

The Global Systemically Important Bank (G-SIB) framework rappresent a response to the chaotic aftermath of the 2008 crisis, when under the G20's watchful eyes, the IMF, FSB, and BIS pooled their efforts to individuate exactly which institutions posed the greatest risk based on three core criteria: size, how irreplaceable a bank's services were (substitutability), and how deeply

intertwined each institution was with the others.

In late 2009, at the Pittsburgh Summit, G20 leaders were already pressing for more stringent control of any bank judged "too big to fail", charging the FSB with drafting concrete measures, stand out among them, heavier capital buffers for the globe's largest banks.

Following, in November 2010 at the Seoul Summit, G20 leaders asked to the Basel Committee's for identifying global SIFIs (Systemically Important Financial Institutions), and in mid-2011, the Basel Committee released a consultative document for a transparent indicator-based methodology.

Following public comment, the Committee published *"Global Systemically Important Banks: Assessment Methodology and the Additional Loss Absorbency Requirement"* (BCBS 207) while the FSB at the same time released initial list of 29 G-SIBs. They exposed a suggested capital surcharges ranging from 1 to 2.5 percent of risk-weighted assets (a deterrent bucket of 3.5 percent was set aside to use at the time it became applicable), with an implementation phase started in 2016 until 2019, subject to rescoring every year.

From 2012 to 2015, the framework was further developed: the BCBS finalized normalization of indicator denominators, capped selected measures so no one alone would run the score of a bank, and started requiring public disclosure of indicator values.

The FSB finalized the Total Loss Absorbing Capacity requirement in November 2015, requiring G-SIBs to hold a minimum amount of long-term debt and equity to absorb losses at resolution, reducing the use of taxpayer bailouts.

Specifically, they created their capital buffers starting from January 2016[2], with related BCBS' empirical analysis proven higher buffers have enhanced resilience, reflected through greater loss-absorbing ability and reduced leverage.

Lastly, in July 2018, the Basel Committee released a revised measure approach with some improvements for more precision and transparency, among the changes there were adjustments to cross-jurisdictional indicator definitions (aligning with BIS consolidated stats), an added measure, a trading volume indicator in the substitutability group, and expansion of consolidation scope to include insurance subsidiaries in some of the selected measures.

[2]The 2% surcharge was phased in over four years: it started at 0.5% in 2016 and then increased by 0.5 percentage points each year, reaching the full 2% by 2019

Regarding implementation by individual states, within the *"EU the Capital Requirements Directive IV"* and *"Capital Requirements Regulation"* implemented G-SII buffers, while the Federal Reserve's 2015 *"Method 2"* required the United States to utilize the combination of the Basel indicator score with an alternative weighting to reflect short-term wholesale funding dependence, taking the higher surcharge of the two. Other jurisdictions (e.g., UK, Switzerland) added further, national Systemic Important Banks buffers on top of the Basel minima.

2.3 Measuring Systemic Importance: An Indicator-Based Methodology and Alternatives

The Basel G-SIB framework relies on an indicator-based methodology that captures multiple dimensions of systemic footprint rather than a single metric. Twelve quantitative indicators are grouped into five equally weighted categories: Size, Interconnectedness, Substitutability (Financial Infrastructure), Complexity, and Cross-Jurisdictional Activity.

GSIB's Indicators

Category (and weighting)	**Individual indicator**	**Indicator weighting**
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the Basel III leverage ratio*	20%
Interconnectedness (20%)	Intra-financial system assets*	6.67%
	Intra-financial system liabilities*	6.67%
	Securities outstanding*	6.67%
Substitutability/financial institution infrastructure (20%)	Assets under custody	6.67%
	Payments activity	6.67%
	Underwritten transactions in debt and equity markets	3.33%
	Trading volume	3.33%
Complexity (20%)	Notional amount of OTC derivatives*	6.67%
	Level 3 assets*	6.67%
	Trading and available-for-sale securities	6.67%
*Extended scope of consolidation to include insurance activities.		

Figure 3: Source Basel Committee on Banking Supervision, "Global systemically important banks: revised assessment methodology and the higher loss absorbency requirement", July 2018

Each bank's reported values for these indicators are normalized by dividing by the aggregate across all banks in the sample (typically the top 75 globally) to produce a score in basis points.

For instance, if Bank A's total exposures represent 5 percent of the sample's total exposures, it receives 500 bps for the size indicator. Category scores are computed as the average of their constituent indicators (with certain caps, e.g., Substitutability is capped so that a single outsized activity cannot dominate), and the overall systemic importance score is the average of the five category scores.

Banks with scores above defined thresholds (currently starting at 130 basis points) are designated as G-SIBs and assigned to capital surcharge buckets accordingly:

130–229 bps = Bucket 1 (1.0 percent surcharge)

230–329 bps = Bucket 2 (1.5 percent)

330–429 bps = Bucket 3 (2.0 percent)

430–529 bps = Bucket 4 (2.5 percent)

with scores at or above 530 bps reserved for the empty top bucket carrying a 3.5 percent surcharge as a disincentive.

This rules-based, transparent system provides banks with clear incentives: they may adjust or decrease their score, and therefore their surcharge, by changing those activities rendering them higher indicators (e.g., decreasing exposures, curtailing thinly substituted business).

Although the G-SIB framework represents a significant step in systemic risk containment, its development and implementation have sparked intense debates, critics and researchers argue that the regulation exemplify the problems and for this reason they suggest alternatives and emphasized potential limitations.

Market-Based Indicator:

Measures already well known as including:

- Change in Conditional Value at Risk (Adrian, Brunnermeier, 2011):

$$\Delta\text{CoVaR}^i_\alpha = \text{CoVaR}_\alpha\big(R_{\text{system}} \mid R_i = \text{VaR}^i_\alpha\big) - \text{CoVaR}_\alpha\big(R_{\text{system}} \mid R_i = \text{VaR}^i_{0.5}\big)$$ [3]

[3] **Elements**: R_i = returns of institution i; R_{system} = returns of the financial system; VaR^i_α = α-quantile of R_i; $\text{CoVaR}_\alpha(\cdot \mid \cdot)$ = α-level VaR of R_{system} conditional on a given state of R_i.

Defined as difference between the system's Value-at-Risk conditional on institution i being at its α-quantile VaR and the system's VaR when i is in its median state, it quantifies the marginal contribution of institution i to downside risk in the system.

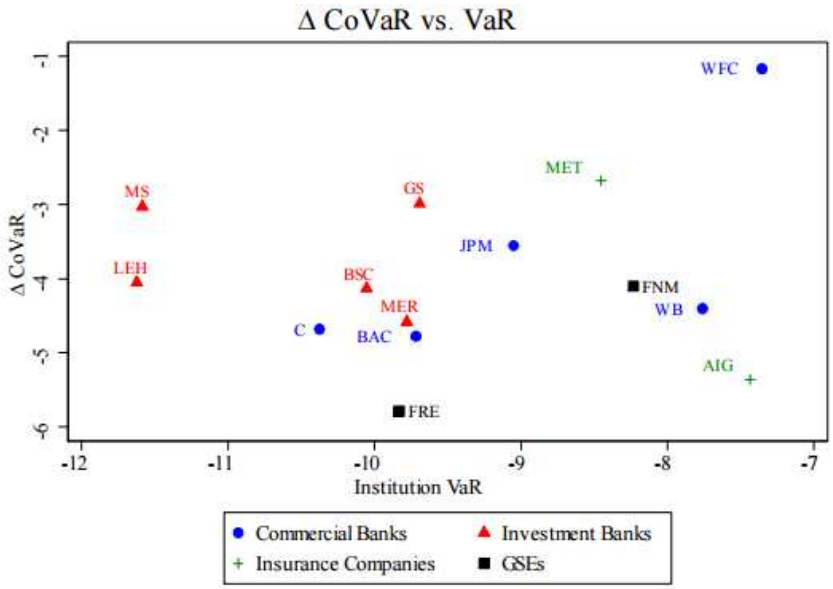


Figure 4: Source Adrian T.et al., "CoVaR", 2011
Relationship between institutions' individual Value at Risk (VaR) and their systemic risk contributions, measured by CoVaR variation for investment banks (red triangles), commercial banks (blue circles), insurance companies (green crosses), and government enterprises (black squares). The absence of a strong linear relationship indicates that institutions' individual risk, as measured by VaR, does not necessarily reflect their systemic importance. For example, institutions such as Lehman Brothers (LEH), despite showing a higher individual VaR, present lower systemic contributions compared to commercial banks like Wells Fargo (WFC), highlighting that systemic relevance depends significantly on factors beyond standalone risk. This proves the necessity to incorporate systemic metrics like CoVaR for a more robust assessment.

•Systemic Expected Shortfall (Acharya et al., 2010):

$$\mathrm{SES}^i_\alpha = \mathbb{E}\big[-R_i \;\big|\; R_{\text{system}} \leq \mathrm{VaR}_\alpha(R_{\text{system}})\big]^4$$

Rappresenting the expected loss of institution i conditional on the system return falling below its α-quantile VaR, it captures how severely i undercapitalizes during systemic crises.

[4]**Elements**: $-R_i$ = loss of institution i; R_{system} = system returns; $\mathrm{VaR}_\alpha(R_{\text{system}})$ = α-quantile of R_{system}.

•Distress Insurance Premium (Huang et al., 2009):

$$\mathrm{DIP}_\alpha = \mathbb{E}^{\mathbb{Q}}\big[-R_{\text{system}} \;\big|\; R_{\text{system}} \leq \mathrm{VaR}_\alpha(R_{\text{system}})\big]^5$$

Equal to the risk-neutral expected loss of the financial system conditional on returns falling below the α-quantile VaR, and Represents the premium (per unit of exposure) required to insure against extreme, system-wide losses.

They utilize market information to estimate the marginal contribution to system risk of a given firm, with a forward looking perspective and may reflect shifting risk views but are generally volatile and opaque. For instance, an ECB study reported that rankings using the ΔCoVaR compared to the Basel indicator scores were highly disturbed by noise and concluded instead that while valuable to use as a complement, the ΔCoVaR would not be an appropriate stand-alone policy index (Busch et al., 2016).

Robust Ranking and Clustering Models: Robust ranking and clustering models seek to find systemically important banks not only by size, but by their position in the financial networks. A proposal for a ranking scheme is based on shock transmission via interbank exposures by Sadoghi (2015), while Battiston et al. (2012) proposed the "DebtRank", an index based on FED emergency loans and linked equity holdings, that proved how also a small shock could trigger the entire system.

While Cerqueti et al. (2020) gave empirical result of the use of higher-order clustering, allowing the analysis of the network's structure at different levels of depth to find tightly linked groups susceptible in a shared way to common shock. These models give a more accurate picture of systemic fragility, highlighting how risk accumulates via unobserved pockets in the network.

However, they are based on informations that are not common and are computationally demanding, consequentaly difficult to apply.

[5] **Elements**: $-R_{\text{system}}$ = system loss; $\mathbb{Q}$ = risk-neutral probability measure; $\mathrm{VaR}_\alpha(R_{\text{system}})$ = α-quantile of system returns.

Network-Based Stress Simulations: The International Monetary Fund (2010) put forward the proposal of calculating a "systemic risk-based capital surcharge" through hypothetically defaulting all banks and simulating contagion of losses across the network. Similar to Allen, Gale (2000) studies, where they demonstrated theoretically that a interbank liquidity network improve brings benefits by risk-sharing among the sector, on the other hand, it increases drastically the risk of a major shock spreading, instead of incomplete network.

While theoretically accurate, this method requires granular, proprietary information and complex models, therefore challenging to use beyond central banks' own stress tests.

Merton–Shapley Framework: The Merton–Shapley approach merges structural models of default with cooperative game theory in order to assign systematic risk to institutions. In this case the contribution of every bank is calculated in accordance with its standalone risk and the way that it interacts with other banks during stress.The process is worthwhile in that both individual and collective vulnerabilities are addressed in a unified manner.

Nonetheless, it demanding in application extensive detail in the form of balance sheet information and important computing capacity in an effort to capture asset behavior and compute Shapley values.

Agent-Based Models (ABM): Agent-based models simulate banks as active decisionmakers who respond to economic shocks in a dynamic and timely manner. They are able to capture rich and dynamic interactions such as hoarding, fire sales, or panic withdrawals that are able to amplify a local shock into a broad-based crisis.

In particular, their greatest strength is in uncovering non-linear feedback effects and emergent behavior that mainstream models are not able to catch. However, they need rich behavioral assumptions, extensive datasets, and powerful hardware. In all their complexity, they offer a dynamic, bottom-up view of systemic risk that is commensurate with the complexity in the real finance system (Squazzoni et al., 2014).

In general, compared to alternatives, the Basel indicator-based method is a pragmatic solution: it strikes an equilibrium between transparency and comparability and the intricacy of more adaptive approaches. Although it has critics, its rules-based structure, annual re-scoring, and precisely defined buckets have rendered it the bedrock for the identification and calibration of the world's systemically important banks' capital buffers.

2.4 Critical views and debates surrounding the G-SIB framework

Despite the G-SIB framework's universal consensus of mitigate systemic risk, it has attracted various critiques ranging from political economy analysis to arguments around the legitimacy of global governance.

Regulatory Capture and Industry Influence: At the heart of the critique there is the question of whether industry lobbying weakened the framework. As seen, the public choice theory posits that complicated rules in concentrated industries provide fertile soil for regulatory capture. Banks can use lobbying influence to shape regulatory details, with evidence from Young (2012) studies. Moreover Quaglia (2017) argue that international standard authorities like BIS lack of direct responsability mechanisms typical of democratic systems, such as media scrutiny and electoral mandates, and this leads to greater potential for influence, as the regulator has a sense of less responsability. Although it depends case by case, Hardy (2006) posited that banks would support tighter rules if they limit risk-taking among weaker peers endangering system safety and soundness, while Schuknecht, Siegerink (2020) contend post-crisis reforms generally advanced despite industry resistance, facilitated through the G20's political in which elected authorities, backed by political legitimacy, introduce stricter regulations despite opposition from the financial industr. However, many scholars cite examples of banks lobbying to ease proposals, such as tweaking risk-weighted asset calculations, postponing phase-in, or calibrating G-SIB surcharges to moderate levels, reflective of "soft

capture" through technical consultations as we will see in the in the next chapter.

Effectiveness and unwanted side effects: There is disagreement among scientific literature on whether G-SIB designation and surcharges actually lower the risk of systemically important institutions or merely redistribute it.

Declaring a bank "systemic" and charging it higher capital may send the opposite message to markets, with an "implicit subsidy" from the national authorities, increasing moral hazard, like an halo effect. Then, another risk is competitive forces: higher surcharges increase the costs to big banks, may slower an excessive growth and may drive certain risky business, such as market making or trading, into the lower regulated channels (for example: non-bank liquidity providers), perhaps adding to system wide vulnerability.

As such, there are proponents who are in favor for the use of activity-based regulation, taking action against risky functions wherever they are performed rather than entity-based buffers. Indeed, regulators in the United States in 2019 flipped from concentrating on specific firms to focusing on risky functions (such as leveraged lending or money-market funds) and found the entity-based system too cumbersome and litigious (Financial Stability Oversight Council, 2019).

Classification Efficacy vs. Dynamic Assessment: Another debate is whether a static list of G-SIBs reviewed yearly, is sufficiently to identify the entire systemic risk's sector.

Skeptics say it may be inaccurate: risk significance can differ across scenarios, so a "one size fits all" label may overlook new threats (e.g., medium-sized bank with large concentrations of exposure to a volatile asset class).

As seen, stress-test based indicator try to calibrate scenario-specific risks, whereas G-SIB classifications are scenario-invariant, but defenders respond that the indicator method picks up structurally important institutions with relatively stable system footprints and other measures, countercyclical buffers, sectoral buffers, supervisory stress testing on a regular basis,

remedy dynamic risk exposures.

Global Governance and Equity: Another criticism targets the representativeness and legitimacy of G-SIB rule-making: The Basel Committee and FSB, while supplemented, are dominated by main large economies and those from emerging markets have reduced influence. Initial G-SIB lists had heavy Western bias, although, now several Chinese and at least one Brazilian bank have been included on the list, moreover, the FSB and BCBS have become more transparent, publishing methodologies, data, and draft proposals subject to public comment, yet technical consultations are dominated by those who have the capacity to participate, typically large banks and industry associations.

These critiques highlight the prospect of the following adjustments that remain essential to continuously find the right balance between transparency, effectiveness, and equity. Empirical evidence on the G-SIB framework's effectiveness show that the introduction of bucket thresholds and surcharges raised capital buffers and may have lowered banks' systemically contributory behavior without causing them too much disruption to their credit provision, however the true effectiveness of the system will be tested in times of crisis.

3 Evolution and Theoretical Models of Regulatory Capture

The relationship between regulators and the industries they oversee has long been a subject of scholarly concern.

This phenomenon, known as regulatory capture, has been described as a process by which regulatory bodies, instead of acting impartially in favor of the public good, end up serving the regulated industries' interests and developing sympathy, if not actually loyalty, towards the regulated industries.

According to the literature, an early theory was proposed by Wilson (1911): public administrators risk to fall under the influence of politicized interests to the point of losing their impartiality, with administrative organizations that can be taken over by dominant constituencies.

Building on this foundation, Bernstein (1955) also advanced a "life cycle" of regulatory commissions, where reaching "old age", regulatory bodies deteriorate into submission to the regulated sector.

Both Wilson and Bernstein, established the basis to see capture as being more than the product of corruption, but as institutional and social developments determined by relations of power and influence.

First of all, an important distinction must be done, Dal Bò (2006) in his work asserts that there are two different ways to interpret the regulatory capture's process: in a larger sense, capture refers to the whole process by which interest organizations influence government policy in a variety of fields, resulting in laws or public policies that ultimately benefit those groups, while the restricted definition of capture, on the other hand, describes circumstances in which a regulated corporation or monopoly exerts excessive control over the institution charged with monitoring it, so influencing regulatory decisions to suit its own interests.

The main difference between these two views is their scope: the narrow perspective concentrates on the direct subversion of a regulatory body by the companies it is intended to regulate, whereas the wide view covers any instance of interest-group influence on policymaking. What we are going to analyze refers to a targeted and precise capture.

In "The Theory of Economic Regulation" Stigler (1971) proposed that concentrated interest groups, industry organizations or firms, have greater incentives and abilities to lobby regulatory officials compared to dispersed consumer or voter groups, and, regulatory authorities end up implementing policies favorable to such groups.

This economic framework was further refined by Becker (1983) who constructed an equilibrium model (based on Cournot-Nash) competition between pressure groups, showing that the most highly organized and resource-spending group usually ends to get the most favorable regulatory policy position, particularly regarding taxes and subsidies.

Rather, where explicit monetary exchange is not involved, the informational superior position becomes leverage, as regulators are unable to verify technically every assertion on their own, for example companies produce incomplete or biased information, and regulators, with few or any validating methods, are forced to rely on industry-provided analysis.

Continuing, Laffont, Tirole (1991) in their article "The Politics of Government Decision Making: A Theory of Regulatory Capture" demonstrated how firms through possession of superior technical information, can manipulate regulators who rely on industry data to design rules. A kind of sophistication, as defined by Hakenes, Schnabel (2014), who explored how product complexity overmatched regulators' capacity to push back against industry interests, producing a kind of "soft capture" advantageous to large, sophisticated banks. Information capture, therefore, may constitute a more dangerous and difficult mechanism than simple economic-money regulatory capture, an evident example is in pre-2008 banking regulation, when the major banks provided own risk models to be used in Basel II implementation.

Obviously, critics complained that the use of their internal models to determine capital needs created hazardous incentives: banks could report risks as lower in order to reduce capital buffers,but many of those were too complicated to be properly contested.

Finally, cognitive or cultural capture has also been emphasized by scholars. Kwak (2014) explained how the ideologically aligned regulators end up becoming like the very industry that they regulate, going to the same

conference, hiring the same professional networks, and internalizing industry norms, starting to "think like" industry. As theoretically confirmed by Carpenter (2013), regulatory professional identities and networks produce an "epistemic community" dominated by industry players.

3.1 Empirical Evidence of Capture in North America and European Union

Regulatory capture has been empirically documented on both sides of the Atlantic, revealing how industry influence can skew policy outcomes in diverse institutional settings.

The International Monetary Fund's working paper by Igan, Lambert (2019) summarized four of their studies about lobbying disclosures to determine whether higher pre-crisis risk exposures among banks led to more intensive lobbying to weaken mortgage regulations, and econometric analysis revealed a positive association between lobbying expenditures and regulatory dilution, identifiable with capture.

Moreover, J. W. Yackee, S. W. Yackee (2006) discovered in larger-scale U.S. rulemakings that agencies tend to revise proposals toward the most active commenters' preferred direction.

Continuing, recent Canadian studies reinforce this pattern, of fifty regulatory amendments reviewed, only four exhibited substantive textual revisions after public consultation, and in all them those changes aligned exclusively with industry feedback (Beaulieu-Guay et al., 2021).

Such results illustrate that, even under well-intentioned procedural frameworks with open consultation, industry actors overwhelmingly shape regulatory details, while single entities opinion rarely translate into effectve modifications.

On the other side, in the European Union, prior to 2008 the qualitative analysis by Tsingou (2008) identified how private sector participants, particularly large multinational banks, participated as co-authors of Basel II rules: through the Institute of International Finance (IIF) and industry organizations, played a deep role in technical drafting, creating risk-weighted capital requirements that numerous critics feel were too soft and influencing the

internal ratings-based method.

Nevertheless, Redert (2022) performed network analysis on EU regulatory consultation and established that, before 2008, a unified "club" of bank lobbies dominated the discussion, which has been associated with more industry-friendly or self-regulatory approaches. After 2008, the consultation network expanded ("from clubs to hubs"), where more non-banks, including consumer organizations and non-financial companies, had the opportunity to contribute, which, according to the research, may have contributed to the emergence of more stringent initial proposals on capital and liquidity requirements.

However, in response, post-crisis reforms tried to contain and counter the phenomenon with a more stringent supervision like CRD IV (banks' capital directive), MiFID II (regulation of markets), and the creation of new authorities like the European Banking Authority (EBA) and the European Securities and Markets Authority (ESMA).

Additionally, Pagliari, Young (2014) reported on how European and international banks created alliances to contrast the Basel III framework. They show that industry arguments about harming credit availability or competitiveness found be take in account among regulators and certain member state governments, leading to compromises for less stringent calculations of the liquidity coverage ratio and more favorable transitional timing.

Moreover, researchers provide evidence that geographic proximity may affect bank's regulation, with a consequent effort by lobbyists to reduce supervisory pressure: Berninger et al. (2018) analyzed the market reactions when the European Banking Authority relocated from London to Paris and the European Medicines Agency moved to Amsterdam.

In order to do it, the authors take two complementary measures: first the actual distance in kilometers between each bank's home country's financial center and the new Paris site of the EBA, as a continuous variable in the regressions; second, use a binary variable that determines if a bank has its headquarters in France, the home country of the transferred authority.

