Macroeconomic and Environmental Effects of Climate Policy Uncertainty: A Sectoral Reallocation Perspective

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Abstract

This paper investigates sectoral reallocations in an economy where climate policy is uncertain. To this end, it develops a Dynamic General Equilibrium model with two sectors - a polluting one and a non-polluting one, along with climate externality and endogenous firm entry. Climate policy uncertainty stems from the possibility that the government may introduce a carbon tax in the next period. I show that, compared to a scenario without climate policy uncertainty, the probability of implementing carbon taxation prompts entrepreneurs to curtail investment in polluting firms' entry while promoting entry into the non-polluting sector. Through general equilibrium effects, these sectoral reallocations deteriorate welfare, generate a drop in economic activity, and increase CO_2 emissions. I provide additional empirical evidence through a VAR model that supports these results. Overall, this paper points out the economic and environmental costs of climate policy uncertainty.

Keywords: Uncertainty, Climate policy, Sectoral Reallocations, Firm Entry
JEL Classification: E10, Q54, Q58, D80

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1 Introduction

Through its impact on the ecosystem and public health, climate change stands as one of the most important challenges of the XXI$^{\text{st}}$ century. It is also a threat to economic stability, as exposed by the former governor of the Bank of England Mark Carney in an influential speech (Carney, 2015). Acknowledging these risks and the importance of mitigating climate change, recent policy-making advocates for the design of "green" tools to align environmental and economic stability objectives. One recent example is the Inflation Reduction Act, promulgated by Biden's administration in 2022, which aims to promote green innovation and green loans. However, the absence of federal climate policy in the United States, coupled with the recent election of Donald Trump, who has previously expressed skepticism toward climate action, introduces substantial uncertainty about future policy implementation, particularly regarding its timing and magnitude. Since agents' decision-making is deeply influenced by their economic and political environment, this uncertainty can significantly affect firms' forward-looking entry decisions in a given sector and the allocation of resources between polluting and sustainable industries. Therefore, understanding how climate policy uncertainty influences sector-specific firms' entry and new product creation is crucial for both policymakers and market participants.

However, while new product creation represents a substantial share of the Gross Domestic Product in the U.S.[1] and despite uncertainty surrounding climate policies, the literature has neglected the interaction between these aspects.

This paper fills this gap by assessing how the potential introduction of a carbon tax affects economic activity and CO_2 emissions, with a special focus on sectoral reallocations. It contributes to the literature by being the first to analyze how climate policy uncertainty affects firms' entry into different sectors.

To this end, I develop a two-sector Dynamic General Equilibrium model calibrated to U.S. data. The model incorporates three key features. First, the economy is adversely affected by greenhouse gas emissions originating from polluting firms operating in the "dirty" sector. This externality alters the production capacities of both the "dirty" and "clean" sectors, leading to suboptimal production levels and advocating for climate policy action. Second, the model includes endogenous firm entry as in Bilbiie et al. (2012). In this set-up of monopolistic competition, each firm produces a unique variety. There is therefore an identity between the number of producers in the economy and the number of products. Consequently, firms' entry is equivalent to the introduction of a new product in the market[2]. Third, I model uncertainty related to the timing of climate policy's implementation following Fried et al. (2021). I assume that the economy starts in a

[1]Bernard et al. (2010) show that the value of new products represents 46.6% of total output in the U.S. over a 5-year horizon. Additionally, Bilbiie et al. (2012) present the importance of accounting for endogenous firm entry in RBC-type models to replicate empirical facts.

[2] In what follows, I thus use the terms "product creation" and "firm entry" as equivalents.

steady state with no climate policy but at each period, the agents expect that the government can introduce it. The decision to invest in sector-specific firms' entry accounts for the probability that future policy-making includes climate policy. These features allow assessing how product-creation dynamics in each sector react to climate policy uncertainty and how it affects economic and environmental variables. I investigate the effect of climate policy uncertainty over several dimensions. I start by conducting a steady-state comparison. I simulate an economy without climate policy nor uncertainty about its future implementation. It provides a benchmark against which I assess the long-run effects of climate policy uncertainty, on the one hand, and climate policy, on the other hand. Next, I explore the dynamic effects of climate policy uncertainty during the transition to a cleaner economy. Following the introduction of a carbon tax, I compare the transition pathways of an economy with no initial uncertainty to one facing uncertainty regarding the future implementation of climate policy.

The model delivers four main results. First, climate policy uncertainty generates sectoral reallocations, favoring entry into the "clean" sector and reducing entry into the "dirty" one. Second, while climate policy enables reducing emissions, uncertainty around it triggers an increase in emissions, highlighting the environmental costs of the absence of commitment in climate policy-making. Third, climate policy uncertainty triggers economic costs through a lower output in the long run, and a stronger recession during the transition to a low-carbon economy. Fourth, climate policy uncertainty has important welfare costs while implementing a climate policy *per se* is welfare-improving. Put it in plain words, it is the uncertainty surrounding climate policies that is detrimental to welfare, rather than the climate policy by itself.

I then conduct a robustness analysis by extending the model in two avenues, each capturing an additional source of climate policy uncertainty. First, I introduce uncertainty on the magnitude of the potential carbon tax on top of the uncertainty related to the timing of its implementation. I find that this source of risk spreading slightly deteriorates output and welfare. Second, if the baseline model considers carbon taxation as the unique instrument to reduce emissions, policy-making (and, therefore, uncertainty around it) has other tools to meet environmental goals. I simulate innovation policy (uncertainty) in the form of subsidies on entry costs in the clean sector and show that additional uncertainty towards another climate policy leads to a higher decrease in output, while the certain introduction of both policies mitigates the drop in economic activity generated by the sole implementation of a carbon tax. Overall, the main findings are robust to alternative modeling approaches for climate policy uncertainty.

