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Can environmental policies put the GINI back in the bottle?

An analysis of the relationship between environmental policy stringency and income inequality in OECD economies

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Abstract

As governments pursue increasingly ambitious environmental policies to address climate change, concerns have grown regarding their potential distributional consequences. While the environmental benefits of stricter regulation are well established, there remains limited consensus over whether such policies increase or reduce income inequality. This thesis examines the relationship between environmental policy stringency and income inequality across OECD economies over the period 1990–2020. Environmental policy stringency is measured using the OECD Environmental Policy Stringency (EPS) Index and its market-based, non-market and technology support sub-indices, which may affect firms, workers and households through different economic channels. Income inequality is measured primarily using the GINI coefficient for disposable income. The study also examines regional income inequality, recognising that the costs and benefits of environmental policies may be unevenly distributed across regions within countries.

A two-way fixed effects model exploits within-country changes in environmental policy stringency over time, controlling for common year effects and time-invariant country characteristics. No statistically significant association is identified between the aggregate EPS Index and income inequality. However, disaggregating the index reveals heterogeneity across policy categories. Market-based and non-market environmental policies are generally associated with lower levels of income inequality, while technology support policies are positively associated with inequality. These relationships are modest, vary in statistical significance across specifications and are not retained when allowing for time-delayed policy effects. No statistically significant association is identified between environmental policy stringency and regional income inequality. Additional analyses focusing on countries' largest observed increases in EPS provide only limited and measure-dependent evidence of further associations with inequality.

This thesis forms part of an evolving strand of empirical studies which examines the relationship between the stringency of a nation's environmental policies and income inequality. It adds to this literature both through its use of a different empirical strategy and its extension to investigate regional income inequality. Additionally, by examining different typologies of environmental policy, it contributes to the existing literature on how different forms of environmental policy may have differing distributional consequences. This analysis adds to the discussion of how equity must be considered alongside environmental effectiveness in policy design in order to support a just and politically sustainable transition to a low-carbon economy.

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1. Declaration on the Use of Artificial Intelligence (AI) Tools

The undersigned Cameron Andrews, student ID 908219, enrolled at Ca' Foscari in the Master's Degree Programme in Economics, Finance and Sustainability, author of the degree thesis *Can environmental policies put the GINI back in the bottle?* thesis supervisor Sanghmitra Gautam, is aware of the penalties provided for in Article 76 of the Consolidated Act set out in Presidential Decree no. 445 of 28 December 2000, and of the loss of benefits provided for in Article 75 of the same Consolidated Act in the event of false or misleading statements, under his/her own responsibility pursuant to Articles 46 and 47 of Presidential Decree no. 445 of 28 December 2000,

2. DECLARES

☐ that he has **NOT** used generative artificial intelligence technologies to support various aspects of the research and writing of the degree thesis;

☒ that he **HAS** used generative artificial intelligence technologies to support various aspects of the research and writing of his final degree thesis, in particular:

- *OpenAI's Large Language Model (LLM) ChatGPT (specifically the models GPT 4 & 5) have been used as part of this thesis*
- provide information on how the tool was used:
 - ☒ revision and optimisation of texts to improve clarity and coherence;
 - ☐ generation of charts and diagrams for data presentation;
 - ☒ support for the automatic drafting of sentences;
 - ☐ production of illustrative images to complement the methodological section;
 - ☒ other – *Generation of Stata code;*
- indicate the sections or chapters concerned – *Abstract & Sections 2-7*
- indicate how the accuracy, quality and reliability of any information or text that may have been generated were verified - *The accuracy, quality and reliability of any information or text that was generated was verified by the author personally. All output was read thoroughly and critically evaluated before inclusion in the final thesis. At no stage was the LLM used to gather information directly from academic papers and therefore there were no hallucinations generated of erroneous results from other analyses or the existing literature more broadly.*

3. DECLARES FURTHER

that all material generated by AI has been carefully checked, reviewed and reworked by the author, who assumes full responsibility for the quality, accuracy and scientific integrity of the work.

2. Introduction

2.1 Environmental Policy

In recent decades, developed economies have implemented increasingly stringent environmental policies in response to climate change, environmental degradation and biodiversity loss. Table 1 lists the major international environmental policy developments between 1990 and 2020. We can see this was a period of significant change. There was both a significant breadth to the forms of policies which were introduced, ranging from market-based measures such as the European Union's Emissions Trading Scheme and command and control policies such as the Copenhagen Amendment, which served to strengthen the existing Montreal Protocol, itself a landmark piece of environmental legislation and a striking example of international cooperation to combat environmental challenges. This was accompanied by a rise in strictness of these policies, with the Paris Agreement building upon the Kyoto Protocol which came before it. These agreements explicitly asked countries to design and implement difficult policies to reduce greenhouse gas emissions to help steer the globe away from the most catastrophic consequences of climate change.

Table 1 – Selected Major International Environmental Policy Developments (1990-2020)¹

Year	Development	Summary
1992–94	Rio Earth Summit / UNFCCC	UNFCCC opened for signature at Rio in 1992 and entered into force in 1994, establishing the principal international framework for addressing climate change.
1992–94	Copenhagen Amendment to Montreal Protocol	Strengthened international controls on ozone-depleting substances and expanded the substances covered by the Montreal Protocol.
1997	Kyoto Protocol adopted	Established binding GHG emissions targets for developed economies, marking major step from cooperation towards quantified commitments.
2003	EU ETS Directive	Established the legislative basis for an EU-wide carbon emissions trading system.
2005	Kyoto Protocol enters into force	Brought the Kyoto framework and its binding emissions commitments formally into operation.
2005	EU ETS launched	Began EU-wide trading of emissions allowances, establishing the world's first major international carbon market.
2008–12	Kyoto first commitment period	Period during which developed-country emissions targets under the Kyoto Protocol formally applied.
2009	EU 2020 Climate & Energy Package	Established EU-wide 2020 climate and energy objectives, including emissions reduction and increased renewable-energy use.
2012	Doha Amendment	Extended the Kyoto framework through a second commitment period covering 2013–2020 with new emissions targets.
2013	EU ETS Phase 3	Major reform introducing an EU-wide emissions cap, greater use of auctioning and broader sectoral and greenhouse-gas coverage.
2015	Paris Agreement adopted	Established new global climate framework based on national commitments, with the goal of keeping warming well below 2°C and pursuing 1.5°C.
2016	Paris Agreement enters into force	Brought the Paris framework formally into operation, establishing the basis for successive national climate commitments.

¹ Notes: Sources - 1992–94 Rio Earth Summit / UNFCCC: United Nations Framework Convention on Climate Change (UNFCCC), <https://unfccc.int/documents/649617>; 1992–94 Copenhagen Amendment to the Montreal Protocol: UNEP Ozone Secretariat, <https://ozone.unep.org/treaties/montreal-protocol/meetings/fourth-meeting-parties/decisions/annex-iii-copenhagen-amendment-1992-amendment-montreal-protocol-agreed-fourth-meeting-parties>; 1997 Kyoto Protocol adopted and 2012 Doha Amendment: UNFCCC, <https://unfccc.int/process-and-meetings/the-kyoto-protocol>; 2005 Kyoto Protocol enters into force: UNFCCC, <https://unfccc.int/process/the-kyoto-protocol/status-of-ratification>; 2008–12 Kyoto Protocol first commitment period: UNFCCC, <https://unfccc.int/resource/docs/convkp/kpeng.html>; 2003 EU Emissions Trading System Directive, 2005 EU Emissions Trading System launched and 2013 EU ETS Phase 3: European Commission, https://climate.ec.europa.eu/areas-action/carbon-markets/about-eu-ets_en; 2009 EU 2020 Climate & Energy Package: EUR-Lex, <https://eur-lex.europa.eu/EN/legal-content/summary/2020-climate-and-energy-package.html>; 2015 Paris Agreement adopted and 2016 Paris Agreement enters into force: UNFCCC, <https://unfccc.int/process-and-meetings/the-paris-agreement>.

Today, the 2015 Paris Agreement still represents a high water mark in regards to global climate ambition and our ability to cooperate in order to combat the most severe environmental challenges, which do not discriminate across boundaries. Furthermore, inherent in the Agreement itself is a recognition of distributional considerations and equity through the principle of *common but differentiated responsibilities and respective capabilities*. This reflects both the greater responsibility for developed countries to lead on the enactment of these policies and a the recognition that developing countries require greater support to deal with the impacts from climate change. Climate change serves to exacerbate present day income inequality, given the poorest in society live in areas most exposed to climate events, are most vulnerable to food security crises and have access to fewer financial resources to protect against shocks (Haddad et al., 2024; Lei et al., 2026; Markkanen & Anger-Kraavi, 2019). In developed economies, social movements such as Extinction Rebellion can be viewed as reflecting increasing public awareness of the unequal impacts of climate change across society (Schonhage et al., 2024)

In the decade since this agreement entered into force, the political urgency attached to environmental action has shown signs of weakening, even while broader support for climate action remains relatively high. Recent UK evidence indicates declining concern about climate change and a reduced sense of urgency around achieving net zero, alongside falling support for policies seeking to influence individual behaviour and preference for businesses and government to bear greater responsibility (DESNZ, 2026; Duffy, 2026). More broadly, evidence from OECD countries indicates that while public contention following the introduction of climate policies is relatively uncommon, particular policy instruments, including carbon taxes, have generated significant opposition (Anisimova & Patterson, 2025). Evidence from France similarly demonstrates substantial opposition to carbon taxation where the policy is perceived as regressive, imposing disproportionate costs on lower-income households (Douenne & Fabre, 2020, 2022). Dechezleprêtre et al. (2022), drawing on survey evidence from 20 countries, find that support for climate policies depends on their perceived distributional consequences for lower-income individuals, and respondents' expectations of the costs or benefits for their own household. Public support therefore appears to depend both on the type of environmental policy introduced and how its costs are distributed.

These distributional concerns have become particularly relevant as environmental objectives compete with other demands on governments. Pressures on public finances following the COVID-19 pandemic, alongside higher interest rates relative to the 2010s, increased defence spending in Europe following Russia's invasion of Ukraine, and demographic pressures on healthcare and state pensions, may constrain governments' capacity to finance large green investments. While the environmental benefits of environmental policies are well established (Acemoglu et al., 2012; Bettarelli et al., 2024; Lai et al., 2026), considerably less consensus exists regarding their wider socioeconomic consequences. In particular, there is growing debate over whether environmental policies disproportionately burden lower-income individuals or alternatively whether they can contribute to a more equitable distribution of income. Understanding these distributional consequences is important because the costs and benefits of environmental policies may fall differently across households, workers, firms and regions. Governments must therefore reconcile ambitious climate objectives with concerns surrounding fairness and the delivery of a just transition when designing politically acceptable climate strategies.

2.2 Income Inequality

Income inequality has become an increasingly prominent economic and political issue. After declining during the decades immediately following the Second World War, inequality has risen across most developed economies since the 1970s (Acemoglu & Autor, 2011; Milanovic, 2025; Morelli et al., 2015). The rapid growth of China in particular has also served to contribute to widening wage differentials between skilled and unskilled workers (Milanovic, 2025), while labour market polarisation has concentrated employment growth at both the upper and lower ends of the income distribution, resulting in *wage polarisation* (Acemoglu & Autor, 2011). Public awareness of these trends increased following the Global Financial Crisis through movements such as Occupy Wall Street and was further reinforced by the publication of Thomas Piketty's *Capital in the Twenty-First Century*.

The increasing prominence of income inequality has been accompanied by growing public concern regarding its consequences. Research from the OECD indicates that concern about income inequality has increased across OECD countries since the 1990s, while a majority of respondents support greater government intervention to reduce disparities, including through more redistributive taxation (OECD, 2021). Evidence from European countries similarly suggests a positive relationship over time between income inequality and preferences for redistribution (Olivera, 2015). More recent cross-country evidence reinforces this relationship, with Hillen & Steiner (2025) finding that increases in disposable-income inequality within countries are associated with increased public support for income redistribution across all income groups. Alongside these concerns surrounding income inequality, the distribution of wealth has also attracted increasing policy attention, including renewed interest in wealth taxation (OECD, 2018). Cross-country survey evidence from G7 economies indicates broad public support for wealth taxation, although the extent of this support depends on how such taxes are designed (Schechtl & Tisch, 2024). More broadly, high levels of economic inequality within a society are seen to lead to unjust outcomes, with access to opportunity driven by inherited characteristics (Haddad et al., 2024). These concerns surrounding the distribution of income and wealth provide an important context for considering the distributional consequences of other major policy interventions, including environmental policy.

The relationship between environmental policy and inequality has become increasingly salient within both academic and political discourse. These developments are connected, as environmental policies can influence income distributions, while existing levels of inequality may determine the desire for and acceptance of these policies. Magnani (2000) finds that inequality influences the adoption of environmental policies within OECD countries, while Bel & Teixidó (2020) argue that higher levels of inequality are associated with more ambitious climate mitigation policies. Conversely, rising inequality may contribute to political polarisation and instability, environmental scepticism and declining public support for climate action (D'Alessandro et al., 2020; Haddad et al., 2024; Magnani, 2000; Markkanen & Anger-Kraavi, 2019). Redistributive taxation regimes are also key in shaping how environmental policies impact inequality (Bettarelli et al., 2024; Känzig, 2023). D'Alessandro et al. (2020) show that progressive taxation policies, such as a wealth tax, can mitigate the adverse effects of carbon taxes. Therefore, environmental policies and economic inequality appear to be closely connected issues that do not exist in isolation from each other.

Environmental policies may affect income distribution through several distinct channels. These instruments may initially impose costs on firms and producers, but part of these costs may be passed through to consumers through higher prices. Market-based instruments, including

carbon taxes and emissions trading schemes, may increase inequality by raising the prices of carbon-intensive goods such as energy and transport, thereby placing a proportionately greater burden on lower-income households (Abbas & Kopp, 2026; Bettarelli et al., 2024; Callan et al., 2009; Känzig, 2023; Leimbach et al., 2024; Markkanen & Anger-Kraavi, 2019; Schonhage et al., 2024; Yu et al., 2021). Similarly, non-market based policies including emissions standards may also serve to increase income inequality by inducing skill-biased technological change. Firms responding to stricter environmental standards may adopt cleaner technologies and innovations which complement the productivity of skilled workers, increasing their relative demand and wages compared with lower-skilled workers (Huang et al., 2025). These distributional effects may be compounded by the, at present, greater reliance on lower-skilled workers in heavily-polluting industries, who may be disproportionately affected by stricter environmental regulation (Wen et al., 2025). Technology support policies, including public expenditure on low-carbon research and development and financial support for renewable technologies such as solar and wind, may operate through different mechanisms again. By promoting innovation and investment, these policies can generate new employment and income opportunities, although their distributional effects may depend on where these opportunities are created and whether their benefits accrue primarily to firms, workers, or households that are able to adopt supported technologies. (Markkanen & Anger-Kraavi, 2019).

The distributional impacts of environmental policies can also have a regional dimension as costs and benefits may be unevenly distributed across households, workers and regions, particularly where affected industries and employment are geographically concentrated (Abbas & Kopp, 2026). For example, regions dependent on carbon-intensive industries may experience concentrated job losses and declining incomes as these activities are phased out, particularly where displaced workers face difficulties transitioning into new employment (Abbas & Kopp, 2026; Markkanen & Anger-Kraavi, 2019). However, the transition to net-zero may create new economic opportunities where renewable energy investment and associated employment are directed towards regions with fewer existing employment opportunities (Markkanen & Anger-Kraavi, 2019). Importantly, these geographically concentrated effects may not be visible in national measures of income inequality. Losses concentrated in particular industrial regions may coexist with gains elsewhere, producing relatively little change in the national distribution while widening disparities between regions. These competing theoretical channels suggest that environmental policy should not be viewed as a uniform policy intervention and highlight the importance of distinguishing between different policy instruments.

2.3 Existing Literature

A systematic review of the existing literature on the relationship between environmental policy and income inequality was undertaken, the methodology for which can be found in the Appendix (Literature Review) section. Although this literature has expanded rapidly in recent years, the evidence remains mixed. A substantial body of research suggests that the distributional consequences of environmental policy depend not only on the overall level of policy ambition, but also on the type of policy instrument employed (Bettarelli et al., 2024) and the transmission channels through which it operates.

A significant strand of the literature examines market-based environmental policies, such as carbon taxes, emissions trading schemes and the removal of fossil fuel subsidies. Several studies conclude that these policies tend to increase income inequality by disproportionately increasing costs for lower-income households, either directly or where costs imposed on firms are passed through into consumer prices, or by increasing the skilled–unskilled wage premium.

Bettarelli et al. (2024) in a cross-country analysis of environmental policy stringency and income inequality, find that stricter market-based policies increase inequality, with these effects stronger in countries with larger shares of low-skilled workers, but are mitigated where redistribution systems are more comprehensive or during periods of fiscal expansion. Känzig (2023) analyses the impacts of price shocks in the EU Emissions Trading Scheme and finds that poorer households suffer larger income losses and reduce their consumption accordingly, and poorer countries are more greatly affected. Similarly, Markkanen & Anger-Kraavi (2019) in their review of the literature, conclude that carbon taxes, the removal of fossil fuel subsidies and financial disincentives for private car use generally increase inequality, particularly in countries with higher pre-existing levels of income inequality. On a theoretical basis, Kuo et al. (2022) demonstrate that more stringent pollution taxes increase the skilled–unskilled wage differential, while Callan et al. (2009) find that the introduction of a carbon tax in Ireland would exacerbate existing income inequalities.

However, the evidence is far from unanimous. Evidence from China suggests that market-based policies may have progressive distributional effects (Chao et al., 2012; Chen et al., 2025; Ee et al., 2018; Wang et al., 2019; Yang & Tang, 2023; Yu et al., 2021). Yu et al. (2021) find that China's Emissions Trading Scheme reduced urban–rural income inequality, particularly in regions with higher carbon emissions and higher levels of GDP per capita. Likewise, Wang et al. (2019) and Yang & Tang (2023) show that China's Environmental Protection Tax increased workers' wages relative to executives and reduced disparities between urban-rural inequality. Chao et al. (2012), Chen et al. (2025) and Ee et al. (2018) all develop theoretical models demonstrating that pollution taxes and emissions trading schemes can reduce income inequality under certain conditions. Collectively, these studies suggest that the distributional effects of market-based policies depend critically on policy design and the environment and context in which they are implemented.

A second strand of the literature considers non-market, or command-and-control, environmental policies, including emissions standards and pollution limits. Much of this literature finds that stricter regulatory policies increase income inequality through their effects on the labour market. The closure of coal mines and fossil fuel power stations can widen income disparities by disproportionately affecting lower-skilled workers, resulting in job losses (Abbas & Kopp, 2026; Markkanen & Anger-Kraavi, 2019). Similarly, Huang et al. (2025); Y. Liu et al. (2023); Qin et al. (2021) find that emissions limits in China increase wage inequality by raising the skilled–unskilled wage premium, particularly within heavily polluting industries. Huang et al. (2025) argue that stricter environmental regulation induces firms to adopt cleaner technologies and innovations which complement the productivity of skilled workers, increasing their relative demand and wages and thereby acting as a form of skill-biased technological change. Y. Liu et al. (2023) find these effects to be persistent over time, but also demonstrate that greater investment in human capital can mitigate the adverse distributional effects of environmental policies. Zhao et al. (2025) likewise show that the forced closure and relocation of chemical plants increased income inequality, and M. Liu et al. (2021) find that pollution limits imposed the greatest costs on low-skilled workers. Wen et al. (2025) similarly report that stronger environmental legislation widens the skilled–unskilled wage gap.

Nevertheless, some studies suggest that non-market policies may instead reduce inequality. Liao & Li (2026) find that air pollution control policies in China reduced income inequality by increasing the productivity of low and middle-income workers through improved environmental quality. On a theoretical basis, Pi & Shi (2019) demonstrate that public pollution abatement can

reduce the skilled–unskilled wage differential where the intensity of skilled urban labour is sufficiently high, while Shimizu & Okamoto (2022) similarly show that non-tradeable pollution permits can reduce income inequality by lowering the skill premium. Zhan & Pu (2026) also find that non-market policies have the ability to reduce the negative effects of climate policy uncertainty on income inequality. These findings illustrate that even within command-and-control policies, distributional outcomes depend on the mechanisms through which regulation affects labour markets and productivity.