Their findings reveal that French banks experienced significant negative

abnormal returns of approximately 2.39% around the relocation announcement, while other european banks showed no significant market reaction.

This pattern suggests that financial markets perceive geographic proximity to regulatory authorities as disadvantageous for supervised institutions, supporting theoretical predictions that closer oversight leads to more intensive and cost-effective monitoring.

The findings align with broader capture theory by suggesting that when regulators can more easily and affordably investigate proximate firms, the resulting intensified oversight creates institutional disadvantages that outweigh any potential benefits seen previously as information access or cognitive capture.

Finally but notably, A. W. Chalmers et al. (2021) analyzed patterns and case of high-level EU and domestic regulators transitioning into banking industry roles, describing how such flows of personnel build dense social networks and raising concerns about regulatory capture or independence.

Specifically, by tracking about 200 senior officials who represented the European Banking Authority, European Securities and Markets Authority, and European Insurance and Occupational Pensions Authority, the authors show that such revolving door movements are not isolated but regular and systematic practice, with close to 40% involving two or more transitions between public and private sectors.

The datasetis builded using public available sources, however, they choose to anonymize the data for ethical and privacy reasons, in order to avoid individual accusation and highlight the systemic patterns.

As evidence of this phenomenon, in 2019, the EBA Executive Director left to become head of the Association for Financial Markets in Europe (AFME), which bring to an EU Ombudsman investigation for conflict of interest risks that defined the situation as an example of "revolving door" problems.

In addition, in 2016, the president of the European Commission moved to Goldman Sachs International as nonexecutive chairman just two months later the end of his cooling-off period [6], raising debates about the independence of

[6]Mandatory time period during which former public or regulatory officials may not accept positions in the private sector

European institutions.

These career patterns enable the accumulation of sector specific human and social capital, like knowledge about the process of regulation, in addition to insiders network.

3.2 Standards, G-SIB Regulation and Consultative Dynamics

The Basel Committee on Banking Supervision is the major international banking regulator, founded in an attempt to stabilize international finance after Bankhaus Herstatt's failure in Germany in 1974. Without a formal legal personality and composed of mostly unelected individuals (chiefly central bankers and national supervisors of the world's richest countries), the BCBS's standards and regulations possess a quite broad influence on global governance of finance.

In fact, Basel is today employed by a variety of international agencies, notably the World Bank and IMF, to determine the soundness of finance in emerging and developing economies.

Following the crisis, Basel III exposed significantly tougher requirements: increased common equity Tier 1, leverage, and liquidity coverage requirements, along with establishing the framework to determine Global Systemically Important Banks (G-SIBs) to be subjected to higher capital charges. The BCBS and the Financial Stability Board (FSB) jointly released, in July 2011, a consultative document on the G-SIB approach, setting out size, interconnectedness, substitutability, complexity and cross-jurisdictional activity as the indicators of systemic significance [7].

About that, the FSB reported 28 consultation responses received and only three from non-industry sources. As previously seen, this level of feedback may demonstrates an informational and cognitive capture: by presenting elaborate quantitative impact studies and competing indicator formulas, banks can used their technical competence to shape the end calibration.

Industry lobbies, for instance, contended that the initial suggestion of a

[7] Consultative Document: Global systemically important banks: Assessment methodology and the additional loss absorbency requirement

maximum 3.5% surcharge over risk-weighted assets would reduce lending, producing data analysis to show how 3.5% could cut GDP growth by as much as 0.3%. In the end, Regulators settled on 2.5% as the maximum, saving the 3.5% bucket as a deterrent but applying it to no bank in the initial cut.

Although the reasons may be other, this convergence with industry's original position means industry feedback played a significant role in determining the result, and may be subject to further research.

Moreover, technical debates about indicators such as "substitutability", for instance how to measure a bank's role in payment services, resulted in adjustments that tended to reduce European banks' scores relative to U.S. counterparts, in particular, The European Banking Federation submitted feedback comment where data showing that European clearinghouses were underrepresented in the proposed metric, potentially inflating European banks' systemic importance.

The final framework incorporated modifications that reduced surcharge values for certain European banks, and represent an example of how regulators may not having equivalent data baselines, were dependent on bank submissions, creating asymmetries.

Furthermore, the very systemic significance (too big to fail) of specific institutions forces regulators to favor stability instead of stringent parameters, causing regulatory accommodation due to fears of destabilizing the finance sector (Haldane, 2010), the very embodiment of hidden capture.

In response to the stricter regulation, financial institutions have demonstrated incredible adaptability in reacting to regulatory signals, practicing "regulatory arbitrage" through moving activities to less regulated areas or finance sectors (i.e., relocating proprietary trading within hedge funds or private equity), or "shadow banking".

These kinds of responses indicate that capture can be found beyond actual amendment of formal rules into strategic business relocation, without violating new rules technically (Adrian, Ashcraft, 2012).

An interesting case of banks adaptation came up with "window-dressing" phenomenon: at the end of the year, when data for determining Global Systemically Important Banks (G-SIB) was collected, banks would lower their

values to escape higher capital requirements. This practice became so common that in 2018-2019, the Basel Committee (Behn et al., 2019) suggested changes to tackle it, using average data rather than just end-year data.

In synthesis, the G-SIB framework's elaboration and improvement reveal the tension between regulators' attempts to improve systemic stability and industry's attempts to ensure profitability.

With multi-round talks under which banks provide confidential data, challenge indicator definitions, and lobby member states, capture takes shape in subtle forms.

The outcome is a modern and adapting framework that, although stronger than its older, carries industry influence in several aspects: standard's calibration , data aggregation rules, definitions of systemic significance, and requirements for reporting.

The mechanisms of regulatory capture are various: economic, cognitive or cultural, informational and structural. Using consultation documents to examine mobilization patterns and lobbying influence has become common practice in scholarly research, likely due to the fact that consultation data are commonly readily available online and easy to access, they just need to be manipuleted in order to extract information.

3.3 Methodological Challenges and Counter Example: When Systemic Importance Leads to Stricter Regulation

After all empirical evidence regarding regulatory capture, it is important to point out that deeper methodological challenges in detecting influence relationships, particularly in complex institutional environments, reflect a deeper problem of identifying regulatory capture.

As Lowery (2013) observes, influence research consistently encounters a fundamental paradox: despite widespread assumptions about the power of organized interests, empirical studies frequently fail to find clear evidence of influence. Much of what constitutes meaningful influence in regulatory settings operates through what Lowery calls "anticipated reactions", where

regulatory decisions are shaped by expectations of industry responses before any observable interaction occurs.

In complex institutional settings with multiple decision points, regulators may adjust their positions in anticipation not only of immediate industry feedback but also of reactions from subsequent review stages, other agencies, or political oversight bodies.

This creates a web of anticipatory behavior that renders traditional measurements of influence inadequate for capturing the full scope of industry impact on regulatory outcomes. In fact, when regulatory proposals pass through multiple stages of review, consultation, and revision, influence exercised at early stages may be invisible by the time final decisions are observed.

The improvement of contemporary consultation processes, designed to enhance transparency, may paradoxically obscure influence by distributing it across different interaction points and making it difficult to track causal relationships between industry input and regulatory outcomes.

Furthermore, not all post-crisis regulatory innovations have fallen to capture dynamics, in particular a counter-example emerges from the implementation of bank stress testing in the United States, which represents one of the most significant regulatory innovations following the 2008 financial crisis. Schneider et al. (2020) conducted a systematic empirical examination of whether measures of potential influence affected stress test outcomes, focusing on the largest trading banks, precisely those institutions most likely to possess both the motivation and capability to influence regulatory decisions.

Their findings directly contradict what regulatory capture theory would predict: rather than receiving preferential treatment, the largest "Too Big to Fail" banks actually faced the most stringent stress tests. The researchers documented that these systemically important banks experienced capital ratio declines that were from two to three percentage points larger than other banks during stress testing scenarios.

The authors tested three distinct pathways through which banks might exercise regulatory influence: direct regulatory connections through executives serving on Federal Reserve Bank boards, political contributions and lobbying

expenditures, and systemic importance itself.

These results suggest that regulators, rather than being captured by the most powerful bank players, actually intensified oversight of those institutions whose failure would impose the greatest costs on the financial system.

Surprisingly, only systemic importance correlated with regulatory treatment - and in the direction opposite to what capture theory would predict.

4 Machine Learning and Natural Language Processing in Policy Analysis

Artificial intelligence has revolutionized data processing and analysis by allowing computers to learn from samples and generate predictions autonomously, without explicit programming.

Machine Learning is a subset of AI that emphasizes the creation of algorithms proficient in recognizing patterns from data and executing predictions or decisions with minimal human involvement, enabling systems to enhance performance over time through experience, thereby serving as a crucial instrument in data-driven analysis.

This, as it evolved, led to Deep Learning, a category of algorithms founded on artificial neural networks with numerous layers, adept in capturing hierarchical and abstract representations of data.

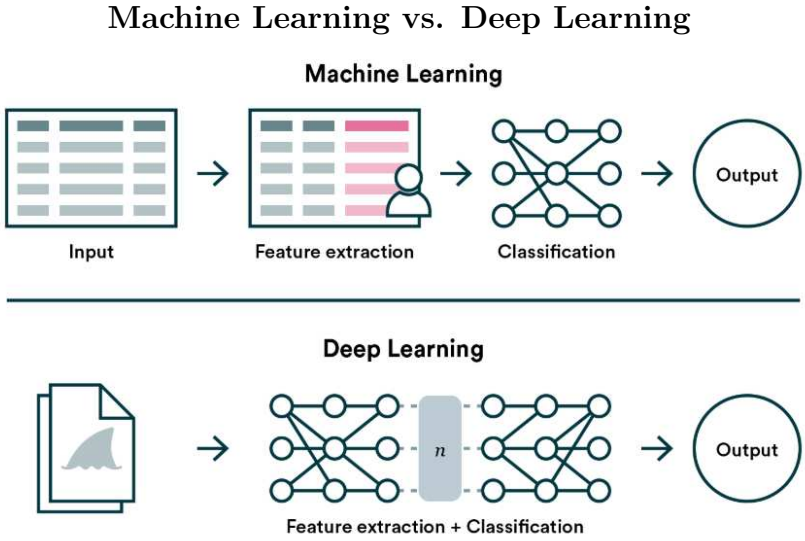


Figure 5: In traditional machine learning, feature extraction is performed manually before classification, while in deep learning it is integreted with classification and automated within the layers of the neural network.

These models have demonstrated outstanding efficacy in intricate tasks including image recognition, audio processing, and, importantly, text analysis. Nonetheless, these methodologies showed significant limitations in comprehending human meaning and context, obstacles overcome with the development of Natural Language Processing, a discipline that intersects

linguistics, computer science, and machine learning, concentrating on empowering machines to comprehend, produce, and deduce human language, depended on conventional linguistic rules, lexicons, and statistical models.
The use of Natural Language Processing has significantly advanced both ML and DL, improved deep neural networks, especially those utilized in NLP.

4.1 Overview of NLP Tools and Models

There are different NLP tools which could be used, based on approaches and levels of abstraction: while some focus on create foundational word representations, others provide complete frameworks for text analysis, and the most advanced offer contextual understanding abilities.

Table 1: Comparison of NLP Tools and Models

Name	**What is it?**	**Resource Type**	**Level**
spaCy	Complete NLP library	Python Library	Advanced: NLP suite
Word2Vec	Algorithm for word embeddings	Model	Basic: words only
GloVe	Algorithm + pre-trained embeddings	Model + Dataset	Basic: words only
BERT	Transformer model	Pre-trained Model	Advanced: context

At the base we find *SpaCy*, a comprehensive NLP library that provides an integrated pipeline for text processing, including tokenization, named entity recognition, and dependency parsing. It can incorporate various embedding models, including Word2Vec, GloVe, and transformer-based models, making it one of the most common library used.

4.2 Word Embeddings: From Words to Vectors

Classical methods represented words as isolated symbols, but word embeddings transformed this into representations where words are projected in continuous vector spaces in which semantic similarity corresponds to geometric proximity.
Two approaches emerged to answer this challenge:

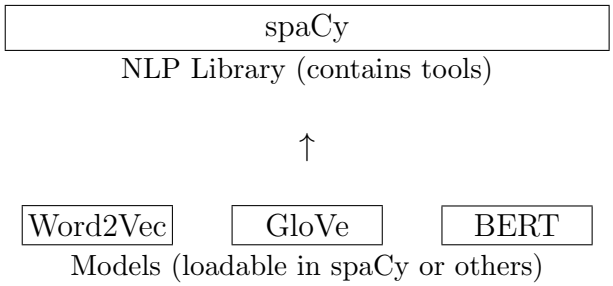


Figure 6: Hierarchical relationship between NLP tools and models

Word2Vec proposed two architectures that acquire word representations by learning context prediction, in particular the first is the Skip-gram model, wichi given a target word, tries predicting its context words surrounding it in a window with size c:

$$J(\theta) = \frac{1}{T}\sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j}|w_t)^{8}$$

This equation essentially learning word rappresentations that preserve semantic structures with patterns of co-occurrence in large textual databases. The probability is calculated with a softmax function:

$$p(w_o|w_i) = \frac{\exp(v_{w_o}^T v_{w_i})}{\sum_{w=1}^{W} \exp(v_w^T v_{w_i})}^{9}$$

It guarantees that probabilities sum to one over the whole vocabulary, with higher dot products between word vectors implying higher co-occurrence probabilities.

The second *Word2Vec* model is Global Vectors, that adopts an alternative approach, merging the advantages of global matrix factorization with window methods involving local context.

[8]Elements: w_t = target word at position t in the sequence; c = context window size, typically ranging from 2 to 10; θ = model parameters including all word embeddings; T = total number of words in the training corpus; j = relative position offset from the target word, excluding $j = 0$ to avoid predicting the word from itself.

[9]Elements: v_{w_o} = output vector representation of context word w_o; v_{w_i} = input vector representation of target word w_i; W = vocabulary size.

It creates a word co-occurrence matrix and optimizes:

$$J = \sum_{i,j=1}^{V} f(X_{ij})(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij})^2$$ [10]

It reduces the loss between the dot product of word vectors and the logarithm of the word's co-occurrence probability, essentially embedding global corpus statistics into the vector representations.

What makes these embeddings exceptional is the ability to capture semantic relationships through vector arithmetic, the famous example used is: $\vec{king} - \vec{man} + \vec{woman} \approx \vec{queen}$, that demonstrates how these models encode conceptual relationships in geometric space.

4.3 The Transformer Revolution

Although word embeddings had given powerful representations, they could not understand context dependent meanings, for example the word "bank" has a different meaning when it appears in "river bank" than when it appears in "savings bank." This limit lead to contextual models, and the Transformer architecture has become the foundation of current NLP.

The Transformer's strong is its *self-attention mechanism* where every word has the ability to pay attention to every other word in the sequence at once. Specifically, for an input sequence, three matrices are calculated by the model: Query (Q), Key (K), and Value (V), each coming from the input embeddings via learned linear transformations.

The attention weights are calculated as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V$$ [11]

[10] Elements: V = vocabulary size; X_{ij} = number of times word i appears in the context of word j across the entire corpus; $f(X_{ij})$ = weighting function that prevents very frequent co-occurrences from dominating the loss; w_i = main word vector for word i; $\tilde{w}_j$ = context vector for word j; b_i, $\tilde{b}_j$ = scalar bias terms for words i and j respectively.

[11] Elements: $Q = XW^Q$ = query matrix used to search for relevant information; $K = XW^K$ = key matrix that represents what information each position contains; $V = XW^V$ = value matrix containing the actual information to be aggregated; d_k = dimension of the key (and query) vectors, typically $d_k = d_{model}/h$ where h is the number of attention heads; $\sqrt{d_k}$ = scaling factor that prevents the dot product from growing too large, which would push the softmax function into regions with extremely small gradients; X = input sequence

The attention mechanism calculates a weighted average of the values, where the weights depend upon the compatibility between the queries and the keys, enabling every position to pay attention to every location in the input sequence in order to get rich contextual interaction.
While, Multi-head attention extends this concept by computing attention in parallel across different representation subspaces:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_h)W^O$$[12]

This allows the model to receive information from different representation subspaces at different positions, with each head focused on the different types of relationships, such as syntactic dependencies or semantic similarities.
Finally, it includes residual connections and layer normalization:

$$\text{Output} = \text{LayerNorm}(x + \text{MultiHead}(x))$$[13]

4.4 BERT: Bidirectional Understanding

BERT (Bidirectional Encoder Representations from Transformers) revolutionized Natural Language Processing by training on a masked language modeling objective. In this case, unlike traditional one direction models (left to right) BERT can try to understand the context from both directions simultaneously through its bidirectional encoder architecture.
At pretraining, BERT masks around 15% of the input tokens and is trained to predict them given surrounding context. This masked part is divided again: 80% of chosen tokens are masked with a special [MASK] token, 10% are masked with random tokens, and 10% are not masked. Then, training

matrix where n is sequence length and d is embedding dimension; W^Q, W^K, W^V = learned parameter matrices that project the input into query, key, and value spaces respectively.

[12]Elements: $\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$ = individual attention head; h = number of attention heads, typically 8 or 16 in practice; W^O = output projection matrix that combines information from all attention heads.

[13]Elements: x = input to the attention layer, preserved through the residual connection.

objective unifies masked language modeling with the next sentence prediction:

$$\mathcal{L} = \mathcal{L}_{\text{MLM}} + \mathcal{L}_{\text{NSP}}{}^{14}$$

This process trains the model to understand both token level and sentence level relationships, ending in rich bidirectional representations.

4.5 GPT: The Generative Paradigm

The Generative Pre trained Transformer (GPT) family models take a different approach with the use of autoregressive language generation, trained to predict the next token in a sequence after given all previous tokens:

$$P(x_1, x_2, ..., x_n) = \prod_{i=1}^{n} P(x_i | x_1, x_2, ..., x_{i-1})^{15}$$

This factorization allows the model to generate fluent text by iteratively predicting one token after another under the conditioning of the previous context, enabling tasks like text completing, creative writing, as well as conversational dialogue.
The training objective is to maximize the model's confidence in predicting the actual sequences found in the training data:

$$\mathcal{L} = \sum_{i} \log P(x_i | x_{<i}; \Theta)$$

[16] A simple command that if used to large scale datasets and large models, returns remarkable abilities.

The architecture employs causal (masked) self attention to ensure that predictions for position i can only depend on positions less than i, maintaining

[14] Elements: $\mathcal{L}_{\text{MLM}}$ = masked language modeling loss, computed as cross-entropy between predicted and actual masked tokens; $\mathcal{L}_{\text{NSP}}$ = next sentence prediction loss, a binary classification task determining if two sentences appear consecutively in the original text.

[15] Elements: $P(x_i | x_1, x_2, ..., x_{i-1})$ = conditional probability of token x_i given all preceding tokens in the sequence.

[16] Elements: Θ = all trainable parameters of the GPT model, including embeddings, attention weights, and feed-forward layers; $x_{<i}$ = all tokens preceding position i in the sequence, providing left-to-right context.

the autoregressive property during training and inference.

$$\text{Attention}_{\text{causal}}(Q, K, V) = \text{softmax}\left(\text{mask}\left(\frac{QK^T}{\sqrt{d_k}}\right)\right)V^{17}$$

This ensures that the model can only attend to previous tokens, whit left to right generation. The numerical vectors of these models become the foundation for virtually all existing NLP tasks, from machine translation and summarization to dialogue and code generation.

4.6 Natural Language Processing Analysis

NLP methodologies, including both conventional and deep learning approaches, are progressively utilized in policy and regulatory study.
It is possible to summarized them in five macro-essential methodologies:

Textual Similarity: Textual similarity algorithms function as a first approach for identifying the possible incorporation of lobbying input in regulatory documents: a sign of influence can be the integration of wording from comments into the final regulation, in particular terminology or arguments proposed by industry organizations in the revised regulatory text.

Researchers have employed text comparison to measure this phenomenon, a relevant study by Livermore et al. (2018) analyzed computational text analysis of nearly three million public comments received by administrative agencies during the Obama administration, demonstrating how natural language processing technologies can identify patterns in regulatory participation.

Their analysis revealed systematic differences in comment sentiment based on agency ideological positioning and established methodological foundations for measuring textual patterns in regulatory processes.

The researchers found that agencies at the ideological center receive more positive sentiment comments while agencies at ideological poles receive

[17]Elements: mask$(\cdot)$ = function that sets upper triangular elements (representing future positions) to $-\infty$ before softmax, ensuring causal attention.

more negative sentiment, providing quantifiable evidence of differential stakeholder engagement that can be detected through computational text similarity analysis methods. This represents measurable evidence of how a form of regulatory influence can be identified through systematic textual analysis.

In the context of the EU, Klüver (2009) introduced a quantitative textual methodology that evaluated interest group impact by analyzing the textual positions of lobbyists in relation to policy results, while, more recent workpaper in computational legal studies (Alschner, 2019) have developed automated text comparison approaches, whit the use of textual overlap, defined as the degree to which two or more texts share identical words, phrases, or segments, rather than profound semantic alignment.

Topic Modeling and Thematic Clustering: Unsupervised [18] topic modeling techniques, such as latent Dirichlet allocation [19] and its variants, allow the identification of dominant topics within extensive document sets without the necessity of predefined categories.

This has been utilized on public comment corpora to delineate the main problems raised by stakeholders, for instance, Levy Levy, Franklin (2014) perform one of the initial studies employing topic modeling on U.S. regulation comments, revealing that it "exposes latent themes" across several submissions.

A U.S. federal pilot project Chief Data Officers Council (2021) in the financial sector utilized hierarchical LDA [20] to categorize thousands of regulatory comments by issue, demonstrating how NLP can identify themes in comments for efficient review. This clustering may be directly beneficial for Basel discussions, as several banks and industry groups

[18] Unsupervised learning is a type of machine learning where the model learns patterns and structures from unlabeled data, without predefined outputs or categories, so without a supervisor's help.

[19] A generative probabilistic model used to discover hidden topics in a collection of data. It assumes that each document is a mixture of multiple topics, and each topic is a distribution over words. LDA identifies these topics by analyzing word co-occurrence patterns across the corpus

[20] An extension of LDA that discovers topics organized in a hierarchy, rather than as a flat set. It models documents as mixtures of topics that are structured in tree-like levels

frequently provide comments on intricate G-SIB requirements.