These theoretical predictions are in line with stylized facts that I investigate through a vector autoregressive analysis. Using the newspapers-based measure of CPU for the United States built by Gavriilidis (2021) alongside macroeconomic and environmental series, I document the sectoral reallocation in response to CPU shocks. I measure new product creation under climate policy uncertainty by investigating the decision to apply for a patent[3]. Within total patent applications, I distinguish between the number of "clean" patents favoring the transition to a low-carbon economy and the number of "dirty" patents associated with fossil-based energy. I show that a CPU shock triggers sectoral reallocation in patenting activity, characterized by an increase in clean patents' applications and a decrease in dirty ones. I also find that CPU shocks trigger a contraction in economic activity and an immediate increase in CO_2 emissions, confirming empirically the economic and environmental costs associated with climate policy uncertainty predicted by the model.

The remainder of the paper is organized as follows. Section 2 presents the literature it builds on and complements. Section 3 explores the empirical effects of climate policy uncertainty. Section 4 presents the model and Section 5 exposes the calibration. Section 6 reports the results of the baseline model's simulation and Section 7 presents the results of the extensions analyzing various sources of climate policy risk spreading. Section 8 concludes.

2 Literature review

This paper first builds on the literature analyzing the effects of economic policy uncertainty. As a seminal contribution, Baker et al. (2016) uses newspaper articles containing terms related to uncertainty, economics, and regulation to build a monthly index of Economic Policy Uncertainty (EPU). They point out that an increase in this index is associated with higher stock price volatility, lower employment, and lower investment. Building on this study, the empirical literature has widely documented a decrease in investment in periods of heightened policy-related uncertainty (see, for example, Dibiasi et al., 2018 or Drobetz et al., 2018). I contribute to this literature by analyzing the effect of policy-related uncertainty on firms' entry dynamics, that can be assimilated to product innovation. That specific dimension is less documented.

The strand of the literature analyzing the responsiveness of innovation in the presence of EPU yields disputed effects. On the one hand, William and Fengrong (2022) show that in OECD countries, between 1990 and 2015, EPU has a *negative* effect on industry-level patenting activities. This decrease in innovation in periods of high uncertainty is complemented by the findings of Wang et al. (2017) and Xu (2020) for R&D expenses, using respectively cross-country and U.S. data. On the other hand, some studies highlight that heightened economic policy uncertainty *increases* patenting activity. He et al. (2020) show that in China, between 2000 and 2017, the number of patent applications increased in periods of high EPU. Using R&D data, Stein and Stone (2013) and Atanassov et al. (2015) find that EPU has a positive effect on corporate innovation also in

[3] I disregard whether the patent is ultimately granted or not, focusing instead on the incentives to introduce a new product to the market, without taking into account whether the patent fulfills innovation objectives. A branch of the literature, starting with Gilbert and Newbery (1982) shows that patents do not necessarily promote innovation, but rather allow monopolistic firms to consolidate their market power.

the United States. The present paper contributes to this literature by investigating the effects of uncertainty related to *climate* policy. Given its sectoral dimension, this type of policy affects more directly polluting industries. By showing that uncertainty surrounding this specific policy spurs an increase in clean patents while reducing dirty patents, this paper underscores the critical importance of the sectoral aspect of economic policy uncertainty.

The analysis of sectoral reallocations under climate policy uncertainty adds to the literature on endogenous market structures. In a pioneer contribution, Bilbiie et al. (2012) (hereafter, BGM) extend the standard Real Business Cycle (RBC) model to include firms' endogenous entry, where the entry process is akin to the creation of new products. Accounting for this extensive margin of production enables their model to perform better than a standard RBC model in replicating some key features observed in U.S. data. This model has then been used to study the interaction between endogenous market structure and monetary policy (e.g. Bergin and Corsetti, 2008); fiscal policy (e.g. Chugh and Ghironi, 2011) or labor market (e.g. Cacciatore and Fiori, 2016). In the current paper, I extend this framework by considering two sectors and climate policy uncertainty. To the best of my knowledge, the current paper is the first to assess how sector-specific firms' entry is affected by climate policy and climate policy uncertainty.

Therefore, this paper also contributes to the literature on the macroeconomic effect of climate policies. Following seminal contributions introducing climate externalities within the RBC framework (Fischer and Springborn, 2011; Heutel, 2012 and Angelopoulos et al., 2013), a branch of literature has emerged and developed "Environmental Dynamic Stochastic General Equilibrium" (E-DSGE) models. These models analyze the effectiveness of climate policies in the presence of nominal rigidities, financial frictions, or in an open economy set-up through a cost-and-benefits analysis of introducing a climate policy at business-cycle frequency (for a survey, see Annicchiarico et al., 2021). The first paper in this literature quantifying the effect of climate policies on the extensive margin of activity using BGM's framework is Annicchiarico et al. (2018) who analyze the interaction between market power, endogenous entry, and climate policies. More recently, Shapiro and Metcalf (2023) developed a model analyzing carbon taxation in an environment combining endogenous entry and technology adoption. Both papers identify the crucial role of market structure in amplifying the economic effects of climate policy. The papers previously mentioned evaluate the effects of a clear climate policy, while my paper focuses on *uncertainty* related to climate policies.