The literature on the impacts of technology support policies is far more scarce. D’Alessandro et al. (2020) use a macroeconomic model to compare alternative policy scenarios for France and find that environmental policies implemented in isolation, including technology support policies, increase income inequality. However, when these policies are combined with progressive redistributive measures, such as wealth taxation and employment guarantee programmes, inequality falls. Related evidence is provided by Markkanen & Anger-Kraavi (2019) who examine a broader range of renewable energy interventions and find that their distributional effects can depend on policy design. Large-scale renewable energy projects can reduce inequality when strategically located in areas with high unemployment, creating new opportunities. However, renewable energy interventions can worsen distributional outcomes where access to their benefits is unequal, while large hydroelectric projects may adversely affect displaced populations where sufficient compensation and support are not provided (Markkanen & Anger-Kraavi, 2019). These studies suggest that the distributional implications of environmental policies concerned with the support of specific technologies depend both on the specific form of intervention and the wider policy environment.

Several other studies examine environmental policies which do not map clearly onto the market-based, non-market or technology support categories used in the OECD EPS Index. Markkanen & Anger-Kraavi (2019) find that investment in public transport infrastructure can reduce income inequality, particularly where improvements are targeted towards the transport needs of lower-income areas, while investment in public transport can also generate new employment opportunities. Lei et al. (2026) examine China's Low Carbon City Pilot Policy, a broad package of environmental measures, and find that it reduced urban income inequality over time by lowering the skilled wage premium, particularly in regions with lower initial levels of inequality. Scown et al. (2020) argue that the European Union's Common Agricultural Policy has increased income inequality while providing limited support for climate-friendly farming. Collectively, these studies provide further evidence that the distributional effects of environmental policy can vary considerably depending on the specific policy intervention being considered.

A further strand of the literature considers whether the distributional effects of national environmental policies vary geographically, creating or reinforcing income disparities between regions. This is distinct from their effect on national income inequality, because the economic activity and carbon-intensity of industries is unevenly distributed across space. Climate policies can reallocate resources across regions (Chen et al., 2025) with positive effects more likely where policies reduce expenditure or generate greater economic opportunities in poorer regions (Markkanen & Anger-Kraavi, 2019). Policy design is therefore an important factor in determining these regional distributional effects. Market-based policies such as taxes on air pollution may reduce or widen regional inequality depending on whether the costs are primarily borne by producers or consumers (Wang et al., 2019). Climate change itself, and the uncertainty surrounding climate policy, has been seen as a potential driver widening income disparities between regions (Lei et al., 2026; Zhan & Pu, 2026).

Non-market based policies have also been identified as potentially contributing to widening regional income inequality. Higher-income regions may have greater capacity to upgrade industrial processes to comply with new environmental regulations, whilst lower-income regions face more difficulties adjusting due to more limited resources and weaker governance (Zhao et al., 2025). The transition to a low-carbon economy can also cause geographic shifts in the labour market. Support for large scale renewable energy projects can generate new employment opportunities, whilst regions reliant on heavily polluting industries may experience geographically concentrated job losses as these activities are phased out (Abbas & Kopp, 2026; Markkanen & Anger-Kraavi, 2019). Displaced workers may also struggle to transition into new sectors, particularly where opportunities for retraining or alternative employment are limited (Abbas & Kopp, 2026). These effects can contribute to labour force and population decline, as well as social unrest, potentially widening inequality between regions (Abbas & Kopp, 2026; Markkanen & Anger-Kraavi, 2019). Where such adverse effects occur, policy support will be required to increase economic diversification in regions that have experienced job losses as a result of the transition (Markkanen & Anger-Kraavi, 2019).

A final strand of the literature, and the most relevant for this thesis, is the study of the impacts of the stringency of the environmental policies collectively introduced in a country on income inequality. Bettarelli et al. (2024) in a cross-country analysis, find no relationship between the overall stringency of environmental policy and inequality. Conversely, Abbas & Kopp (2026) find that in their analysis of European OECD members stricter environmental policies are associated with higher levels of income inequality. However, this result does not hold when considering income inequality based on disposable income, with the authors suggesting that the redistributive capacity of the state helps to mitigate the adverse distributional effects of these environmental policies. Alongside these national effects, the regional distribution of the impacts of environmental policy is also an important consideration. Policies which produce relatively limited changes in inequality at the national level may nevertheless have uneven effects across regions, particularly where affected industries and employment are geographically concentrated. At this stage no identified study has examined whether environmental policy stringency is systematically associated with income inequality between regions within countries.

Overall, the existing literature provides mixed evidence regarding the relationship between environmental policy and income inequality and suggests that different policy instruments may operate through distinct distributional mechanisms. A significant proportion of the empirical evidence is derived from Chinese case studies, raising questions regarding the external validity of these findings for OECD economies more broadly. While a substantial literature examines the distributional consequences of specific environmental policies, only two studies identified in this review, Bettarelli et al. (2024) and Abbas & Kopp (2026), examine the relationship between environmental policy stringency as a whole and income inequality. In addition, examining market-based, non-market and technology support policies separately is important because these policy categories may operate through different economic mechanisms, as suggested in the literature, and may therefore have differing associations with income inequality.

2.4 Research Question and Contribution

This thesis investigates whether more stringent environmental policies are associated with higher or lower levels of income inequality, measured using the GINI coefficient. The research question addressed is:

How is environmental policy stringency associated with income inequality, including regional income inequality, in OECD countries?

Environmental Policy Stringency is measured using the OECD (EPS) Index. The disaggregated sub-indices, namely market-based, non-market and technology support policies allow different policy typologies to be analysed separately. This is important because the policy categories differ not only in their design, but also in the actors they initially affect and the channels through which their costs or benefits may be distributed.

Income inequality is measured using the GINI coefficient, while regional inequality is measured using the coefficient of variation between regional incomes. A two-way fixed effects model is used to account for both country-specific and time-specific effects. The identifying variation available to the TWFE model is also examined, assessing how much variation in environmental policy stringency remains after accounting for country and year fixed effects. The analysis controls for GDP per capita, population, trade openness and manufacturing as a share of gross value added. Alternative specifications use different measures of income inequality and lagged policy variables, to address potential measurement error and to capture potential time-delayed effects. Additionally, analysis is undertaken to determine whether the timing of the increases in the stringency of policy is in itself predictive of the relationship between EPS and inequality. Finally, as an extension, the analysis also considers whether EPS is associated with regional income inequality within countries, recognising that national measures of inequality may conceal geographically concentrated distributional effects where the costs and benefits of environmental policies are unevenly distributed across regions.

This thesis sits most closely alongside the work of Abbas & Kopp (2026) and Bettarelli et al. (2024). Table 2 provides a comparison of the three studies, highlighting similarities and differences in their samples, policy measures, inequality outcomes and empirical approaches. While this thesis uses a broadly similar sample and range of environmental policy measures, it differs through the use of a two-way fixed effects approach that exploits within-country changes in policy stringency over time. The analysis also extends the existing literature to within-country regional income disparities, an outcome not directly considered by either study.

The selection of variables also aids comparability with the existing literature. The principal dependent variable, the GINI coefficient for disposable income, is used by both Abbas & Kopp (2026) and Bettarelli et al. (2024), facilitating comparison with their findings. Similarly, the OECD EPS Index used as the principal independent variable is directly comparable with Bettarelli et al., (2024), and closely aligned with the measure of environmental policy stringency employed by Abbas & Kopp (2026). Finally, the selection of control variables was informed by those commonly used across the existing literature examining environmental policy and income inequality.

The results indicate that the estimated association with income inequality differs across policy categories. While no statistically significant association is identified between the aggregate EPS Index and income inequality, analysis of the sub-indices reveals heterogeneous associations. This suggests that examining only the aggregate EPS Index may conceal differences in the estimated associations of its constituent policy categories. In doing so, the analysis provides

further evidence on the association between environmental policy stringency and income inequality across OECD economies, while applying a different empirical approach and extending the analysis to within-country regional income inequality.

The findings provide points of both agreement and divergence with the two most relevant studies. The absence of a statistically significant association for aggregate EPS is consistent with Bettarelli et al., (2024) while the lack of a significant association with disposable income inequality is consistent with Abbas & Kopp (2026). However, the results for market-based policies differ notably from Bettarelli et al., (2024), with this thesis finding a negative association in some specifications rather than the positive association they identify. As discussed further in Section 5, this contrast may partly reflect the composition of the OECD sample and the role of redistributive institutions, given existing evidence that the distributional effects of market-based policies vary with income levels, workforce composition, pre-existing inequality and the extent of redistribution. The contribution of this thesis therefore lies in providing additional evidence using a different empirical approach, extending the analysis to regional inequality, and demonstrating that the estimated associations between particular environmental policy categories and inequality are not uniform across studies.

Table 2 – Thesis Contribution Relative to Existing Literature

Feature	Bettarelli et al. (2024)	Abbas and Kopp (2026)	This thesis
Sample Countries	39 developed and developing	26 European OECD	32 OECD
Sample Period	1990–2020	1990–2022	1990–2020
Policy measure	OECD aggregate EPS index and sub-indices	OECD Climate Actions and Policies Measurement Framework (CAPMF) index of domestic policy stringency	OECD aggregate EPS index and sub-indices
Inequality measures	OECD disposable-income GINI & four additional measures of income dispersion	Pre-tax, disposable-income and post-tax GINI coefficients	OECD disposable, gross- and market income GINI, World Bank GINI, Regional income inequality variation in primary and disposable income
Empirical approach	IV Strategy	Group Mean Estimator	TWFE Model
Main finding	Higher inequality following stricter policy, but only for market-based policies.	Greater stringency associated with higher pre and post-tax inequality, but no significant association with disposable-income inequality.	No significant association for aggregate EPS. Market-based and non-market policies have generally negative associations with GINI, tech has a positive association. No significant association is found for between-region inequality.

These findings have clear policy relevance. As governments continue to strengthen environmental policies in pursuit of climate objectives, understanding their distributional consequences will become increasingly important for maintaining public support and ensuring a just transition. The implementation of more stringent environmental policies may exacerbate polarisation (Schonhage et al., 2024). For example, carbon pricing has been found to reduce support for climate change policies, especially amongst poorer households (Känzig, 2023). As Sovacool et al. (2021) note, we have to consider the “pragmatic concern of [not] making such transitions self-defeating, for by harming those most vulnerable among us they will [invariably] lead to resistance and crises of legitimacy.”

The remainder of this thesis is structured as follows. Firstly, a detailed explanation of the methodology used to conduct the data analysis of this project is provided. Second, the results of the data analysis are presented, followed by an in-depth discussion. Finally, the conclusions from this thesis are provided.

3. Methodology

3.1 Research Design

This thesis adopts a quantitative research design to examine the relationship between environmental policy stringency and income inequality across OECD countries. The central objective of this analysis is to estimate whether changes in environmental policy are associated with changes in the distribution of disposable income, both nationally and between regions within countries, whilst accounting for factors that may simultaneously influence both variables. The relationship between environmental policy and inequality is inherently complex. Policies are implemented within broader political institutions and economic systems, while income inequality evolves gradually in response to structural changes and labour market conditions.

Panel data analysis allows for the exploitation of variation within countries and over time, and is able to account for unobserved heterogeneity between countries. Countries differ in many persistent characteristics, including political institutions, legal systems and historical patterns of economic development, which may influence both the adoption of environmental policies and the distribution of income. If these characteristics are omitted from the empirical model, estimated relationships may suffer from omitted variable bias. By exploiting repeated observations for the same countries over time, panel estimation techniques substantially reduce this concern by controlling for time-invariant country-specific characteristics.

This analysis employs a two-way fixed effects framework. The fixed effects estimator identifies the relationship between environmental policy stringency and income inequality using variation within countries over time, rather than relying on differences between countries. In doing so, it removes the influence of all unobserved characteristics that remain constant throughout the sample period. Country fixed effects account for persistent national characteristics, while time fixed effects capture global shocks and common time trends affecting all countries simultaneously including international economic crises and common technological developments. This approach strengthens the internal validity of the analysis by reducing potential sources of omitted variable bias that could otherwise distort the estimated relationship.

The key identifying assumption is therefore that, conditional on the included controls and fixed effects, the remaining country-year variation associated with changes in EPS is not driven by other unobserved time-varying factors that also affect inequality. The estimated coefficients are interpreted as conditional associations rather than causal effects. Although the fixed-effects framework reduces several potential sources of omitted variable bias, the research design cannot rule out the influence of unobserved country-specific factors that vary over time and are correlated with both environmental policy stringency and income inequality.

The analysis distinguishes between different types of environmental policy rather than treating policy stringency as a homogeneous treatment. While the overall EPS index provides an aggregate measure of policy ambition, environmental policies differ substantially in their design and underlying economic mechanisms. Market-based instruments, non-market measures and technology support policies may each influence income distribution through different channels, affecting firms, workers and households in different ways. Consequently, after estimating the relationship using the aggregate EPS index, the empirical analysis separately examines these three policy categories. This allows the thesis not only to assess whether environmental policy is associated with changes in inequality overall, but also whether these associations differ

according to the type of policy instrument employed. This disaggregated approach allows the estimated associations to be compared across the three EPS sub-indices.

The remainder of this methodology section first describes the data and construction of the variables used in the analysis, before setting out the econometric specification and robustness tests and limitations of the analysis, and finally presenting a validation of the identification strategy.

3.2 Data

This study uses an unbalanced panel dataset of 32 OECD economies covering the period 1990-2020. The full list of countries included in the dataset and the number of observations for each of the main variables can be found in the Appendix (Dataset) section.

The sample period and set of countries was primarily defined by data availability from the OECD's Environmental Policy Stringency Index, given its crucial role as the variable of interest in all specifications. The OECD offers data for the EPS index (and sub-indices) for a set of 40 countries, 34 OECD members and six non-members. For the purposes of the analysis the data from the non-OECD members were excluded². Two more countries, Canada and Mexico, were excluded from the sample due to missing data for one of the control variables (trade openness), leaving 32 countries for this analysis.

The final sample was constructed by merging individual country-year observations across all variables using country identifiers and calendar years. As different variables exhibit differing levels of data availability across countries and years, the number of observations varies between specifications. The estimation samples are therefore unbalanced due to differences in the availability of dependent and control variables, with the number of observations used in each specification reported in the corresponding regression tables.

The regional inequality analysis uses a materially smaller sample than the individual income inequality analysis, primarily due to the more limited availability of comparable regional income data. An additional sample restriction is applied to ensure that the regional inequality measures are based on a sufficient number of regional observations within each country, resulting in the exclusion of Luxembourg and Hungary from the regional inequality dataset. The final regional estimation samples are further determined by the availability of corresponding EPS and control-variable data. This reduced coverage should therefore be taken into account when comparing the regional results with those obtained for national income inequality.

OECD countries provide an appropriate sample for analysing the relationship between environmental policy stringency and income inequality for several reasons. Firstly, these countries have implemented some of the most comprehensive environmental policies, leading to greater scope for variation. Secondly, OECD member countries comprise a relatively comparable group of predominantly high-income countries. Thirdly, these countries maintain high-quality and internationally comparable data, which enables reliable cross-country analysis. The empirical analysis relies almost exclusively on secondary data obtained from the OECD³. This focus on a single international data source improves the comparability of observations across countries and minimises inconsistencies arising from differences in statistical methodologies. The decision to focus on OECD economies also reflects practical considerations

² The six countries are as follows: Brazil, China, India, Indonesia, South Africa, Russia

³ The exception being the alternative measure of economic inequality from the World Bank, the GINI Index.

regarding data availability. The EPS index is produced solely by the OECD, and mostly focuses on member countries.

Despite these advantages, several limitations associated with the dataset should be acknowledged. Firstly, the OECD sample is composed predominantly of high-income economies, meaning that the findings may not generalise to developing economies. Secondly, the EPS index measures the notional stringency of environmental policies rather than their effectiveness or degree of enforcement. Overall, the assembled dataset provides a robust foundation for examining the relationship between environmental policy stringency and income inequality by combining comparable measures of environmental policy, income distribution and macroeconomic characteristics over an extended period. Further information on this dataset is available in the Appendix (Data) section.

3.3 Variables

The selection of variables is guided by the existing literature on the relationship between environmental policy and income inequality. The principal objective is to estimate the relationship between environmental policy stringency and income inequality whilst accounting for other factors that may influence both variables. The main dependent variable is the disposable income GINI coefficient, obtained from the OECD Income Distribution Database. The use of the GINI coefficient for disposable income is consistent with the approach adopted by Abbas & Kopp (2026) and Bettarelli et al. (2024) facilitating comparison with the closest existing studies. The GINI coefficient is the most widely used summary measure of income inequality and ranges from zero, representing perfect equality, to one, representing complete inequality. It measures the extent to which the distribution of income deviates from perfect equality.

The analysis distinguishes between three OECD measures of income inequality. Market income captures income received from market sources, such as wages and capital income, before taxes and transfers. Gross income additionally incorporates transfers and benefits, while disposable income accounts for both transfers received and taxes paid and therefore more closely reflects the income ultimately available to households. Disposable income is consequently used as the primary measure of income inequality, providing an appropriate basis for evaluating the broader social consequences of environmental policy, while also offering the highest level of data availability of the three measures. The GINI coefficients for market and gross income are used as alternative specifications, allowing the results to be compared across income measures capturing different stages of redistribution. Comparing these measures can also provide some insight into whether an observed association is more apparent before or after taxes and transfers, although the analysis cannot identify the contribution of any particular redistribution mechanism. Further information on these variables is available in the Appendix (Data) section.

An alternative specification uses the GINI Index from the World Bank⁴. This is primarily a measure of disposable income inequality for the chosen sample (as this is the measure mostly used in high income countries, which reflects the status of most OECD countries). These data provide a useful alternative specification, both because of the very high degree of correlation with GINI disposable income (0.95, see Table 4), but more importantly as it offers better coverage across the sample period (which the summary statistics found in Table 3 show). For this reason these

⁴ This has been resized to span from 0 to 1, rather than 0 to 100, and as such will be referred to as a coefficient rather than an index from here on.

data provides a strong robustness check and is a key alternative specification to test the validity of the associations highlighted in the results of this thesis.

For the regional inequality section of this thesis, income data were collected on a regional basis, also from the OECD. Specifically, regional income per capita (PPP-converted) in constant USD was collected for both primary and disposable income, with regional inequality calculated separately using each measure. Primary income captures income received by households through participation in production and ownership of assets, including wages, self-employment income and property income. Disposable income accounts for taxes, social contributions, benefits and other current transfers, and therefore captures regional income disparities after redistribution. Using both measures therefore allows the analysis to compare regional disparities before and after the taxes and transfers captured in the regional income data. More detailed definitions of both measures are provided in the Appendix (Data) section.

The OECD's Territorial Level 3 (TL3) regions were selected in preference to the larger Territorial Level 2 (TL2) regions, providing greater geographical granularity and allowing countries with relatively few TL2 regions to be included in the analysis. TL2 regions represent larger subnational areas, such as Greater London in the United Kingdom, while TL3 regions divide countries into smaller territorial units, such as Camden. The precise administrative units corresponding to TL2 and TL3 differ between countries; for example, in Italy these classifications correspond to 21 TL2 regions and 107 TL3 provinces. Further information is provided in the Appendix (Data) section⁵.

Using these data, a measure of regional inequality was constructed. This measures not income inequality within individual regions, but rather inequality between regions within the same country. The measure therefore captures the extent to which incomes differ across regions for each country-year observation. This was measured using the coefficient of variation calculated for each country and year in the sample. The coefficient of variation is defined as:

- $CV = \sigma/\mu$

Where:

- σ = standard deviation of regional incomes within a country-year
- μ = mean regional income within that same country-year

A higher coefficient of variation therefore indicates a greater level of regional income inequality. To ensure that the coefficient of variation was calculated using a sufficient number of regional observations, a minimum of five TL3 regions was required for each country-year income measure. The resulting regional inequality measures were subsequently merged with the main dataset. The regional inequality analysis uses a smaller estimation sample than the individual income inequality analysis, with the final sample in each specification determined by the availability of regional income data, EPS and the other variables included in the model.