Sentiment and Tone Analysis: Sentiment analysis use lexicons, a predefined vocabulary in which each word has a label or score indicating its feeling (positive, negative, neutral), or machine learning techniques to identify positive, negative, or emotionally charged words, indicating the degree of criticism or support from industry replies on a proposal.
Although formal comment letters employ courteous wording and variations in tone might be not easy to detect, an empirical analysis of International Accounting Standards Board (Shields et al., 2019) consultations revealed that utilizing textual tone analysis on comment letters, the negative tone frequently coincides with stakeholders' dissent and may predict lobbying success or failure in influencing the final standard.
Sentiment analysis has been utilized in wider regulatory contexts, such as the development of indices of regulatory sentiment in last accademic papers, however its direct application to consultation feedback remains still developing, in our case sentiment measure might assess the general reaction of Basel Committee recommendations or highlight the sections of a document that generate the most disagreement among banks.
Beyond pure tone, researchers are interested in tracking the evolution of meaning in regulation language, from draft to final form, across time. Semantic change detection might involve comparing word use or embedding-based representations across different document versions, in this field academics NLP (Alschner, 2019) provides techniques such as dynamic topic models and temporal word embeddings to identify changes in language. Although, specific applications in finance are limited, similar efforts are more present in legislative analysis, where automated legal text comparison methods can accurately identify the modifications made by regulators in response to industry comments through time.

In summary, various text-mining techniques, ranging from simple similarity metrics to sophisticated topic models and classifiers, have been utilized in the examination of regulatory consultations, with effectiveness results.

Nevertheless, each case is unique, the most suitable methodology depends on several aspects such as length, database dimensions, or domain language.

4.7 Natural Language Processing & Bank for International Settlements

The Basel Committee's post-crisis revisions serve as case studies, a research entitled "Who Influences Global Banking Standards? A Quantitative Analysis of Basel III" by Bengtsson (2023) revealing that industry comments reflecting specific jurisdictions' interests were connected with modifications in the Basel language. While showing direct causality in global contexts is challenging, these instances demonstrate academics use of textual similarity, semantic analysis, and regulation review to deduce effect.

Bengtsson's quantitative analysis employed sophisticated coding methodologies to categorize 214 consultation responses across multiple stakeholder dimensions, including geographical origin, sectoral affiliation, and institutional characteristics. The study developed a systematic scoring system to measure preference alignment, and created a quantitative scoring system (PrefMet) that assigned values of +1, 0, or -1 to measure the degree to which stakeholder preferences were reflected in final regulatory outcomes.

The coding methodology distinguished between stakeholders expressing "concern" (viewing proposed changes as too strict or economically consequential) versus "support" (endorsing proposals or calling for even stricter regulation).

The research increasingly demonstrates that text data may be utilized to identify and quantify regulatory effect. Through similarity ratings, emotion and length correlations, or monitoring incorporated language, these studies demonstrate that public consultation is not purely performative; in several instances, the substance of comments is at least largely mirrored in the outcomes.

The Basel III analysis revealed systematic patterns: private stakeholders were eight times more likely to express concern with overall regulatory impact than public stakeholders, while financial sector participants showed odds ratios

ranging from 2.8 to 6.3 across different policy areas compared to other private sector stakeholders.

This area of study, however, must confront substantial methodological obstacles, which we will explore next.

4.8 Methodological Challenges and Limits of NLP in Policy Texts

There are particular challenges when using NLP in legal and policy texts, and several of authors advise caution when interpreting the results. Researchers have to manage a number of related limitations when applying computational text analysis to regulatory documents.

For example, a basic issue results from the difference between textual and semantic similarity is the ambiguity of textual influence: similar language in a final regulation and a comment letter does not always mean that the stakeholder drove the change in question, it could be coincidental or suggest a common viewpoint.

Additionally, influence can be used through unrecorded methods like informal conversations or during conferences and meetings with industry representatives. These interactions may even influence draft texts before they are even made available for public comment, since text-based similarity acts as a proxy and needs to be carefully examined combined with contextual information, research consequently faces a validity problem, as noted by Klüver (2009).

These difficulties are greatly exacerbated by the complex nature of legal language: automated text comparison prioritizes textual rather than semantic similarity and is unable to discern between legally significant and minor variations.since it lacks intrinsic legal knowledge and is unable to understand the technical terms and context that define regulatory discourse.

A single alteration in wording, like substituting "may" for "shall," could drastically alter legal responsibilities and obligations. As seen in Alschner (2019) studies, these tools should be viewed as supplements to expert analysis rather than as replacements.

Computational analysis is complicated by the issue of specialized corpora: the corpus of consultation documents and comment letters is relatively domain-specific compared to social media or general text. The language of financial policy is extremely specialized, with terms like particular acronyms or ratios that general purpose NLP models might find difficult to process and be understood without fine-tuning [21], making domain adaptation particularly difficult. To solve it, fine-tuning methods frequently calls for large datasets, and if there are not enough documents, the results could be erratic or wildly simplistic.

As a result, scalability and generalizability are often limited as analysts must carefully preprocess data using particular dictionaries or customized taxonomies for banking terminology, particularly suitable for the financial domain.

While, sentiment detection in regulatory frameworks is more complicated, classifier-based sentiment analysis techniques may incorrectly identify respectful objections as neutral because official policy language rarely contains explicit emotional indicators.

So researchers have had to develop specialized lexicons to accurately convey tone in accounting or financial remarks in order to overcome this limitation, but doing so adds subjectivity as results may vary depending on how "negative" tone is interpreted in technical discourse.

All these difficulties are exacerbated by the possibility of overfitting and false confidence: advanced techniques could identify statistically significant patterns in remarks that aren't really relevant and produce artificial patterns that do not accurately reflect real policy preferences or influence.

However, the most significant methodological challenge is probably the causality and endogeneity problem, since text analysis frequently reveals correlations rather than establishing true causal relationships.

When an authority modifies a regulation following several complaints from banks, is the modification attributable to the explicit feedback or to underlying political and economic factors that both banks and regulators separately addressed?

[21] the process of taking a pretrained machine learning model and training it on a task-specific dataset to adapt it to a particular application or domain

Even though comments might seem significant, the choice may actually be influenced by political or internal consensus that is not visible to textual analysis, given in this way the possibility of a false positives.

To adress it researchers, (Young, 2012) (Klüver, 2009) (Pagliari, Young, 2014) should often combine text analysis with contextual data or authentic validation using process tracing techniques, such as reviewing meeting minutes ideas.repec.org and interviews to determine whether textual changes were genuinely prompted by public input.

Through in-depth case studies, empirical research has put light on these complexities. By looking through historical documents and speaking with participants, academics have examined how industry lobbying contributes during the Basel Committee process. Young (2012) came to the conclusion that private access rarely corresponded to equal influence, in particular in his analysis of the Basel II Accord.

Through countless meetings and comment letters, lobbyists were heavily involved, however, this access did not always translate into influence, and in certain instances, industry input even pushed regulations to be stricter rather than weaker.

Nevertheless, according to A. Chalmers, Malik (2021) a possibility could be found in migration strategies and rule: in their research on post-crisis financial regulation in Europe and around the world, when an industry encounters regulations that it strongly opposes, it may be able to have certain clauses removed completely or move to a different venues or jurisdiction for resolution. For instance, banks could push for flexibility when regulations are applied regionally if they are unable to secure positive changes at the international level.

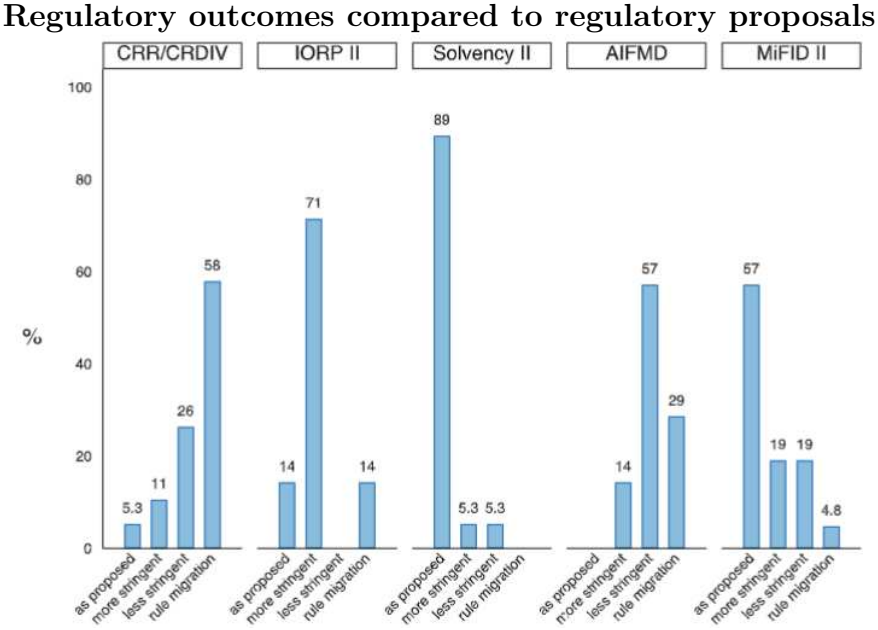


Figure 7: In some cases access to industries failed in deregulation, and end up as proposed or subject to rule migration. This supports Young (2012) point that influence isn't guaranteed with access, and A. Chalmers, Malik (2021) warning about rule migration.
Chalmers A. et al., "Rule omission, rule migration and the limits of financial industry power" 2021, Figure 1.

As described, a text analysis of a single document may not capture the full picture and the the real impact could appear later during national implementation.

In order to overcome these limitations, researchers are increasingly supporting hybrid approaches that integrate qualitative validation with quantitative text analysis.

These dynamics are highlighted by researchers such as Pagliari, Young (2014), who argue that in order to fully capture the influence pathway process tracing and data science should be integrated, however, they also acknowledge that these mixed-method approaches demand a lot more resources and expertise than purely computational approaches.

Finally, critiques go beyond methodological issues and argue against the basic assumptions of computational text analysis. Some academics warn against relying too much on computational analysis in regulatory politics, claiming that text analysis of comment overrepresents industry perspectives because the selection of which comments are submitted is endogenous within itself.

In conclusion, whereas NLP and text analysis offer robust methods for interpreting and measuring policy feedback, the literature advises for a cautious and knowledgeable use, legal-regulatory language is not simply another corpus.

These problems do not diminish the significance of text-as-data methodologies, but it need specific knowledge, customized approaches, and frequently a human intermediary outcomes' interpretation.

Consultative influence is a socio-political process: text analysis can observe part of it but cannot fully explain the strategic interactions, power imbalances, and informal negotiations that underlie regulatory outcomes.

For the specific example of Basel Committee discussions on G-SIB regulations, various methodological techniques from the literature appear applicable. A researcher may employ textual similarity to analyze Basel consultation materials against final standards, or to compare industry comment letters with those texts, in order to identify alignments. Topic modeling might quickly explain the major issues made by global banks versus, say, NGOs or academics in the consultation, indicating if industrial focus (e.g. calibration of capital surcharges) dominated the topic. emotion analysis may delineate which sections of the proposal had affirmative support and which generated negative emotion, so aiding in the identification of controversial aspects.

5 Methodology

5.1 Data Collection and Dataset Composition

The transparency initiatives adopted by the Basel Committee following the 2008 financial crisis have resulted in a rich repository providing an unprecedented opportunity to examine the regulatory development process in a public way. The empirical foundation of this study is based on a comprehensive dataset of regulatory documents and stakeholder consultations gathered from the Bank for International Settlements official website.

The methodology is applied on two different round of public consultation, the only two for the GSIB framework, dated 2011 and 2017-2018.

All the collected documents were classified into three primary categories:

Consultative Documents: Draft proposals released by the Basel Committee for public comment, containing preliminary methodologies, proposed indicators, and calibration approaches.

Final Standards: The definitive regulatory texts incorporating modifications following the consultation period, representing the official G-SIB framework as implemented.

Stakeholder Comments: Submissions from banks, industry associations, academics, and other interested parties responding to the consultative documents.

Moreover, additional documents were collected to improve the methodology through an enhanced dictionary, and for future research, the include:

- •Credit Risk
- •Leverage Ratio
- •Liquidity Risk
- •Market Risk
- •Operational Risk
- •Basel Core Principles
- •Financial Conglomerates (FiCo)
- •Accounting and Auditing

The analysis employs two complementary versions of the Loughran-McDonald financial sentiment dictionary:

Standard Loughran-McDonald Dictionary: last updated in February 2024, was specifically developed by analyzing the language of financial documents including 10-K and 10-Q filings[22]. Unlike general-purpose sentiment dictionaries such as Harvard IV-4 or Linguistic Inquiry and Word Count, it is able to capture the unique semantic sense of financial language where terms like "liability" or "risk" represent neutral technical terminology rather than negative sentiment.

Enhanced Merged Dictionary: The enhanced version extends the standard dictionary with the addition of some specialized regulatory terms and the adjustment of the sentiment score based on the analysis of additional Basel Committee documents collected previously. The critical innovation concerns in the introduction of the multiplier column, where terms such as "absolutely," "severely," or "significantly" receive multipliers of 1.5, amplifying the sentiment scores of surrounding words within a 3 words window, while other such as "partially" or "weakly" receive a multipliers of 0.8 reducing the tone, capturing in this way every shades of the sentiment text.

The technical implementation of data collection employed a multi-modal approach to handle diverse document formats.

Using Python's Pdfplumber library for standard PDF extraction and Pytesseract with Pdf2image for OCR processing of scanned documents, this system ensures comprehensive text capture across the different type of file.

Ultimately, a data enhancement process enriches each document with classification attributes essential for subsequent analysis, from file identifiers to institutional and geographic characteristics.

5.2 Topic Analysis on Stakeholder Comments

The method to perform an appropriate topic modeling analysis for regulatory texts presents the unique challenges of analyzing small, highly specialized corpora. Our methodological path through multiple failed attempts reveals important insights about the limitations of traditional NLP approaches when

[22] 10-K and 10-Q are standard forms used by public companies to provide annual and quarterly reports to the U.S. Securities and Exchange Commission

applied to domain-specific regulatory language.

The first approach employed traditional Latent Dirichlet Allocation (LDA), in particular two distinct strategies were tested:

The first one was a document level LDA, where each stakeholder comment was treated as an independent document. Despite experimenting with various hyperparameters (e.g. topic numbers ranging), the resulting topics lacked of semantic coherence, in particular topics mixed unrelated regulatory concepts, with terms like "capital", "disclosure" and "market" appearing together without meaningful thematic connection.

Subsequently, recognizing that the corpus size might be insufficient, a different approach was attempted merging all stakeholder comments into a single massive document, then segmented into overlapping chunks[23] using four different strategies:

- •Sliding window with proportional overlap
- •Semantic overlap based on complete sentences
- •Adaptive overlap adjusting to text length
- •Paragraph-based chunking preserving natural document structure

Despite these strategies, the LDA results remained unsatisfactory largely due to the small size and extreme specialization of the corpus, for optimal results it must be used results thousands of documents [24]. In detail, important regulation words such as "capital," "disclosure," or "market" appear over various topics and are commonly accompanied by each other, and at the same time, eliminating them (classifying them as stop words) would drastically reduce the logical and semantic meaning of the topics, with the result that LDA could not isolate them into manageable and significant themes.

Looking for a more appropriate semantic model for topic analysis, attention turned to Transformer architectures specifically tailored to financial texts, focusing on extracting document embeddings for subsequent clustering.

FinBERT is a BERT based model pretrained on financial communications with domain specific understanding of financial terminology, but with a limitation: FinBERT imposes a 512 token limit input, while the average regulatory

[23]Chunks refer to smaller segments of text created by dividing a larger document into manageable pieces

[24]Sievert & Shirley (2014) – LDAvis: A method for visualizing and interpreting topics

comment exceeds 3.000 tokens, and many are over 10.000.

BigBird may address the input length problem, a transformer variant engineered to process sequences up to 4.096 tokens using sparse attention[25] mechanisms.

However, it was still insufficient for an appropriate topic modelling, due to the non-specific BERT model.

There may be several reasons for these fails, for instance: the corpus size, far below the thousands typically required for unsupervised topic discovery.LDA performs optimally with large document collections, while regulatory consultations inherently produce smaller, focused corpora.

Furthermore, the semantic density exhibited by regulatory comments with specialized terminology and complex argumentative structures. Traditional topic models, designed for broader document or social-media comments collections with more varied vocabulary, struggle to understand difference between the small variations in highly technical language.

Given these limitations, our methodology implements an innovative hybrid approach that begins with the automatic extraction of topics from the regulatory document structure, based on the Basel Committee documents, where chapters and subsections identified each distinct themes.

In particular we employed pattern recognition to identify hierarchical headings in the documents and then to distinguish substantive regulatory content from administrative material:

```
def _classify_section(self, title):
    t = title.strip().lower()
    if self.toc_words.search(t):
        return "toc"
    if self.annex_words.search(t):
        return "annex"
    if self.intro_words.search(t):
        return "intro"
    return "topic"
```

[25]Sparse attention is a technique that reduces computational complexity by allowing the model to compare only selected tokens, instead of comparing each token with all others as full attention does in standard Transformers

For every topic, the system automatically generates three types of analytical components: technical keywords, regulatory patterns and practical queries.
This system, in addition to avoid the problems seen previously, leaves room for adaptability. If, for example, for a given document the topics are represented by chapters instead of subchapters, they can be taken individually, or, if it is necessary to include the introduction or particular annexes, they can simply be removed from the classification.
The extracted topics are then loaded dynamically into our analysis framework. The system offers flexibility in how subsections are handled - they can either be aggregated with their parent chapters for a broader topical view, or treated as individual topics for more granular analysis. This adaptability ensures that the topic structure aligns with the specific analytical needs while preserving the regulatory document's intended organization.

Once topics are loaded from the structure, the system asks the user whether they want to aggregate the subsections whit their parent chapter and identify them as topics or not. In our case, there is no need to aggregate them.
Then, the analysis proceeds through three complementary detection mechanisms:

Keyword Matching: Each regulatory topic is defined by keywords automatically extracted from the document sections, capturing the technical terminology specific to each regulatory area.

Pattern Recognition: Regular expressions are generated based on the extracted keywords and regulatory language indicators found in each section, with pattern complexity used to weigh the evidence, giving higher importance to more specific matches.

Semantic Search: Using the Sentence Transformer model (all-MiniLM-L6-v2), semantic similarity is computed between the automatically generated queries and text segments, enabling the detection of important parts even when keywords and phrasing don't match exactly.

To address the challenge of common regulatory terminology that could appear across multiple topics but it is equally important, our methodology implements a keyword statistics system which distinguishes between unique and common keywords, with keywords that appear in more than 40% of

topics are classified as "common keywords" and receive reduced weight in the relevance calculation.

Moreover, to ensure robust and comparable topic detection across heterogeneous documents, our methodology incorporates advanced normalization techniques:

Keyword Normalization: The frequency of topic specific keywords is normalized by document length (per 1.000 words), then scaled using a logarithmic transformation to avoid the influence of outliers, and a minimum score of 0.0 is enforced with a maximum cap at 1.0.

Pattern Normalization: The number of regular expression matches per topic is normalized (per 10.000 words) and then transformed using a square root function divided by $\sqrt{25}$ to prevent excessive influence from repetitive matches, with results capped at 1.0.

Semantic Scoring: For shorter documents (under 1.000 words), the semantic evidence is attenuated by a factor of 0.8 to reflect limited context.

The keywords normalization formula incorporates:

```
keyword_density = (keyword_score / text_length) * 1000
keyword_norm = np.log1p(keyword_density) / np.log1p(50)
keyword_norm = min(max(keyword_norm, 0.0), 1.0)
```

Pattern normalization follows:

```
pattern_density = (pattern_score / text_length) * 10000
pattern_norm = min(np.sqrt(pattern_density) / np.sqrt(25), 1.0)
```

Each topic receives a composite score combining three evidence streams, with weights varying by document length:

```
relevance_score = (keyword_norm * weights['keyword'] +
                   pattern_norm * weights['pattern'] +
                   semantic_norm * weights['semantic'])
```

The score does not represent a probability distribution, but an absolute measure of how much a topic is discussed from 0 to 1 within the paper, independent of other topics. Confidence levels are determined by evidence combination:

- •High: $\geq$3 evidence types present (norm >0.1) and score >0.7
- •Medium: $\geq$2 evidence types present and score >0.4
- •Low: Otherwise

This automated approach ensures that the topic analysis remains aligned with the actual structure of the regulatory text, it allow to eliminate potential bias from manual topic selection.

5.3 Sentiment Analysis Framework

Several methodologies have been tried in sentiment score analysis before adopting the Lexicon-based approach.

FinBERT and the Sentometrics package in R were two popular approaches in the current literature, although the results obtained were less precise. FinBERT, trained on financial texts is not particularly suitable on regulatory consultation comments, in particular it might exaggerated positive sentiment, incorrectly interpreting constructive criticism or politely worded objections as supportive statements. For instance, phrases like "we appreciate the Committee's efforts, however..." might be interpreted as positive by FinBERT while dictionary methods focus on the high number of negative content following "however". Moreover, to fine-tuning the model are required at least two or three thousand documents labeled.

On the other hand, Sentometrics package, while offering a sophisticated sentence-level tokenization approach and a proportional normalization method, produced results differing notably from standard methods due to methodological differences.

Our implementation utilizes two complementary dictionaries: Standard Loughran-McDonald Dictionary and the Enhanced version.

Before proceeding, it was crucial to perform an adequate preprocessing phase to match dictionary format exactly: expanding contractions, removing unnecessary elements, converting in uppercase, select and remove stopword unless they have a sentiment score, and reverses sentiment polarity for positive or negative terms:

```
# Expand contractions
for contraction, expansion in self.contractions.items():
```

```
    text = re.sub(r'\b' + contraction + r'\b', expansion, text)

# Remove URLs and emails
text = self.url_pattern.sub(' ', text)
text = self.email_pattern.sub(' ', text)

# Remove numbers
text = self.number_pattern.sub(' ', text)

# Remove special characters (keep basic punctuation)
text = self.special_chars_pattern.sub(' ', text)

# CONVERT TO UPPERCASE (match dictionary format)
text = text.upper()
```

Successively, the enhanced dictionary's multiplier feature was implemented:

```
if self.use_multiplier and 'Multiplier' in row and pd.notna(row['Multiplier']):
    multiplier = float(row['Multiplier'])
    # Apply to surrounding context (±3 words)
    for j in range(max(0, i-3), min(len(words), i+4)):
        if j != i and words[j] in self.dictionary.index:
            neighbor_row = self.dictionary.loc[words[j]]
            if neighbor_row.get('Positive', 0) == 1:
                positive_count += (multiplier - 1) * 0.5
```

Finally, the code calculates comprehensive metrics:

Tone: (Positive Words - Negative Words) / Total Words.

Sentiment Percentages: Category counts normalized by document length.

Dictionary Match Rate: Proportion of words found in sentiment dictionary.

With comparative analysis between standard and enhanced dictionary.

5.4 Topic-Based Sentiment Analysis Methodology

Subsequently, to go deeper, the topic based sentiment analysis system employs a two-stage approach to analyze regulatory comments, combining topic detection with targeted sentiment analysis to provide nuanced insights into stakeholder opinions on specific regulatory issues.