In this respect, the current paper takes part in a narrow but rapidly growing literature on climate policy uncertainty. Previous research first examined empirically specific events triggering uncertainty related to the potential future environmental policy. Exploiting an unanticipated event, the U.S. cap-and-trade climate bill in April 2010, Lemoine (2017) shows that it had detrimental environmental effects by increasing greenhouse gas emissions and increasing excess returns in "brown" industries. The literature also shows that climate policy uncertainty might lead to a decrease in the market valuation of "brown" firms, as evidenced by Sen and Von Schickfus (2020) in Germany, or a delay in investment (see, for example, the negative effects of the Clean Air Interstate Rule on investment documented by Dorsey, 2019). I generalize these findings by studying more systematically the effect of climate policy uncertainty rather than focusing on a specific event.

This approach is enabled by the development of continuous CPU indices. Following the seminal contribution of Baker et al. (2016), recent papers apply natural language processing techniques to climate subjects. In particular, Gavriilidis (2021) develops a newspapers-based measure of CPU for the United States. I use this index on the empirical part of the present paper and investigate its effects on sectoral reallocation, output, and CO_2 emissions. Basaglia et al. (2021) and Noailly et al. (2022) build CPU indices for the U.S., and Berestycki et al. (2022) develop a CPU index for 12 OECD countries and study the effect of CPU on macroeconomic outcomes. They empirically show that heightened CPU is associated with a decrease in investment. The present paper complements these findings by assessing the potential sector-specific impacts of CPU, distinguishing between clean and dirty sectors and focusing on sectoral reallocations. Additionally, while the above-mentioned papers are purely empirical, I develop a model allowing to understand the general equilibrium effects of climate policy uncertainty.

The general equilibrium analysis I develop contributes to the literature that introduces uncertainty related to climate policy in theoretical frameworks. To model climate policy uncertainty, the literature offers alternative approaches. First, Bretschger and Soretz (2022) and Khalil and Strobel (2023) model a stochastic carbon tax, assuming that an active climate policy exists, but its magnitude can deviate from its historical average in response to volatility shocks. Using respectively an endogenous growth model and a DSGE framework, they show that an increase in CPU leads to a portfolio reallocation, where investors divert from brown assets, affecting the real economy. Second, Campiglio et al. (2024) model CPU assuming weak commitment from policymakers who announce a carbon pricing path but may default on it. In this setup, firms choose to allocate their investments between clean and dirty capital based on their heterogeneous beliefs about future carbon prices. Their model, calibrated to European data, shows that CPU results in important environmental costs, hindering the transition to a decarbonized economy. In contrast to these models, I assume the absence of an active climate policy, with agents anticipating its potential future introduction. Specifically, in the U.S., where there is no federal carbon tax, the uncertainty centers on the *possible enactment* of such a policy. I thus follow Fried et al. (2021) who develop a Dynamic General Equilibrium model with climate policy risk (CPR). In this framework, each period, there is a probability that the government will introduce a carbon tax next period, leading to a decrease in emissions due to the reduction in brown investment. They also show that CPR decreases the total capital stock, inducing a recession. I build on this paper and complement it by explicitly modeling the pollution externality. I also add to the analysis of this paper by endogenizing firms' entry decisions, allowing me to investigate the effects of climate policy and climate policy uncertainty on sectoral firm entry and the *extensive* margin of activity, an aspect that has been neglected so far but with potential important implications given the importance of new products creation in the United States.

3 Empirical Motivation

This section underscores the relevance of accounting for the interaction between climate policy uncertainty and sectoral reallocations by conducting an empirical investigation of the macroeconomic and environmental effects of climate policy uncertainty (CPU).

3.1 Data and Descriptive Statistics

To empirically assess the effects of CPU on sectoral reallocations, I use U.S. data, observed at a quarterly frequency between 1987Q2 and 2013Q4. The time frame is constrained by data availability, which I detail below.

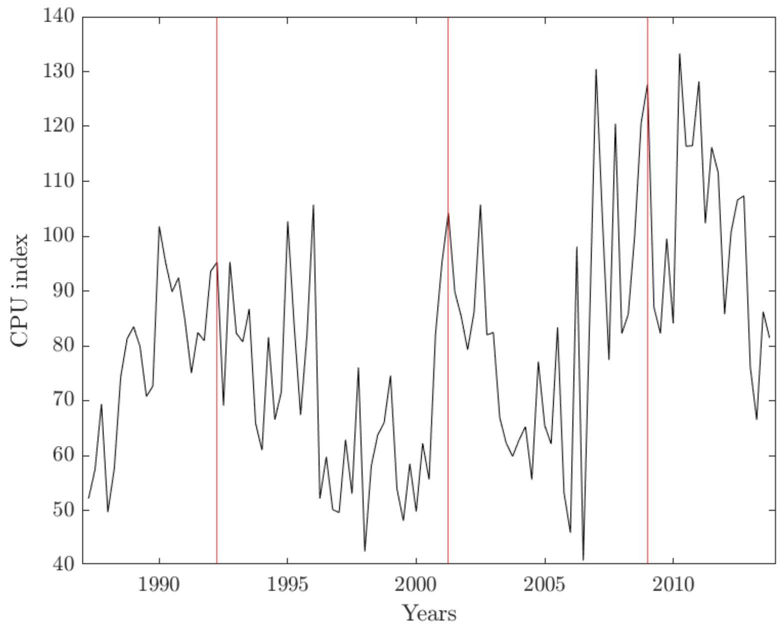
I measure Climate Policy Uncertainty using the index developed by Gavriilidis (2021). Following the methodology of Baker et al. (2016), the construction of this index relies on monthly newspaper coverage of terms of a lexicon related to the terms “climate”, “policy” and “uncertainty”. The obtained series is normalized to have a mean value of 100 on the whole period. More details can be found in Appendix A. This index is available at a monthly frequency between April 1987 and August 2022. To convert this index into a quarterly series, I compute its average value within a quarter.