The coefficient of variation was chosen for several reasons. Firstly, it is straightforward to calculate and the available OECD regional income data provides strong coverage for constructing the measure across the sample period. More importantly, the coefficient of variation is a relative measure of dispersion. By scaling the standard deviation by the mean, it allows regional income disparities to be assessed relative to the average income level of a

⁵ More information is also available here: <https://www.oecd.org/en/data/datasets/oecd-geographical-definitions.html>

country. This makes comparisons across countries and over time more meaningful, given differences in average income levels across the sample. A limitation of the coefficient of variation is that, like the mean itself, it can be sensitive to outliers. Extremely high incomes in a small number of regions may therefore disproportionately increase the measured level of regional inequality.

The principal explanatory variable is the Environmental Policy Stringency (EPS) index developed by the OECD. In contrast to analyses that focus on individual policies such as carbon taxes or emissions trading schemes, the EPS index represents a broader measure of the policy environment within a single indicator. A breakdown of how the aggregate EPS measure is constructed is shown in Figure 1. In addition to the aggregate EPS measure, the OECD database also provides separate indices for market-based instruments, non-market policies and technology support policies, allowing the analysis to investigate whether policy approaches that operate through economic mechanisms exhibit different distributional associations. This allows a comparison of the associations for different policy categories, although the analysis does not directly test the economic channels through which any relationship might arise. The use of the OECD EPS Index is directly comparable with Bettarelli et al. (2024) and closely aligned with the measure of environmental policy stringency employed by Abbas & Kopp (2026).

Figure 1 – Environmental Policy Stringency Methodology (Kruse et al., 2022)

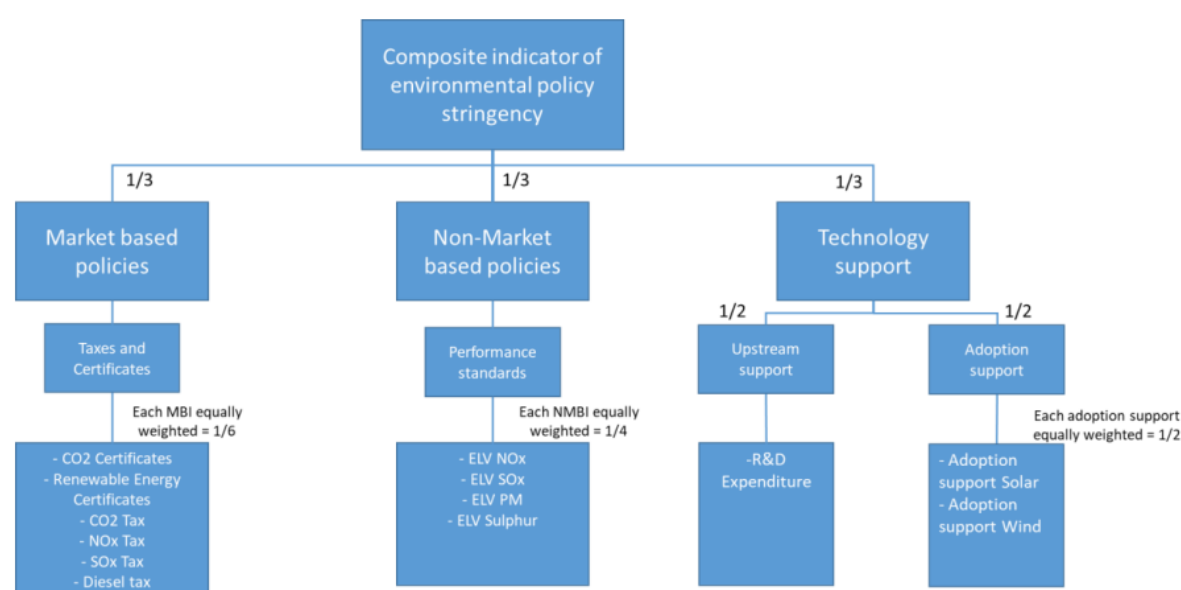
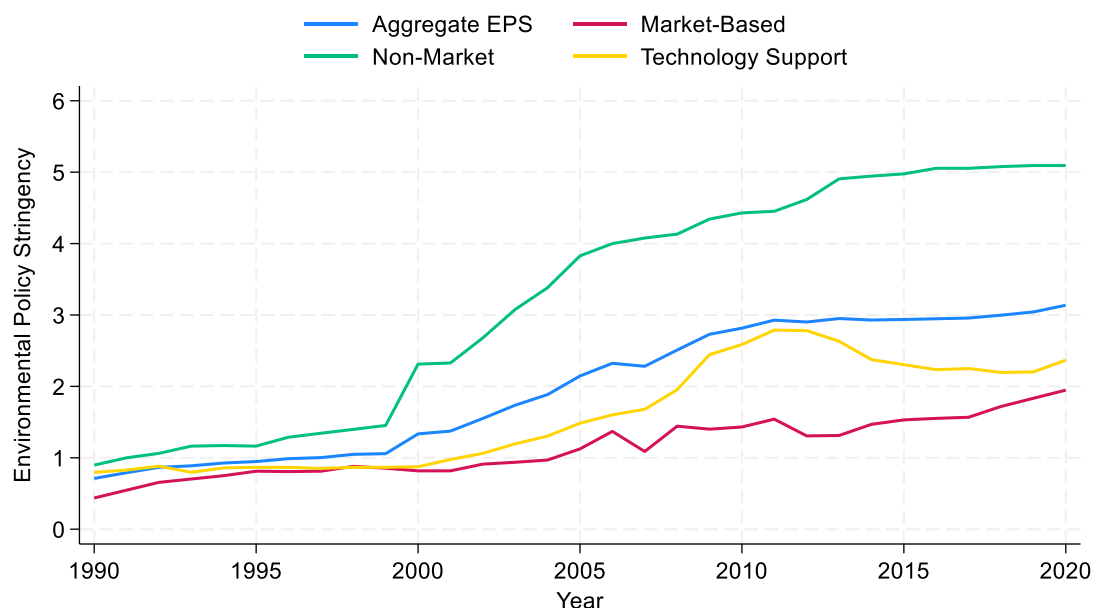


Figure 2 shows the average value of the aggregate EPS index and the sub-indices over time in the full sample. These measures are scored on a scale from 0 to 6, with the higher the value the stricter the policy. This illustrates that environmental policies in OECD economies have become stricter over the past 30 years. A notable inflection point examining the graph is just before the turn of the millennium. Following this inflection point the growth in the stringency of non-market based environmental policies accelerates much faster than previously. This may align with the timing of the historic Kyoto Protocol signed in December 1997, which was the first international treaty specifically designed to cut greenhouse gas emissions.

Figure 2 – Average EPS over Time (1990-2020) – Full Sample



To account for other factors that may influence the relationship between environmental policy stringency and income inequality, the empirical analysis includes a range of macroeconomic control variables commonly used across the existing literature examining these issues. Data for each of these variables are obtained from the OECD. The inclusion of these controls reduces the likelihood that the estimated EPS coefficients reflect omitted influences rather than the relationship of interest.

Gross domestic product (GDP) per capita is included to account for differences in levels of economic development across countries. Omitting GDP per capita could bias estimates of the relationship between environmental policy and inequality if both variables are correlated with levels of income. Population is included to control for differences in country size. Trade openness, measured as the sum of exports and imports as a proportion of GDP is a widely used indicator of a country's degree of economic openness and integration in regards to the global economy. This may also impact how the stringency of environmental policies affect the distribution of income within a country.

Manufacturing as a % of Gross Value Added is included to control for differences in countries' industrial composition. Manufacturing industries are generally more polluting and thus are more directly affected by environmental regulation. Employment in manufacturing has also historically been associated with relatively high wages for lower-skilled workers. As such, shifts away from manufacturing may influence income inequality independently of environmental policies. Further information on all the variables used is available in the Appendix (Data) section.

Summary statistics of all the variables used in this analysis can be found in Table 3. We can see that the sample comprises countries with both small and large populations (varying from 250,000 to 333 million) and is on average a group of rich countries by global economic standards, with an average GDP per capita of around \$45,000 over the sample period⁶. Given that manufacturing's

⁶ For reference, the World Bank classifies High-Income countries as those with a GNI per capita of approximately \$14,000 (Mestre et al., 2025)

share of GVA is on average around 17%, we can infer that as one would expect of the OECD, these are wealthy, predominantly service-based economies. Examining the EPS statistics one can see that there is a wide range of values, with two of the sub-indices having observations comprising the full 0-6 range. It is also notable that non-market environmental policies, such as emission limits, are considerably more stringent than the other three measures. Thus we can state that on average the sample has enacted stricter non-market based policies across the period when compared to other policy typologies.

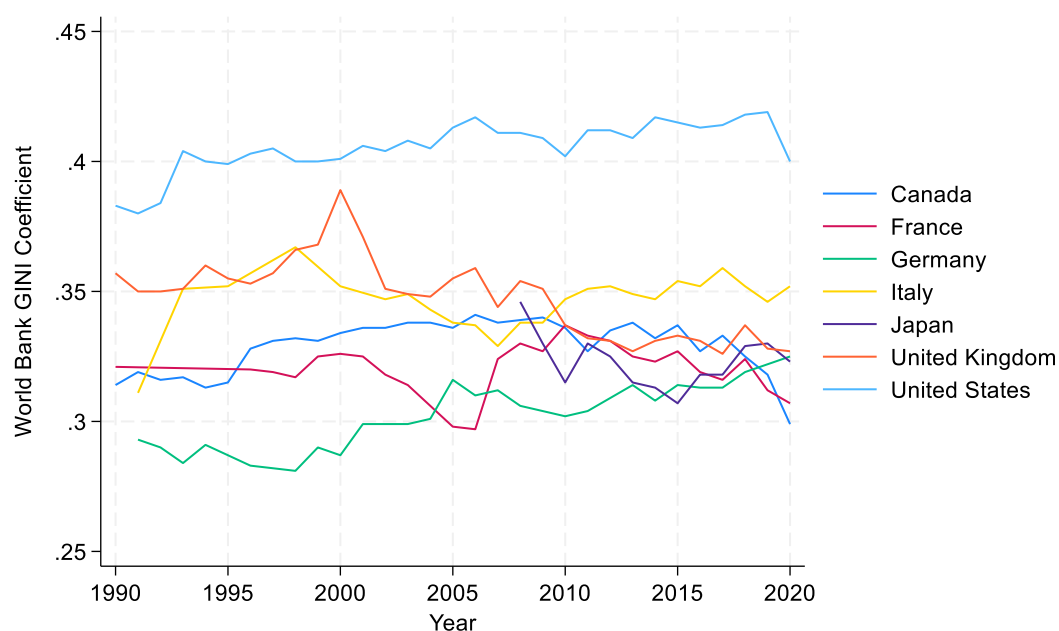
Table 3 - Summary Statistics

Variable	N	Mean	SD	Min	P25	Median	P75	Max
EPS	992	1.99	1.18	0.00	1.06	2.03	2.94	4.89
EPS Market	992	1.14	0.81	0.00	0.67	1.00	1.50	4.17
EPS Non-Market	992	3.22	1.99	0.00	1.50	3.25	5.00	6.00
EPS Tech	992	1.61	1.33	0.00	0.50	1.50	2.50	6.00
GINI Market income	383	0.47	0.05	0.37	0.44	0.48	0.51	0.58
GINI Gross Income	368	0.34	0.05	0.25	0.30	0.32	0.37	0.50
GINI Disposable Income	401	0.30	0.05	0.21	0.26	0.30	0.33	0.50
World Bank Gini coefficient	677	0.32	0.05	0.20	0.28	0.32	0.35	0.57
Regional Inequality (Disposable)	377	0.31	0.51	0.03	0.09	0.13	0.28	2.44
Regional Inequality (Primary)	313	0.39	0.54	0.06	0.14	0.19	0.38	2.46
GDP per capita (000)	865	45.42	18.75	12.24	33.50	44.35	54.91	130.16
Population (millions)	992	32.94	55.53	0.25	5.31	10.32	46.43	331.53
Trade Openness	864	0.82	0.54	0.16	0.50	0.67	0.98	3.74
Manufacturing (%GVA)	896	17.22	5.54	5.08	12.90	17.01	20.85	37.31

The level of the GINI statistics is also of interest, with the average for the three statistics outside of market income clustered between 0.3-0.34. For context, the World Bank defines a country as having ‘high inequality’ where the GINI coefficient is above 0.4 (Haddad et al., 2024). Thus we can characterise our sample as a set of countries, on average over the sample period, with a moderate level of income inequality. Figure 3 below serves to illustrate this by showing the GINI coefficient in the G7 over the sample period⁷. Here we can see that the GINI coefficient broadly converges in the same 0.3-0.35 range, with the United States serving as an outlier. Regarding the trend of inequality, this appears to be broadly flat over the sample period.

⁷ This sub-sample was chosen to aid readability and is an illustrative comparison. Canada is not included in the final sample due to it lacking data for one of the chosen control variables.

Figure 3 – GINI Coefficient in G7 Economies 1990-2020 data from World Bank



The summary statistics also show that the different measures of income inequality used by the OECD have noticeably different means and thus we can infer that they are materially different measures. The contrast between the three is further illustrated in Figure 4. Moving from market, to gross, to disposable income, the level of redistribution increases, which decreases inequality and thus the GINI coefficient. When considering the GINI coefficient from the World Bank, we see that it most closely aligns with the disposable and gross income measures, whilst having a higher range. One should note the differing number of observations available for each measure of economic inequality. As previously noted disposable income has the highest number of observations of the three OECD measures of income inequality, whilst the data from the World Bank offers substantially more coverage across the sample than all three.

Figure 4 – Measures of Income Inequality

Measure of Income	Redistribution	Level of Inequality	Gini Coefficient
Market	Increasing ↓	Decreasing ↓	Decreasing ↓
Gross			
Disposable			

The regional inequality summary statistics are also of interest. It should be noted that these observations constitute a materially smaller sample due to the level of data availability and the stipulation regarding the minimum number of TL3 regions required to calculate a valid coefficient of variation. The figure for disposable income is markedly lower than the corresponding figure for primary income. This is consistent with the expectation that, following taxes and transfers, variation in incomes between regions decreases on average. To examine trends in regional inequality over the sample period, Figure 5 graphs the coefficient of variation of regional disposable income for the seven countries with the highest number of observations. The figure indicates a broadly flat trend over time, alongside significant variation between countries. New Zealand, for example, records values between approximately 0.6 and 0.8, while the Czech Republic and Belgium remain below 0.2 throughout the period shown.

Figure 5 – Regional Income Inequality (Disposable) – Selected Sample of Countries (1990-2020)

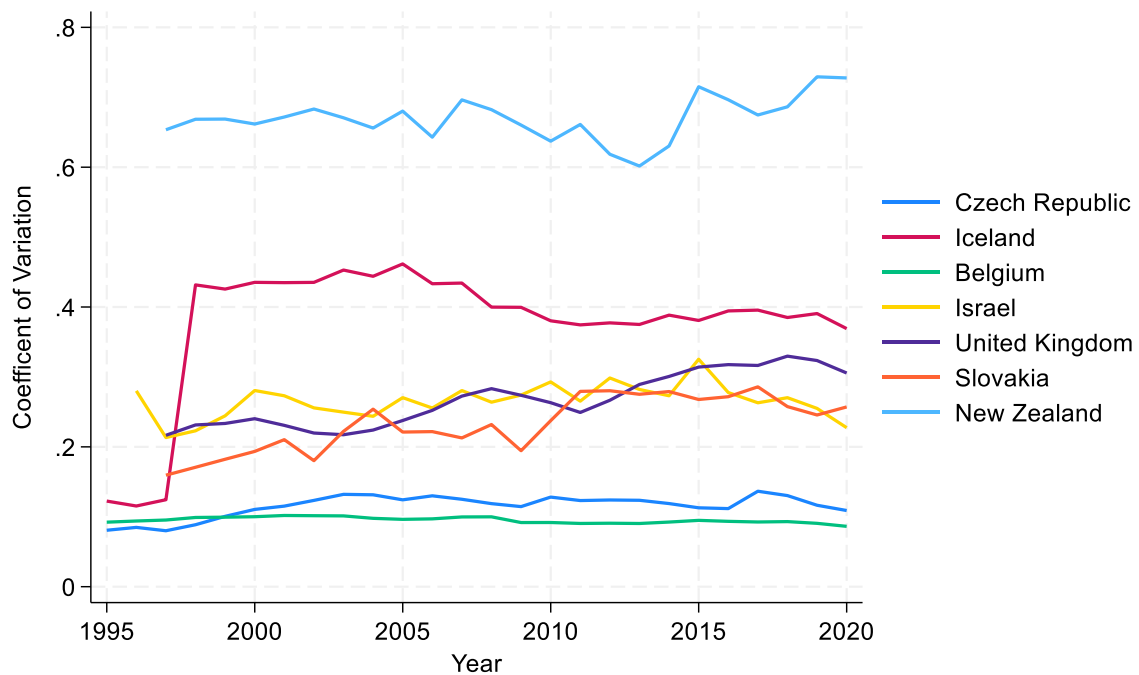


Table 4 presents the correlation matrix for all variables included in the empirical analysis, with the green cells on the diagonal indicating perfect correlations between identical variables. The matrix provides an overview of the relationships between the explanatory and control variables and does not indicate any unexpected patterns that warrant further investigation.

Table 4 – Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) EPS	1.00	0.70	0.93	0.83	-0.14	0.13	-0.12	-0.30	0.04	0.11	0.44	0.08	0.32	-0.11
(2) EPS Market	0.70	1.00	0.56	0.41	-0.24	-0.12	-0.24	-0.36	0.44	0.48	0.23	-0.03	0.07	-0.08
(3) EPS Non-Market	0.93	0.56	1.00	0.63	0.01	0.30	0.07	-0.26	-0.04	0.01	0.40	0.06	0.37	-0.08
(4) EPS Tech	0.83	0.41	0.63	1.00	-0.15	0.05	-0.16	-0.15	-0.15	-0.09	0.41	0.14	0.24	-0.11
(5) GINI Disposable Income	-0.14	-0.24	0.01	-0.15	1.00	0.39	0.94	0.95	0.03	0.07	-0.16	0.45	-0.36	-0.30
(6) GINI Market income	0.13	-0.12	0.30	0.05	0.39	1.00	0.66	0.43	-0.23	-0.21	-0.14	0.23	-0.11	-0.06
(7) GINI Gross Income	-0.12	-0.24	0.07	-0.16	0.94	0.66	1.00	0.88	-0.08	-0.05	-0.08	0.47	-0.33	-0.34
(8) World Bank Gini coefficient	-0.30	-0.36	-0.26	-0.15	0.95	0.43	0.88	1.00	-0.09	-0.07	-0.22	0.43	-0.32	-0.21
(9) Regional Inequality (Disposable)	0.04	0.44	-0.04	-0.15	0.03	-0.23	-0.08	-0.09	1.00	1.00	0.10	-0.15	-0.16	-0.21
(10) Regional Inequality (Primary)	0.11	0.48	0.01	-0.09	0.07	-0.21	-0.05	-0.07	1.00	1.00	0.09	-0.11	-0.18	-0.23
(11) GDP per capita (000)	0.44	0.23	0.40	0.41	-0.16	-0.14	-0.08	-0.22	0.10	0.09	1.00	0.01	0.63	-0.33
(12) Population (millions)	0.08	-0.03	0.06	0.14	0.45	0.23	0.47	0.43	-0.15	-0.11	0.01	1.00	-0.38	-0.02
(13) Trade Openness	0.32	0.07	0.37	0.24	-0.36	-0.11	-0.33	-0.32	-0.16	-0.18	0.63	-0.38	1.00	-0.06
(14) Manufacturing (%GVA)	-0.11	-0.08	-0.08	-0.11	-0.30	-0.06	-0.34	-0.21	-0.21	-0.23	-0.33	-0.02	-0.06	1.00

3.4 Econometric Model

To estimate the relationship between environmental policy stringency and income inequality, this thesis employs a two-way fixed effects framework. The baseline econometric specification can be expressed as follows:

$$GINI_{it} = \beta_0 + \beta_1 EPS_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where $GINI_{it}$ represents the GINI coefficient within country (i) at time (t). EPS_{it} denotes the Environmental Policy Stringency index and in alternative specifications the sub-indices for

market, non-market and technology support policies . The vector X_{it} includes a set of time-varying control variables, namely, GDP per capita, population, trade openness and manufacturing share. The model attempts to avoid unnecessary complexity and minimise the risk of overfitting by limiting the number of control variables. The term μ_i captures country-specific fixed effects, λ_t captures time fixed effects common to all countries, and ε_{it} is the error term.