Following the identification of regulatory topics dynamically loaded from the document structure, the score is assigned using the same methodology as the topic analysis:

- **Keyword Matching**: Keywords from the extracted topics are matched and normalized
- **Regular expression Patterns Recognition**: Patterns generated from topic keywords
- **Semantic Similarity Queries**: Using sentence embeddings with cosine similarity

The topic extraction algorithm implements the same relevance scoring system described previously, with weighted combinations adapting to document length: for short documents (under 1,000 words) using keyword density (40%), pattern matching (35%), and semantic similarity (25%), with adjustments based on document length to account for varying text volumes, then once topic relevant text is extracted, sentiment analysis is performed exclusively on these portions with the Loughran-McDonald enhanced dictionary.

This approach provides several benefits with the sentiment analyzer applied only for topic's text, avoiding dilution from unrelated content, providing each stakeholder with an overview of their sentiment tone on a specific topic, capturing how the same author may have different sentiments toward different regulatory aspects.

In this way, we were able to obtain even more precise results than the traditional document level analysis. For example, while the aggregate analysis shows overall sentiment score, the topic based approach reveals significant variations in stakeholder opinions on specific aspects of regulation, for example it clearly identifies that cross-jurisdictional indicators generate the most negative sentiment, or that discussions about the timing of implementation are positively received.

5.5 Regulatory Proposal Extraction

The verification of whether regulatory proposals were implemented in final standards presented significant challenges for our methodology.

The initial approach tried to extract key terms, actions or specific details from the consultative document, and then search for these elements within the definitive regulatory text.

Although, special logic handled semantic reversals, such as recognizing that a proposal to "remove the cap" would be rejected if the final text maintained standard like "limiting the maximum score to 500 basis points", but despite sophisticated pattern matching and search strategies, this approach yielded inconsistent results.

The main problem was the difference between proposals which employ conditional and future-oriented language "The Committee proposes to...", while regulations use prescriptive, present-tense formulations with no linguistic markers connecting them to their consultative origins. An implemented proposal "expand the scope to include insurance subsidiaries" might appear in the final document simply as "insurance subsidiaries are subject to the following requirements", while a rejection could be implicit, with absence of mentions.

Recognizing the textual level matching was insufficient, therefore the second approach employed advanced semantic embeddings.

Using Jina embeddings v3[26], the code:

- •Generated high-dimensional vector representations for proposals.
- •Created overlapping chunks of the definitive document.
- •Calculated cosine similarity between proposal embeddings and document chunks.
- •Applied multiple search methods including semantic similarity, pattern-based matching, and entity-based matching.

This approach showed improvement, successfully identifying some cases where proposals and implementations shared semantic meaning, however, it still failed to achieve robust results, with many false positives, therefore the

[26]A state of the art text embedding model designed for high-quality semantic similarity computation

core challenge persisted: the conceptual transformation from proposal to implementation.

The solution we reached was to implement a proposal identification function combining linguistic analysis with domain-specific filtering:

```
target_lemmas = {'propose', 'revise', 'amend', 'introduce',
                 'remove', 'expand'}
context_words = {'committee', 'framework', 'methodology',
                 'assessment', 'requirement'}
```

The extraction process developed concerns:

- •Identifies action lemmas[27] using spaCy's en_core_web_sm model.
- •Validates regulatory context within a 10-token window.
- •Extracts up to 50 tokens before and after, respecting sentence boundaries.
- •Applies multi-stage filtering to eliminate false positives.

To enhance recall, the system implements targeted pattern matching for common proposal formulations:

```
# Pattern for committee proposals
pattern1 = r'The Committee (?:proposes to|recommends|seeks to) ([^.]+\.)'


# Pattern for numbered proposals
pattern2 = r'^\s*\d+\.\s+(Removal|Expansion|Amendment|Inclusion|
                          Revision|Modification)[^.]+\.'
```

It is important to mention that due to the high false positive rate and the specific nature of banking regulatory language, the extraction patterns and keywords are suitable specifically to Basel Committee documents, reducing generalizability but improving precision.

5.6 NLI Implementation Verification

The second step of proposal verification regards determine whether a given paragraph from the definitive document logically entails the implementation

[27]Lemmas are the base or dictionary form of words, e.g., "proposing" and "proposed" both have the lemma "propose"

of a specific proposal, instead of searching for similar text or matching patterns as done in failed trials.

This shift from similarity to inference motivated the adoption of Natural Language Inference (NLI)[28] using Facebook's BART-large-mnli model.

The NLI system creates hypothesis pairs testing if document paragraphs logically entail proposal implementation:

```
pairs.append({
    'premise': paragraph,
    'hypothesis': f"The document implements {proposal_clean}",
    'type': 'implementation'
})
```

Implementation likelihood is calculated as:

```
implementation_likelihood = (entailment_score - contradiction_score) / total_score
```

Status determination follows:

IMPLEMENTED: Implementation likelihood >0.3 with high entailment

REJECTED: Contradiction score >1.5× entailment score

PARTIALLY_IMPLEMENTED: Positive likelihood <0.3

UNCLEAR: Inconclusive NLI results

Even with the NLI approach, implementation verification remains imperfect. The system successfully identifies clear cases of implementation and rejection but struggles where some proposal elements are accepted while others are modified, and implicit implementations where the regulatory intent is preserved but expressed through entirely different mechanisms. To achieve high-stakes results, it remains essential a finally human verification.

The overall framework demonstrates how advanced NLP methods may be essential to perform a good analysis, However, where certain phases sacrifice generalizability for domain-specific precision, this study has some limitations that should be addressed in future research.

[28]NLI is a natural language processing task that determines the logical relationship between two text fragments: entailment, contradiction, or neutral

6 Results: Evidence from G-SIB Public Consultations

The application of our methodology to the last Basel Committee's G-SIB consultations of 2018 reveals interesting results that could be useful to draw a complex framework of stakeholder influence, where technical arguments, institutional entities, and geographic interests intersect together.

Based on our analysis of 18 comment letters from stakeholders, the landscape of regulatory concerns emerges with remarkable clarity.

The topic relevance score represents how relevant a topic is within each document, combining as seen previously keyword matching, pattern matching, and semantic similarity on a scale from 0 to 1, then multiplied by 100 (higher values indicate greater topic presence/relevance).

The most prevalent topics were *removal of the cap on the substitutability category* (appearing in 13 documents, 72.2%), *expansion of the scope of consolidation to include insurance subsidiaries* (12 documents, 66.7%), and *amendment to the definition of cross-jurisdictional indicators* (9 documents, 50.0%).

The intensity of engagement, how central that theme is in the document, varies significantly across topics:

- *Removal of the cap on the substitutability category* commands an average relevance score of 96.6% in documents where it appears, ranging from 89.8% in German Banking Industry Committee response to 102.3% in British Bankers Association response (due to the scoring system that combines multiple indicators, the final value could exceed 100%, which does not represent a limit). With this exceptionally high engagement, this technical issue represents a critical operational concern across the industry, the technical nature of the *removal of the substitutability cap*, involving complex calculations of payment systems activity, assets under custody, and underwriting volumes, may provide fertile ground for industry expertise to shape regulatory outcomes with technical complexity. Stakeholders argued that the cap artificially limited the risk sensitivity of the framework, potentially misallocating capital requirements.

•*Expansion of the scope of consolidation to include insurance subsidiaries*, shows an average relevance score of 91.8%, with particularly intense coverage from the Japanese Bankers Association (99.4%) and French Banking Federation (99.5%), suggesting widespread concern about the competitive and operational implications of including insurance activities in the consolidation scope. Being recurrent in national institutions, it could be that as national representation, they prefer to calibrate their argumentation toward certain topics that could affect the general banking system.

•*Amendment to the definition of cross-jurisdictional indicators* emerged with an average relevance score of 87.1% across the 9 documents addressing it. The consistent coverage reflects growing concerns about the measurement of cross-border exposures in an increasingly interconnected global financial system.

•*Inclusion of a new indicator for short-term wholesale funding* shows substantial coverage (8 documents, 44.4%) with an average relevance score of 90.2%. This suggests focused concern about funding stability measures in the post-crisis regulatory framework.

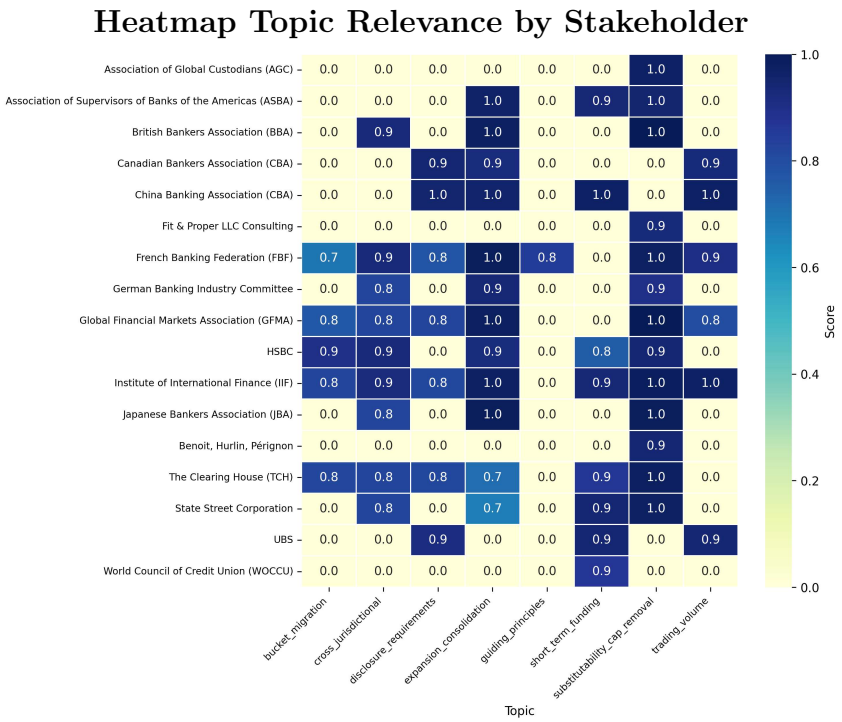


Figure 8: It is possible to observe easily who focuses on what, which stakeholders are specialized and which ones cover multiple topics.

Continuing, our topic analysis across different stakeholder categories reveals particular patterns:

Private Institutions (9 organizations)

Demonstrated a focused approach on:

- 77.8% (7 of 9) addressed *removal of the cap on the substitutability category*
- 66.7% (6 of 9) covered *inclusion of a new indicator for short-term wholesale funding*
- 55.6% (5 of 9) discussed *expansion of the scope of consolidation to include insurance subsidiaries*
- 55.6% (5 of 9) addressed *amendment to the definition of cross-jurisdictional indicators*
- 55.6% (5 of 9) covered *transitional schedule*
- 44.4% (4 of 9) discussed *revision to the disclosure requirements*

Average of 4.7 topics per institution, suggesting substantial but targeted engagement.

The high engagement with *removal of the substitutability cap* (77.8%) reflects the industry's focus on topics with direct operational impact, particularly those affecting their competitive position in custody, clearing, and underwriting services, while the attention to *short-term wholesale funding* indicators (66.7%) reflects private institutions' sensitivity to funding cost implications.

National Institutions (6 organizations)

Showed comprehensive coverage with an average of 4.5 topics per institution, and a interesting rate of 100% (6 of 6) of the institutions that address *expansion of the scope of consolidation to include insurance subsidiaries*, reflecting their role in representing domestic banking interests while maintaining systemic stability.

In particular, their topic selection often is aligned with specific national

market characteristics and regulatory policy. For instance, the French Banking Federation's exceptional focus on *expansion of the scope of consolidation to include insurance subsidiaries*,(99.5%) and *removal of the cap on the substitutability category* (97.5%) aligns with France's implementation of the Banking Union framework and the integration of bancassurance models prevalent in the European market during 2014-2018, when French authorities were actively to harmonize their supervision of financial conglomerates with European Banking Authority guidelines, particularly regarding the treatment of insurance subsidiaries within banking groups.

Moreover, in the same period, the China Banking Association focus on *inclusion of a new indicator for short-term wholesale funding* (97.0%) and *inclusion of a new indicator of trading volume* (97.0%) aligns with two major developments: the implementation of Bond Connect and expansion of Stock Connect programs to increase international trading volumes, and the reinforced government supervision of financial conglomerates following the Anbang case, when the government took control of the group due to systemic risks arising from the opacity of its combined banking and insurance operations.

International Institution (1 organization)

Focused on systemic issues with targeted coverage (3.0 topics average).

Academic Contributors (1 organization)

Concentrated on specific methodological concerns with focused engagement (1.0 topics average).

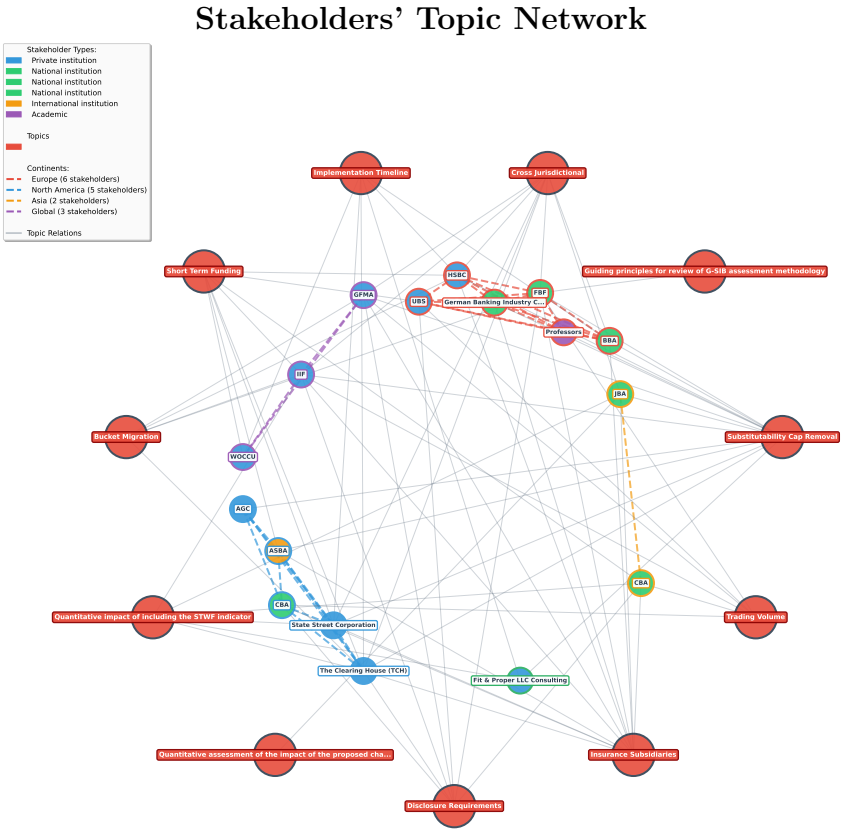


Figure 9: Relationships between topics and stakeholders, characterized by institution type and continental position.

The full list of stakeholder topic relevance scores is reported in Appendix .1.

6.1 Tone of Influence: Sentiment Patterns

By comparing standard and enhanced Loughran-McDonald dictionaries, FinBERT deep learning models, and the Sentometrics framework, we uncover not just what stakeholders say, but how they transmit their messages.

The sentiment scores range from -1 to 1, with values close to zero reflecting the formal, technical, and emotionally neutral nature of regulatory comments. Since most words lack emotional valence, the tone is calculated across all words, resulting in typically low absolute values.

Overall, the aggregate sentiment across all documents tends to be negative, but the distribution and interpretation vary by methodology:

- **Loughran-McDonald Standard:** Average tone of -0.9%
- **Enhanced Dictionary with Multipliers:** Average tone of -0.36%

- **finBERT** Average tone of 10.44%
- **Sentometrics (R implementation):** Average tone of -0.45%

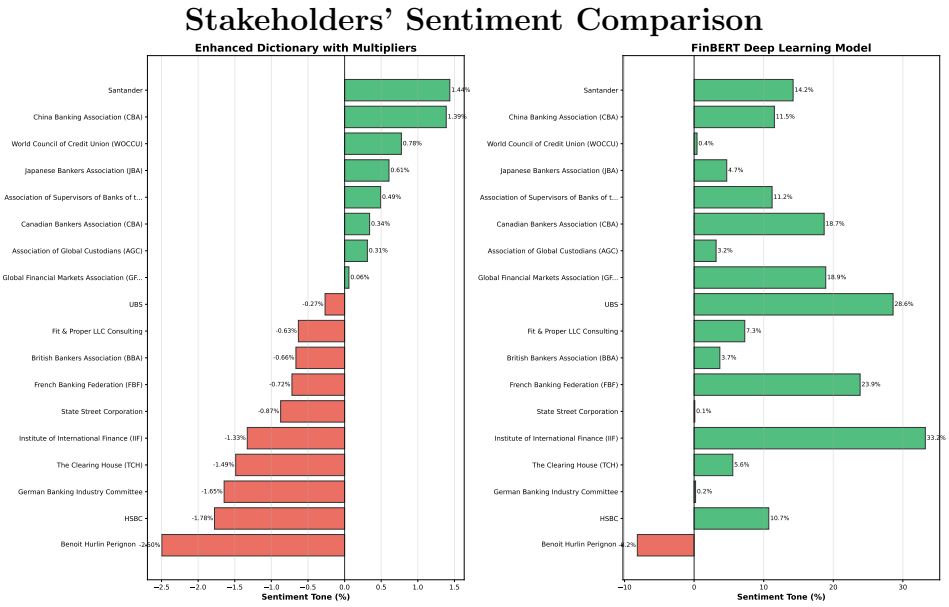


Figure 10: FinBERT model overestimates the score.

The main difference between Python and R implementations depends from a crucial methodological distinction: Python normalizes by total words while Sentometrics normalizes by sentiment words only.

The increase in positivity using the enhanced dictionary hides specific changes: while the net tone barely moves, the enhanced approach nearly triples positive word detection (from 23 to 69 average words) and increases negative detection by two-thirds (from 50 to 85 words). This suggests the standard financial dictionary misses the nuanced vocabulary in regulatory comments, but it depends also on multipliers.

FinBERT presents a strikingly different picture: an average tone of 0.1044, classifying all the documents as neutral. Specifically, the two techniques give opponent signs many times, but in most of these the tone obtainable from the text, coincides with the lexicon, for instance:

- **UBS** – The letter is formally polite, with a constructive and appreciative register (" would like to thank...", "UBS supports the evolution of the G-SIB assessment...",)but the central message is a long list of criticisms,

they "specifically highlight our concerns" and repeatedly uses critical language: the STWF indicator "seems duplicative," they are "further concerned" about the trading volume indicator, and express "concern" about cross-jurisdictional weightings.

- **Global Financial Markets Association (GFMA)** – They do not support the inclusion of various requirements, labeling as "duplicative", call for the elimination of inequalities in calculations from one jurisdiction to another.

- **British Bankers' Association (BBA)** – In this case the tone is equal between lexicon and FinBERT, but it seems last one tends to exaggerate.

- **French Banking Federation (FBF)** – The form is diplomatic, but the heart of the text is one of opposition: the FBF is "strongly opposed" to the inclusion of insurance subsidiaries, "does not support" the inclusion of derivatives in the new indicators nor the introduction of the trading volume indicator, and believes that the whole set-up does not reflect the reduction in systemic risk achieved after 2013.

- **State Street Corporation** – The response much focused on critical issues ("unpersuasive", "double counting") and calls for reconsideration. In contrast, FinBERT, when faced with institutional formulas of politeness ("we appreciate the opportunity," "we generally support") returns an overall positive sentiment.

Technical limitations related to domain-specific vocabulary, neutral results, and manual verification lead us to exclude finBERT as an effective method.

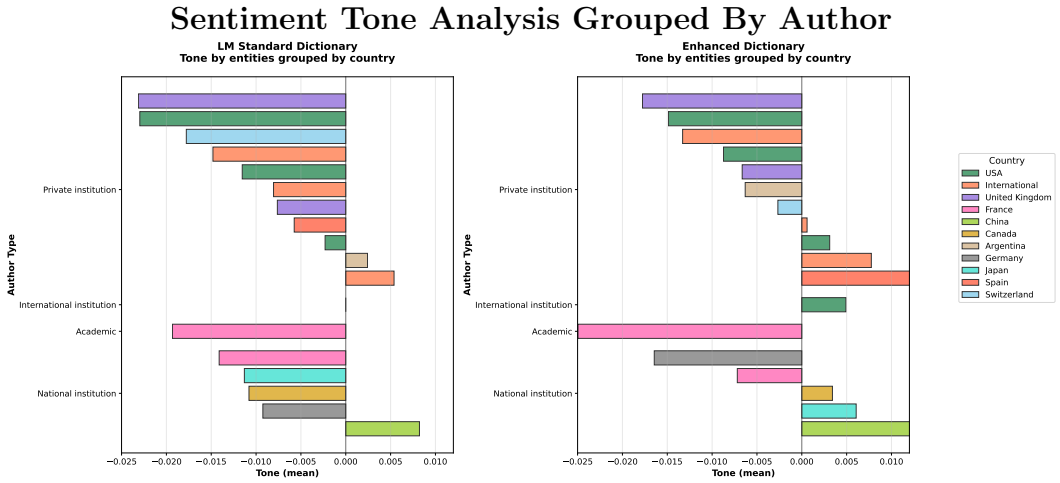


Figure 11: Comparison of sentiment tone distribution across institution types using LM Standard (left) and Enhanced Dictionary (right) methods, with colored segment represents individual countries within institutional categories.

Geographic analysis reveals that regulatory sentiment is not uniformly distributed but follows patterns reflecting distinct regulatory cultures and economic interests:

North American stakeholders (n=5)

demonstrate more moderated negativity:

- Average tone: −0.95% (standard) and −0.24% (enhanced)
- Moderate use of positive words 1.12% (standard)
- High use of negative words 2.08% (standard)

This negativity reflects both cultural communication styles and substantive positions. U.S. banks, operating under different domestic regulations, perceive G-SIB requirements as additional layers rather than integrated measures.

European stakeholders (n=7)

display the most negativity:

- Average tone: −1.39% (standard) and −0.88% (enhanced)
- Balanced vocabulary usage 2.26% negative, 0.87% positive (standard)

European responses demonstrate a strategy of "diffuse criticism" highlighting numerous specific concerns. This reflects European banks' deeper integration

with Basel processes, probably due to the concentration of major GSIBs that express concerns and explicit opposition.

Asian stakeholders (n=2)

exhibit the most neutral tone:

- Average tone: −0.15% (standard) and 1.00% (enhanced)
- High percentage of positive words 1.19% and low percentage of negative words 1.34% (standard)

Chinese banks balance appreciation for Basel's efforts with targeted requests to consider emerging market needs, a diplomatic approach that may reflect these jurisdictions' relatively recent full integration into global regulatory frameworks.