Figure 1 plots the quarterly index during the sample span used in this analysis and identifies three examples of peaks using red horizontal lines.
This figure shows the presence of cyclical changes in uncertainty related to climate policy. Low periods of uncertainty are followed by highly uncertain periods around climate policy events, where the index peaks, as identified by the three red lines[4]. For example, in March 2001, President Bush announced that the United States wouldn’t implement the Kyoto Protocol, an international agreement ratified in 1997 that aimed to reduce greenhouse gas emissions. This rejection leads to an increase in uncertainty regarding the implementation of climate policy and reflects a severe climate policy uncertainty shock. This example highlights that a peak in this index reflects that

[4] A more detailed presentation of the peaks in this index, at a monthly frequency, can be found in the paper by Gavriilidis (2021).

potential future climate policy might be more or less stringent[5].

Figure 1: Climate Policy Uncertainty Index (1987Q2 - 2013Q4)



NOTE: This figure displays the evolution of the CPU index, at a quarterly frequency, between 1987Q2 and 2013Q4. Red horizontal lines identify three examples of the major peaks in this index, in the following chronological order: Adoption of the United Nations Framework Convention on Climate Change (1992Q2), President Bush's rejection of Kyoto Protocol (2001Q1), Todd Stern's statement about new climate change Treaty (2009Q1).

To isolate unexpected uncertainty shocks, I follow the identification procedure suggested by the empirical literature on uncertainty (see, notably Bloom (2009) or Jurado et al. (2015), among others). I use the quarterly S&P500 index, which is by definition a forward-looking variable to control for the market's expectations. This index is provided at a daily frequency by the Federal Reserve Bank of St. Louis. To convert it into a quarterly index, I use the daily average over a quarter. I also control for overall Economic Policy Uncertainty (EPU) using the index built by Baker et al. (2016), as fluctuations in general economic policy uncertainty can significantly influence the macroeconomic environment and environmental outcomes. By including EPU, I aim to isolate the "pure' impact of climate-related uncertainty, distinguishing it from shifts in overall policy uncertainty that could confound the results.

[5] Berestycki et al. (2022) developed indices to capture the "direction" of the uncertainty - i.e. whether future climate policy might be more or less stringent. However, this index is only available at yearly frequency, limiting the statistical power of an analysis conducted with yearly data.

To assess the effect of CPU shocks on macroeconomic variables and environmental outcomes, I use the U.S. quarterly Gross Domestic Product (GDP) provided by the Federal Reserve Bank of St. Louis. It is measured in billions of dollars, is seasonally adjusted, and I express it in real terms using the quarterly Implicit Price Deflator (Index 2012 = 100), also provided by the Federal Reserve Bank of St. Louis. Concerning environmental outcomes, I measure CO_2 emissions using the Total Carbon Dioxide Emissions From Energy Consumption by Source provided by the U.S. Energy Information Administration. This variable is measured in million metric tons of carbon dioxide.

The goal of this empirical analysis is to analyze the sectoral reallocations in response to CPU shocks. To measure it, a natural candidate would be the number of firm entering in the economy or the number of new products introduced in each sector. However, these data are scarce. On the one hand, the U.S. Census Bureau provides data on firm entry through the Business Formation Statistics. However, the historical data on entry by NAICS sectors, allowing to distinguish entry in "clean" sectors from entry in the "dirty" ones, are only available at yearly frequency, starting in 1997[6]. Since the CPU index used in the empirical analysis ends in 2021, it would leave us with only 24 observation points. On the other hand, tracking the creation of new products is challenging. One approach involves using product barcode data to detect the introduction of new products, but access to this information is restricted, and, in general, does not cover all sectors of activity[7].
To overcome these challenges, I proxy the decision to enter into an industry (or to create a new product within a given industry) relying on patent data. The underlying hypothesis is that patent application and product introduction are significantly and positively correlated, which is consistent with recent analyses (Baslandze et al., 2020). I use the CRIOS-PatStat database (Coffano and Tarasconi, 2014), which offers rich and detailed information on patenting activity from 1978 to 2016. I restrict the sample to 2013Q4 because I observe a decline in patenting activity after 2014 that does not correspond with the pattern of patent applications, indicating potential measurement errors toward the end of the sample period[8]. For each patent, I retrieve its application date. I do not use information on future granting or not, since I seek to analyze the incentives to innovate following CPU shocks, without considering if the innovation is indeed patented after the prosecution process and without considering the quality of this patent nor its ability to increase the productivity of the patenting firm. Following Moshirian et al. (2021), I restrict the database to keep only the earliest application date for a given patent. This approach helps avoid the potential double-counting

[6] Data on firm entry are available at a monthly frequency, but do not include the NAICS codes of new entrants, preventing me to isolate firms entering into the "clean" industry and to investigate the sectoral reallocations.

[7] For example, Baslandze et al. (2020) measure product creation using the Nielsen Retail Measurement Services database, which only covers the consumer goods sector.