Similarly, to estimate the relationship between environmental policy stringency and regional income inequality, the econometric specification is as follows:

$$RegionalInequality_{it} = \beta_0 + \beta_1 EPS_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where $RegionalInequality_{it}$ represents the coefficient of variation of regional incomes within country i at time t , capturing inequality in income between regions within the same country rather than inequality between individuals. All other variable have the same notation as in the previous income inequality equation.

The inclusion of country fixed effects is central to the identification strategy. These effects absorb all unobserved, time-invariant country characteristics that may influence both environmental policy and income inequality. By controlling for these factors, the estimation focuses exclusively on within-country variation over time, thereby reducing the risk of omitted variable bias arising from cross-country differences. Time fixed effects are included to control for global shocks and common economic trends that affect all countries simultaneously.

The key identifying assumption is therefore that, conditional on the included controls and fixed effects, the remaining country-year variation associated with changes in EPS is not driven by other unobserved time-varying factors that also affect inequality. The coefficient of interest, β_1 , therefore captures the average within-country association between changes in environmental policy stringency and changes in income inequality, conditional on the control variables.

Standard errors are clustered at the country level. This allows for serial correlation and heteroskedasticity within countries over time, inflating the standard errors accordingly. While the fixed effects framework mitigates omitted variable bias, it does not eliminate concerns regarding endogeneity. Policy adoption may be influenced by economic conditions, raising the possibility of reverse causality.

3.5 Robustness and Limitations

To account for the possibility that the effects of environmental policy may operate with a delay, alternative specifications incorporating lagged values of the EPS index are considered. Environmental policy interventions may take time to affect production decisions, labour markets and regional economic activity. Including lagged policy variables therefore provides a robustness check on the timing of the estimated relationship.

As an additional robustness analysis, an alternative specification focuses on country-specific increases in environmental policy stringency. For each country and EPS measure, the year containing the largest annual increase in stringency is identified, and a binary indicator distinguishes subsequent years from the spike year and preceding period. This provides an alternative means of examining whether inequality differs following countries' largest observed increases in environmental policy stringency, where common movements in EPS across countries may limit the identifying variation available in the baseline specification. As a further extension, the spike indicators are interacted with their corresponding continuous EPS

measures, allowing the estimated association between policy stringency and inequality to differ following each country's largest observed increase in stringency. This provides an additional test of whether the estimated association differs between the periods before and after these country-specific increases. As with the preceding spike specification, this analysis is treated as a robustness exercise and does not provide a causal identification strategy.

Alternative specifications where the measure of inequality is replaced are also used to test the robustness of the results. For income inequality, the baseline usage of disposable income inequality is replaced with both gross and market income. In addition, an alternative measure of economic inequality is used, the GINI coefficient utilising data from the World Bank. When analysing regional inequality, disposable regional income is replaced with primary regional income, allowing disparities before and after redistribution to be compared. Where the coefficient of interest remains stable, this is viewed as an indication of the robustness of the estimated associations.

The chosen research design has limitations that should be acknowledged. This analysis cannot establish a more definitive causal relationship in the same manner as a natural experiment, for example. While the fixed effects framework substantially mitigates omitted variable bias arising from time-invariant factors, time-varying unobserved influences may still affect both environmental policy and income inequality. The regional analysis is subject to an additional limitation arising from the smaller sample size, reducing the precision with which regional associations can be estimated. In addition, reverse causality cannot be entirely discounted as governments may adopt certain environmental policies in response to prevailing economic conditions. As such, the results of this analysis should be interpreted as evidence of conditional associations rather than definitive proof of a causal relationship.

3.6 Identification

The purpose of this section is to assess whether the EPS measures contain sufficient variation to support the identification strategy used in the TWFE specification. One potential concern is that EPS may exhibit common trends across countries over time, meaning that the inclusion of year fixed effects could absorb a substantial proportion of the observed variation. Once country fixed effects are also accounted for, the relationship between EPS and inequality may therefore be estimated from a more limited source of country-year variation.

In an attempt to illustrate this, Figure 6 shows graphically the level of the aggregate EPS index in the G7 economies⁸ over the sample period. This shows that there is clear variation in EPS over time within countries. However, there is also a substantial degree of co-movement between countries, with environmental policy seeming to display a common international trend, with the data from the G7 countries tracking each other closely over time. Figure 7 shows the values of the technology sub index of EPS in the G7 over the sample period. Graphically, this indicates a greater degree of variation between and within countries. These findings do also indicate the heterogeneous nature of the data of each EPS measure. Graphs showing the evolution of the other two sub-indices (market-based and non-market based policies) over the sample period can be found in the Appendix.

⁸ This sub-sample was chosen to aid readability. Canada was not included in the final sample due to lacking data for one of the control variables. As these graphs serve to motivate the identification strategy Canada is not included, despite being a G7 member.

Figure 6 – EPS in G7 Economies (1990-2020)

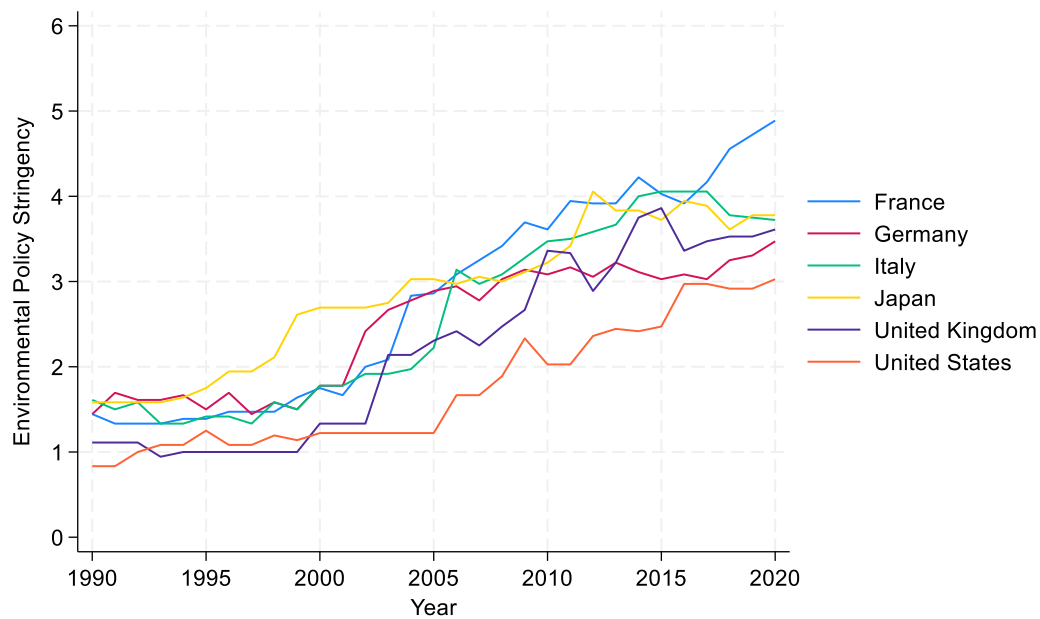
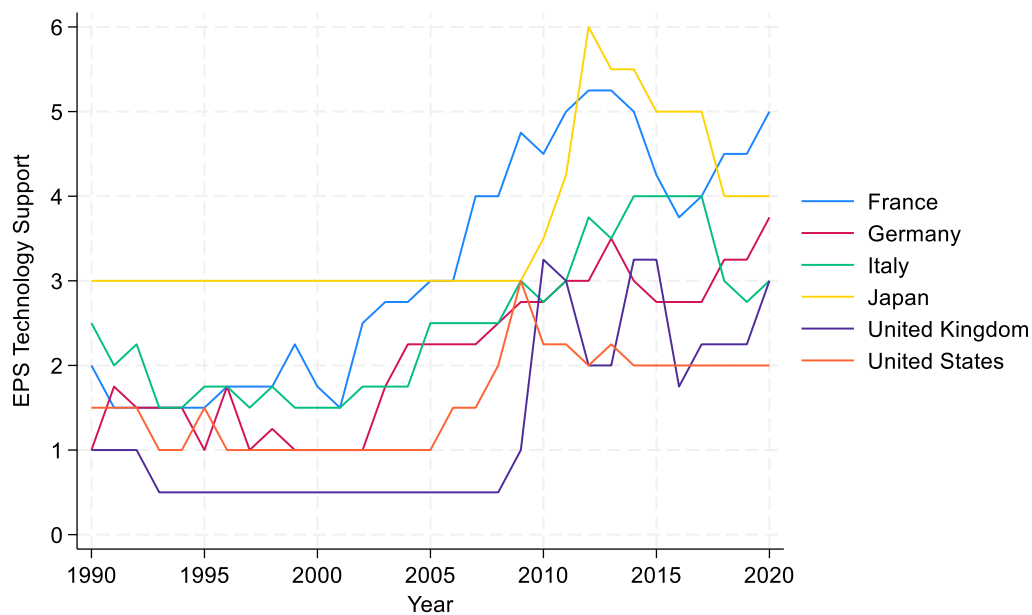


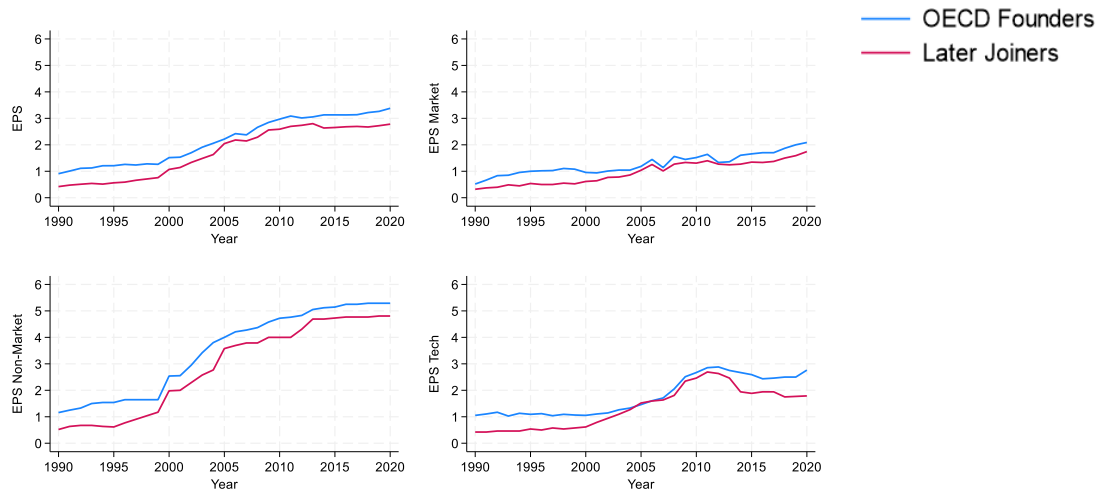
Figure 7 – EPS Technology sub-index in G7 Economies (1990-2020)



Whilst we have now illustrated how environmental policy stringency evolved over the sample period in a sub-set of broadly comparable countries, it is also of interest whether there are significant differences in that evolution within the broader sample. To examine this, the sample was divided into a number of groups based on a country's level of income, geographic location and date of joining the OECD. The results for the last of these three divisions are shown below, in Figure 8, whilst results obtained from the other two divisions can be found in the Appendix (Additional EPS Graphs) Section. This divides the sample into countries which were founding

members of the OECD vs those which joined at a later date.⁹ The panel shows the results for each of the four EPS measures. The charts once more serve to illustrate the trends we have seen thus far. Namely that, a) EPS measures tend to broadly increase over time and b) there appears to be a common international trend in this evolution, which is relatively consistent across countries. Here we see no clear indication that whether a country was a member of the OECD (and the level of wealth, and institutional maturity this usually implies) serves as a differentiator for the evolution of the stringency of environmental policy over time. This may also indicate a relative homogeneity of the exclusively OECD sample used in this analysis. Thus, further investigation is required as to whether there is adequate variation between countries over time in EPS for the proposed TWFE model to be effective.

Figure 8 EPS (Aggregate and Sub-Indices) (1990-2020) – OECD Founders vs Joiners



Tables 5 and 6 investigate this issue further by examining the variation in each EPS measure within the estimation samples used for the baseline and alternative specifications respectively. To do so, an auxiliary regression is estimated separately for each EPS measure, as follows:

$$EPS_{it} = \alpha_i + \lambda_t + u_{it}$$

where EPS_{it} represents the relevant aggregate EPS measure or sub-index for country i in year t , α_i represents country fixed effects, λ_t represents year fixed effects, and u_{it} is the residual. The auxiliary regressions are estimated using the same samples as the corresponding specifications, requiring non-missing observations for the dependent variable, EPS measure and all control variables; however, the controls themselves are not included in the auxiliary regressions.

The within-country standard deviation captures variation in EPS over time within countries, while the standard deviation of the residual captures the country-year variation remaining after country and year fixed effects have been removed. This residual variation is the source of variation relevant to identification in the main TWFE specification. The final column shows the residual standard deviation as a proportion of the within-country standard deviation.

The results show that the inclusion of country and year fixed effects absorbs a proportion of the variation in EPS, meaning that the estimated relationships rely on a narrower source of variation

⁹ OECD **Founders** in sample: Austria, Belgium, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Türkiye, United Kingdom, United States. **Later Joiners**: Chile, Czech Republic, Estonia, Hungary, Israel, Korea, Poland, Slovakia, Slovenia

than is apparent from the raw data. Nevertheless, substantial variation remains in absolute terms across the aggregate EPS measure and each of the three sub-indices. These findings also indicate the heterogeneous nature of the data of each sub-index, with the EPS technology measure having greater within-country and residual variation, with this having been illustrated graphically in Figure 7.

Table 5 – Standard Deviation in Baseline Specification

EPS Measure	Raw SD	Within-country SD	Country + year residualised SD	Residualised / within-country
Overall EPS	0.931	0.446	0.261	58.56%
Market-based EPS	0.855	0.359	0.263	73.13%
Non-market EPS	1.396	0.707	0.437	61.79%
Technology support EPS	1.320	0.758	0.612	80.75%

Table 6 – Standard Deviation in Alternative Specification¹⁰

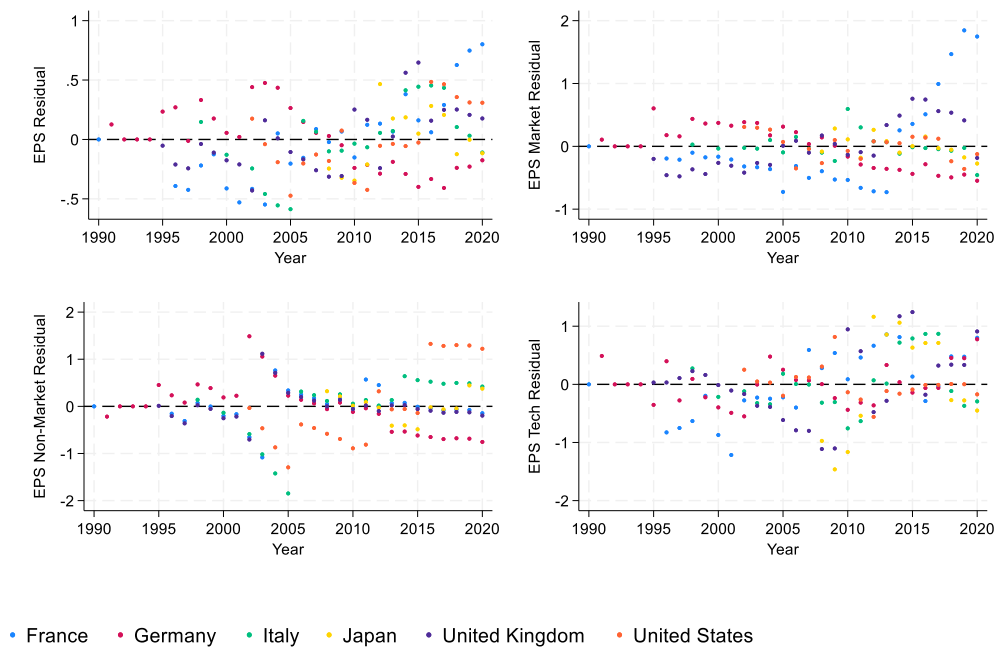
EPS Measure	Raw SD	Within-country SD	Country + year residualised SD	Residualised / within-country
Overall EPS	1.026	0.764	0.311	40.78%
Market-based EPS	0.848	0.477	0.335	70.28%
Non-market EPS	1.620	1.333	0.589	44.17%
Technology support EPS	1.367	0.957	0.697	72.76%

To investigate this matter more deeply Figure 9 displays the residuals for G7 members (minus Canada)¹¹ over the sample period, obtained from the auxiliary regressions described above. The figure uses the estimation sample corresponding to the World Bank GINI coefficient, as this measure offers the best coverage over the sample period. Each graph shows the residuals obtained for, in turn, the aggregate EPS measure and the three sub-indices after country and year fixed effects have been removed. Results obtained using the estimation sample corresponding to the OECD GINI coefficient for disposable income can be found in the Appendix section (Additional EPS Graphs). These results show that the residuals are dispersed around zero, with no obvious pattern emerging over time. They provide no evidence of systematic or potentially problematic trends in the residuals across these countries. The residuals fluctuate around zero over time, indicating that meaningful country-year variation remains after accounting for country and year fixed effects.

¹⁰ The alternative specification uses the World Bank's GINI coefficient as the dependent variable.

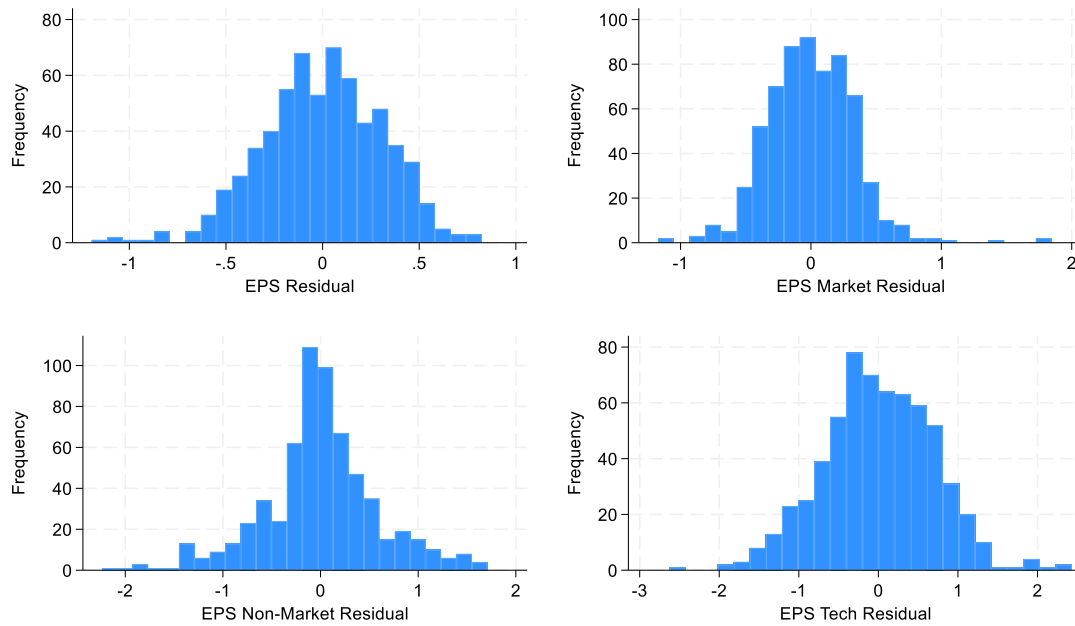
¹¹ Canada is excluded due to lacking observations for one of the control variables in the regressions used. G7 grouping is chosen for readability, whilst Canada is removed from the final sample.