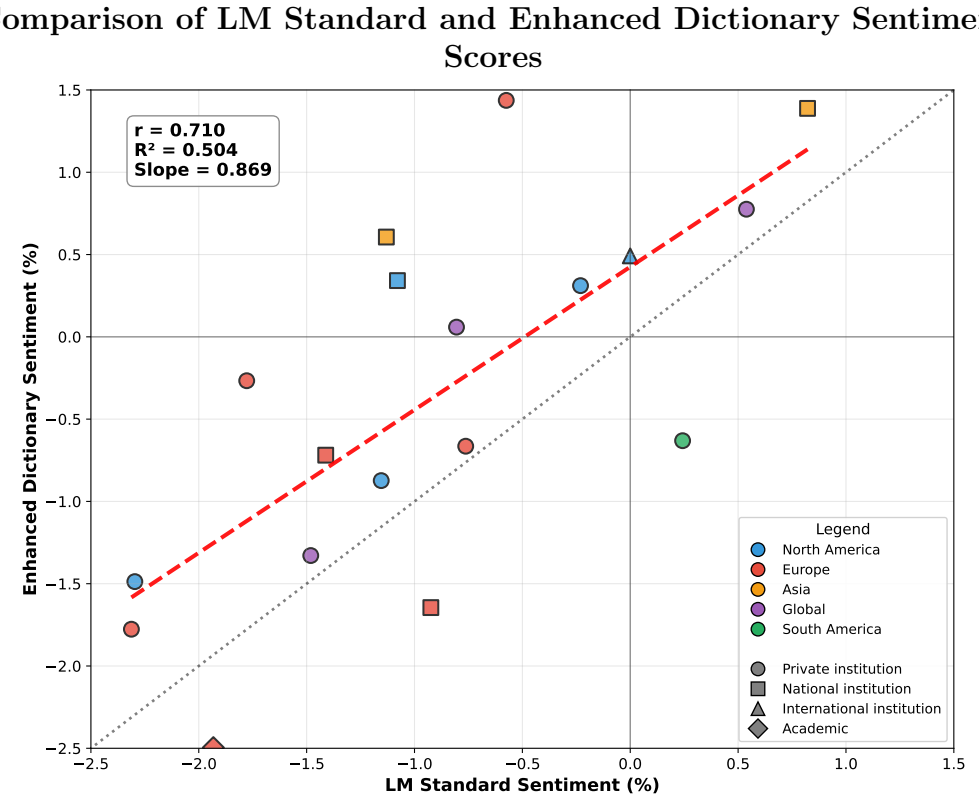


Figure 12: Scatter plot of the relationship between LM Standard and Enhanced Dictionary methods sentiment scores among stakeholders, coloured by country and shaped by institution type. The strong positive correlation ($r = 0.710$, $R^2 = 0.504$) shows method consistency, and the regression slope of 0.869 shows how Enhanced method is less negative in its evaluations comparatively. Geographical clustering verifies that variation in regulatory sentiment by continent is genuine and consistently registered by both methods.

The sentiment analysis summary report can be found in Appendix .2.

6.2 Topic Based Sentiment Analysis

Going deeper into the topic-based sentiment analysis results, we can provide a more nuanced analysis of the relationship between stakeholder sentiment and regulatory outcomes.

Beyond sentiment tone, we calculated variance score among topics, which indicates how much polarized is the scenario. An high value (as with quantitative impact of STWF, $\sigma = 0.0262$) prove divergent opinions, while low variance may signal a unified position.

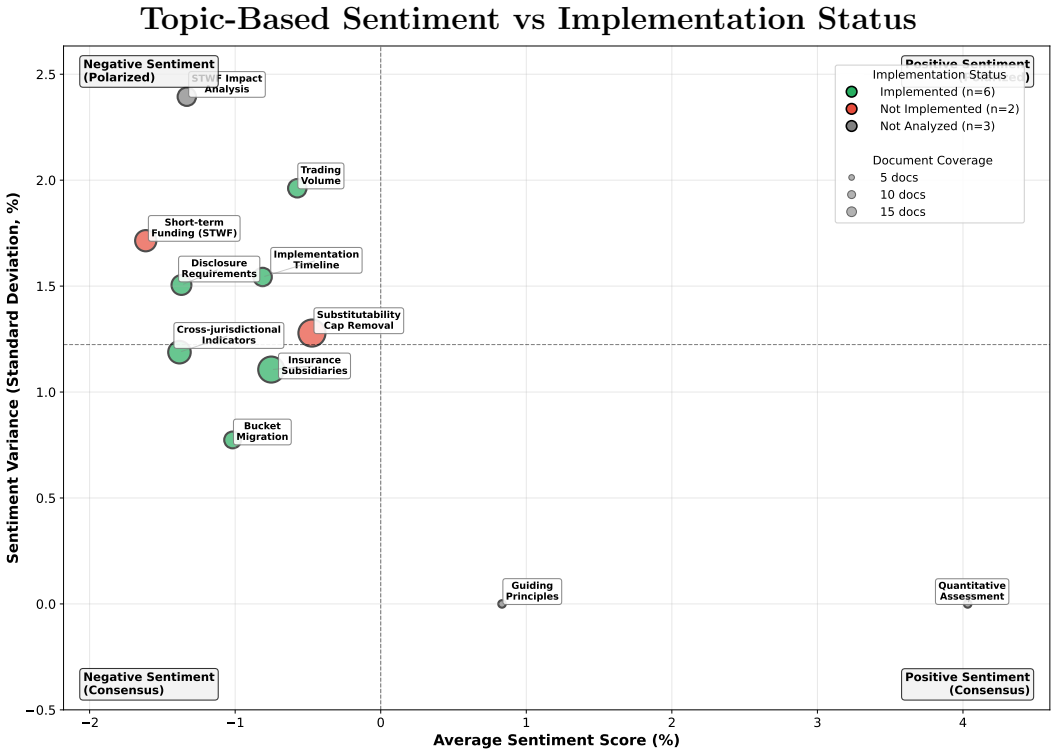


Figure 13: Each bubble represents a regulatory topic, positioned by average sentiment score and stakeholder polarization measured as standard deviation, while bubble size indicates document coverage. A striking implementation paradox emerges: topics with negative sentiment like disclosure requirements (-1.37%) and cross-jurisdictional indicators (-1.38%) were implemented (green bubbles), while short-term funding (STWF) with similarly negative sentiment (-1.61%) was not implemented (red bubble). Topics with positive sentiment like quantitative assessment (+4.03%) and guiding principles (+0.83%) were not analyzed for implementation (gray bubbles), suggesting implementation decisions were driven by systemic priorities rather than stakeholder preferences.

Among the various regulatory discussions, including those which do not represent a proposal, we observe a striking range of sentiment scores, ordered from most positive to most negative:

Positive Sentiment (Both Implemented):

- Quantitative assessment (0.0403) and Guiding principles (0.0083) are the most positive sentiment scores, though with minimal coverage (1 document), suggesting strong acceptance when regulatory impacts are properly quantified, support for clear methodological frameworks or a general disinterest.

Least Negative Sentiment (Not Implemented):

- Substitutability cap removal (-0.0047): Despite having the least negative sentiment among all opposed topics and extensive coverage (13 documents) it was not implemented, with a general consensus about the topic, based on a standard deviation of 0.0124. Stakeholders as HSBC and The Clearing House showed notable private sector opposition at 0.0237 and -0.0212. Industry arguments focused on the evidence that cap provides stability and predictability in capital calculations, with concerns that removal would disproportionately impact custodian banks and securities services providers. The decision to not implement may reflect regulators' recognition that the technical benefits of removal did are less than the operational disruption with a potential concentration of higher capital requirements on specific business models.

Moderate Negative Sentiment (Mixed Outcomes):

- Trading volume indicator (-0.0057): Implemented despite negative sentiment, the high variance ($\sigma = 0.0196$) reveals a split between stakeholders who saw merit in capturing trading activity as a systemic risk indicator and those who viewed it as redundant with others existing measures.

  Despite this polarization the regulator proceeded with implementation, in order to prioritize the lessons from 2008 about how trading interconnectedness can amplify systemic risk.

- Insurance subsidiaries (-0.0075): Implemented despite a consistent opposition across stakeholders. German Banking Industry Committee expressed the strongest concerns (-0.0253), possibly reflecting Germany's unique banking structure with Landesbanken.

- Transitional schedule (-0.0081): Implemented with moderate opposition and high variance ($\sigma = 0.0154$), suggesting divided views on timing with a relative degree of relevance among lobbies.

- Bucket migration (-0.0102): Implemented despite the sentiment score, with lowest variance ($\sigma = 0.0077$) among major topics, demonstrating unified opposition in particular from private institutions like HSBC (-0.0168) and TCH (-0.0163), and suggesting that even stakeholders who supported enhanced G-SIB measures found the migration mechanism problematic.
  Stakeholders argued that the proposed framework could create procyclical effects, and forces the banks to raise capital during stressed periods when scores naturally increase.

Strong Negative Sentiment (Divergent Outcomes):

- Quantitative impact of STWF (-0.0133): Not implemented, shows the highest variance ($\sigma = 0.0239$) that reflects fundamental disagreements about methodology and data quality for measuring short term funding risks. In particular, some stakeholders argued the empirical basis for the proposed calibrations, while others worried about a double count with the already existed liquidity regulations.
  Unlike other topics, the high variance and negative sentiment aligned with the not implementation, suggests regulators recognized the lack of consensus indicated genuine technical issues. This represents a case where the different and maybe confused stakeholder's opinions signaled implementation risks to regulators.

- Disclosure requirements (-0.0137): Implemented despite being among the most opposed topics, with moderate variance ($\sigma = 0.0163$). Probably the regulator proceeded with implementation based on the principle that

trasparency is essential for market and systemic risk monitoring in the post crisis regulatory framework.

- Cross-jurisdictional indicators (-0.0138): Implemented despite it appeared in 9 documents with consistent opposition. Stakeholders argued that existing measures already captured crossborder risks adequately and that a new indicators would penalize internationally active banks.
  The relatively low variance ($\sigma = 0.0126$) suggests unified concern across different stakeholder types.

- Short-term wholesale funding (-0.0161): The most negative average sentiment, reflected concerns about penalizing traditional banking activities and creating competitive disadvantages versus less regulated shadow banking, it was not implemented. HSBC reported the strongest opposition at -0.0424, demonstrated acute private sector concerns about funding cost implications.

We notice how sentiment patterns vary significantly by stakeholder type: academic stakeholders show focused positions on their area of expertise, with limited engagement (1.0 topic average) but clear technical concerns on substitutability issues.
In contrast, private institutions demonstrate a pragmatic strategy with an average sentiment of -0.0147, showing the most pronounced negative sentiment about short term wholesale funding indicators and quantitative STWF impacts, which reflect direct operational and cost concerns. However, about topics such as transitional schedules, private actors show more neutral responses, possibly recognizing the inevitability of implementation or trying to influence details.
National institutions maintain a careful balance, with a sentiment score that changes by classification: industry associations show slightly positive average sentiment (0.0039), while other national institutions more negative (-0.0029). Their engagement covers a wide range of topics (4.5 topics average), but their strongest reservations emerge on technical issues like disclosure requirements and insurance subsidiaries treatment, in fact, the

universal coverage of insurance subsidiaries by all national institutions (100%) underscores its systemic importance for domestic banking systems.
International institutions adopt a systemic perspective, with the most balanced sentiment among all groups (0.0029).
The topic sentiment analysis summary report can be found in Appendix .3.

6.3 Proposal Implementation Analysis

The phase concerns proposal and regulatory implementation represents the crucial test of influence. Our analysis identified 30 distinct regulatory proposals within consultation documents, tracked their characteristics.
We can classify the proposals based on:

- **Explicitly Numbered Proposals (11 instances):** These proposals, identified by the code based on the presence of a number (usually indicating the paragraph number) represent the most correct results, each proposal is repeated twice.
- **Embedded Proposals (19 instances):** These proposals, although extracted from the system based on the required characteristics, are mostly false positives or citations.

The effective proposals, after removed duplicated were:

•Removal of the cap on the substitutability category

•Expansion of the scope of consolidation to include exposures under insurance subsidiaries

•Amendments to the definition of cross-jurisdictional indicators

•Inclusion of a new trading volume indicator (with modified weights in the substitutability category)

•Revisions to disclosure requirements

•Inclusion of a new indicator for Short-Term Wholesale Funding (STWF)

Moreover, two minor proposals are presented in the consultation but are not detected:

•Further guidance on bucket migration and associated Higher Loss Absorbency (HLA) surcharge

•Transitional schedule for implementation

The Natural Language Inference approach to implementation verification was applied to the 11 numbered proposals, the code manages to find the part of the definitive text that most closely matches the proposal, but it cannot determine whether or not it is implemented.
All 11 proposals received identical confidence scores of 0.5, indicating maximum uncertainty, and requires a manual verification to confirm whether or not them have been implemented.
Of these, in the end, only two were not implemented in the definitive version:

- Removal of the cap on the substitutability category
- Inclusion of a new indicator for Short-Term Wholesale Funding (STWF)

In the previous chapter we have seen how linguistic transformation, context dependency, partial implementation and technical abstraction can affected the results.

7 Composite Influence Index (CII)

Quantifying regulatory influence is not a simple process: due to its subjective variables, it presents unique methodological challenges that extend beyond common measures. After thoroughly examining alternative methods, we adopted a *Composite Influence Index (CII)* to reflect stakeholder influence on G-SIB regulations, motivated by several considerations:

- **Multidimensionality:** Regulatory influence is inherently multidimensional, whereas typical simple measures (such as meeting counts or economic contributions) are one-dimensional. Influence in technical regulatory proceedings occurs along various dimensions: correspondence between stakeholder views and outcomes, technical soundness of rationales, intensity level, and coordination. A composite index aims to capture all these dimensions at once.

- **Technical nature:** The technical nature of banking regulation means that sentiment scores or textual analysis alone cannot capture the full extent of influence.

- **Direct measurement:** Unlike other works that infer influence from proxies, here stakeholder positions are directly observed from textual data, enabling a single, precise stakeholder impact metric.

The index uses the automated topic extraction system, but to determine which topics were ultimately implemented, a verification process asks to the user to classify each topic as implemented (y), not implemented (n), or not applicable (na).

7.1 Model Architecture and Components

The Composite Influence Index for stakeholder i is calculated as:

$$CII_i = \sum_{j=1}^{4} w_j \cdot \hat{C}_{ij}$$

Where:

- w_j represents the weight for component j
- $\hat{C}_{ij}$ represents the normalized score for stakeholder i on component j

Each component score is normalized using min-max scaling to ensure comparability:

$$\hat{C}_{ij} = \frac{C_{ij} - \min(C_j)}{\max(C_j) - \min(C_j)}$$

The Composite Influence Index is constructed from four theoretically motivated components, each related to a distinct dimension of regulatory influence measured in the previous chapter:

- **Topic Outcome Alignment Score (30%):** It measures the degree to which stakeholder preferences align with regulatory outcomes as achieved.

  Formula:

  $$Alignment_i = \frac{\sum(Relevance_{ik} \times MatchIndicator_{ik})}{\sum Relevance_{ik}}$$

  Where:

  - $MatchIndicator = 1$ if *(Sentiment > 0 AND Topic implemented) OR (Sentiment < 0 AND Topic NOT implemented)*, 0 otherwise.
  - Topics classified as "not applicable" are excluded from this calculation.

  Example: The Clearing House (TCH)

  - substitutability_cap_removal: relevance = 0.93, sentiment = −0.012, not implemented → **MATCH**
  - short_term_wholesale_funding: relevance = 0.88, sentiment = −0.015, not implemented → **MATCH**
  - insurance_subsidiaries: relevance = 0.84, sentiment = −0.008, implemented → **NO MATCH**
  - trading_volume: relevance = 0.86, sentiment = 0.003, implemented → **MATCH**

- Alignment depends on weighted matches across all proposal topics

- **Sentiment Convergence Score (25%):** It detects convergence between stakeholder positions and regulatory choices.
  Formula:

$$Convergence_i = 0.5 \cdot I(AvgSent_{nonimpl} < 0) + 0.5 \cdot I(AvgSent_{impl} \geq -0.01)$$

  The threshold to distinguish neutral sentiment was set at –0.01 based on the empirical distribution of sentiment scores observed in the regulatory corpus.
  Example: Institute of International Finance (IIF)

  - Avg sentiment on non-implemented topics (substitutability cap, short-term funding) $< 0 \rightarrow$ contributes 0.5
  - Avg sentiment on implemented topics (cross-jurisdictional, insurance, trading volume, disclosure, transitional, bucket migration)
  - If avg implemented sentiment $\geq -0.01 \rightarrow$ contributes additional 0.5
  - Final convergence score ranges from 0 to 1

- **Technical Influence Score (25%):** It reflects the technical expertise and refinement of stakeholder inputs.
  Formula:

$$\begin{aligned} TechScore_i = 0.4 \cdot \min\left(\frac{HighConfTopics}{5}, 1\right) \\ + \ 0.3 \cdot \left(\frac{AvgEvidenceTypes}{3}\right) \\ + \ 0.3 \cdot \min\left(\frac{\log(DocLength)}{10}, 1\right) \end{aligned}$$

Example: China Banking Association (CBA)

- High confidence topics = 11 (all topics) → 11/5 = 1.0 (capped)
- Avg evidence types = 3.0 (maximum: keyword, pattern, semantic) → 3.0/3 = 1.0
- Doc length from sentiment analysis ≈ 1500 words → log(1500)/10 = 0.718
- Score = $0.4 \times 1.0 + 0.3 \times 1.0 + 0.3 \times 0.718 = 0.915$

- **Engagement Intensity Score (20%):** It measures the depth of stakeholder engagement across proposals.

Formula:

$$Intensity_i = 0.4 \cdot \left(\frac{ProposalTopics_i}{TotalProposalTopics} \right) + 0.4 \cdot NormRelevance_i + 0.2 \cdot \min(|AvgSentiment| \times 100, 1)$$

Where proposal topics exclude those classified as "not applicable" and relevance scores are dynamically normalized based on the dataset's 95th percentile.

Example: State Street Corporation

- Proposal topics covered = 5 out of 8 total proposals → 5/8 = 0.625
- Avg relevance = 0.81, with 95th percentile at 0.99 → 0.81/0.99 = 0.806
- Avg $|sentiment|$ = 0.0119 → 0.0119 × 100 = 1.19 (capped at 1)
- Score = $0.4 \times 0.625 + 0.4 \times 0.806 + 0.2 \times 1.0 = 0.7724$

Final Normalization All components are normalized using Min-Max scaling:

$$Normalized\_Score = \frac{Score - Min\_Score}{Max\_Score - Min\_Score}$$

This ensures each component is on a 0–1 scale before final weighted combination:

$$CII = 0.30 \times TopicAlign + 0.25 \times SentConv + 0.25 \times TechInfl + 0.20 \times EngageInt$$

To ensure robust sentiment measurement some methodological adjustments were implemented, such as, the application of a cap to limit values to a maximum of 1 in the Technical Influence Score and Engagement Intensity Score, to prevent statistical outliers from disproportionately influencing the overall scores.

7.2 Model Limitations and Alternative Approaches

Although the CII comprehensively measures regulatory influence, several limitations must be considered:

- **Causal inference:** The model estimates associations, but does not establish causality. Regulatory outcomes may also be affected by external variables outside public consultation.
- **Weight subjectivity:** Component weights, while theoretically motivated, are subjective and results depend on these assumptions.
- **Temporal dynamics:** The model provides a static snapshot based on a single consultation round and does not account for evolving influence over time.
- **Alternative approaches:** Network models and structural equation modeling were considered, but data limitations (no network data, small sample size) made them impractical. Simple regression models ignore multidimensionality.

8 Results and Interpretation

Influence scores are approximately normally distributed with modest right skew, ranging from 0.153 to 0.884. The concentration of scores shows a clear separation between high-influence stakeholders (above 0.6) and others, suggesting that influence tends to concentrate among technically sophisticated participants with comprehensive engagement strategies.

8.1 Influence by Stakeholder Group

- **International Institution** (CII = 0.672, $n = 1$): shows a high individual influence, though limited to one observation (ASBA).
- **Academic** (CII = 0.586, $n = 1$): demonstrates substantial influence through perfect topic alignment and sentiment convergence, though the score reflects focused expertise on specific methodological issues about substitutability cap.
- **Private Institutions** (mean CII = 0.541, $n = 9$): show high average influence, with a substantial variance (0.155–0.884), indicating heterogeneous influence strategies.
- **National Institutions - Industry Associations** (mean CII = 0.515, $n = 4$): exhibit moderate influence, balancing member representation with technical engagement.
- **National Institutions** (mean CII = 0.291, $n = 2$): display the lowest average influence, potentially constrained by official diplomatic protocols and broader constituency considerations.

8.2 Profiles of the Most Influential Stakeholders

- **State Street Corporation** (CII = 0.884): achieved exceptional influence through perfect scores in topic alignment and sentiment convergence, combined with high technical influence (0.857) and moderate engagement intensity (0.601). 2761 word submission on six issues demonstrates the vantages of strategic focus over volume.

- **Association of Supervisors of Banks of the Americas (ASBA)** (CII = 0.672): a second position for an international institution, to prove how supervisory regional networks can efficiently merge different regulatory viewpoints from several jurisdictions and convert potential fragmentation into unified influence through cooperation across the Americas.

- **Institute of International Finance (IIF)** (CII = 0.661): maintained strong influence through great technical influence (0.984) and maximum engagement intensity (1.000), it compensates lower topic alignment scores through comprehensive topic partecipation.

- **China Banking Association** (CII = 0.653): achieved high influence with perfect technical scores (1.000), an example of how national associations can leverage technical expertise to match international institutions, representing its rapidly evolving domestic market to shape international standards that accommodate the world's second largest banking system.

- **The Clearing House (TCH)** (CII = 0.643): rounded out the top five through consistently high scores across technical influence (0.957) and engagement intensity (0.903).
  As the oldest banking association in the United States (1853), TCH's continued relevance demonstrates how traditional financial infrastructure providers have successfully evolved.

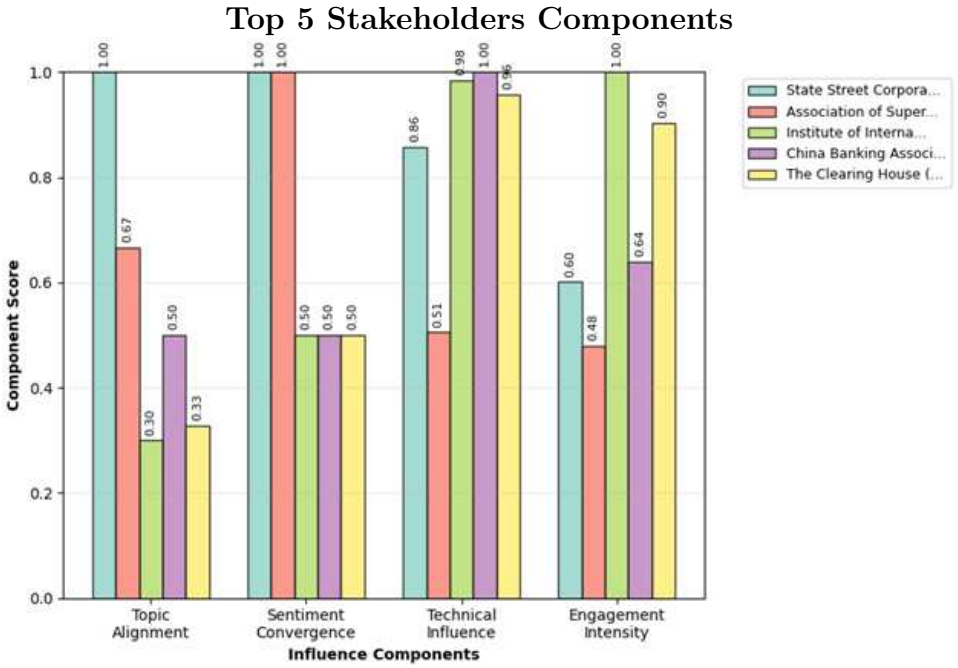


Figure 14: Breakdown of the four influence component scores (topic alignment, sentiment convergence, technical influence, and engagement intensity) for the top 5 most influential stakeholders. State Street's perfect alignment and convergence scores contrast with IIF's reliance on technical depth and engagement volume.