[8] In Appendix B, I plot the full series of patents application by U.S. residents from the CRIOS-Patstat database alongside the evolution of patents application from the World Bank for the same period (data available here). After 2013Q4, the CRIOS-PatStat data shows a sharp decline in patent counts, a pattern not observed in other data sources.

of patents for the same invention, as some inventors may file for the same patent in multiple countries. Then, for each quarter, I count the number of applications filed by U.S. residents. To capture sectoral reallocation, I retrieve the International Patent Classification (IPC) code of each patent. It allows me to isolate "clean" patents using the *IPC Green Inventory*, which identifies "clean" technologies according to the Secretariat of the United Nations Framework Convention on Climate Change (UNFCCC). The definition of "clean" technology used by the UNFCCC is broad, encompassing not only climate change technologies but also a range of other environmental interventions (such as waste management).[9] There is no such classification for "dirty" patents. Therefore, I define them following the nomenclatures used by Dechezleprêtre et al. (2021) and Aghion et al. (2016).

Table 1 reports the total number of patents, the total number of clean patents, and the total number of dirty patents, both for the whole sample and for the United States during the sample span. I report on the third column, for each category, the share represented by U.S. patents. In the two last rows, I respectively compute the share of clean (resp. dirty) patents, defined as the ratio of clean (resp. dirty) over total patents.

Table 1: Descriptive statistics - Number of patents (1987 - 2013)

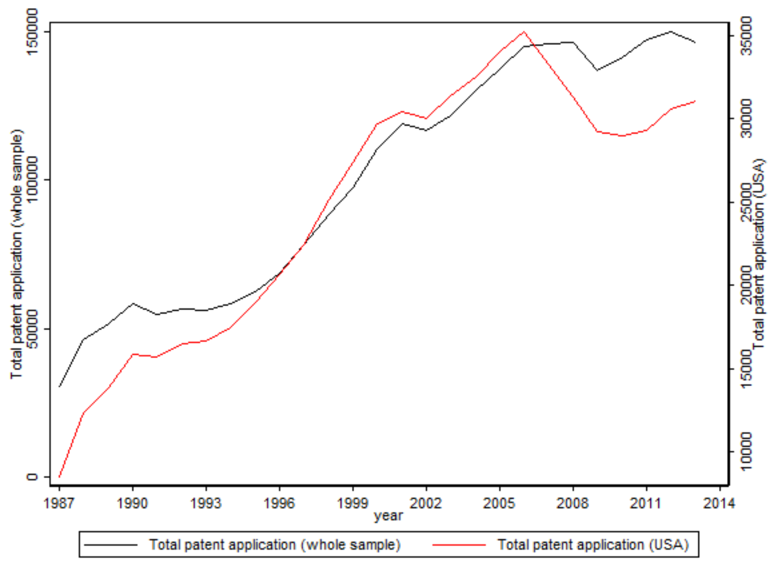
	United States	Total	Share U.S. / Total
Total number of patents	668 369	2 703 955	24.71%
Total number of "clean" patents	11 663	57 865	20.15%
Total number of "dirty" patents	3 134	12 176	25.73%
Share "clean" patents	1.74%	2.14%	
Share "dirty" patents	0.47%	0.45%	

The CRIOS-PatStat database covers slightly less than 3 billion patents between 1987Q2 and 2013Q4. The patents applied by U.S. residents represent almost 25% of the total patenting activity reported in this database. Besides, the type of patents filed by U.S. applicants is representative of the whole patenting activity. Indeed, around 20% of the clean patents and 25% of the dirty ones composing the database are applied by a U.S. resident. In addition, the wide majority of patents are neither clean nor dirty, as they respectively represent only 1.74% and 0.5% of applied patents in the U.S. These magnitudes align with the share of clean and dirty patents in the whole sample.

Figure 2 plots the evolution of the total number of applications during the period of the analysis, in the whole database (black line) and for the USA (red line).

[9] The full list of "clean" technologies can be found here.

Figure 2: Evolution of the total number of patent applications (1987 - 2013)



It shows an upward trend during the sample span, and the trend in the USA follows the general trend, aligning with the surge in patenting activity documented during the last decades. In Appendix C, I focus on the evolution in patenting activity in the USA, distinguishing between the total number of patents (black line), the number of dirty patents (brown line) and the number of clean patents (green line). Sectorial patent applications also exhibit an upward trend. Interestingly, despite the growing concern over climate-related issues, clean patent applications decline toward the end of the sample, whereas applications for dirty patents rise. This anecdotal evidence might suggest a lack of government credibility regarding the implementation of a stringent climate policy.

3.2 Vector Autoregressive Analysis

I employ a Structural Vector Autoregressive model to investigate the response of macroeconomic and environmental variables following a CPU shock. The SVAR has the following form:

$$Y_t = B_1\ Y_{t-1} + ... + B_p\ Y_{t-p} + \epsilon_t \text{ with } \epsilon_t \sim \mathcal{N}(0, \Sigma).$$