Figure 9 – EPS Residuals G7 countries (1990-2020) [World Bank GINI coefficient sample]



The preceding figures illustrate how the residuals vary across countries and years, but it is also useful to examine how they are distributed across the estimation sample as a whole. Figure 10 therefore presents histograms of the country-year residuals obtained from the auxiliary regressions described above for each of the four EPS measures. Each residual represents an individual country-year observation after country and year fixed effects have been removed. The distributions are broadly centred around zero across all four EPS measures, while also displaying a meaningful degree of dispersion. Figure 10 presents the results for the estimation sample corresponding to the World Bank GINI coefficient, with the corresponding results for the OECD disposable-income sample reported in the Appendix.

Figure 10 – Residuals [World Bank GINI coefficient sample]



Taken together, this analysis shows that the inclusion of country and year fixed effects does reduce the variation in EPS available for identification, but does not eliminate it. The residual standard deviations remain meaningfully above zero, while the country-year residuals displayed in Figure 10 are distributed around zero with substantial dispersion. This indicates that meaningful country-year variation in EPS remains after accounting for time-invariant country characteristics and common year effects, providing variation on which the TWFE estimates can be based. These checks therefore address the concern that the fixed effects may absorb most of the identifying variation in EPS. However, they do not establish causal identification or resolve the potential influence of unobserved time-varying confounders or reverse causality.

4. Results

4.1 Income Inequality

The relationship between environmental policy stringency (EPS) and income inequality was examined using the two-way fixed effects model outlined in the methodology section, with standard errors clustered at the country level. Results are presented in Tables 7–10. More information on these regressions can be found in the table notes, and more context is provided on the specifics of each variable used in the data section of the Appendix.

Table 7 reports the baseline results using the aggregate Environmental Policy Stringency (EPS) Index. Columns 1-4 use the different measures of economic inequality discussed in the variables section of the methodology. Column 5 replaces the standard EPS measure with a one-period lagged indicator, using the previous year's EPS value to account for potential time-delayed policy effects. Across all model specifications, no statistically significant relationship is observed between EPS and inequality. Standard errors are large relative to the coefficients, leading to high p-values. The sign of the coefficients is also inconsistent between the different specifications. These results suggest that when considering the aggregate measure of environmental policy stringency, there is no systematic association with income inequality.

Table 8 examines the market-based policy sub-index. The columns 1-5 follow the same layout as defined previously. In contrast to the aggregate measure, the estimated coefficients are consistently negative, indicating that more stringent market-based environmental policies are associated with lower levels of income inequality. This relationship is statistically significant at the 10 percent level in the baseline model, but the significance of this result is not robust to changes in specification or the introduction of the lagged policy variable.

Table 9 presents the results for the non-market policy sub-index. As with market-based policies, the estimated coefficients are consistently negative across all specifications, implying that stricter non-market environmental policies are associated with lower levels of income inequality. Here the baseline model shows no significant relationship, although in all three alternative specifications this becomes significant at the 10 per cent level. This result is not robust when considering the lagged policy variable.

The final results from the income inequality analysis are shown in Table 10, which considers the technology support policy sub-index. Unlike the previous policy categories, the estimated coefficients are consistently positive, indicating that more generous technology support policies are associated with higher levels of income inequality. The relationship is statistically significant at the 10 per cent level in the baseline specification with the relationship remaining statistically significant for two of the three alternative measures of inequality. Once more, no time-lagged policy effect is identified.

Table 7 – EPS Regression Results

	Main specification	Robustness specifications			
	(1)	(2)	(3)	(4)	(5)
	GINI Disposable Income	GINI Market Income	GINI Gross Income	GINI (World Bank)	GINI Disposable Income
EPS	0.00387 (0.0054)	0.00377 (0.0054)	-0.00128 (0.0038)	-0.00008 (0.0037)	
L.EPS					0.00124 (0.0053)
GDP per capita (000)	-0.00061 (0.0005)	-0.00266*** (0.0005)	-0.00057 (0.0007)	-0.00070 (0.0004)	-0.00062 (0.0005)
Population (millions)	0.00087 (0.0009)	0.00274 (0.0026)	0.00137 (0.0011)	0.00054 (0.0004)	0.00102 (0.0009)
Trade Openness	0.00142 (0.0148)	-0.02886 (0.0400)	-0.01823 (0.0220)	0.01635 (0.0183)	0.00021 (0.0149)
Manufacturing (%GVA)	0.00018 (0.0007)	0.00299** (0.0011)	0.00116 (0.0007)	-0.00002 (0.0011)	0.00017 (0.0007)
Observations	401	383	368	625	400
Median per country	14	12	14	21	14
Countries	32	32	31	31	32
R-squared	0.2419	0.0682	0.2464	0.2083	0.2502
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. GDP per capita is expressed in thousands and population in millions. EPS refers to Environmental Policy Stringency and ranges from 0 to 6. Market-based, non-market and technology are three EPS sub-indices capturing different forms of environmental policy. GINI disposable, market and gross income refer to measures of income inequality ranging from 0 to 1. GINI (World Bank) is a measure of economic inequality from the World Bank and ranges from 0 to 1. The lagged specification uses a one-period lag of the relevant EPS measure, corresponding to the previous year's EPS value, to test for delayed associations between environmental policy stringency and inequality. The estimation samples cover observations from 1990 to 2020. Further information on all variables is provided in the Data section of the Appendix.

Table 8 – EPS Market Regression Results

	Main specification	Robustness specifications			
	(1)	(2)	(3)	(4)	(5)
	GINI Disposable Income	GINI Market Income	GINI Gross Income	GINI (World Bank)	GINI Disposable Income
EPS Market	-0.00596*	-0.00041	-0.00462	-0.00587	
	(0.0031)	(0.0048)	(0.0033)	(0.0036)	
L.EPS Market					-0.00207
					(0.0035)
GDP per capita (000)	-0.00052	-0.00266***	-0.00050	-0.00066	-0.00060
	(0.0005)	(0.0005)	(0.0008)	(0.0005)	(0.0005)
Population (millions)	0.00111	0.00293	0.00137	0.00047	0.00113
	(0.0010)	(0.0025)	(0.0011)	(0.0004)	(0.0010)
Trade Openness	-0.00505	-0.03099	-0.02198	0.01396	-0.00179
	(0.0142)	(0.0409)	(0.0220)	(0.0173)	(0.0143)
Manufacturing (%GVA)	0.00019	0.00298**	0.00123	-0.00006	0.00019
	(0.0007)	(0.0011)	(0.0008)	(0.0010)	(0.0007)
Observations	401	383	368	625	400
Median per country	14	12	14	21	14
Countries	32	32	31	31	32
R-squared	0.2798	0.0663	0.2571	0.2556	0.2612
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is expressed in thousands and population in millions. EPS refers to Environmental Policy Stringency and ranges from 0 to 6. Market-based, non-market and technology are three EPS sub-indices capturing different forms of environmental policy. GINI disposable, market and gross income refer to measures of income inequality ranging from 0 to 1. GINI (World Bank) is a measure of economic inequality from the World Bank and ranges from 0 to 1. The lagged specification uses a one-period lag of the relevant EPS measure, corresponding to the previous year's EPS value, to test for delayed associations between environmental policy stringency and inequality. The estimation samples cover observations from 1990 to 2020. Further information on all variables is provided in the Data section of the Appendix.

Table 9 – EPS Non-Market Regression Results

	Main specification	Robustness specifications			
	(1)	(2)	(3)	(4)	(5)
	GINI Disposable Income	GINI Market Income	GINI Gross Income	GINI (World Bank)	GINI Disposable Income
EPS Non-Market	-0.00052 (0.0020)	-0.00482* (0.0027)	-0.00277* (0.0014)	-0.00310* (0.0018)	
L.EPS Non-Market					-0.00208 (0.0023)
GDP per capita (000)	-0.00065 (0.0005)	-0.00277*** (0.0005)	-0.00062 (0.0007)	-0.00071 (0.0004)	-0.00069 (0.0005)
Population (millions)	0.00111 (0.0009)	0.00309 (0.0025)	0.00147 (0.0009)	0.00076* (0.0004)	0.00117 (0.0009)
Trade Openness	-0.00008 (0.0148)	-0.03084 (0.0405)	-0.01814 (0.0209)	0.01680 (0.0173)	0.00011 (0.0144)
Manufacturing (%GVA)	0.00020 (0.0007)	0.00313*** (0.0010)	0.00126* (0.0007)	0.00002 (0.0010)	0.00028 (0.0007)
Observations	401	383	368	625	400
Median per country	14	12	14	21	14
Countries	32	32	31	31	32
R-squared	0.2573	0.0609	0.2443	0.2233	0.2567
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. GDP per capita is expressed in thousands and population in millions. EPS refers to Environmental Policy Stringency and ranges from 0 to 6. Market-based, non-market and technology are three EPS sub-indices capturing different forms of environmental policy. GINI disposable, market and gross income refer to measures of income inequality ranging from 0 to 1. GINI (World Bank) is a measure of economic inequality from the World Bank and ranges from 0 to 1. The lagged specification uses a one-period lag of the relevant EPS measure, corresponding to the previous year's EPS value, to test for delayed associations between environmental policy stringency and inequality. The estimation samples cover observations from 1990 to 2020. Further information on all variables is provided in the Data section of the Appendix.

Table 10 – EPS Technology Regression Results

	Main specification	Robustness specifications			
	(1)	(2)	(3)	(4)	(5)
	GINI Disposable Income	GINI Market Income	GINI Gross Income	GINI (World Bank)	GINI Disposable Income
EPS Technology	0.00348*	0.00442*	0.00158	0.00348*	
	(0.0020)	(0.0023)	(0.0016)	(0.0018)	
L.EPS Technology					0.00229
					(0.0022)
GDP per capita (000)	-0.00061	-0.00266***	-0.00058	-0.00061	-0.00058
	(0.0005)	(0.0005)	(0.0008)	(0.0005)	(0.0005)
Population (millions)	0.00066	0.00241	0.00115	0.00049	0.00082
	(0.0007)	(0.0024)	(0.0010)	(0.0004)	(0.0009)
Trade Openness	0.00059	-0.02898	-0.01697	0.01151	-0.00052
	(0.0139)	(0.0400)	(0.0210)	(0.0152)	(0.0148)
Manufacturing (%GVA)	0.00036	0.00321***	0.00127*	0.00018	0.00026
	(0.0006)	(0.0010)	(0.0007)	(0.0010)	(0.0006)
Observations	401	383	368	625	400
Median per country	14	12	14	21	14
Countries	32	32	31	31	32
R-squared	0.2408	0.0682	0.2341	0.1845	0.2481
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. GDP per capita is expressed in thousands and population in millions. EPS refers to Environmental Policy Stringency and ranges from 0 to 6. Market-based, non-market and technology are three EPS sub-indices capturing different forms of environmental policy. GINI disposable, market and gross income refer to measures of income inequality ranging from 0 to 1. GINI (World Bank) is a measure of economic inequality from the World Bank and ranges from 0 to 1. The lagged specification uses a one-period lag of the relevant EPS measure, corresponding to the previous year's EPS value, to test for delayed associations between environmental policy stringency and inequality. The estimation samples cover observations from 1990 to 2020. Further information on all variables is provided in the Data section of the Appendix.

4.2 Regional Inequality

The second stage of the empirical analysis examines the relationship between environmental policy stringency and regional income inequality, with these results shown in Tables 11-14. In columns 1 and 2 of these tables the two measures of regional inequality generated are used, utilising disposable and primary income respectively. Column 3 replaces the standard EPS measure with a one-period lagged indicator, using the previous year's EPS value to account for potential time-delayed policy effects. Once more, further information on these regressions can be found in the table notes, and more context is provided on the specifics of each variable used in the data section of the Appendix.

Table 11 – Regional Inequality - EPS Regression Results

	Main specification	Robustness specifications	
	(1) Regional Inequality (Disposable)	(2) Regional Inequality (Primary)	(3) Regional Inequality (Disposable)
EPS	-0.00080 (0.0166)	-0.01365 (0.0125)	
L.EPS			0.04885 (0.0523)
GDP per capita (000)	0.00582 (0.0041)	0.00555 (0.0043)	0.00778 (0.0058)
Population (millions)	0.00553 (0.0068)	0.01219 (0.0088)	-0.00014 (0.0107)
Trade Openness	-0.04153 (0.0683)	-0.07277 (0.1072)	-0.11921 (0.1314)
Manufacturing (%GVA)	-0.00866 (0.0074)	-0.00802 (0.0074)	-0.00834 (0.0074)
Observations	371	313	371
Median per country	21	21	21
Countries	18	15	18
R-squared	0.0001	0.0008	0.0612
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is expressed in thousands and population in millions. EPS refers to Environmental Policy Stringency and ranges from 0 to 6. Regional inequality is measured using the coefficient of variation of regional income within each country for both disposable and primary income. The lagged specification uses a one-period lag of the relevant EPS measure, corresponding to the previous year's EPS value, to test for delayed associations between environmental policy stringency and inequality. The estimation samples cover observations from 1995 to 2020. Further information on all variables is provided in the Data section of the Appendix.

Across all four tables, no statistically significant relationship is identified between EPS and regional inequality. This is true when considering the aggregate EPS index, the sub-indices, different measures of regional inequality and when allowing for a time-lagged effect.

The signs of the coefficients are consistent across specifications for both market based and technology support policies but not for the aggregate index or the non-market policies. Standard errors are large relative to the coefficients of interest. Furthermore, when comparing the signs of the relationships to the results from Tables 7-10 there are also notable differences. For the regional inequality analysis, market-based policies have positive estimated coefficients whilst technology support policies have negative estimated coefficients. This is the inverse of the results found in Tables 8 and 10 respectively. These coefficients are consistent in sign across specifications, whilst for the aggregate EPS Index and non-market policies this differs between specifications.

Table 12 – Regional Inequality – EPS Market Regression Results

	Main specification (1) Regional Inequality (Disposable)	Robustness specifications	
		(2) Regional Inequality (Primary)	(3) Regional Inequality (Disposable)
EPS Market	0.04100 (0.0544)	0.03743 (0.0522)	
L.EPS Market			0.05232 (0.0604)
GDP per capita (000)	0.00576 (0.0038)	0.00604 (0.0041)	0.00602 (0.0040)
Population (millions)	0.00035 (0.0113)	0.00583 (0.0131)	-0.00143 (0.0120)
Trade Openness	-0.04966 (0.0718)	-0.08031 (0.0941)	-0.05450 (0.0763)
Manufacturing (%GVA)	-0.00797 (0.0070)	-0.00787 (0.0077)	-0.00799 (0.0070)
Observations	371	313	371
Median per country	21	21	21
Countries	18	15	18
R-squared	0.1147	0.0197	0.1672
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is expressed in thousands and population in millions. EPS refers to Environmental Policy Stringency and ranges from 0 to 6. Regional inequality is measured using the coefficient of variation of regional income within each country for both disposable and primary income. The lagged specification uses a one-period lag of the relevant EPS measure, corresponding to the previous year's EPS value, to test for delayed associations between environmental policy stringency and inequality. The estimation samples cover observations from 1995 to 2020. Further information on all variables is provided in the Data section of the Appendix.

It should be noted that the regional inequality analysis is based on a smaller sample, reflecting more limited regional data availability and the requirement for a minimum number of regions to construct a meaningful coefficient of variation. The results should therefore be interpreted in light of this reduced sample size.

Table 13 – Regional Inequality – EPS Non-Market Regression Results

	Main specification	Robustness specifications	
	(1) Regional Inequality (Disposable)	(2) Regional Inequality (Primary)	(3) Regional Inequality (Disposable)
EPS Non-Market	0.00378 (0.0148)	-0.00273 (0.0129)	
L.EPS Non-Market			0.03645 (0.0430)
GDP per capita (000)	0.00598 (0.0042)	0.00596 (0.0044)	0.00723 (0.0054)
Population (millions)	0.00498 (0.0070)	0.01078 (0.0092)	0.00059 (0.0105)
Trade Openness	-0.05090 (0.0785)	-0.08623 (0.1175)	-0.13756 (0.1601)
Manufacturing (%GVA)	-0.00860 (0.0075)	-0.00792 (0.0076)	-0.00796 (0.0070)
Observations	371	313	371
Median per country	21	21	21
Countries	18	15	18
R-squared	0.0000	0.0001	0.0335
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is expressed in thousands and population in millions. EPS refers to Environmental Policy Stringency and ranges from 0 to 6. Regional inequality is measured using the coefficient of variation of regional income within each country for both disposable and primary income. The lagged specification uses a one-period lag of the relevant EPS measure, corresponding to the previous year's EPS value, to test for delayed associations between environmental policy stringency and inequality. The estimation samples cover observations from 1995 to 2020. Further information on all variables is provided in the Data section of the Appendix.

Table 14 – Regional Inequality - EPS Tech Regression Results

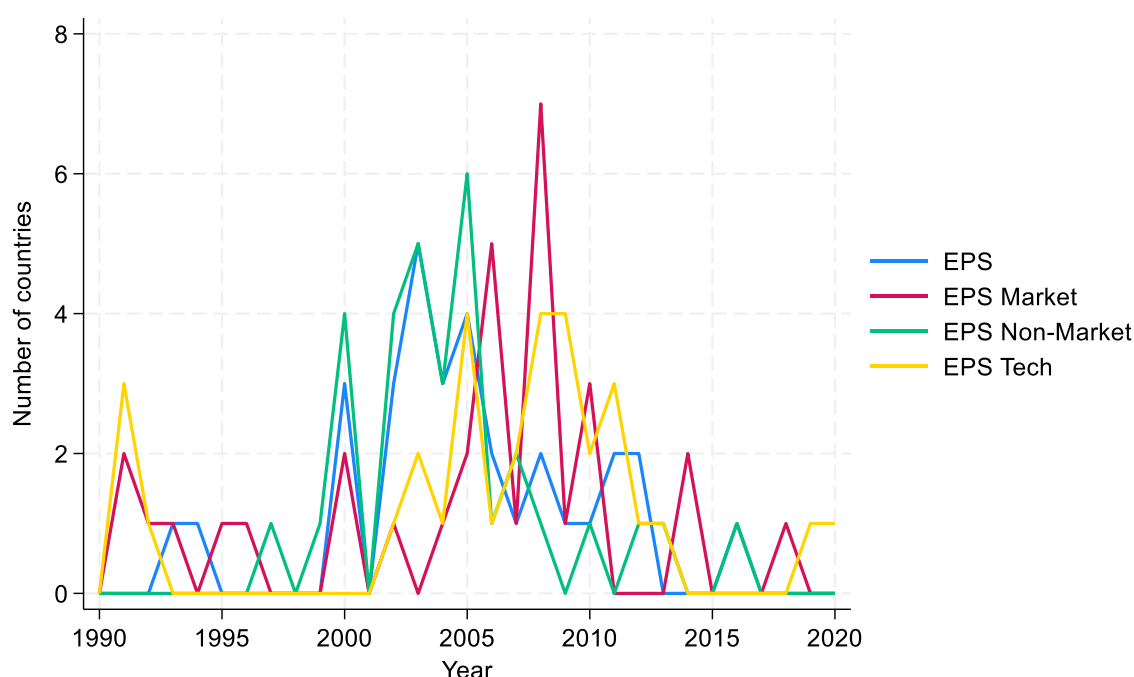
	Main specification	Robustness specifications	
	(1) Regional Inequality (Disposable)	(2) Regional Inequality (Primary)	(3) Regional Inequality (Disposable)
EPS Technology	-0.00897 (0.0112)	-0.01166 (0.0149)	
L.EPS Technology			-0.00492 (0.0109)
GDP per capita (000)	0.00528 (0.0033)	0.00516 (0.0033)	0.00547 (0.0032)
Population (millions)	0.00631 (0.0056)	0.01197 (0.0074)	0.00583 (0.0055)
Trade Openness	-0.02545 (0.0489)	-0.06183 (0.0754)	-0.03346 (0.0490)
Manufacturing (%GVA)	-0.00885 (0.0076)	-0.00818 (0.0076)	-0.00858 (0.0074)
Observations	371	313	371
Median per country	21	21	21
Countries	18	15	18
R-squared	0.0005	0.0004	0.0002
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is expressed in thousands and population in millions. EPS refers to Environmental Policy Stringency and ranges from 0 to 6. Regional inequality is measured using the coefficient of variation of regional income within each country for both disposable and primary income. The lagged specification uses a one-period lag of the relevant EPS measure, corresponding to the previous year's EPS value, to test for delayed associations between environmental policy stringency and inequality. The estimation samples cover observations from 1995 to 2020. Further information on all variables is provided in the Data section of the Appendix.