These findings contribute to regulatory influence theory in several ways:

1. **"Soft capture" without domination**: private institutions exert more influence than national or international institutions, but not tyrannical control, with the presence of different industry form in the top five positions, it could be aligned with recent theories emphasizing technical expertise over explicit power.

2. **Strategy over category:** The wide variance within private institutions (0.155–0.884) suggests that influence depends more on strategic choices than institutional category.

3. **Role of technical expertise:** extremely high technical scores support the idea that technical expertise and substantive research remain primary currencies of regulatory influence in technical sectors.

The Composite Influence Index reveals a stratified influence landscape in the Basel G-SIB consultation: State Street Corporation achieved exceptional influence (CII = 0.884), substantially above other stakeholders, yet the

presence of diverse institution types among high influencers suggests the process remained open to varied perspectives.

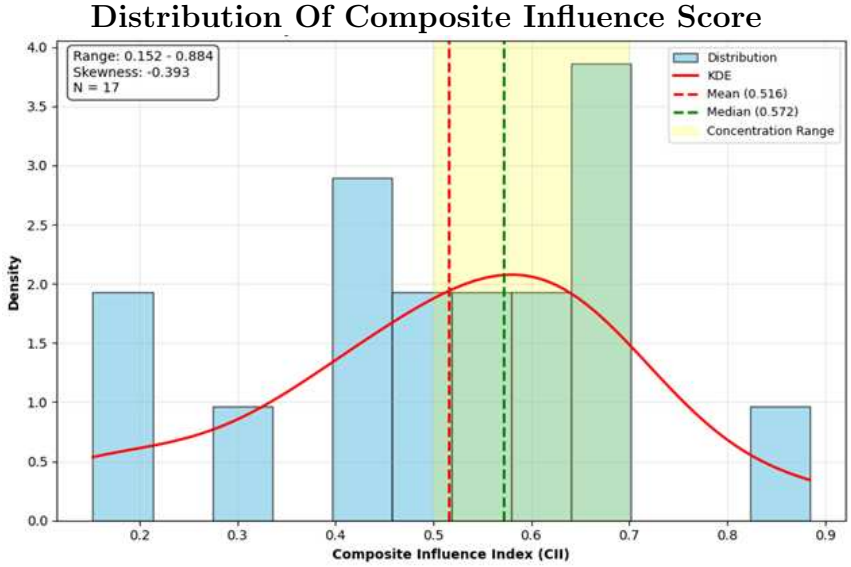


Figure 15: The plot shows the density histogram, kernel density estimate, mean and median values. It proved the absence of any "winner takes all" dynamic and suggested that the Basel consultation was characterized by pluralistic, rather than, oligopolistic influence.

The detailed influence analysis results can be found in Appendix .4.

9 Robustness Checks

Comprehensive robustness analysis reveals exceptional stability in our influence measurements while highlighting specific areas of sensitivity.

9.1 Weight Sensitivity

The weight sensitivity analysis demonstrates exceptional stability in stakeholder rankings. With ±10% variations in component weights, all Kendall's tau coefficients[29] equal 1.000, which indicates relative stakeholder positions remain virtually unchanged despite weight adjustments. Remarkably, the top five preservation equals 100% across all weight variations, suggesting that influence differences among elite stakeholders are robust to reasonable weight changes.

9.2 Component Removal

In the component removal analysis tests, all four components show perfect Spearman's rho correlations[30] of 1.000. It confirms that robust influence hierarchyis maintained even when components are removed, suggesting that influence patterns are captured consistently across multiple dimensions.

[29]Kendall's tau is a rank correlation coefficient measuring the ordinal association between two measured quantities. A value of 1.0 indicates perfect rank preservation.

[30]Spearman's rho measures the monotonic relationship between original and modified rankings. A value of 1.0 indicates that while absolute positions may change, the relative ordering relationship is preserved.

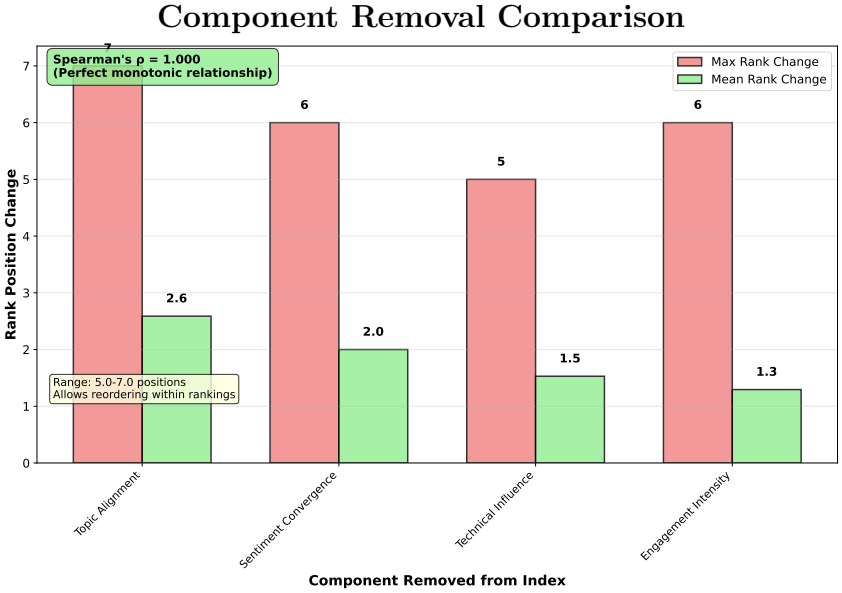


Figure 16: Component removal impact on stakeholder rankings. Perfect monotonic relationships (Spearman's rho = 1.000) combine with moderate maximum rank changes (5-7 positions). Topic alignment shows the highest sensitivity (max change = 7), while technical influence shows the greatest stability (max change = 5).

Maximum rank changes range from 5 to 7 positions, notably lower than initially expected, with mean rank changes between 1.3 and 2.6 positions. This pattern indicates great index stability, with no single component dominates the index structure.

9.3 Bootstrap Analysis

Bootstrap analysis provides further insight into the uncertainty of influence measurements.

According with the literature, we performed 1000 bootstrap iterations, in each iteration 18 stakeholders were resampled stakeholders with replacement from the original dataset, meaning stakeholders could appear multiple times or not at all in each bootstrap sample. This process resulted in each stakeholder appearing between 587 and 672 times across all iterations (mean = 641), providing a robust basis for confidence interval estimation through repeated measurement under varying sample compositions.

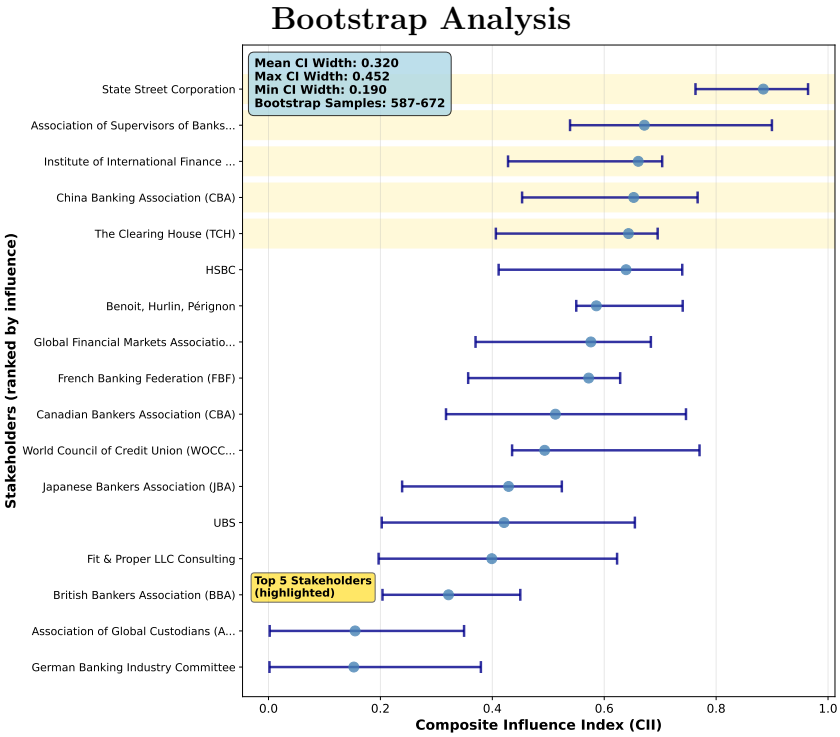


Figure 17: Bootstrap confidence intervals for influence scores. High influence stakeholders like State Street show narrower intervals (0.201), while mid tier stakeholders show wider uncertainty bands (up to 0.452), it suggests the measurement precision correlates with influence level, with higher influential stakeholders that present stable scores even when we resample the data.

Confidence intervals show moderate width (mean 0.320, maximum 0.452), with notable variation by influence level. The confidence interval provides the range within which we anticipate the true influence score of a stakeholder to lie, accounting for sampling variability.

It suggests that influence measurements become more reliable as stakeholder influence level increases. Here, bootstrap CIs are constructed by resampling and recalculating the influence index.

9.4 Alternative Normalization

Testing alternative normalization methods confirms robustness: the Pearson correlation[31] between min-max and z-score normalized results equals 0.9995, with an almost perfect linear relationship. Moreover, 100% of the top

[31]Pearson correlation measures the linear relationship between influence scores under different normalization methods. The near-perfect value (0.9995) indicates that normalization choice has virtually no impact on influence measurements.

five stakeholders maintain their positions under alternative normalization (same_top5 = 1.0), indicating that elite influence positions are invariant to normalization method.

9.5 Interpretation and Implications

The robustness analysis reveals exceptionally stable influence measurements, and suggests that the four component structure effectively captures the multidimensional nature of regulatory influence. However, to leave no doubt, with larger datasets and additional consultation rounds, it is possible to improve index robustness.

10 Analysis of the 2011 Consultation: Building the Foundation

The following analysis uses the same methodology we developed for the 2018 consultation, though with human intervention to adapt some thresholds for topic analysis based on empirical tests specific to this round.
The 2011 consultation represents a different but fundamental regulatory moment than the 2017-2018 round. With 41 stakeholders submitting comments, more than double compared to later consultation, this inaugural round reached unprecedented engagement as the financial industry discussed the creation of an entirely new regulatory section.
Unlike the previous analyzed consultation that debated specific calibrations within an established framework, this one focused on foundational architectural questions.
It also represents an opportunity to verify the accuracy and replicability of the methodology used so far.

10.1 Topic Analysis

Through the extraction of chapters and subchapters, the following topics are identified, each treated as an individual topic:

- *Bucketing approach* (Implemented)
- *Common Equity Tier 1* (Implemented)
- *Going-concern contingent capital (high-trigger contingent capital)* (Not implemented)
- *Group treatment* (Implemented)
- *Impact of requiring additional loss absorbency for G-SIBs* (Discussion without proposal)
- *Indicator-based measurement approach* (Implemented)
- *Interaction with Pillar 2* (Implemented)

- *Periodic review and refinement* (Implemented)
- *Supervisory judgement* (Implemented)
- *The magnitude of additional loss absorbency* (Implemented)

The pattern of engagement reveals remarkable concentration around three core concerns that would basically define the framework's structure.
With 41 stakeholders who generated 215 topic assignments, the consultation achieved an average relevance score of 83.7%, this indicates highly focused engagement. *Group treatment* topic dominated: 38 documents, that's 92.7% of submissions. Then came *Periodic review and refinement* with *Bucketing approach*, both at 35 documents (85.4%). This concentration shows us the core architectural concerns were clear: how to consolidate complex banking groups, categorize them, and ensure the framework could adapt over time.
Stakeholders engaged with 5.2 topics on average, though variation across institution types was significant: private institutions, such as BNP Paribas and J.P. Morgan, they covered 6 and 8 topics each, for a comprehensive discussion, while national industry associations showed remarkable consistency, for instance the Canadian Bankers Association achieved exceptional intensity across 7 topics. Meanwhile academic contributors varied wildly: Chris Barnard focused on just three topics, while Pennacchi, Vermaelen & Wolff produced the longest submission in the entire dataset (16,916 words) yet addressed only three topics.

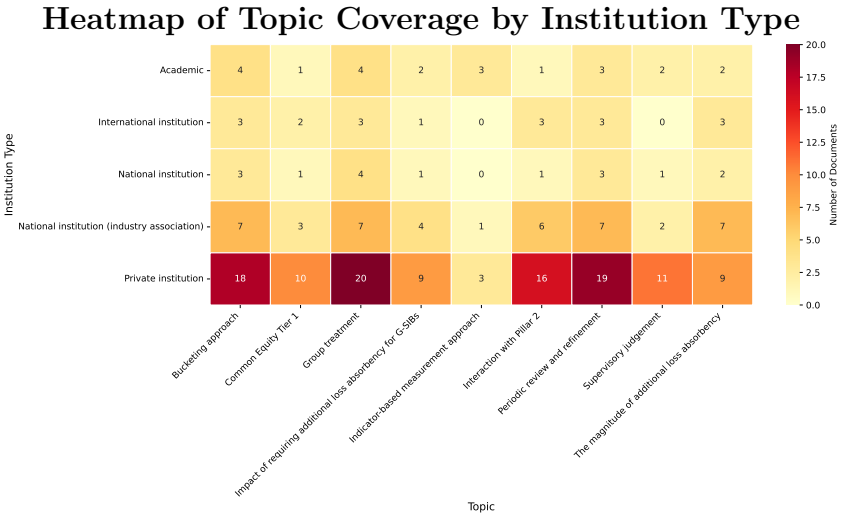


Figure 18: The heatmap displays document counts for each topic-institution combination. Private institutions dominate most topics (darker colors), however, interest varies significantly across institution types, with some topics receiving little to no attention from specific groups.

The full list of stakeholder topic relevance scores is reported in Appendix .5.

10.2 Sentiment Analysis

The sentiment landscape reveals an industry still in crisis, 31 of 41 submissions (that's 75.6%) showed negative sentiment below -0.01, and the average tone hit -0.0164 using the LM Standard dictionary. The enhanced dictionary showed slight moderation at -0.0149, diplomatic language softened fundamental opposition but didn't hide it. With 81.5 negative words versus 32.0 positive words per submission on average, we see a 2.5:1 ratio, that may suggests existential concern rather than technical disagreement.

The European Association of Co-operative Banks achieved the most negative sentiment: -0.0390, which probably reflects their fundamental concerns about how G-SIB frameworks would apply to mutual ownership structures. Meanwhile, the American Bankers Association followed at -0.0357, and the Danish Ministry at -0.0321. On the other hand, academic Zhen Li provided the only positive score ($+0.0092$), and the British Bankers Association nearly reached neutrality at $+0.0018$.

Private institutions showed the highest variance in sentiment as expected (standard deviation: 0.0098). The range went from J.P. Morgan's relatively

neutral −0.0041 to ABA's strongly negative −0.0357. This heterogeneity really contrasts with European stakeholders' more unified negativity during their sovereign debt crisis. The full list of stakeholder sentiment scores is reported in Appendix .6.

10.3 Topic-Based Sentiment Analysis

When we combine topic coverage with sentiment, sophisticated targeting emerges. *Group treatment* appeared in 38 documents but generated average sentiment of −0.0206 (±0.0244), European banks were particularly negative here. *Common Equity Tier 1* saw only 17 stakeholders discuss it, yet it triggered strong opposition: −0.0296 (±0.0192).

The most revealing finding concerns the *Indicator-based measurement approach*. Just 7 documents addressed it, but it is important to mention that the very common vocabulary used in the consultative chapter could affected the results. However, it generated the most negative sentiment of all: −0.0390 (±0.0318), which proves fundamental skepticism.

Periodic review and refinement achieved the least negative sentiment, just −0.0101 (±0.0225), in this case stakeholders valued adaptation mechanisms even while they opposed initial calibrations. This pattern would characterize their long-term strategies: accept evolution, resist specifics.

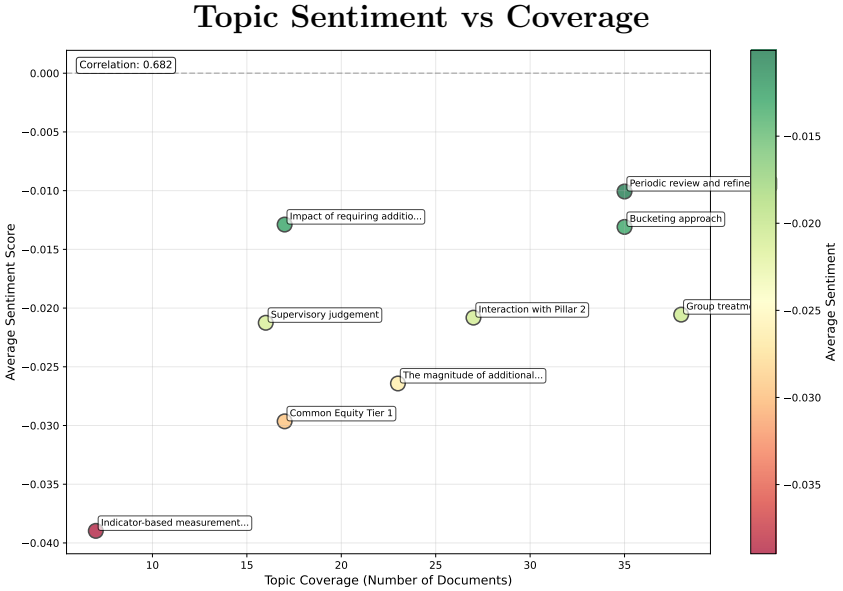


Figure 19: The scatter plot reveals a positive correlation (r=0.682) between topic coverage and negative sentiment. More frequently discussed topics tend to have moderate negative sentiment scores, with "Indicator-based measurement approach" showing the most negative sentiment despite moderate coverage.

The magnitude of additional loss absorbency showed both high negativity (-0.0264) and exceptional variance (± 0.0314) probably due to different banking systems with different concerns.

Nine of ten topics achieved implementation, a 90% adoption rate that contrasts sharply with all that negative sentiment, and just *going-concern contingent capital* excluded.

The implementation of strongly opposed provisions (*Common Equity Tier 1* at -0.0296 sentiment, *Group treatment* at -0.0206) demonstrates something clear: regulators prioritized systemic stability over what the industry preferred, requirements and standards inevitable following the latest crises.

The topic sentiment analysis summary report can be found in Appendix .7.

10.4 Composite Influence Index

By combining the various components, it is possible to calculate the Composite Influence Index, which reveals how influence distributed across 41 stakeholders as they shaped the framework's foundation.

The distribution shows both concentration among sophisticated participants and, compared to 2018, a more balanced distribution of influence across

stakeholders. The high technical scores is correlated with an overall influence, while, extreme sentiment positions generally reduced impact though.

Private institutions had the widest influence variance, their strategies ranged from comprehensive technical arguments to focused business model defense. In contrast, national industry associations clustered more consistently, with their ability to aggregate member concerns proved effective in these architectural debates. Academic contributors showed variable impact. For them, influence depended more on strategic alignment than how long their submissions were, and an almost complete technical coverage of the topics.

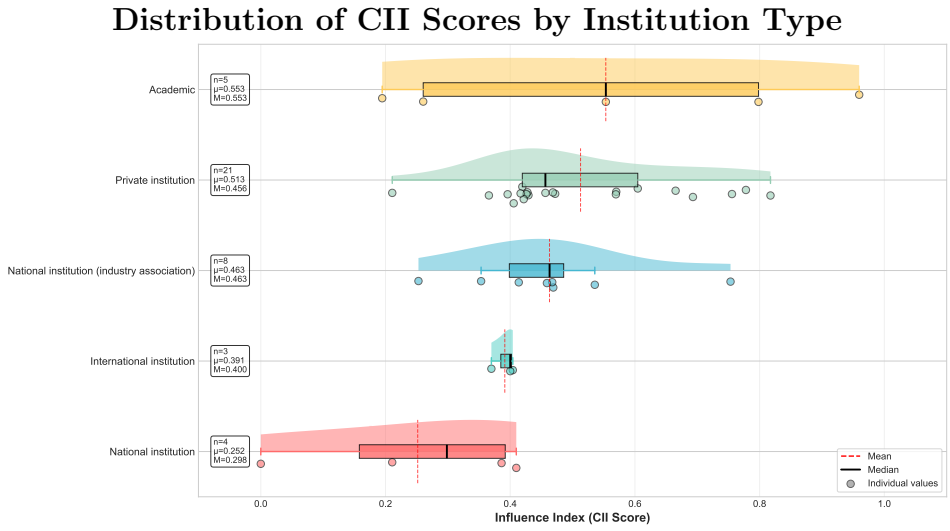


Figure 20: Figure 20: The raincloud plot shows CII score distributions across institution types. Academic institutions have the highest mean influence ($\mu = 0.553$) but also the greatest variability. Private institutions show the largest sample size (n=21) with moderate influence scores, while National institutions demonstrate the lowest mean influence ($\mu = 0.252$).

The detailed influence analysis results can be found in Appendix .8.

10.5 Robustness

To verify that our influence measurements are reliable, we conducted again several robustness tests. The bootstrap analysis with 1000 iterations gave us confidence that top influencers truly earned their positions, and it suggests genuine effectiveness, not measurement artifact.

In the removal component test, the rankings stayed mostly the same, with correlations above 0.85. Stakeholders might shift a few positions up or down,

never more than five spots, but the overall picture remained consistent. This tells us something important: no single factor drives the entire index, instead all four components contribute meaningfully to the final scores.
The same stability appeared when we adjusted the component weights, we tried giving more or less importance to different factors, varying them by 20% in either direction, yet the top influencers stayed at the top. Different calculation methods, like using z-scores instead of our standard approach, produced nearly identical results with 0.94 correlation.
The influence patterns we found seems consistent.