The vector $Y_t = [\text{GDP}_t\ \ \text{Patent}_t\ \text{CO}_{2,t}\ \text{S\&P500}_t\ \text{EPU}_t\ \text{CPU}_t]'$ comprises six endogenous variables, observed at a quarterly frequency. The variable Patent_t successively represents the total number of patents, the number of clean patents, and the number of dirty patents. These three series exhibit a seasonality pattern, which is also observable in the series of CO_2 emissions. I remove the seasonal component using the X-13 method of the U.S. Census Bureau, estimating the seasonal component

of each series using an ARIMA(0,1,1) model. Then, given the trend observed in the deseasonalized series and in the other series composing the VAR, I stationarize all of them by expressing the variables in percentage deviation from their trend, which I extract using a one-sided HP filter.[10,11] B_1, ..., B_p are the autoregressive matrices where p is the number of lags included in the analysis. To choose it, I rely on the BIC criteria and set $p = 1$. Σ is the error variance-covariance matrix.
I assess the macroeconomic and environmental effects of CPU shocks by analyzing the impulse response functions (IRF) of the times series following orthogonalized shocks to the CPU index. To this aim, I apply a lower triangular Choleski decomposition of the error variance-covariance matrix, ordering the CPU index in the last position and controlling for the S&P500 index (following Jurado et al., 2015) and overall economic policy uncertainty. This recursive identification procedure allows estimating the IRF of all the variables in response to a CPU shock, after removing the variations in CPU induced by the shocks of the other variables.[12]

I report in Figure 3 the IRF following a Climate Policy Uncertainty shock. The black dashed line represents the mean response of the times series following a one-standard-deviation increase in Climate Policy Uncertainty while the blue area is the 68 percent confidence interval.

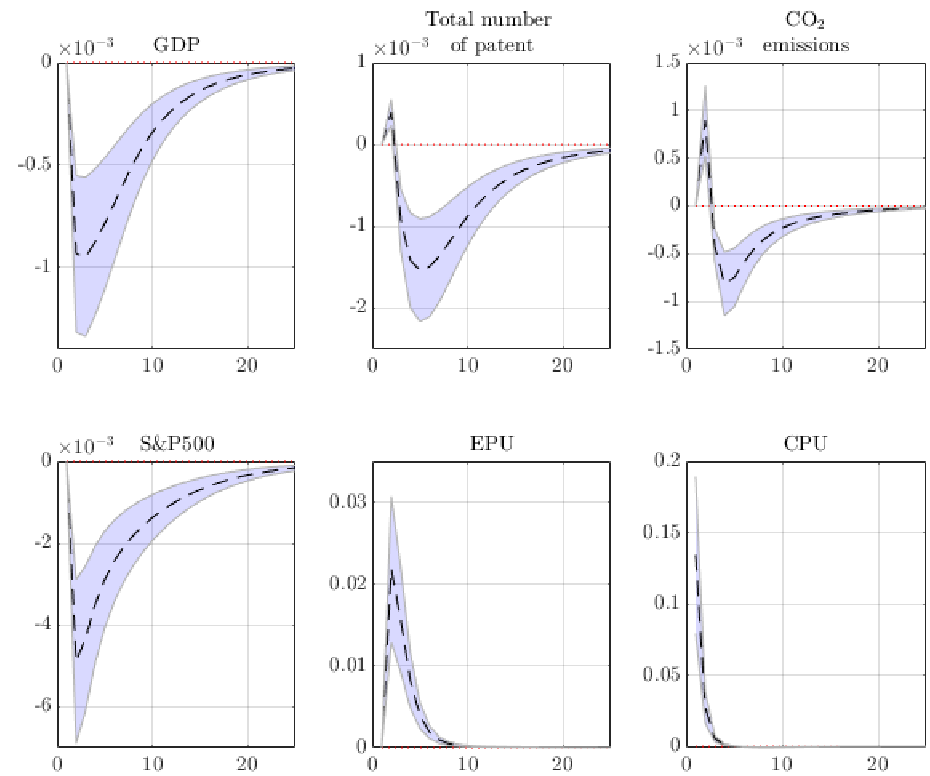
A shock to Climate Policy Uncertainty has effects on macroeconomic aggregates. Gross Domestic Product experiences a rapid fall of around 0.1% in the quarter following the shock. If this decrease is small, the confidence interval shows that it is significant, and lasts for at least 15 quarters following the shock. This drop in economic activity generated by uncertainty shocks is in line with the literature. For comparison, the VAR analysis of the effect of EPU realized by Baker et al. (2016) reveals that EPU shocks lead to a 1.2% drop in economic activity.
Following the shock, the total patents' applications slightly increase by 0.5% on impact before decreasing in the quarters following the shock. This long-lasting fall aligns with the literature on uncertainty: through the real options channel, investors adopt a "wait-and-see" behavior inducing them to postpone investment in the presence of heightened uncertainty. A decrease in investment in the context of climate policy uncertainty is also reported by Berestycki et al. (2022). I will then distinguish in Figure 4 between the number of clean and the number of dirty patents' applications to dig deeper into potential reallocation

[10] The more standard two-sided HP filter detrends the series using future observations, which violates the backward-looking nature of VAR models. I conduct a robustness check where I detrend the series using the two-sided HP filter. The results hold.

[11] Appendix D presents the series used in the VAR. I plot in Appendix D.1 the original series and the deseasonalized ones and in Appendix D.2 the original series and the detrended ones.

[12] Alternatively, another identification strategy would be to order the CPU index in third position, after the S&P500 and the EPU indices. The underlying assumption is that CPU shocks, orthogonalized with markets' expectations, and purged from overall policy uncertainty, affect the other variable on impact (Bloom (2009)). I conduct a robustness exercise using this alternative ordering. It does not alter the results.