4.3 Spike Analysis

Analysis of the underlying EPS data also allows one to identify the year in which each country within the sample experienced its largest increase in environmental policy stringency across each of the four EPS measures. This is displayed graphically in Figure 11 below. The graph shows that the increases were broadly clustered between 2000 and 2010, which aligns with a number of key environmental policy developments displayed in Table 1. During this period, the Kyoto Protocol entered into force, the EU's Emissions Trading System was launched, and the EU introduced a renewable energy directive supporting the deployment of renewable energy sources.

Figure 11 – EPS Spikes over time



The common trends in environmental policy stringency observed across countries in Figure 6 raise the possibility that movements in EPS may be too similar across countries to provide substantial identifying variation. As a robustness analysis, an alternative specification is therefore estimated which focuses on country-specific changes in policy stringency. For each country and EPS measure, the year containing the largest annual increase in stringency is identified as a policy-stringency ‘spike’. A binary indicator is then constructed which takes a value of zero in the spike year and all preceding years, and one in all subsequent years. This indicator replaces the continuous EPS measure in the regression specification, allowing inequality within the same country to be compared before and after its largest observed increase in environmental policy stringency, while retaining country and year fixed effects and the baseline controls. This provides an alternative test of whether inequality differs following these country-specific increases and whether the main findings are sensitive to the common evolution of EPS across countries.

Table 15 reports the results of the alternative spike specification using the World Bank GINI measure. No statistically significant difference in inequality is identified following the largest annual increase in aggregate EPS, non-market EPS or technology-support EPS. However, the

coefficient on the market-based EPS spike indicator is negative and statistically significant at the 5% level, indicating that inequality is lower in the period following the identified market-based EPS spike relative to the spike year and preceding period. This result is consistent with the negative association between market-based environmental policy stringency and inequality observed elsewhere in the analysis. However, the spike specification should be interpreted as a robustness exercise rather than as establishing a causal effect, with the coefficient capturing an average difference in inequality before and after the identified policy-stringency spike.

Table 15 – Spike Analysis Regression Results – GINI World Bank Sample

	(1) GINI (World Bank)	(2) GINI (World Bank)	(3) GINI (World Bank)	(4) GINI (World Bank)
EPS Spike	-0.00014 (0.0042)			
EPS Market Spike		-0.01062** (0.0046)		
EPS Non-Market Spike			0.00192 (0.0049)	
EPS Tech Spike				-0.00504 (0.0048)
GDP per capita (000)	-0.00070 (0.0004)	-0.00067 (0.0005)	-0.00070 (0.0004)	-0.00080* (0.0004)
Population (millions)	0.00054 (0.0004)	0.00027 (0.0004)	0.00051 (0.0004)	0.00063* (0.0004)
Trade Openness	0.01631 (0.0186)	0.01875 (0.0179)	0.01674 (0.0187)	0.01870 (0.0180)
Manufacturing (%GVA)	-0.00002 (0.0011)	0.00002 (0.0011)	-0.00004 (0.0011)	-0.00014 (0.0011)
Observations	625	625	625	625
Median per country	21	21	21	21
Countries	31	31	31	31
R-squared	0.2080	0.1551	0.2054	0.2107
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is expressed in thousands and population in millions. EPS spike variables are binary indicators equal to one in years after a country's largest annual increase in the corresponding Environmental Policy Stringency measure, and zero in the spike year and all preceding years. GINI (World Bank) is a coefficient measuring economic inequality from the World Bank and ranges from 0 to 1. The estimation samples cover observations from 1990 to 2020. Further information on all variables is provided in the Data section of the Appendix.

Table 16 extends the spike analysis to regional inequality, measured using the coefficient of variation of regional disposable income. This applies the same alternative specification to the regional dimension of inequality, comparing regional inequality within countries before and after the largest annual increase in each EPS measure. No statistically significant difference is identified following the largest observed increase in aggregate EPS or any of the three sub-indices. The absence of significant results is consistent with the baseline regional inequality analysis, which similarly provides no evidence of a systematic association between environmental policy stringency and regional income inequality. This same exercise, completed for the OECD GINI Disposable Income sample, can be found in the Appendix (Spike Analysis) section.

Table 16 – Spike Analysis Regression Results – Regional Inequality (Disposable Income)

	(1)	(2)	(3)	(4)
	Regional Inequality (Disposable)	Regional Inequality (Disposable)	Regional Inequality (Disposable)	Regional Inequality (Disposable)
EPS Spike	-0.00487 (0.0114)			
EPS Market Spike		-0.07447 (0.0596)		
EPS Non-Market Spike			0.00340 (0.0267)	
EPS Tech Spike				-0.05145 (0.0457)
GDP per capita (000)	0.00582 (0.0039)	0.00629 (0.0040)	0.00589 (0.0041)	0.00471 (0.0029)
Population (millions)	0.00533 (0.0057)	0.00590 (0.0076)	0.00540 (0.0061)	0.00795 (0.0051)
Trade Openness	-0.04418 (0.0602)	0.00239 (0.0470)	-0.04128 (0.0564)	-0.01009 (0.0473)
Manufacturing (%GVA)	-0.00862 (0.0075)	-0.00983 (0.0075)	-0.00874 (0.0082)	-0.00970 (0.0080)
Observations	371	371	371	371
Median per country	21	21	21	21
Countries	18	18	18	18
R-squared	0.00002	0.00157	0.00002	0.00612
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is expressed in thousands and population in millions. EPS spike variables are binary indicators equal to one in years after a country's largest annual increase in the corresponding Environmental Policy Stringency measure, and zero in the spike year and all preceding years. Regional inequality is measured using the coefficient of variation of regional disposable income, with higher values indicating greater inequality in income across regions within a country. The estimation samples cover observations from 1995 to 2020. Further information on all variables is provided in the Data section of the Appendix.

4.4 Interaction Analysis

As a further extension of the spike analysis, the continuous EPS measures are interacted with their corresponding EPS spike indicators to examine whether the association between environmental policy stringency and inequality differs following a country's largest annual increase in policy stringency. This specification therefore retains information on the level of environmental policy stringency while allowing its association with inequality to differ between the periods before and after the identified spike. The interaction term is the primary coefficient of interest: a positive coefficient indicates that the estimated association between EPS and inequality becomes more positive, or less negative, following the spike, while a negative coefficient indicates that it becomes more negative, or less positive. As with the preceding spike analysis, this specification is treated as an extension of the robustness analysis rather than as a causal identification strategy.

The results in Table 17 provide some evidence that the association between EPS and inequality differs following the identified spikes when using the World Bank GINI measure. The interaction term is positive and statistically significant at the 1% level for aggregate EPS and at the 10% level for both market-based EPS and technology-support EPS, while the interaction for non-market EPS is not statistically significant. The positive interaction coefficients indicate that, for these measures, the estimated association between EPS and inequality becomes more positive, or less negative, following the identified spike. Importantly, these interaction coefficients capture a change in the estimated association rather than the level or statistical significance of the association in the post-spike period itself. The results therefore provide some evidence that the relationship between environmental policy stringency and inequality may differ before and after countries' largest observed increases in policy stringency, although the evidence varies across policy categories. These estimates should be interpreted cautiously and do not establish that the identified spike itself caused a change in the association.

When the same specification is applied to regional disposable-income inequality in Table 18, none of the four interaction terms is statistically significant. This provides no evidence within the regional sample that the association between environmental policy stringency and regional inequality systematically differs following the identified policy-stringency spikes. The same exercise using the OECD disposable-income GINI sample is reported in the Appendix (Interaction Analysis) section.

Table 17 – Interaction Analysis Regression Results – GINI World Bank Sample

	(1)	(2)	(3)	(4)
	Aggregate EPS	Market-Based EPS	Non-Market EPS	Technology Support EPS
EPS Measure	-0.00609 (0.0038)	-0.01286*** (0.0042)	-0.00519** (0.0020)	0.00133 (0.0023)
EPS Spike	-0.01670** (0.0070)	-0.02246** (0.0096)	-0.00279 (0.0125)	-0.01657** (0.0077)
EPS Measure × EPS Spike	0.00797*** (0.0028)	0.01032* (0.0054)	0.00242 (0.0023)	0.00393* (0.0022)
GDP per capita (000)	-0.00052 (0.0005)	-0.00064 (0.0005)	-0.00070 (0.0004)	-0.00076* (0.0004)
Population (millions)	0.00066* (0.0003)	0.00022 (0.0004)	0.00079* (0.0004)	0.00071** (0.0003)
Trade Openness	0.01170 (0.0173)	0.02075 (0.0171)	0.01614 (0.0181)	0.01338 (0.0138)
Manufacturing (%GVA)	0.00015 (0.0011)	-0.00002 (0.0010)	0.00006 (0.0010)	0.00010 (0.0010)
Observations	625	625	625	625
Median per country	21	21	21	21
Countries	31	31	31	31
R-squared	0.2097	0.1324	0.2222	0.1904
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. GDP per capita is expressed in thousands and population in millions. Each column uses the EPS measure identified in the column heading. EPS Spike is a binary indicator equal to one in all years after a country's largest annual increase in the corresponding EPS measure, and zero in the spike year and all preceding years. EPS Measure × EPS Spike captures whether the association between the corresponding EPS measure and inequality differs in the post-spike period. GINI (World Bank) is a coefficient measuring economic inequality from the World Bank and ranges from 0 to 1. Further information on all variables is provided in the Data section of the Appendix.

Table 18 – Interaction Analysis Regression Results – Regional Inequality (Disposable Income)

	(1)	(2)	(3)	(4)
	Aggregate EPS	Market-Based EPS	Non-Market EPS	Technology Support EPS
EPS Measure	-0.03980 (0.0305)	-0.00759 (0.0263)	-0.00934 (0.0115)	-0.01236 (0.0156)
EPS Spike	-0.08533 (0.0648)	-0.14175 (0.1236)	-0.05184 (0.0337)	-0.07781 (0.0705)
EPS Measure × EPS Spike	0.04395 (0.0401)	0.07407 (0.0744)	0.01976 (0.0192)	0.01429 (0.0153)
GDP per capita (000)	0.00627 (0.0044)	0.00666 (0.0043)	0.00594 (0.0043)	0.00448 (0.0027)
Population (millions)	0.00469 (0.0075)	-0.00783 (0.0188)	0.00178 (0.0096)	0.01087** (0.0044)
Trade Openness	-0.09193 (0.1055)	-0.05749 (0.0829)	-0.10230 (0.1138)	0.00444 (0.0501)
Manufacturing (%GVA)	-0.00663 (0.0060)	-0.00756 (0.0058)	-0.00701 (0.0067)	-0.00984 (0.0082)
Observations	371	371	371	371
Median per country	21	21	21	21
Countries	18	18	18	18
R-squared	0.00104	0.09513	0.02111	0.01045
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. GDP per capita is expressed in thousands and population in millions. Each column uses the EPS measure identified in the column heading. EPS Spike is a binary indicator equal to one in all years after a country's largest annual increase in the corresponding EPS measure, and zero in the spike year and all preceding years. EPS Measure × EPS Spike captures whether the association between the corresponding EPS measure and inequality differs in the post-spike period. Regional inequality is measured using the coefficient of variation of regional disposable income, with higher values indicating greater inequality in income across regions within a country. Further information on all variables is provided in the Data section of the Appendix.

4.5 Summary of Results

Overall, the empirical results suggest that analysing the aggregate EPS Index may obscure differences in associations across policy categories. While no statistically significant association is identified between overall environmental policy stringency and income inequality, the sub-index analysis reveals evidence of heterogeneous associations between policy stringency and income inequality. The estimated coefficients for market and non-market policies are generally negative, whereas those for technology support policies are generally positive, with statistically significant associations identified in some specifications. No indication of time-lagged policy effects is found. However, these associations are relatively modest and not consistently robust across all specifications.

The spike analysis provides some additional evidence of lower income inequality following countries' largest observed increases in market-based environmental policy stringency when using the World Bank GINI measure. Extending this analysis by interacting the EPS measures with their corresponding spike indicators provides some evidence that the association between environmental policy stringency and income inequality differs following countries' largest observed increases in policy stringency, although these findings are not consistent across EPS and inequality measures. Furthermore, no evidence is found that environmental policy stringency is associated with regional income inequality, either in the baseline analysis, when comparing inequality before and after countries' largest observed increases in environmental policy stringency, or when allowing the association between EPS and regional inequality to differ following these policy changes.

These findings should not be interpreted as establishing a causal effect of environmental policy stringency on inequality. While the two-way fixed-effects framework controls for time-invariant country characteristics and common time shocks, unobserved country-specific factors varying over time may still influence both environmental policy and inequality. The analysis is also constrained by data availability and, particularly for regional inequality, a smaller sample size. Finally, given the number of regressions estimated, some marginally significant results may occur by chance. Therefore, while the findings provide some evidence that the form of environmental policy may matter for understanding its association with income inequality, they should be interpreted as suggestive associations rather than causal effects.

5. Discussion

The results presented in the previous section indicate that the associations between environmental policy stringency and income inequality are not uniform, but instead depend on the form of environmental policy instrument being considered. This suggests that analysing environmental policy stringency as a single aggregate measure may obscure important differences in the distributional effects of different categories of policies, which may initially affect different economic actors and operate through different channels.

The analysis identifies a negative association between market-based environmental policies and disposable income inequality. In other words, more stringent market-based policies, such as carbon taxes and emissions trading schemes, are associated with lower levels of inequality in disposable income. As this relationship is not observed when considering either market or gross income inequality, this contrast is consistent with redistribution being one possible explanation. Revenue generated from carbon taxes may be recycled through progressive taxation, reducing disposable income inequality. The more stringent these policies are, the more revenue they are likely to generate, and the greater the redistributive potential. The finding is therefore consistent with one section of the literature, with Chao et al. (2012), Ee et al. (2018), Yang & Tang (2023) and Yu et al. (2021) all reporting that market-based environmental policies can reduce inequality.

Conversely, these results contrast with the section of the existing literature that contends that market based policies serve to worsen income inequality (Bettarelli et al., 2024; Känzig, 2023; Markkanen & Anger-Kraavi, 2019). However, this effect is seen to be stronger in poorer countries (Känzig, 2023), those with larger shares of low-skilled workers (Bettarelli et al., 2024), and high levels of pre-existing inequality (Bettarelli et al., 2024; Markkanen & Anger-Kraavi, 2019), whilst the effects are mitigated in countries with comprehensive redistribution systems (Bettarelli et al., 2024). Given that the OECD sample comprises countries that are broadly rich by global standards (which can broadly translate to a lower share of low-skilled workers), are on average not deemed ‘high’ inequality countries by the World Bank (with a GINI coefficient on average below 0.4), and have some of the most progressive taxation policies globally, this may help to explain why no regressive effect is found here. In other words, differences in sample composition and redistributive institutions may mean those findings are not fully applicable to the OECD sample used in this study, and thus may contribute to the contrast in findings.

A similarly negative relationship is identified between non-market environmental policies and gross and market income inequality. This stands in contrast to the association observed for market-based policies, with this relationship emerging before the full suite of taxes and transfers are considered. Because the negative estimates are more apparent for market and gross income than for disposable income, labour-market changes are one possible interpretation. One reason for this may be that stricter command-and-control policies may affect production decisions and subsequently labour demand within highly polluting industries. Although this analysis controls for the size of the manufacturing sector, it does not capture changes in the composition of jobs within these industries themselves. Stricter emissions standards may cause firms to implement cleaner production processes and/or to increase automation which may reduce wage premiums. In support of this, Bu et al. (2024) find that emissions limits in China increased labour demand within technologically intensive and polluting firms, but specifically for lower-skilled, lower-wage workers. Similarly, stricter environmental regulation may increase compliance costs for these same companies, reducing their ability to sustain historic wage premiums.

The weaker result for disposable income is also consistent with taxes and transfers moderating an association before full redistribution. This interpretation is consistent with the increasing emphasis placed on delivering a ‘just transition’ whereby governments accompany stricter environmental regulation with targeted financial support for affected workers and communities

(Bettarelli et al., 2024; Markkanen & Anger-Kraavi, 2019). While the findings of this analysis align with studies reporting that command-and-control policies can reduce inequality (Lei et al., 2026; Liao & Li, 2026; Pi & Shi, 2019; Shimizu & Okamoto, 2022), they contrast with a large body of literature arguing that such policies widen wage inequality (Huang et al., 2025; Y. Liu et al., 2023; Markkanen & Anger-Kraavi, 2019; Qin et al., 2021; Zhao et al., 2025). These conflicting findings suggest that the distributional consequences of command and control environmental policies are likely to depend on both labour market characteristics and the institutional environment within which they are implemented (Bettarelli et al., 2024).

In contrast, technology support policies are associated with higher levels of disposable income inequality. More generous support for low-carbon innovation, including public expenditure on research and development, may serve to benefit higher-income individuals disproportionately. A possible explanation for this is that these policies increase demand for high-skilled workers, which increases the skill premium and widens income inequality. The benefits from these policies may be disproportionately captured by individuals positioned to benefit from low-carbon innovation, high-skilled workers with expertise complementary to new technologies, and households with sufficient financial capital to adopt subsidised technologies. For example, policies such as feed-in tariffs for residential solar panels can only be used by households with enough capital to invest in these renewable technologies, which may limit the accrual of benefits to wealthier individuals. This interpretation is consistent with D'Alessandro et al. (2020) who similarly find that technology support policies increase income inequality when implemented without accompanying redistributive measures, such as wealth taxation.

When the aggregate EPS Index is considered, no statistically significant relationship with income inequality is identified. This result is unsurprising given the differing directions of the associations observed across the individual policy categories and thus the differently signed sub-index estimates offer one possible reason why the aggregate specification shows no clear association. This reinforces one of the central findings of this thesis - examining only the aggregate EPS Index may conceal heterogeneity in the distributional consequences of environmental policies. The result is consistent with Bettarelli et al. (2024) who find no overall relationship between aggregate environmental policy stringency and income inequality and Abbas & Kopp (2026) who find no significant association between environmental policy stringency and disposable income inequality. On a similar note, the review conducted by Markkanen & Anger-Kraavi (2019) concludes that a large number of environmental policies have mixed effects on income inequality.

Finally, no statistically significant relationship is observed between environmental policy stringency and regional income inequality. The analysis provides no evidence that changes in national environmental policy stringency are systematically associated with widening or narrowing income disparities between regions within countries. However, one should note that these results are based on a smaller sample. Although previous studies identify relationships between particular environmental policies and regional income inequality (Markkanen & Anger-Kraavi, 2019; Wang et al., 2019; Zhao et al., 2025), these studies do not examine environmental policy stringency as a whole. The broader focus of the empirical strategy used in this analysis, both geographically and in terms of policy coverage, may help to explain why no association is found here.

More broadly, regional income inequality may reflect long-standing structural differences between regions, including variations in productivity, educational attainment and historical patterns of economic development. These structural characteristics may be unlikely to change substantially in response to changes in national environmental policy over the time horizon considered in this analysis. The absence of a systematic association with between-region inequality does not itself imply that particular workers or communities are unaffected.

Environmental policies may generate substantial gains or losses within individual regions without producing a sufficiently consistent change in the relative income levels of regions across countries to be detected in this analysis. While environmental policies may have distributional effects within particular regions, these results provide no evidence of a systematic association between national environmental policy stringency and the distribution of income between regions within OECD economies.