10.6 Temporal Evolution: From Foundation to Refinement

Looking at stakeholders who participated in both the 2011 and 2018 consultations reveals a particular evolution in how the industry learned to engage with regulators.
The group of experienced lobbies included major banks like HSBC and UBS alongside industry associations such as IIF, GFMA, JBA and CBA. Together they show us how the conversation shifted from foundational resistance to technical negotiation over seven years.
The most striking change was in sentiment, in fact back in 2011 the average tone was at -0.0164 reflecting deep postcrisis resistance while by 2018 it had moderated to -0.009 as we saw in Chapter 6. Not just a numerical shift but a fundamental change in approach, with stakeholders which had moved from existential opposition to debates about calibration details.
The way stakeholders engaged with topics also varied, in 2011 they tried to cover everything with an average of 5.2 topics per submission but by 2018 this had dropped to 4.7 topics, prefering depth more than breadth.
This whole evolution from what was essentially a constitutional convention to a technical committee perfectly captures how major regulatory frameworks mature over time. For instance, The Institute of International Finance exemplifies successful adaptation maintaining strong influence across both consultations while shifting from broad architectural concerns to targeted

technical expertise, while similarly GFMA adapted its approach from comprehensive coverage attempting to influence every aspect of the framework to focused interventions on specific calibrations that mattered most to its members.

In contrast some stakeholders struggled with this transition, banks that maintained the same comprehensive approach from 2011 trying to influence multiple topics with general arguments saw their relative influence decline by 2018 when the discussion required specific technical depth. The successful adapters like IIF and major industry associations learned to concentrate their resources on fewer topics but with greater technical sophistication matching the evolution of the regulatory dialogue.

Geographic patterns also show particular features, north american stakeholders who were already familiar with technical regulatory engagement from Dodd-Frank maintained consistent influence, instead european institutions showed mixed results with some like the French Banking Federation improving their position while others particularly British institutions struggled with the transition as evidenced by BBA's significant decline, while asian stakeholders demonstrated varied outcomes with China Banking Association gaining influence while Japanese banks saw modest decline.

Strategic Evolution: Winners and Losers in Regulatory Influence

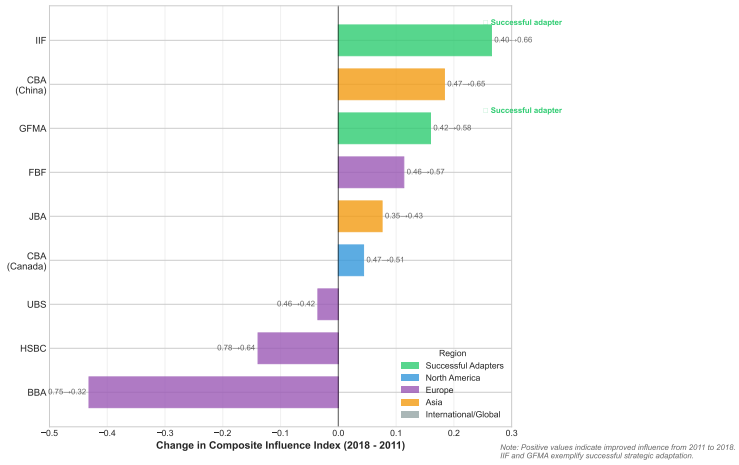


Figure 21: Figure 21:Change in Composite Influence Index from 2011 to 2018. IIF and GFMA (green) exemplify successful strategic adaptation, while BBA shows the largest decline. Colors indicate geographic regions.

11 Conclusions

Viewed from the perspective of both GSIB consultation rounds, what becomes clear is a profile much richer and more nuanced than any individual metric alone can capture: a landscape of regulation in which influence is multidimensional, subtle, and shaped as much by language and expertise as by institutional power.

11.1 Influence as a System, Not a Seizure

Our Composite Influence Index found State Street Corporation achieving exceptional influence with 0.884 CII score in 2018, substantially above the mean of 0.518.

However, the distribution of influence scores from 0.153 to 0.884 revealed a pluralistic and not monopolized process, and this goes against the conventional narrative of regulatory capture and suggests a more dynamic "web of technical negotiation".

Participation patterns tell their own story: decreasing from 41 stakeholders in 2011 to just 18 by 2018 may indicate declined interest, but such a reduced group achieved more concentrated influence.

This focus does not mean control, however, observed in the unsuccessful implementation of both removal of substitutability caps and of the STWF indicator, even with differing levels of industry support.

11.2 Topics and Tensions

Topic modeling identified the most significant issues as short term financing requirements, the removal of the substitutability cap, and the treatment of insurance subsidiaries as most frequently mentioned.

But frequency didn't neatly correspond to influence, in some cases, unpopular proposals became enacted despite opposition from stakeholders, to demonstrate influence in regulation is not absolute.

The most interesting findings relate to how stakeholder sentiment influenced regulatory decisions. In 2011 the 90% of topics achieved implementation despite 75.6% of submissions showing negative sentiment below -0.01, but

it is important to mention the particular historical period, when the banking system required a robust regulatory framework to avoid another crisis.
This pattern shows us that negative sentiment alone doesn't determine outcomes as strongly opposed provisions like Common Equity Tier 1 with its -0.0296 sentiment and Group treatment at -0.0206 were implemented anyway because they aligned with postcrisis regulatory priorities.

11.3 Patterns of Influence

Tracking influence patterns across both consultations demonstrates incredible consistency in the ways different types of stakeholders interact with regulatory proceedings: private institutions consistently beating public stakeholders by a mean CII score of 0.541 compared with 0.291 in 2018 and comparable patterns in 2011 at 0.513 compared with 0.252.
But such advantage runs on technical sophistication rather than brute political power, technical influence scores represent the best correlated component with overall CII at 0.857.
From a geographical point of view, European banks demonstrate their criticism during both periods with sentiment average of -0.0139 in 2018, this might be an attempt to counter regulations that affect their bancassurance structures, with higher integration especially in topics such as insurance subsidiaries.
Instead, American banks employing a more pragmatic approach with tempered negativity at -0.0095, embracing regulatory inevitability.
Asian actors managing their relatively recent membership within global regulating frameworks via diplomatic neutrality of -0.0015, their attitudes reflect emerging market viewpoints and adaptation towards established norms.

11.4 Conclusions on Research Hypotheses

The empirical results and analyses conducted allow for a critical evaluation of the hypotheses that guided the research.
H1: Negative sentiment in stakeholder submissions is associated with a higher likelihood of regulatory adjustment in the corresponding area.
The hypothesis H1 is not confirmed across both consultation rounds. As

seen previously, the 2011 consultation provides striking evidence against this hypothesis with high general negative sentiment and 90% of implementation rate.

Proposals with strongly negative sentiment were systematically implemented, including Common Equity Tier 1 (-0.0296), Group treatment (-0.0206), and the Indicator based measurement approach which generated the most negative sentiment of all at -0.0390.

The 2018 consultation reinforces these findings, we observed how cross-jurisdictional indicators (-0.0138), disclosure requirements (-0.0137), bucket migration (-0.0102), and insurance subsidiaries (-0.0075) were all implemented despite negative sentiment. Most revealing, the substitutability cap removal, which had the least negative sentiment at just -0.0047 and extensive coverage in 13 documents, was not implemented along with the STWF indicator.

A deeper read of the evidence suggests how influence worked in the consultation: instead of an aggressive, transactional type of capture, the trend is consistent with what this thesis defines as soft capture: technically detailed, large volume submissions influenced the calibration and the framing of individual elements, particularly where the proposals of the Committee offered space for discretionary adjustment.

Where proposals involved core business lines or data oriented indicators, the link between sentiment and adjustment is tighter, indicating a channel that runs through technical critique rather than pure opposition.

H2: Private financial institutions exert a greater and more direct influence on the final regulatory outcomes of the GSIB framework than public or academic stakeholders.

The results partially confirm H2. The Composite Influence Index shows that private financial institutions (mean CII = 0.541) participate more actively and achieve higher influence than national institutions (0.291) in public consultations.

However, the academic stakeholder achieved 0.586 CII, higher than private institution average, though the single observation limits generalizability. The

2011 data reinforces the same pattern with academics averaging of 0.626 versus privates at 0.517, followed by the other author entities.
Notably, the wide variance within private institutions (from 0.155 to 0.884 in 2018) suggests that institutional category alone does not determine influence. State Street Corporation's score of 0.884 demonstrates that strategic engagement and technical sophistication matter more than institutional type.

H3: Financial institutions designated as GSIBs by the FSB following consultation rounds demonstrate higher regulatory influence and/or more negative sentiment than non-designated institutions during the consultation process.
The hypothesis H3 is partially confirmed with evidence. Among the 13 GSIBs identified in the FSB's initial 2011 list and present among the comment letters, 77% satisfied at least one criterion of higher negative sentiment tone or CII, specifically, 46% displayed negative sentiment while 46% achieved influence scores above the consultation mean of 0.4737.
Notably, the most systemically important institutions demonstrated both characteristics: HSBC combined exceptional influence (0.7780) with negative sentiment (-0.0178), while Bank of China showed both above average influence (0.6046) and negative tone (-0.0035). Major U.S. banks split their approach: JP Morgan Chase and Citigroup focused on influence (0.7556 and 0.6931 respectively) with neutral to positive sentiment, while Goldman Sachs expressed concerns (-0.0019) alongside substantial influence (0.4721).
The 2017 data provides a consistent support, Among the 4 GSIBs tracked, HSBC maintained its pattern of high influence (0.6390) with negative sentiment (-0.0178), State Street achieved exceptional influence (0.8844), while UBS showed more moderate engagement (0.4210).

These patterns reveal that future GSIBs engage distinctively in consultations, either through critical feedback to reflect operational concerns about designation, or through intensive technical engagement to shape the framework.

11.5 Looking Ahead

The research reveals that despite the lack of legal authority, the Basel Committee actually is capable to achieve what harder structures often fail at, drawing a solid regulatory framework in financial industries without getting captured by it.

This institutional design perhaps achieves what formal structures struggle to accomplish, incorporating industry knowledge without surrendering to industry control, maintaining flexibility without sacrificing coherence, achieving global coordination without global government.

This study is just a static frame in an evolving landscape of regulation. Future research could extend the analysis across multiple consultation rounds, incorporate informal communication channels, and explore the longitudinal dynamics of stakeholder-regulator relationships.

The questions are as compelling as they are urgent: How does influence accumulate over time? How do regulatory norms evolve through repeated interaction? Can AI ever fully captures the subtleties of institutional behavior?

In the end this research shows influence isn't random or completely controlled but follows patterns based on who knows what, how they position themselves in the sector, and where they come from institutionally.

The soft capture identified here perhaps representing the optimal achievable outcome given the constraints of governing global finance without global government.

12 Appendix

.1 Stakeholder Topic Relevance Scores 2018

Association of Global Custodians (AGC) (Private institution) – 1190 words: substitutability_cap_removal 97.1%.

Association of Supervisors of Banks of the Americas (ASBA) (International institution) – 853 words: insurance_subsidiaries 96.1%, substitutability_cap_removal 95.2%, short_term_funding 93.5%.

Benoit, Hurlin, Pérignon (Academic) – 838 words: substitutability_cap_removal 93.8%.

British Bankers Association (BBA) (National institution (industry association)) – 9253 words: substitutability_cap_removal 102.3%, insurance_subsidiaries 97.8%, cross_jurisdictional 93.2%, implementation_timeline 71.3%.

Canadian Bankers Association (CBA) (National institution (industry association)) – 759 words: disclosure_requirements 93.9%, trading_volume 92.9%, insurance_subsidiaries 92.3%.

China Banking Association (CBA) (National institution (industry association)) – 1518 words: short_term_funding 97.0%, trading_volume 97.0%, short_term_funding_impact 96.6%, insurance_subsidiaries 95.8%, disclosure_requirements 95.7%.

Fit & Proper LLC Consulting (Private institution) – 1169 words: short_term_funding_impact 94.7%, substitutability_cap_removal 93.0%, implementation_timeline 65.5%.

French Banking Federation (FBF) (National institution (industry association)) – 3132 words: insurance_subsidiaries 99.5%, substitutability_cap_removal 97.5%, cross_jurisdictional 93.1%, trading_volume 90.2%, gsib_methodology_review 84.6%, disclosure_requirements 77.5%, bucket_migration 69.3%.

German Banking Industry Committee (National institution) – 761 words: insurance_subsidiaries 93.7%, substitutability_cap_removal 89.8%, cross_jurisdictional 82.4%.

Global Financial Markets Association (GFMA) (Private institution) – 4841 words: substitutability_cap_removal 99.9%, insurance_subsidiaries 98.4%, cross_jurisdictional 82.4%, disclosure_requirements 82.2%, trading_volume 79.9%, bucket_migration 76.6%.

HSBC (Private institution) – 6133 words: substitutability_cap_removal 94.1%, cross_jurisdictional 93.3%, insurance_subsidiaries 92.5%, bucket_migration 90.0%, short_term_funding 75.4%, implementation_timeline 61.2%.

Institute of International Finance (IIF) (Private institution) – 5292 words: substitutability_cap_removal 98.6%, insurance_subsidiaries 97.4%, trading_volume 97.0%, short_term_funding

93.5%, cross_jurisdictional 92.1%, bucket_migration 82.4%, short_term_funding_impact 82.4%, disclosure_requirements 80.9%.

Japanese Bankers Association (JBA) (National institution) – 1414 words: insurance_subsidiaries 99.4%, substitutability_cap_removal 98.9%, short_term_funding_impact 94.2%, cross_jurisdictional 82.4%, quantitative_impact_assessment 81.1%.

State Street Corporation (Private institution) – 2761 words: substitutability_cap_removal 97.6%, short_term_funding 94.3%, cross_jurisdictional 82.4%, short_term_funding_impact 82.4%, insurance_subsidiaries 66.8%, implementation_timeline 60.1%.

The Clearing House (TCH) (Private institution) – 9112 words: substitutability_cap_removal 98.2%, short_term_funding_impact 93.6%, short_term_funding 86.6%, cross_jurisdictional 82.4%, bucket_migration 81.3%, disclosure_requirements 81.0%, insurance_subsidiaries 71.3%, implementation_timeline 62.4%.

UBS (Private institution) – 966 words: short_term_funding 94.4%, trading_volume 93.9%, disclosure_requirements 91.2%.

World Council of Credit Union (WOCCU) (Private institution) – 3634 words: short_term_funding 87.1%, implementation_timeline 53.9%.

.2 Stakeholder Sentiment Scores 2018

REGULATORY SENTIMENT ANALYSIS - FINAL REPORT

==========

1. ANALYSIS OVERVIEW

This report presents sentiment analysis results using two dictionaries:

- Loughran-McDonald Standard Dictionary

- Merged Dictionary with Multipliers

Total Comments Analyzed: 18

2. KEY FINDINGS - DICTIONARY COMPARISON

Total Comments: LM=18.0000, Merged=18.0000, Diff=0.0000

Avg Dictionary Matches: LM=1918.6667, Merged=1919.7778, Diff=1.1111

Avg Positive Count: LM=23.3889, Merged=69.6917, Diff=46.3028

Avg Negative Count: LM=49.5556, Merged=84.9861, Diff=35.4306

Avg Tone: LM=−0.0090, Merged=−0.0036, Diff=0.0054

Tone Std Dev: LM=0.0092, Merged=0.0112, Diff=0.0020

3. SENTIMENT DISTRIBUTION - LM STANDARD

Negative (tone < -0.01): 9 (50.0%)

Neutral (-0.01 to 0.01): 9 (50.0%)

Positive (tone > 0.01): 0 (0.0%)

4. SENTIMENT DISTRIBUTION - MERGED

Negative (tone < -0.01): 5 (27.8%)

Neutral (-0.01 to 0.01): 11 (61.1%)

Positive (tone > 0.01): 2 (11.1%)

5. PREPROCESSING IMPACT

Average original text length: 20641 characters

Average processed text length: 16416 characters

Average reduction: 20.5%

6. MOST EXTREME COMMENTS - LM STANDARD

Most Negative:

- HSBC (Private institution): −0.0231

- The Clearing House (TCH) (Private institution): −0.0230

- Benoit, Hurlin, Pérignon (Academic): −0.0193

Most Positive:

- China Banking Association (CBA) (National institution (industry association)): 0.0082

- World Council of Credit Union (WOCCU) (Private institution): 0.0054

- Fit & Proper LLC Consulting (Private institution): 0.0024

.3 Stakeholder Topic Sentiment Scores2018

TOPIC-SPECIFIC SENTIMENT SUMMARY

`cross_jurisdictional`:

- Avg Tone: −0.0138 (±0.0126)
- Documents: 9
- Avg Relevance: 0.871
- Positive/Negative: 0.027/0.040

`insurance_subsidiaries`:

- Avg Tone: −0.0075 (±0.0116)
- Documents: 12
- Avg Relevance: 0.918
- Positive/Negative: 0.031/0.038

`bucket_migration`:

- Avg Tone: −0.0102 (±0.0087)
- Documents: 5
- Avg Relevance: 0.799
- Positive/Negative: 0.039/0.049

`gsib_methodology_review`:

- Avg Tone: 0.0083 (±nan)
- Documents: 1
- Avg Relevance: 0.846
- Positive/Negative: 0.052/0.043

`short_term_funding`:

- Avg Tone: −0.0161 (±0.0183)
- Documents: 8
- Avg Relevance: 0.902
- Positive/Negative: 0.028/0.044

`trading_volume`:

- Avg Tone: −0.0057 (±0.0215)
- Documents: 6
- Avg Relevance: 0.918
- Positive/Negative: 0.033/0.039

`quantitative_impact_assessment`:

- Avg Tone: 0.0403 (±nan)
- Documents: 1
- Avg Relevance: 0.811
- Positive/Negative: 0.060/0.019

`short_term_funding_impact`:

- Avg Tone: −0.0133 (±0.0262)

- Documents: 6
- Avg Relevance: 0.907
- Positive/Negative: 0.025/0.039

`substitutability_cap_removal`:
- Avg Tone: -0.0047 (± 0.0133)
- Documents: 13
- Avg Relevance: 0.966
- Positive/Negative: 0.044/0.049

`disclosure_requirements`:
- Avg Tone: -0.0137 (± 0.0163)
- Documents: 7
- Avg Relevance: 0.860
- Positive/Negative: 0.023/0.036

`implementation_timeline`:
- Avg Tone: -0.0081 (± 0.0169)
- Documents: 6
- Avg Relevance: 0.624
- Positive/Negative: 0.023/0.031

KEY FINDINGS

Most polarized topics (high variance in sentiment):
- `short_term_funding_impact`: $\sigma = 0.0262$
- `trading_volume`: $\sigma = 0.0215$
- `short_term_funding`: $\sigma = 0.0183$

Most positive topics:
- `quantitative_impact_assessment`: 0.0403
- `gsib_methodology_review`: 0.0083
- `substitutability_cap_removal`: -0.0047

Most negative topics:
- `short_term_funding`: -0.0161
- `cross_jurisdictional`: -0.0138
- `disclosure_requirements`: -0.0137

.4 Stakeholder CII Scores 2018

- **The Clearing House (TCH)**
  Influence Index: 0.79
  Topic Alignment: 1.00
  Sentiment Convergence: 1.00
  Technical Influence: 0.59
  Engagement Intensity: 0.46
- **State Street Corporation**
  Influence Index: 0.68
  Topic Alignment: 0.71
  Sentiment Convergence: 1.00
  Technical Influence: 0.50
  Engagement Intensity: 0.47
- **Institute of International Finance (IIF)**
  Influence Index: 0.63
  Topic Alignment: 0.32
  Sentiment Convergence: 0.50
  Technical Influence: 0.96
  Engagement Intensity: 0.87
- **World Council of Credit Union (WOCCU)**
  Influence Index: 0.62
  Topic Alignment: 1.00
  Sentiment Convergence: 1.00
  Technical Influence: 0.12
  Engagement Intensity: 0.20
- **British Bankers Association (BBA)**
  Influence Index: 0.62
  Topic Alignment: 0.14
  Sentiment Convergence: 0.50
  Technical Influence: 1.00
  Engagement Intensity: 1.00
- **Fit & Proper LLC Consulting**
  Influence Index: 0.60
  Topic Alignment: 1.00
  Sentiment Convergence: 1.00
  Technical Influence: 0.03
  Engagement Intensity: 0.20

- **Benoit, Hurlin, Pérignon**
  Influence Index: 0.59
  Topic Alignment: 1.00
  Sentiment Convergence: 1.00
  Technical Influence: 0.01
  Engagement Intensity: 0.20
- **HSBC**
  Influence Index: 0.59
  Topic Alignment: 0.50
  Sentiment Convergence: 0.50
  Technical Influence: 0.77
  Engagement Intensity: 0.60
- **Association of Supervisors of Banks of the Americas (ASBA)**
  Influence Index: 0.58
  Topic Alignment: 0.35
  Sentiment Convergence: 0.50
  Technical Influence: 0.82
  Engagement Intensity: 0.73
- **Global Financial Markets Association (GFMA)**
  Influence Index: 0.57
  Topic Alignment: 0.47
  Sentiment Convergence: 0.50
  Technical Influence: 0.75
  Engagement Intensity: 0.60
- **Association of Global Custodians (AGC)**
  Influence Index: 0.56
  Topic Alignment: 1.00
  Sentiment Convergence: 1.00
  Technical Influence: 0.03
  Engagement Intensity: 0.00
- **Canadian Bankers Association (CBA)**
  Influence Index: 0.55
  Topic Alignment: 0.50
  Sentiment Convergence: 0.50
  Technical Influence: 0.61
  Engagement Intensity: 0.60
- **French Banking Federation (FBF)**
  Influence Index: 0.45

Topic Alignment: 0.17

Sentiment Convergence: 0.00

Technical Influence: 0.92

Engagement Intensity: 0.87

- **Japanese Bankers Association (JBA)**

  Influence Index: 0.43

  Topic Alignment: 0.33

  Sentiment Convergence: 0.50

  Technical Influence: 0.45

  Engagement Intensity: 0.47

- **UBS**

  Influence Index: 0.43

  Topic Alignment: 0.35

  Sentiment Convergence: 0.50

  Technical Influence: 0.42

  Engagement Intensity: 0.47

- **China Banking Association (CBA)**

  Influence Index: 0.33

  Topic Alignment: 0.00

  Sentiment Convergence: 0.50

  Technical Influence: 0.46

  Engagement Intensity: 0.47

- **German Banking Industry Committee**

  Influence Index: 0.04

  Topic Alignment: 0.00

  Sentiment Convergence: 0.00

  Technical Influence: 0.00

  Engagement Intensity: 0.20

.5 Stakeholder Topic Relevance Scores 2011

American Bankers Association (ABA) (Private inst.) – 6528 words: bucketing_approach 91.0%, periodic_review_and_refinement 89.2%, the_magnitude_of_additional_loss_absorbency 85.8%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 85.6%, supervisory_judgement 84.4%, group_treatment 72.7%, interaction_with_pillar_2 68.1%.

Americans for Financial Reform (AFR) (Private inst.) – 4603 words: impact_of_requiring_additional_loss_absorbency_for_g-sibs 88.6%, group_treatment 87.3%, common_equity_tier_1 84.7%, periodic_review_and_refinement 78.7%, interaction_with_pillar_2 77.5%, bucketing_approach 77.2%.