Figure 3: Impulse Responses after a Climate Policy Uncertainty shock

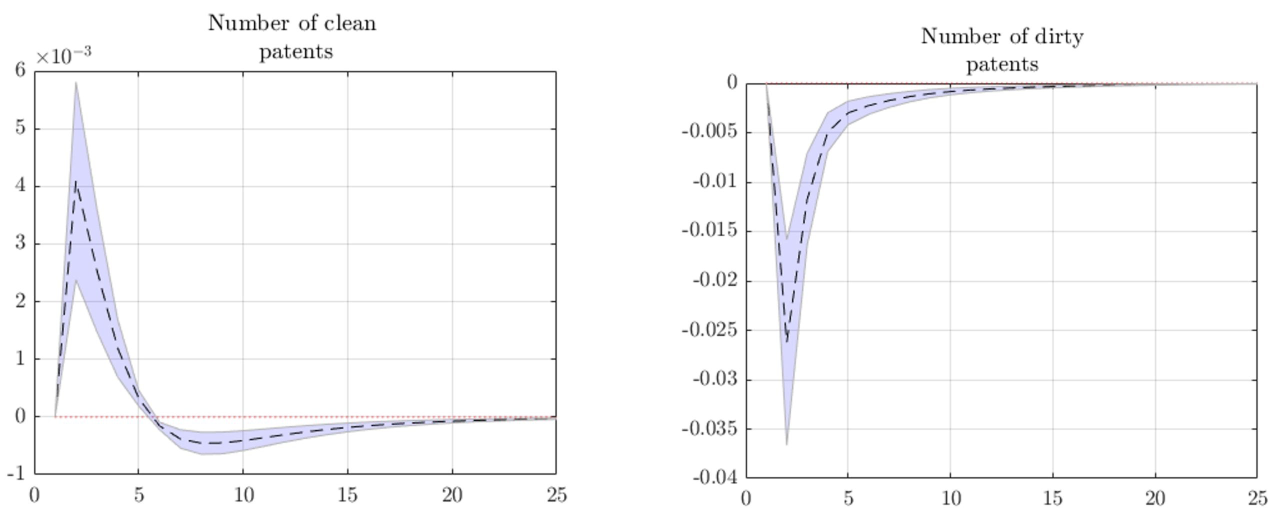


NOTE: The CPU index is ordered in the last position. Black dashed lines are mean responses of the endogenous variables to a one-standard-deviation increase in the innovation to CPU. Blue-shaded areas represent 68 percent error bands. The estimation is conducted between 1987Q2 and 2013Q4.

Turning to the third panel of Figure 3, in response to an unexpected increase in climate-policy-related uncertainty, CO_2 emissions immediately increase. This initial surge contrasts with the findings of Gavriilidis (2021), who reports an immediate decrease in emissions following CPU shocks. Interestingly, when I replicate the specification used in Gavriilidis (2021), which does not control for overall EPU, I also find a decrease in CO_2 emissions on impact. This divergence suggests a potential omitted variable bias in specifications that exclude EPU. Without controlling for EPU, the estimated impact may conflate the specific uncertainty surrounding climate policy with broader fluctuations in economic policy uncertainty. By including EPU as a control, I isolate the "pure" impact of climate policy uncertainty, thereby obtaining a more precise estimate of how this specific type of uncertainty influences emissions. The observed increase in emissions can be interpreted through the lens of the "green paradox" literature (see Sinn, 2008 for a seminal contribution), which suggests that anticipated stricter future regulations can prompt firms to accelerate emissions-intensive activities in the short term, exploiting the current regulatory environment before potential future restrictions. Lemoine (2017) provides empirical support for this behavior, showing that uncertainty around the implementation of the U.S. cap-and-trade bill in April 2010 led to a spike in greenhouse gas emissions. Two quarters following the shock, emissions decrease by 0.1%, a magnitude that is consistent with the results reported by Gavriilidis (2021). Finally, the stock market experiences losses in response to CPU shocks, aligning with the literature on general uncertainty and with the event studies in the presence of climate policy uncertainty. This long-lasting drop in the S&P index highlights that firms' valuations is negatively affected by CPU shocks, potentially affecting firms' entry.

To investigate the mechanisms behind the adjustments in patenting activity and potential sectoral reallocations, Figure 4 reports the results when the variable "Patent_t" is the number of clean patents (left-hand-side) and when it measures the number of dirty patents (right-hand-side).

Figure 4: Impulse Responses after a Climate Policy Uncertainty shock: Clean and Dirty



NOTE: The CPU index is ordered in the last position. Black dashed lines are mean responses of the endogenous variables to a one-standard-deviation increase in the innovation to CPU. Blue-shaded areas represent 68 percent error bands. The estimation is conducted between 1987Q2 and 2013Q4.

The left-hand side of the figure shows that CPU shocks immediately and significantly increase patent applications in the clean sector. In contrast, the right-hand side reports a significant and long-lasting decrease in patenting activity in the dirty sector, which is directly affected by climate policy uncertainty. This result reveals the reallocation in patenting activity favoring clean technologies and discouraging dirty ones. While several studies document an increase in low-carbon innovation induced by climate policy (e.g. Calel and Dechezleprêtre, 2016, for the European Union

Emissions Trading System)[13], this result is the first to point out the “direction” of patenting activity in response to climate policy *uncertainty*.