Taken together, these findings suggest that environmental policy does not exert a single, uniform association with income distribution. The differing signs of the sub-index estimates are consistent with the possibility that different policy categories operate through different economic actors and transmission channels. Market-based and non-market policies are associated with lower levels of income inequality, whereas technology support policies are associated with higher levels of inequality, while no relationship is observed for the aggregate EPS Index or regional income inequality. The absence of a significant regional association suggests that these distributional differences do not translate clearly into systematic changes in income disparities between regions. Although the statistical associations which are identified in this analysis are relatively modest and should be interpreted with appropriate caution, the results suggest further investigation of whether and why these associations differ between policy types could be fruitful.

6. Conclusion

This study finds that the estimated relationship between environmental policy stringency and income inequality is not uniform, but instead depends on the type of environmental policy being implemented. The estimated associations suggest that market-based and non-market policies are associated with lower levels of income inequality in some specifications, while technology support policies are associated with higher levels of income inequality. Whilst interpreting these results with caution, the findings are consistent with the theory that different environmental policies operate through different transmission mechanisms, affecting firms, workers and households in different ways and thereby producing differing distributional associations. For example market-based policies such as carbon taxes may increase governments' ability to redistribute tax revenues. Non-market policies, such as emissions standards, may potentially reduce wage premiums or drive automation in highly polluting industries. In contrast, technology support policies such as public investment in low-carbon R&D may disproportionately benefit high-skilled workers whose expertise is complementary to new technologies.

This analysis shows the importance of distinguishing between different forms of environmental policy. Whilst no statistically significant relationship is found between the aggregate EPS index and income inequality, analysing the individual sub-indices displays important differences. No evidence is found of a statistically significant association between environmental policy and regional income inequality, either through the aggregate index or any of its constituent policy categories. This should not be interpreted as evidence that environmental policies have no geographically concentrated effects, but rather that such effects do not appear to translate into a systematic association with income disparities between regions in the available smaller sample. Similarly, the spike analysis provides limited additional evidence of differences in income inequality following countries' largest observed increases in environmental policy stringency, with lower inequality identified following the market-based EPS spike when using the World Bank GINI measure, but not replicated across alternative measures of inequality. Extending this analysis to allow the association between EPS and inequality to differ following the identified policy-stringency spikes provides some evidence of such differences when using the World Bank GINI measure. However, these findings vary across EPS measures, are not replicated using the OECD disposable-income GINI measure, and are not observed for regional inequality.

The empirical findings should be interpreted with caution. Most results are only significant at relatively low conventional significance levels, with the estimated associations modest and not consistently robust when considering alternative model specifications or allowing for lagged policy effects. As a result, the analysis provides suggestive evidence, not a causal interpretation, regarding the associations between environmental policy and income inequality. In addition, the identification strategy relies on the remaining within-country variation in EPS over time after accounting for country and year fixed effects, which limits the variation available to identify the relationship between environmental policy stringency and inequality. The regional analysis is additionally constrained by the smaller sample size.

Despite the limitations of this analysis, the findings have clear policy relevance. As governments continue to strengthen environmental policies in order to meet climate targets, greater attention should be given to how the costs and benefits of different policy instruments are distributed across households, workers, firms and regions, as well as to their environmental effectiveness. Policies that reduce emissions while simultaneously limiting increases in income inequality are likely to command greater public support and prove more politically durable. Equally, delaying ambitious climate action because of concerns surrounding its short-term distributional effects will exacerbate intergenerational inequality through the long-term consequences of climate

change (Schonhage et al., 2024) and climate policy uncertainty itself can lead to greater income inequality (Zhan & Pu, 2026).

Consequently, understanding how different forms of environmental policy affect income distribution is essential for designing policies that are both environmentally effective and socially and politically sustainable. In an era characterised by both accelerating climate change and persistently high levels of income inequality across OECD economies, understanding how different environmental policies affect the distribution of income is essential for designing a just and politically sustainable transition to a low-carbon economy, in order to avoid furthering social unrest caused by greater disparities between the rich and poor in our societies.

7. Appendix

7.1 Literature Review

The process of conducting the literature review was as follows. Firstly, the below queries were constructed to search the online academic databases Scopus and Web of Science respectively:

Scopus:

- (TITLE-ABS-KEY ("environmental policy" OR "environmental regulation" OR "climate policy" OR "climate regulation") AND TITLE-ABS-KEY ("inequality" OR "wage" OR "regional inequality") AND NOT TITLE-ABS-KEY ("health")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SUBJAREA , "MULT") OR LIMIT-TO (SUBJAREA , "ECON") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "ENVI"))

Web of Science:

- *(environmental policy or environmental regulation or climate policy or climate regulation) AND (inequality or wage or regional inequality) NOT health (Title) or (environmental policy or environmental regulation or climate policy or climate regulation) AND (inequality or wage or regional inequality) NOT health (Abstract) or (environmental policy or environmental regulation or climate policy or climate regulation) AND (inequality or wage or regional inequality) NOT health (Author Keywords) and English (Languages) and Article (Document Types) and Environmental Studies or Environmental Sciences or Economics or Green Sustainable Science Technology or Development Studies or Political Science or Public Administration or Social Sciences Interdisciplinary or Social Issues (Web of Science Categories)*

These queries were run on the 1st of June 2026, yielding 1022 results on Scopus and 2219 results on WoS. For this review the top 25 results were gathered when sorting by most relevant and the top 25 when sorting by most cited, from both databases. Duplicates were removed from these results, to leave 81 studies. Using the online tool *Research Rabbit*, the 10 most referenced papers from the original sample of 81 were identified, taking the total to 91 papers. After a prioritisation exercise, 10 of these 91 papers were judged as high priority and used to create a focused sub-sample. Inputting these 10 papers into *Research Rabbit*, a forwards and backwards citation search was completed. Specifically the five papers most frequently referenced by the subset (backwards), and the five papers that cite the largest number of the subset (forwards) were added to the literature review, where these had not been previously included in the sample. Thus 101 papers were considered as part of the systematic review.

7.2 Dataset

Table 19 below details the countries included in the dataset and the number of observations for each of the main variables used as part of the econometric analysis for each country. To aid readability some of the variables in the dataset have not been included in this table. Only one of the EPS variables is displayed, but the number of observations for each country is consistent across the aggregate EPS index and the 3 sub-indices, full coverage. Alternative measures of inequality, with the exception of the GINI coefficient from the World Bank, are not displayed for similar reasons. In these cases the coverage is more sparse than that in the baseline specification. In the regression tables one can see when these measures are used the number of observations in these tests decreases accordingly. This may reduce the precision of the estimates obtained using these alternative measures.

Table 19 – Countries and Observations in Dataset

Country	First Year	Last Year	EPS	GINI Disposable	World Bank GINI	GDP (pc)	Population	Trade Openness	Manufacturing (%)	Regional Inequality Disposable
AUS	1990	2020	31	5	10	31	31	31	31	0
AUT	1990	2020	31	14	25	26	31	26	31	0
BEL	1990	2020	31	3	22	26	31	26	26	26
CHE	1990	2020	31	15	19	30	31	31	26	0
CHL	1990	2020	31	6	14	25	31	25	25	0
CZE	1990	2020	31	17	21	26	31	26	28	26
DEU	1990	2020	31	11	30	30	31	30	30	21
DNK	1990	2020	31	10	21	30	31	26	31	21
ESP	1990	2020	31	14	27	26	31	26	26	0
EST	1990	2020	31	8	24	26	31	26	26	15
FIN	1990	2020	31	31	21	31	31	31	31	21
FRA	1990	2020	31	1	26	31	31	31	31	0
GBR	1990	2020	31	19	31	26	31	26	31	24
GRC	1990	2020	31	18	21	26	31	26	26	0
HUN	1990	2020	31	17	23	26	31	26	26	0
IRL	1990	2020	31	18	23	26	31	26	26	21
ISL	1990	2020	31	17	17	30	31	26	26	26
ISR	1990	2020	31	10	22	26	31	26	26	25
ITA	1990	2020	31	18	24	26	31	25	31	0
JPN	1990	2020	31	1	13	14	31	27	27	20
KOR	1990	2020	31	10	10	26	31	31	31	21
LUX	1990	2020	31	6	31	26	31	26	26	0
NLD	1990	2020	31	10	20	26	31	26	31	10
NOR	1990	2020	31	14	21	26	31	31	31	10
NZL	1990	2020	31	15	0	30	31	31	31	24
POL	1990	2020	31	16	27	26	31	26	26	0
PRT	1990	2020	31	18	18	26	31	26	26	0
SVK	1990	2020	31	17	19	26	31	26	26	24
SVN	1990	2020	31	17	23	25	31	25	26	21
SWE	1990	2020	31	8	23	28	31	28	31	21
TUR	1990	2020	31	9	20	31	31	26	26	0
USA	1990	2020	31	8	31	31	31	19	24	0

7.3 Data¹²

7.3.1 GINI Income Inequality (OECD)

From the Income distribution database using the income definition since 2012. The Gini index measures the extent to which the distribution of income among individuals or households within an economy deviates from a perfectly equal distribution. The Gini index measures the area between the Lorenz curve and the hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. A Gini index of zero represents perfect equality and 1, perfect inequality.

- Market Income – Income individuals receive from the market – wages, capital gains etc. Before taxes, transfers and redistributions.
- Gross Income – Income individuals receive from the market – wages, capital gains etc, then taking into account transfers/benefits such as child benefit, unemployment benefit, but before redistributive taxes.
- Disposable Income - Disposable income is derived from the balance of primary incomes of an institutional unit or sector by adding all current transfers, except social transfers in kind, receivable by that unit or sector and subtracting all current transfers, except social transfers in kind, payable by that unit or sector; it is the balancing item in the Secondary Distribution of Income Account
- Disposable income is defined by the Canberra Group as total income less current transfers paid. Such transfers comprise: employers' social insurance contributions; employees' social insurance contributions; taxes on income; regular taxes on wealth; regular inter-household cash transfers; and regular cash transfers to charities. This measure of income is usually the preferred measure for income distribution as it is more free of the impact of the institutional arrangements in relation to total income. Disposable income is also a closer approximation of receipts available for individual and household consumption.

7.3.2 GINI Index (World Bank)

Data from the World Bank, Poverty and Inequality Platform. Data are based on primary household survey data obtained from government statistical agencies and World Bank country departments. The exact measure used is country dependent, with disposable income mostly used in Latin America and high-income countries while a measure of consumption inequality is used mostly in low and lower-middle income countries, in large part because of data availability constraints (Haddad et al., 2024). Data for high-income economies are mostly from the Luxembourg Income Study database.

The Gini index is derived from the Lorenz curve, which plots the cumulative welfare share (on the y-axis) against the cumulative population share (on the x-axis). A 45-degree line is defined over the Lorenz curve as a line of perfect equality. The Gini index ranges from 0 (perfect equality) to 100 (complete inequality).¹³

¹² All data from OECD, with the exception of GINI Inequality from the World Bank.

¹³ This variable has been resized to range from 0 to 1, to align with the GINI coefficients from the OECD data.

7.3.3 Environmental Policy Stringency

The OECD Environmental Policy Stringency Index (EPS) is a country-specific and internationally comparable measure of the stringency of environmental policy ranging from zero (least stringent) to six (most stringent).

Market-Based - This sub-index groups policies that put a price on pollution:

- **CO₂ Trading Schemes:** CO₂ trading schemes set a cap on the total amount of CO₂ emissions that can be emitted. Regulated entities can buy and sell allowances to emit CO₂ to each other as needed. The stringency of CO₂ trading schemes is measured using the average annual permit price. The higher the price the more stringent the policy.
- **Renewable Energy Trading Scheme:** Renewable Energy Trading Schemes (also known as Green Trading Schemes) are a system for trade in renewable energy certificates based on the obligation to source a mandated percentage of electricity from green sources. The higher this percentage the more stringent the policy.
- **CO₂ Taxes:** The stringency of a CO₂ tax is measured by the tax rate for CO₂ emissions.
- **Nitrogen Oxides (NOx) Tax:** The stringency of the NOx tax is measured by the tax rate for NOx emissions.
- **Sulphur Oxides (SOx) Tax:** The stringency of the SOx tax is measured by the tax rate for emissions.
- **Fuel Tax (Diesel):** The stringency is measured using the tax for a litre of diesel fuel used in transport for industry as a share of the pre-tax diesel price.

Non-Market based policies - This sub-index entails policies that mandate emission limits and standards:

- **Emission Limit Value (ELV) for nitrogen oxides (NOx):** The indicator represents the maximum concentration of nitrogen dioxide emissions permitted for a large, newly built coal-fired power plant, as a proxy for emissions standards in the energy generation sector. The lower the value the more stringent the policy.
- **ELV for sulphur oxides (SOx):** The indicator represents the maximum concentration of sulphur dioxide emissions permitted for a large, newly built coal-fired power plant, as a proxy for emissions standards in the energy generation sector. The lower the value the more stringent the policy.
- **ELV for Particulate Matter (PM):** The indicator represents the maximum concentration of particulate matter (PM) emissions permitted for a large, newly built coal-fired power plant, as a proxy for emissions standards in the energy generation sector. The lower the value the more stringent the policy.
- **Sulphur content limit for diesel:** The indicator represents the stringency of the diesel fuel standard with regard to the maximum concentration of sulphur permitted in diesel for automobiles. The lower the value the more stringent the policy.

Technology Support policies - This sub-index entails policies that support innovation in clean technologies and their adoption:

- **Public research and development expenditure (R&D):** The indicator represents the amount spent by the government for R&D on low-carbon energy technologies relative to

the size of the country's nominal GDP. It includes renewable energy sources, energy efficiency, carbon capture and storage (CCS), nuclear, hydrogen and fuel cells, other power and storage technologies, as well as other cross-cutting technologies and research. It is calculated by dividing a country's public R&D expenditure by its nominal GDP.

- Renewable energy support for Solar and Wind: This indicator represents the level of the price support for solar and wind energy technologies from feed-in tariffs (FIT) and renewable energy auctions, relative to the global levelized cost of electricity (LCOE). Over recent years, some countries replaced FITs by auctions. To capture this shift in policymaking the indicator represents the average awarded price from a wind or solar auction for country-year observations that replaced FITs by auction designs. The level of the price support is divided by the global LCOE to account for the decline in the costs of renewable energy production over the past decades.

7.3.4 Regional Income

The OECD regional income dataset provides measures of primary and disposable household income for large (TL2) and small (TL3) regions, where available. Income is measured from a macroeconomic perspective using regional accounts and is reported per capita in constant USD, converted using purchasing power parities (PPP). The use of constant prices and PPP conversion improves comparability across both countries and time.

Primary income refers to income received by households as a result of their participation in production and ownership of assets. It includes compensation of employees (wages, salaries and employers' social contributions), gross operating surplus, gross mixed income from self-employment, and property income including net interest, dividends and rent.

Disposable income represents the income available to households after accounting for redistribution through taxes, social contributions and benefits, as well as other current transfers. It therefore reflects household income after the principal redistributive mechanisms captured within the regional accounts have been taken into account.

7.3.5 Territorial Levels

Regions are classified by the OECD on two territorial levels reflecting the administrative organisation of countries. OECD small (TL3) regions are contained in a TL2 region. For example, the TL2 region of Aquitaine in France encompasses five TL3 regions: Dordogne, Gironde, Landes, Lot-et-Garonne and Pyrénées Atlantiques. The 435 OECD large (TL2) regions represent the first administrative tier of subnational government, for example, Texas in the United States. The 2420 OECD small (TL3) regions correspond to administrative regions, except in Australia, Canada, Latvia and the United States. For European countries, TL regions are largely consistent with the Eurostat NUTS2 and NUTS3 2024 classification. TL3 regions are contained in a TL2 region, except in the United States. For Costa Rica, Israel and New Zealand, the TL3 level is equivalent to the TL2 level. All the regions are defined within national borders.

7.3.6 Trade Openness (Imports + Exports / GDP)

Annual GDP and components expenditure approach in national currency. Chain-linked volume, neither seasonally or calendar adjusted Gross Domestic Product (GDP) and its components according to the expenditure approach. In the expenditure approach, the main components of GDP are: final consumption expenditure of households and non-profit institutions serving

households (NPISH) plus final consumption expenditure of General Government plus gross fixed capital formation (or investment) plus net trade (exports minus imports).

Imports of goods and services from the System of National Accounts consists of purchases, barter, or receipts of gifts or grants, of goods and services by residents from non-residents. The treatment of exports and imports in the System of National Accounts is generally identical with that in the balance of payments accounts as described in the Balance of Payments Manual. Exports of goods and services – SNA Exports of goods and services consist of sales, barter, or gifts or grants, of goods and services from residents to non-residents.

7.3.7 GDP per capita (chain - linked rebased)

Gross domestic product (GDP) at constant prices refers to the volume level of GDP, measured in \$USD PPP.¹⁴ Constant price estimates of GDP are obtained by expressing values in terms of a base period. In theory, the price and quantity components of a value are identified and the price in the base period is substituted for that in the current period. Two main methods are adopted in practice. The first, referred to as "quantity revaluation", is based on a methodology consistent with the above theory (i.e., by multiplying the current period quantity by the base period price). The second, commonly referred to as "price deflation", involves dividing price indexes into the observed values to obtain the volume estimate. The price indexes used are built up from the prices of the major items contributing to each value. Per capita is defined as data for each person.

7.3.8 Manufacturing as % of GVA

The fourth chapter of the National Accounts at a Glance presents indicators from a production perspective. Manufacturing is defined as the physical or chemical transformation of materials of components into new products, whether the work is performed by power-driven machines or by hand, whether it is done in a factory or in the worker's home, and whether the products are sold at wholesale or retail. Included are assembly of component parts of manufactured products and recycling of waste materials. Manufacturing is a subcategory of 'industry'. Gross value added, the value of output less the value of intermediate consumption; it is a measure of the contribution to GDP made by an individual producer, industry or sector; gross value added is the source from which the primary incomes of the System of National Accounts are generated and is therefore carried forward into the primary distribution of income account

7.3.9 Population

Historical annual population data from 1961, resized to be measured in millions of people. The data is available for all member countries as well as for the EU27 and G20 countries, Argentina, Brazil, China, India, Indonesia, Russia, Saudi Arabia, Singapore, South Africa and the World total. The data refer to mid-year estimates of the population.

¹⁴ These data has been resized to be measured in thousands (\$000).

7.4 Additional EPS Graphs

Shown below in Figures 12 and 13 is the evolution of the EPS sub-indices for market-based and non-market based policies in the G7 economies over the sample period¹⁵. Here we can see both a broadly common international trend over these three decades, with the level of policy stringency broadly increasing over time. One can see that by 2020 non-market policies such as emission limits are much more restrictive on average in the G7 than market-based policies like carbon taxes.