Association of German Banks (National inst.) – 3186 words: bucketing_approach 98.2%, periodic_review_and_refinement 95.6%, the_magnitude_of_additional_loss_absorbency 90.1%, group_treatment 88.3%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 86.6%, interaction_with_pillar_2 82.1%, common_equity_tier_1 80.1%.

Association of Public Banks, Germany (National inst.) – 1319 words: group_treatment 54.6%.

BNP Paribas (Private inst.) – 11003 words: supervisory_judgement 92.6%, periodic_review_and_refinement 89.4%, bucketing_approach 87.6%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 87.1%, the_magnitude_of_additional_loss_absorbency 85.3%, common_equity_tier_1 78.1%, group_treatment 77.2%, interaction_with_pillar_2 75.5%.

Banco Santander (Private inst.) – 1883 words: supervisory_judgement 94.3%, periodic_review_and_refinement 87.7%, interaction_with_pillar_2 81.1%, group_treatment 80.4%, bucketing_approach 79.8%.

Banco de la República (National inst.) – 1177 words: the_magnitude_of_additional_loss_absorbency 96.0%, bucketing_approach 95.2%, periodic_review_and_refinement 88.3%, group_treatment 71.6%, supervisory_judgement 46.6%.

Bank of China (Private inst.) – 731 words: the_magnitude_of_additional_loss_absorbency 92.5%, periodic_review_and_refinement 87.8%, interaction_with_pillar_2 87.2%.

Bank of Communications (Private inst.) – 502 words: supervisory_judgement 85.3%, bucketing_approach 82.4%, group_treatment 70.0%.

Barclays (Private inst.) – 6674 words: group_treatment 87.7%, common_equity_tier_1 84.9%, bucketing_approach 80.0%, periodic_review_and_refinement 79.6%, interaction_with_pillar_2 77.1%.

British Bankers Association (BBA) (National inst.) – 2304 words: group_treatment 89.0%, interaction_with_pillar_2 87.8%, the_magnitude_of_additional_loss_absorbency 85.3%, periodic_review_and_refinement 85.0%, bucketing_approach 78.9%.

Canadian Bankers Association (CBA) (National inst.) – 2161 words: periodic_review_and_refinement 96.9%, the_magnitude_of_additional_loss_absorbency 96.6%, supervisory_judgement 95.4%, bucketing_approach 91.4%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 89.0%, interaction_with_pillar_2 75.8%, group_treatment 70.1%.

Chris Barnard (Academic) – 895 words: periodic_review_and_refinement 91.2%, bucketing_approach 86.8%, indicator-based_measurement_approach 80.8%.

Citigroup (Private inst.) – 1441 words: indicator-based_measurement_approach 84.4%, periodic_review_and_refinement 75.7%, group_treatment 72.4%, common_equity_tier_1 71.3%, interaction_with_pillar_2 62.6%.

Danish Ministry of Economic and Business Affairs (National inst.) – 395 words: periodic_review_and_refinement 86.9%, bucketing_approach 78.3%, group_treatment 77.9%.

European Association of Co-operative Banks (EACB) (International inst.) – 1659 words: the_magnitude_of_additional_loss_absorbency 87.9%, periodic_review_and_refinement 84.6%, interaction_with_pillar_2 83.5%, group_treatment 77.6%, bucketing_approach 77.2%.

European Banking Federation (EBF) (International inst.) – 4495 words: periodic_review_and_refinement 91.6%, the_magnitude_of_additional_loss_absorbency 89.5%, bucketing_approach 89.3%, group_treatment 89.0%, common_equity_tier_1 82.4%, interaction_with_pillar_2 81.6%.

French Banking Federation (FBF) (National inst.) – 2473 words: interaction_with_pillar_2 90.9%, group_treatment 88.2%, periodic_review_and_refinement 87.3%, the_magnitude_of_additional_loss_absorbency 84.6%, bucketing_approach 84.4%, common_equity_tier_1 83.4%.

Global Financial Markets Association (GFMA) (Private inst.) – 8199 words: the_magnitude_of_additional_loss_absorbency 89.3%, periodic_review_and_refinement 86.6%, bucketing_approach 86.5%, common_equity_tier_1 85.3%, group_treatment 83.0%, interaction_with_pillar_2 79.8%.

Goldman Sachs (Private inst.) – 1023 words: supervisory_judgement 86.6%, periodic_review_and_refinement 85.6%, bucketing_approach 84.1%, group_treatment 78.3%, indicator-based_measurement_approach 69.8%.

HSBC (Private inst.) – 2121 words: group_treatment 82.6%, bucketing_approach 81.7%, periodic_review_and_refinement 80.0%, interaction_with_pillar_2 77.5%, supervisory_judgement 68.3%.

Institute of International Finance (IIF) (Private inst.) – 6615 words: bucketing_approach 93.8%, periodic_review_and_refinement 91.2%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 86.3%, supervisory_judgement 81.7%, group_treatment 81.6%, interaction_with_pillar_2 74.0%.

International Banking Federation (IBFed) (International inst.) – 3006 words: bucketing_approach 90.9%, periodic_review_and_refinement 90.3%, group_treatment 88.9%, interaction_with_pillar_2 87.9%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 85.7%, the_magnitude_of_additional_loss_absorbency 85.1%, common_equity_tier_1 77.5%.

Intesa Sanpaolo (Private inst.) – 1367 words: periodic_review_and_refinement 92.0%, interaction_with_pillar_2 89.6%, bucketing_approach 89.3%, common_equity_tier_1 81.4%, group_treatment 81.0%.

Investment Company Institute (ICI) (Private inst.) –

13558 words: bucketing_approach 79.4%, group_treatment 69.9%.

Italian Banking Association (ABI) (National inst.) – 569 words: group_treatment 66.1%, interaction_with_pillar_2 66.1%, bucketing_approach 65.0%.

J.P. Morgan (Private inst.) – 2086 words: the_magnitude_of_additional_loss_absorbency 97.8%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 96.7%, bucketing_approach 91.2%, group_treatment 87.1%, common_equity_tier_1 86.6%, periodic_review_and_refinement 86.5%, interaction_with_pillar_2 82.3%.

Japanese Bankers Association (JBA) (National inst.) – 1269 words: bucketing_approach 92.8%, the_magnitude_of_additional_loss_absorbency 92.4%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 91.5%, periodic_review_and_refinement 91.0%, common_equity_tier_1 88.7%.

National Research University HSE (Academic) – 2239 words: bucketing_approach 92.8%, supervisory_judgement 91.1%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 89.7%, periodic_review_and_refinement 87.6%, group_treatment 79.1%.

Pennacchi, Vermaelen & Wolff (Academic) – 16916 words: bucketing_approach 89.3%, the_magnitude_of_additional_loss_absorbency 87.6%, group_treatment 61.1%.

Rajnish (Academic) – 2617 words: the_magnitude_of_additional_loss_absorbency 94.8%, periodic_review_and_refinement 94.2%, bucketing_approach 94.1%, supervisory_judgement 91.5%, group_treatment 87.8%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 84.9%, indicator-based_measurement_approach 81.6%, common_equity_tier_1 79.1%.

Royal Bank of Scotland Group (RBS) (National inst.) – 3048 words: periodic_review_and_refinement 96.7%, group_treatment 90.9%, the_magnitude_of_additional_loss_absorbency 88.0%, bucketing_approach 87.7%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 87.7%, common_equity_tier_1 80.5%, interaction_with_pillar_2 79.3%.

Sciteb (Private inst.) – 661 words: periodic_review_and_refinement 83.7%, bucketing_approach 81.6%, group_treatment 71.2%.

Standard Chartered (Private inst.) – 2741 words: group_treatment 92.9%, interaction_with_pillar_2 92.0%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 87.6%, periodic_review_and_refinement 85.9%.

Swedish Bankers Association (National inst.) – 2324 words: periodic_review_and_refinement 92.2%, bucketing_approach 91.4%, the_magnitude_of_additional_loss_absorbency 91.3%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 88.1%, group_treatment 78.3%, indicator-based_measurement_approach 77.8%, supervisory_judgement 77.0%, interaction_with_pillar_2 75.7%.

The Bank of New York Mellon, State Street & Northern Trust (Private inst.) – 3170 words: supervisory_judgement 89.2%, the_magnitude_of_additional_loss_absorbency 80.9%, periodic_review_and_refinement 80.9%, bucketing_approach 79.3%, common_equity_tier_1 77.3%, group_treatment 68.8%.

The Clearing House Association & IIB (Private inst.) – 15369 words: bucketing_approach 89.4%, periodic_review_and_refinement 85.2%, the_magnitude_of_additional_loss_absorbency 83.2%, supervisory_judgement 83.2%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 83.0%, common_equity_tier_1 79.1%, group_treatment 70.7%, interaction_with_pillar_2 67.8%.

The Hong Kong Association of Banks (HKAB) (National inst.) – 691 words: the_magnitude_of_additional_loss_absorbency 94.2%, periodic_review_and_refinement 88.9%, group_treatment 88.8%.

UBS (Private inst.) – 2112 words: the_magnitude_of_additional_loss_absorbency 94.7%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 92.4%, common_equity_tier_1 88.1%, bucketing_approach 84.5%, interaction_with_pillar_2 83.7%, supervisory_judgement 83.0%, periodic_review_and_refinement 81.2%, group_treatment 75.1%.

UniCredit (Private inst.) – 5491 words: periodic_review_and_refinement 92.1%, bucketing_approach 92.0%, impact_of_requiring_additional_loss_absorbency_for_g-sibs 83.5%, the_magnitude_of_additional_loss_absorbency 82.7%, group_treatment 82.2%, interaction_with_pillar_2 79.1%, supervisory_judgement 77.7%, indicator-based_measurement_approach 69.9%.

World Council of Credit Union (WOCCU) (Private inst.) – 3634 words: bucketing_approach 89.3%, the_magnitude_of_additional_loss_absorbency 87.6%, group_treatment 61.1%.

Zhen Li (Academic) – 909 words: interaction_with_pillar_2 73.0%, group_treatment 68.5%, indicator-based_measurement_approach 57.7%.

.6 Stakeholder Sentiment Scores 2011

REGULATORY SENTIMENT ANALYSIS - FINAL REPORT

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1. ANALYSIS OVERVIEW

This report presents sentiment analysis results using two dictionaries:

- Loughran-McDonald Standard Dictionary

- Merged Dictionary with Multipliers

Total Comments Analyzed: 41

2. KEY FINDINGS - DICTIONARY COMPARISON

Total Comments: LM=41.0000, Merged=41.0000, Diff=0.0000

Avg Dictionary Matches: LM=2404.2439, Merged=2405.6829, Diff=1.4390

Avg Positive Count: LM=32.0488, Merged=84.8134, Diff=52.7646

Avg Negative Count: LM=81.5366, Merged=130.7927, Diff=49.2561

Avg Tone: LM=−0.0164, Merged=−0.0149, Diff=0.0014

Tone Std Dev: LM=0.0098, Merged=0.0132, Diff=0.0034

3. SENTIMENT DISTRIBUTION - LM STANDARD

Negative (tone < -0.01): 31 (75.6%)

Neutral (-0.01 to 0.01): 10 (24.4%)

Positive (tone > 0.01): 0 (0.0%)

4. SENTIMENT DISTRIBUTION - MERGED

Negative (tone < -0.01): 26 (63.4%)

Neutral (-0.01 to 0.01): 14 (34.1%)

Positive (tone > 0.01): 1 (2.4%)

5. PREPROCESSING IMPACT

Average original text length: 24173 characters

Average processed text length: 19828 characters

Average reduction: 18.0%

6. MOST EXTREME COMMENTS - LM STANDARD

Most Negative:

- European Association of Co-operative Banks (EACB) (International institution): −0.0390

- American Bankers Association (ABA) (Private institution): −0.0357

- Danish Ministry of Economic and Business Affairs (National institution): −0.0321

Most Positive:

- Zhen Li (Academic): 0.0092

- British Bankers Association (BBA) (National institution (industry association)): 0.0018

- J.P. Morgan (Private institution): −0.0041

.7 Stakeholder Topic Sentiment Scores 2011

TOPIC-SPECIFIC SENTIMENT SUMMARY

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amendment_to_the_definition_of_cross-jurisdictional_indicators:

- Avg Tone: −0.0138 (±0.0126)
- Documents: 9
- Avg Relevance: 0.871
- Positive/Negative: 0.027/0.040

expansion_of_the_scope_of_consolidation_to_include_exposures_under_insurance_subsidiaries:

- Avg Tone: −0.0075 (±0.0116)
- Documents: 12
- Avg Relevance: 0.918
- Positive/Negative: 0.031/0.038

further_guidance_of_bucket_migration_and_associated_hla_surcharge:

- Avg Tone: −0.0102 (±0.0087)
- Documents: 5
- Avg Relevance: 0.799
- Positive/Negative: 0.039/0.049

guiding_principles_for_review_of_g-sib_assessment_methodology:

- Avg Tone: 0.0083 (±nan)
- Documents: 1
- Avg Relevance: 0.846
- Positive/Negative: 0.052/0.043

inclusion_of_a_new_indicator_for_short-term_wholesale_funding:

- Avg Tone: −0.0161 (±0.0183)
- Documents: 8
- Avg Relevance: 0.902
- Positive/Negative: 0.028/0.044

inclusion_of_a_new_indicator_of_trading_volume:

- Avg Tone: −0.0057 (±0.0215)
- Documents: 6
- Avg Relevance: 0.918
- Positive/Negative: 0.033/0.039

quantitative_assessment_of_the_impact_of_the_proposed_changes:

- Avg Tone: 0.0403 (±nan)
- Documents: 1
- Avg Relevance: 0.811
- Positive/Negative: 0.060/0.019

quantitative_impact_of_including_the_stwf_indicator:

- Avg Tone: −0.0133 (±0.0262)

- Documents: 6
- Avg Relevance: 0.907
- Positive/Negative: 0.025/0.039

removal_of_the_cap_on_the_substitutability_category:
- Avg Tone: −0.0047 (±0.0133)
- Documents: 13
- Avg Relevance: 0.966
- Positive/Negative: 0.044/0.049

revision_to_the_disclosure_requirements:
- Avg Tone: −0.0137 (±0.0163)
- Documents: 7
- Avg Relevance: 0.860
- Positive/Negative: 0.023/0.036

transitional_schedule:
- Avg Tone: −0.0081 (±0.0169)
- Documents: 6
- Avg Relevance: 0.624
- Positive/Negative: 0.023/0.031

KEY FINDINGS

Most polarized topics (high variance in sentiment):
- quantitative_impact_of_including_the_stwf_indicator: $\sigma = 0.0262$
- inclusion_of_a_new_indicator_of_trading_volume: $\sigma = 0.0215$
- inclusion_of_a_new_indicator_for_short-term_wholesale_funding: $\sigma = 0.0183$

Most positive topics:
- quantitative_assessment_of_the_impact_of_the_proposed_changes: 0.0403
- guiding_principles_for_review_of_g-sib_assessment_methodology: 0.0083
- removal_of_the_cap_on_the_substitutability_category: −0.0047

Most negative topics:
- inclusion_of_a_new_indicator_for_short-term_wholesale_funding: −0.0161
- amendment_to_the_definition_of_cross-jurisdictional_indicators: −0.0138
- revision_to_the_disclosure_requirements: −0.0137

.8 Stakeholder CII Scores 2011

- **Rajnish**
  Influence Index: 0.96
  Topic Alignment: 0.87
  Sentiment Convergence: 1.00
  Technical Influence: 1.00
  Engagement Intensity: 1.00
- **Intesa Sanpaolo**
  Influence Index: 0.82
  Topic Alignment: 0.61
  Sentiment Convergence: 1.00
  Technical Influence: 0.91
  Engagement Intensity: 0.79
- **Chris Barnard**
  Influence Index: 0.80
  Topic Alignment: 1.00
  Sentiment Convergence: 1.00
  Technical Influence: 0.53
  Engagement Intensity: 0.57
- **HSBC**
  Influence Index: 0.78
  Topic Alignment: 0.61
  Sentiment Convergence: 1.00
  Technical Influence: 0.82
  Engagement Intensity: 0.70
- **J.P. Morgan**
  Influence Index: 0.76
  Topic Alignment: 0.32
  Sentiment Convergence: 1.00
  Technical Influence: 0.90
  Engagement Intensity: 0.92
- **British Bankers Association (BBA)**
  Influence Index: 0.75
  Topic Alignment: 0.38
  Sentiment Convergence: 1.00
  Technical Influence: 0.94
  Engagement Intensity: 0.77

- **Citigroup**
  Influence Index: 0.69
  Topic Alignment: 0.37
  Sentiment Convergence: 1.00
  Technical Influence: 0.80
  Engagement Intensity: 0.66
- **Standard Chartered**
  Influence Index: 0.67
  Topic Alignment: 0.34
  Sentiment Convergence: 1.00
  Technical Influence: 0.78
  Engagement Intensity: 0.59
- **Bank of China**
  Influence Index: 0.60
  Topic Alignment: 0.35
  Sentiment Convergence: 1.00
  Technical Influence: 0.52
  Engagement Intensity: 0.60
- **Sciteb**
  Influence Index: 0.57
  Topic Alignment: 0.35
  Sentiment Convergence: 1.00
  Technical Influence: 0.45
  Engagement Intensity: 0.50
- **Investment Company Institute (ICI)**
  Influence Index: 0.57
  Topic Alignment: 0.45
  Sentiment Convergence: 1.00
  Technical Influence: 0.47
  Engagement Intensity: 0.33
- **National Research University Higher School of Economics (HSE)**
  Influence Index: 0.55
  Topic Alignment: 0.00
  Sentiment Convergence: 1.00
  Technical Influence: 0.86
  Engagement Intensity: 0.44
- **Italian Banking Association (ABI)**
  Influence Index: 0.54

Topic Alignment: 0.33

Sentiment Convergence: 1.00

Technical Influence: 0.44

Engagement Intensity: 0.38

- **Goldman Sachs**

  Influence Index: 0.47

  Topic Alignment: 0.40

  Sentiment Convergence: 0.00

  Technical Influence: 0.82

  Engagement Intensity: 0.73

- **Canadian Bankers Association (CBA)**

  Influence Index: 0.47

  Topic Alignment: 0.18

  Sentiment Convergence: 0.00

  Technical Influence: 0.96

  Engagement Intensity: 0.88

- **UniCredit**

  Influence Index: 0.47

  Topic Alignment: 0.16

  Sentiment Convergence: 0.00

  Technical Influence: 0.92

  Engagement Intensity: 0.95

- **Swedish Bankers Association**

  Influence Index: 0.47

  Topic Alignment: 0.15

  Sentiment Convergence: 0.00

  Technical Influence: 0.92

  Engagement Intensity: 0.96

- **French Banking Federation (FBF)**

  Influence Index: 0.46

  Topic Alignment: 0.17

  Sentiment Convergence: 0.00

  Technical Influence: 0.93

  Engagement Intensity: 0.88

- **UBS**

  Influence Index: 0.46

  Topic Alignment: 0.14

  Sentiment Convergence: 0.00

Technical Influence: 0.87

Engagement Intensity: 0.99

- **Barclays**

  Influence Index: 0.43

  Topic Alignment: 0.20

  Sentiment Convergence: 0.00

  Technical Influence: 0.89

  Engagement Intensity: 0.74

- **BNP Paribas**

  Influence Index: 0.43

  Topic Alignment: 0.00

  Sentiment Convergence: 0.00

  Technical Influence: 0.94

  Engagement Intensity: 0.96

- **Banco Santander**

  Influence Index: 0.43

  Topic Alignment: 0.21

  Sentiment Convergence: 0.00

  Technical Influence: 0.85

  Engagement Intensity: 0.75

- **The Clearing House Association & Institute of International Bankers (IIB)**

  Influence Index: 0.42

  Topic Alignment: 0.00

  Sentiment Convergence: 0.00

  Technical Influence: 0.93

  Engagement Intensity: 0.94

- **The Bank of New York Mellon, State Street & Northern Trust (Custodian Banks)**

  Influence Index: 0.42

  Topic Alignment: 0.15

  Sentiment Convergence: 0.00

  Technical Influence: 0.85

  Engagement Intensity: 0.82

- **Global Financial Markets Association (GFMA)**

  Influence Index: 0.42

  Topic Alignment: 0.00

  Sentiment Convergence: 0.00

Technical Influence: 0.96

Engagement Intensity: 0.88

- **Association of German Banks (Bundesverband deutscher Banken)**
  Influence Index: 0.41
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.95
  Engagement Intensity: 0.88
- **Royal Bank of Scotland Group (RBS)**
  Influence Index: 0.41
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.92
  Engagement Intensity: 0.89
- **American Bankers Association (ABA)**
  Influence Index: 0.41
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.94
  Engagement Intensity: 0.85
- **European Banking Federation (EBF)**
  Influence Index: 0.40
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.90
  Engagement Intensity: 0.90
- **International Banking Federation (IBFed)**
  Influence Index: 0.40
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.90
  Engagement Intensity: 0.88
- **Institute of International Finance (IIF)**
  Influence Index: 0.40
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.98
  Engagement Intensity: 0.75

- **Banco de la República (Central Bank of Colombia)**
  Influence Index: 0.39
  Topic Alignment: 0.12
  Sentiment Convergence: 0.00
  Technical Influence: 0.83
  Engagement Intensity: 0.72
- **European Association of Co-operative Banks (EACB)**
  Influence Index: 0.37
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.88
  Engagement Intensity: 0.74
- **Americans for Financial Reform (AFR)**
  Influence Index: 0.37
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.87
  Engagement Intensity: 0.75
- **Japanese Bankers Association (JBA)**
  Influence Index: 0.35
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.83
  Engagement Intensity: 0.73
- **Pennacchi, Vermaelen & Wolff**
  Influence Index: 0.26
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.64
  Engagement Intensity: 0.51
- **The Hong Kong Association of Banks (HKAB)**
  Influence Index: 0.25
  Topic Alignment: 0.00
  Sentiment Convergence: 0.00
  Technical Influence: 0.52
  Engagement Intensity: 0.62
- **Bank of Communications**
  Influence Index: 0.21

Topic Alignment: 0.00

Sentiment Convergence: 0.00

Technical Influence: 0.44

Engagement Intensity: 0.51

- **Danish Ministry of Economic and Business Affairs**

  Influence Index: 0.21

  Topic Alignment: 0.00

  Sentiment Convergence: 0.00

  Technical Influence: 0.42

  Engagement Intensity: 0.52

- **Zhen Li**

  Influence Index: 0.19

  Topic Alignment: 0.00

  Sentiment Convergence: 0.00

  Technical Influence: 0.47

  Engagement Intensity: 0.38

- **Association of Public Banks, Germany (Bundesverband Öffentlicher Banken Deutschlands)**

  Influence Index: 0.00

  Topic Alignment: 0.00

  Sentiment Convergence: 0.00

  Technical Influence: 0.00

  Engagement Intensity: 0.00

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