Figure 12 – EPS Market sub-index in G7 Economies (1990-2020)

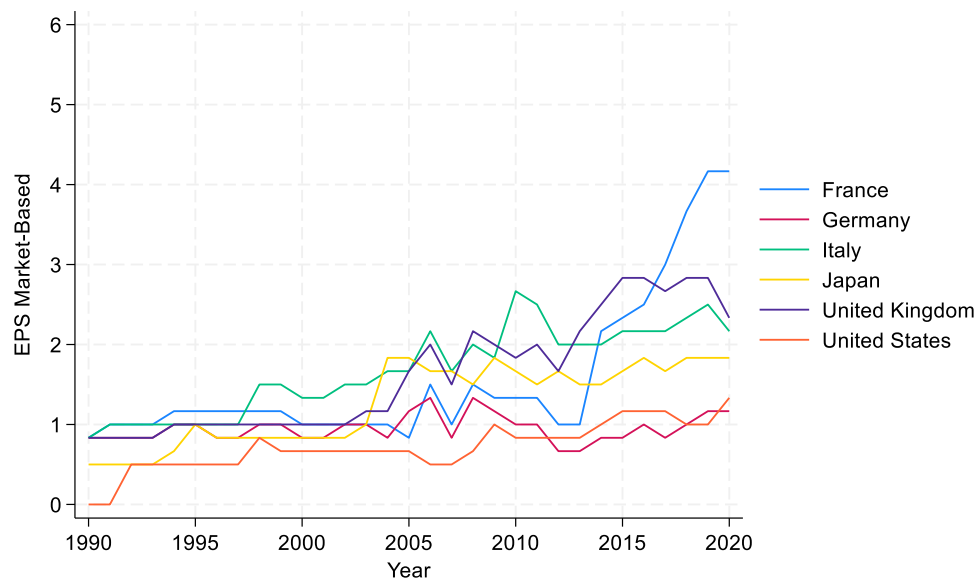
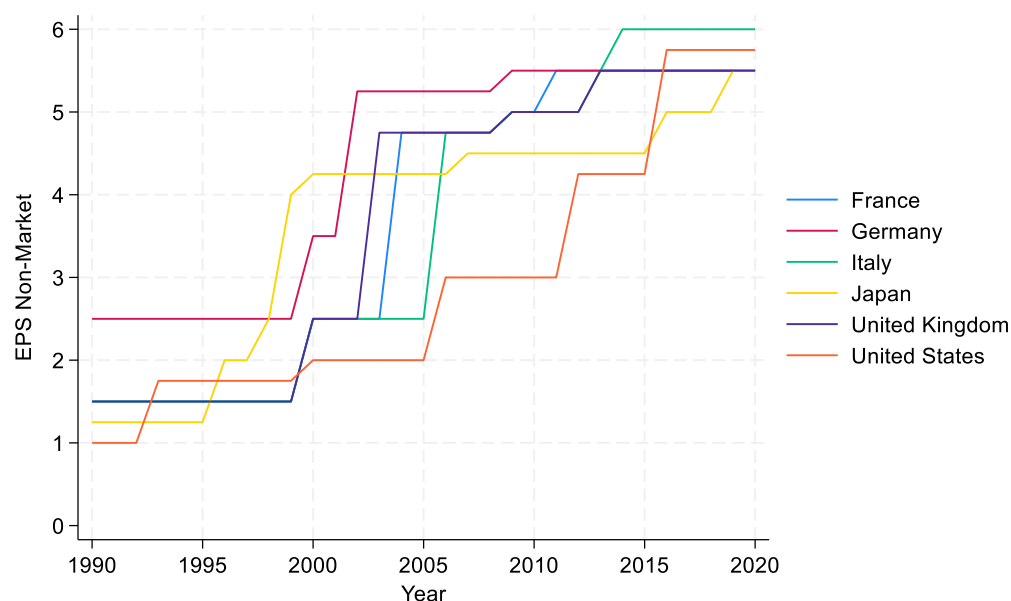


Figure 13 – EPS Non-Market sub-index in G7 Economies (1990-2020)

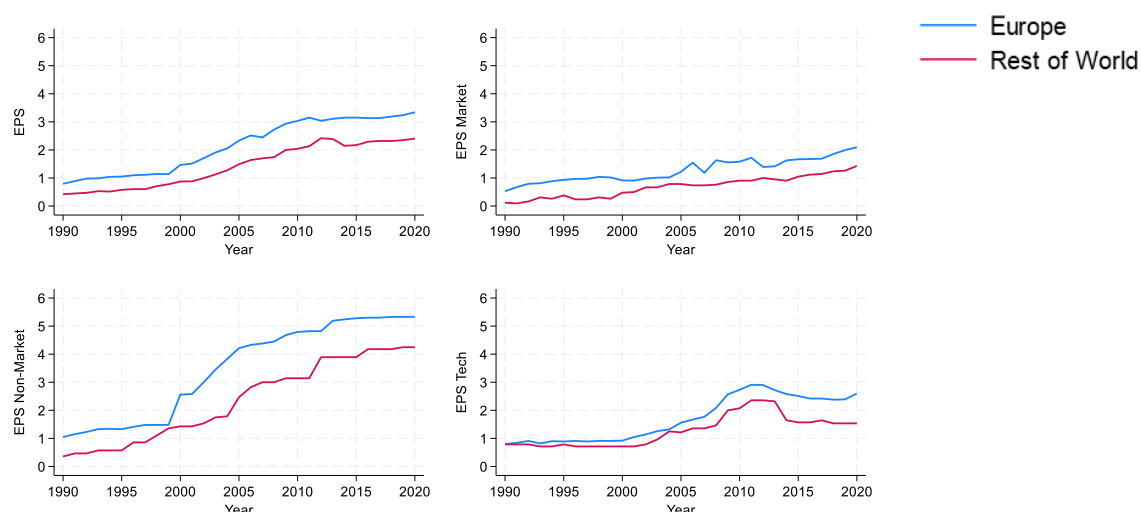


¹⁵ Once again, note that Canada was not included in the final sample. As these graphs serve to motivate the identification strategy, Canada has not been included, despite being a G7 member.

These graphs also serve to illustrate some of the limitations with the TWFE model that is used as part of the identification strategy, namely that there is a significant common trend between countries and as such the remaining variation which is relied upon is fairly narrow. To further investigate how the evolution of environmental policy measures compares across different sub-groupings of the sample Figures 14 & 15 show how this evolution compares when dividing the sample based on geographic location and income. Given the European-centric nature of the OECD membership, on a geographic basis the sample is divided most simply between those members in Europe and the rest of the world¹⁶ to view whether these groups exhibit differing trends. Results are shown for both the aggregate EPS index and the three sub-indices. These results indicate the common international trend also observed within the G7 economies. There is no clear indication that there is a substantial difference in the evolution in the stringency of environmental policy over the sample period based on where a country is located.

The sample countries were also sub-divided into three income grouping terciles to view if environmental policy evolved differently between countries of differing levels of wealth. The sample was divided into a lower income, middle income and higher income group¹⁷, based on the average level of GDP per capita within each country across the sample period. Given this is an exclusively OECD sample, these labels do not correspond to global definitions for these terms and are used for simplicity. These results are once more shown for both the aggregate EPS index and the three sub-indices. Again, a clear common international trend is shown and no clear difference is identifiable in the evolution of EPS over time between the different income groupings. This helps to motivate the need to investigate further to better determine the validity of the chosen identification strategy.

Figure 14 EPS (Aggregate and Sub-Indices) (1990-2020) – Europe vs Rest of World



¹⁶ Sample countries included in **Europe**: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom. **Rest of World**: Australia, Chile, Israel, Japan, South Korea, New Zealand, Türkiye, United States

¹⁷ Sample countries included in **Lower Income**: Chile, Greece, Hungary, Poland, Portugal, Slovakia, Türkiye. **Middle income**: Czech Republic, Estonia, Israel, Italy, South Korea, Slovenia, Spain. **Higher income**: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Japan, Luxembourg, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom, United States

Figure 15 EPS (Aggregate and Sub-Indices) (1990-2020) – Income Groups

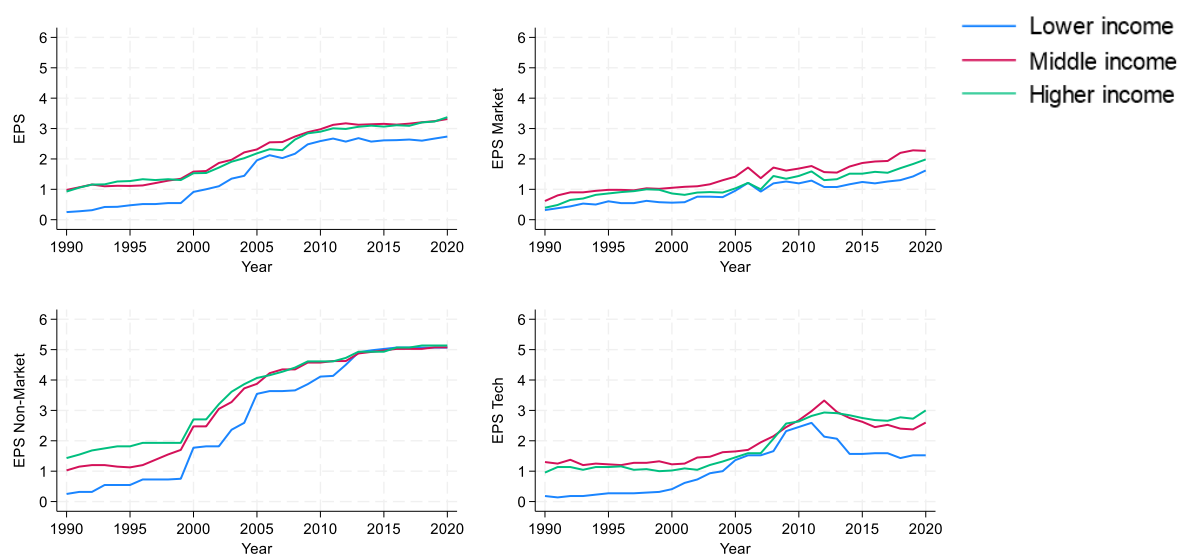
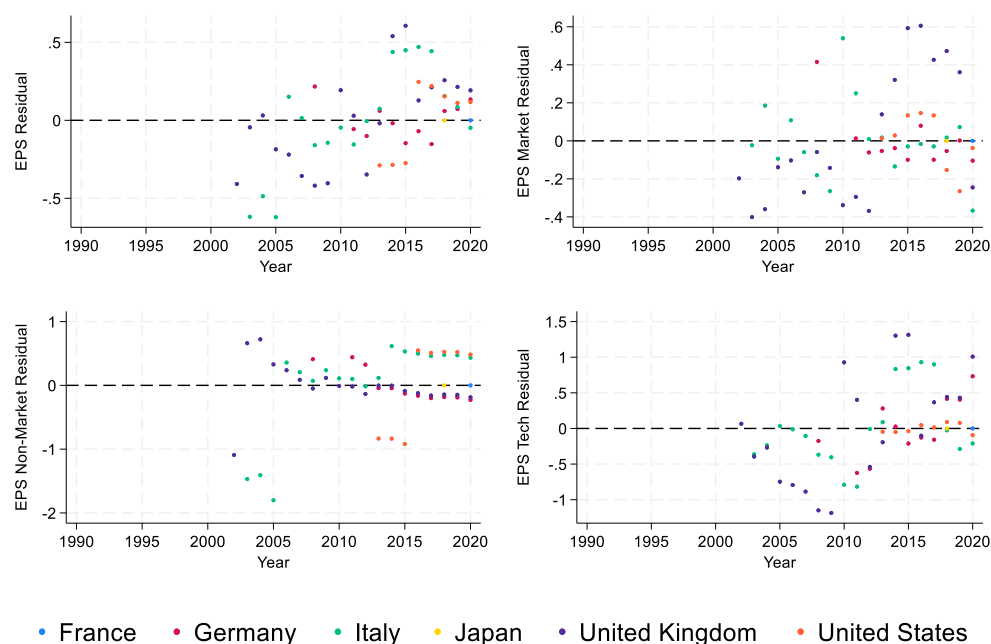


Figure 16 display the residuals obtained for each member of the G7 (excluding Canada)¹⁸ from the auxiliary regressions described in the Identification section, using the estimation sample corresponding to the OECD GINI coefficient for disposable income. Results are shown for the aggregate EPS index and each of the three sub-indices after country and year fixed effects have been removed. As with the corresponding results presented in the methodology section, the residuals are dispersed around zero, with no obvious pattern emerging over time. This figure also illustrates the more limited coverage provided by the OECD disposable-income GINI coefficient over the sample period when compared with the World Bank GINI coefficient.

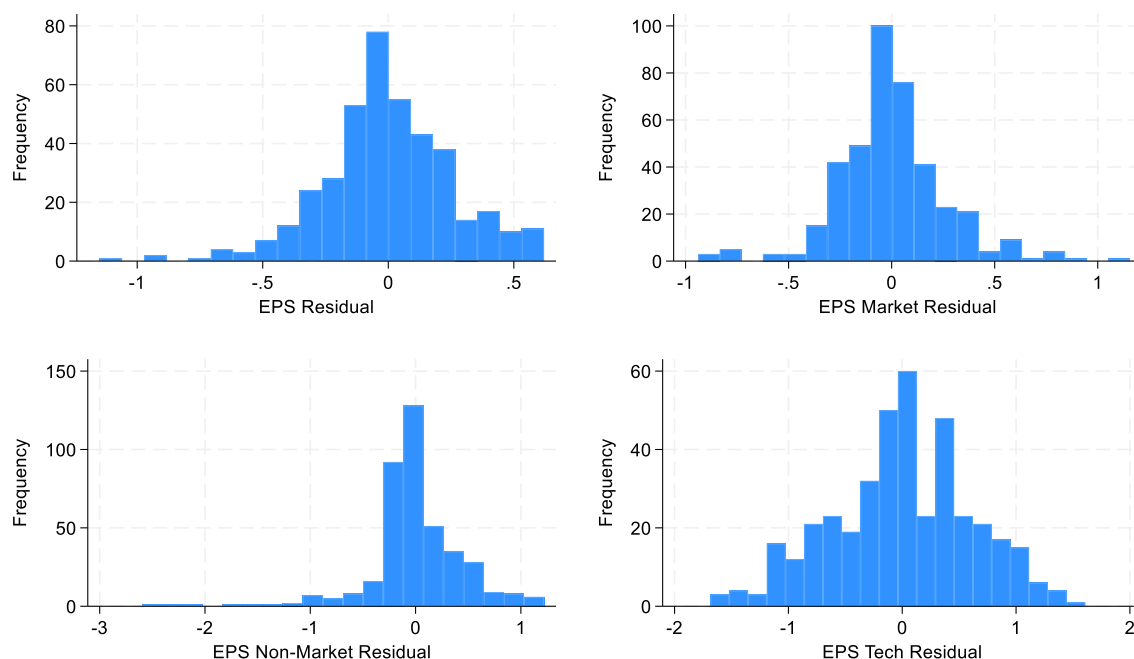
Figure 16 – EPS Residuals G7 countries (1990-2020) [OECD GINI disposable income sample]



¹⁸ Canada is excluded due to lacking data for one of the control variables used in these regressions.

Figure 17 presents histograms of the country-year residuals for the aggregate EPS measure and each of its three sub-indices, using the OECD disposable-income estimation sample. Each observation represents the residual for an individual country-year after accounting for country and year fixed effects. Consistent with the corresponding World Bank GINI coefficient results presented in Figure 10, the residuals are broadly centred around zero while retaining meaningful dispersion, further illustrating that variation in EPS remains after accounting for country and year fixed effects.

Figure 17 – Residuals [OECD GINI coefficient disposable income sample]



7.5 Spike Analysis

Table 20 below shows the results of the spike analysis using the OECD disposable-income GINI measure. No statistically significant difference in inequality is identified following the largest annual increase in aggregate EPS or any of the three sub-indices. This differs from the results reported in the main body of the thesis using the World Bank GINI coefficient, where inequality was lower following the identified market-based EPS spike at the 5% significance level. This statistically significant difference is therefore not replicated when using the OECD disposable-income GINI measure. However, the spike specification should be interpreted as a robustness exercise rather than as establishing a causal effect, with the coefficients capturing average differences in inequality before and after the identified policy-stringency spikes.

Table 20 – EPS Spike Analysis Regression Results – OECD Disposable Income Sample

	(1)	(2)	(3)	(4)
	GINI (Disposable)	GINI (Disposable)	GINI (Disposable)	GINI (Disposable)
EPS Spike	-0.00271 (0.0051)			
EPS Market Spike		0.00223 (0.0056)		
EPS Non-Market Spike			-0.00386 (0.0049)	
EPS Tech Spike				-0.00105 (0.0043)
GDP per capita (000)	-0.00062 (0.0005)	-0.00066 (0.0005)	-0.00066 (0.0005)	-0.00064 (0.0005)
Population (millions)	0.00119 (0.0009)	0.00109 (0.0009)	0.00121 (0.0008)	0.00111 (0.0010)
Trade Openness	-0.00127 (0.0155)	0.00074 (0.0147)	-0.00213 (0.0155)	0.00009 (0.0150)
Manufacturing (%GVA)	0.00016 (0.0007)	0.00017 (0.0007)	0.00028 (0.0007)	0.00015 (0.0007)
Observations	401	401	401	401
Median per country	14	14	14	14
Countries	32	32	32	32
R-squared	0.2543	0.2551	0.2547	0.2563
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. GDP per capita is expressed in thousands and population in millions. EPS spike variables are binary indicators equal to one in years after a country's largest annual increase in the corresponding Environmental Policy Stringency measure, and zero in the spike year and all preceding years. GINI (Disposable) is a coefficient measuring disposable-income inequality from the OECD and ranges from 0 to 1. The estimation samples cover observations from 1990 to 2020. Further information on all variables is provided in the Data section of the Appendix.

7.6 Interaction Analysis

Table 21 extends the analysis by interacting each continuous EPS measure with its corresponding spike indicator, allowing the association between environmental policy stringency and inequality to differ following the identified policy-stringency spike. None of the four interaction terms is statistically significant when using the OECD disposable-income GINI measure, providing no evidence that the association between EPS and inequality systematically differs following countries' largest observed increases in policy stringency. This contrasts with the World Bank GINI specification reported in the main body, where a statistically significant positive interaction term is identified for aggregate EPS and, more weakly, for market-based and technology-support EPS. Taken together, the interaction results therefore provide limited and measure-dependent evidence that the association between environmental policy stringency and income inequality differs following large observed increases in policy stringency.

Table 21 – Interaction Analysis Regression Results – OECD Sample (Disposable Income)

	(1) Aggregate EPS	(2) Market-Based EPS	(3) Non-Market EPS	(4) Technology Support EPS
EPS Measure	0.00178 (0.0061)	-0.00943** (0.0040)	-0.00005 (0.0024)	0.00359 (0.0031)
EPS Spike	-0.00903 (0.0084)	-0.00342 (0.0086)	-0.00603 (0.0131)	-0.00303 (0.0070)
EPS Measure × EPS Spike	0.00287 (0.0026)	0.00441 (0.0037)	0.00055 (0.0023)	0.00008 (0.0029)
GDP per capita (000)	-0.00057 (0.0005)	-0.00053 (0.0005)	-0.00064 (0.0005)	-0.00062 (0.0005)
Population (millions)	0.00080 (0.0008)	0.00099 (0.0009)	0.00114 (0.0009)	0.00069 (0.0008)
Trade Openness	-0.00369 (0.0177)	-0.00463 (0.0148)	-0.00368 (0.0178)	0.00094 (0.0144)
Manufacturing (%GVA)	0.00033 (0.0007)	0.00023 (0.0006)	0.00031 (0.0007)	0.00028 (0.0006)
Observations	401	401	401	401
Median per country	14	14	14	14
Countries	32	32	32	32
R-squared	0.2457	0.2822	0.2565	0.2416
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the country level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is expressed in thousands and population in millions. Each column uses the EPS measure identified in the column heading. EPS Spike is a binary indicator equal to one in all years after a country's largest annual increase in the corresponding EPS measure, and zero in the spike year and all preceding years. EPS Measure × EPS Spike captures whether the association between the corresponding EPS measure and inequality differs in the post-spike period. GINI (Disposable) is a coefficient measuring disposable-income inequality from the OECD and ranges from 0 to 1. Further information on all variables is provided in the Data section of the Appendix.

7.7 OECD

At the time of writing the following 38 countries shown below in Figure 18 constitute the member countries of the OECD. Any countries not included in this group were removed from the dataset and thus were not used as part of any statistical analysis. Furthermore, due to a lack of data availability six of these countries were not included in the final analysis. Colombia, Costa Rica, Latvia and Lithuania did not have data for the EPS index (or sub-indices) and so were not included in this analysis. Canada and Mexico did not have data for one of the control variables (trade openness), and so were also excluded.

Figure 18 – OECD Member Countries¹⁹

 Australia	>	 Greece	>	 New Zealand	>
 Austria	>	 Hungary	>	 Norway	>
 Belgium	>	 Iceland	>	 Poland	>
 Canada	>	 Ireland	>	 Portugal	>
 Chile	>	 Israel	>	 Slovak Republic	>
 Colombia	>	 Italy	>	 Slovenia	>
 Costa Rica	>	 Japan	>	 Spain	>
 Czechia	>	 Korea	>	 Sweden	>
 Denmark	>	 Latvia	>	 Switzerland	>
 Estonia	>	 Lithuania	>	 Türkiye	>
 Finland	>	 Luxembourg	>	 United Kingdom	>
 France	>	 Mexico	>	 United States	>
 Germany	>	 Netherlands	>		

¹⁹ Accessed via the following website (14/09/2026):

<https://www.oecd.org/en/about/members-partners.html>

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