Overall, these empirical results are in line with the uncertainty literature as they suggest that CPU shocks have negative macroeconomic and financial effects characterized by a drop in the GDP and in stock prices. Additionally, I show that uncertainty towards climate policy triggers a sectoral reallocation in the patenting activity. If the innovators adopt a “wait-and-see” behavior regarding total and dirty innovation, by decreasing them, they increase patent applications in low-carbon technologies. This result suggests that they exploit heightened uncertainty regarding climate policy to earn a first-mover advantage, innovating at an early stage, before the implementation or the tightening of the climate policy. It should be noted that the production process of a patent is long. The rapid surge in clean patenting activity suggests that the increased number of applications following the shocks comes from pre-existing patents, reinforcing the interpretation of strategic innovation decisions. This empirical investigation further uncover the environmental costs of climate policy uncertainty through an initial surge in CO_2 emissions.[14]

After presenting empirical evidence on the effect of climate policy uncertainty on sectoral reallocations, the remainder of the paper develops a theoretical model to understand the channels through which uncertain climate policies alter new-product creation dynamics and the macroeconomic and environmental consequences of these reallocations.

4 Model

In this section, I develop a dynamic general equilibrium model to investigate and quantify the channels through which climate policy uncertainty affects sectoral reallocations and their consequences on macroeconomic and environmental outcomes. I extend the endogenous entry model of Bilbiie et al. (2012) to include two types of sectors: a dirty one, whose production triggers an environmental externality, and a clean sector. Two forces prevent one sector from disappearing. First, the goods produced by these sectors are imperfect substitutes. Second, hours worked are imperfectly substitutable between sectors. The economy is populated by households, firms, and a

[13] Additionally, endogenous growth models show that more stringent environmental regulation is associated with higher innovation (Bovenberg and Smulders, 1995 and Porter and Linde, 1995). Using a long-run perspective, these models show that firms tend to innovate more in “clean” technologies when facing environmental policies, leading to a “directed technical change” (Acemoglu et al., 2012) favoring the transition to a low-carbon economy.

[14] The results are robust to alternative specifications. Appendix E reports the IRF when the variables are detrended using a two-sided HP filter and Appendix F presents the estimation following an alternative Choleski decomposition, where the CPU index is placed in third position, after controlling for the stock-market prices and overall EPU. In the two cases, the results hold.

government. The production is divided into a final good sector producing on a competitive market. To this aim, it buys and combines the two sectoral goods offered by dirty and clean retailers. These retailers aggregate the production of a continuum of varieties in each sector to produce the sectoral good. Clean and dirty variety-producing firms' entry into the market is subject to a sunk entry cost. The free entry condition equalizes the value of the firm (which is the present discounted value of the new entrant's future profits) with the sunk cost. It allows determining endogenously the number of producers in each sector. In this setup, there is a strict identity between the number of firms and the number of products. Therefore, firms' entry is akin to the creation of a new good.

To evaluate the response of product creation in the presence of climate policy uncertainty, I assume that there is no climate policy in this economy, but agents believe that a climate policy, in the form of a carbon tax on the dirty sector's emissions, can be introduced in the next period. In what follows, I indicate with an asterisk (*) the variables in the potential post-tax steady state. For the sake of conciseness, I only specify the equations that are different in the post-tax steady state compared to the pre-tax.

4.1 Firms

The production process of goods is divided between three types of firms: variety-producing firms for each sector, retailers (intermediate firms) for each sector, and final firms. Retailers produce different types of goods that are imperfect substitutes by bundling varieties produced under monopolistic competition. Retailers are distinguished according to the sectoral goods they produce, either the clean or the dirty one[15]. The final firm produces the consumption good by combining the intermediate sectoral goods into a final consumption good and sells it to the household.

4.1.1 Final good firms

The representative final good producer has a technology that aggregates non-perfectly substitutable inputs. She decides on the quantity of clean and dirty inputs (respectively denoted Y_t^c and Y_t^d) she buys at prices P_t^c and P_t^d[16]. Then, she packages them into the final consumption good Y_t and sells Y_t to households in a perfectly competitive market, at price P_t. She chooses the input quantities that maximizes her profits (1) subject to the supply constraint (2):

$$P_t Y_t - \left(P_t^c Y_t^c + P_t^d Y_t^d\right) \tag{1}$$

[15] In what follows, I use "intermediate" and "sectoral" goods as synonyms.

[16] c and d respectively stand for *clean* and *dirty*.

$$Y_t = \left(\omega^{\frac{1}{\varepsilon}}(Y_t^c)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\omega)^{\frac{1}{\varepsilon}}(Y_t^d)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{2}$$

ω is the share of clean input in the production process of the final good while $\varepsilon \in (1, +\infty)$ denotes the elasticity of substitution between clean and dirty inputs. It is greater than 1 since I assume that clean inputs can be used as substitutes for dirty ones.

The profit maximization yields the following intermediate demand functions, respectively for clean and dirty inputs:

$$Y_t^c = \omega\left(\frac{P_t^c}{P_t}\right)^{-\varepsilon} Y_t, \qquad Y_t^d = (1-\omega)\left(\frac{P_t^d}{P_t}\right)^{-\varepsilon} Y_t \tag{3}$$

P_t denotes the aggregate price index on the final good market, and is given by:

$$P_t = \left(\omega(P_t^c)^{1-\varepsilon} + (1-\omega)(P_t^d)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} \tag{4}$$

I normalize $P_t = 1$ and set it as the numeraire.

4.1.2 Intermediate goods firms

Producers of intermediate goods are divided into two sectors, producing respectively "clean" and "dirty" sectoral goods used by the final sector as inputs. This section describes the production process of these intermediate goods.

In each sector (clean and dirty), a representative intermediate firm bundles varieties y_t^k produced by a continuum of monopolistically competitive firms, to produce the intermediate good Y_t^k, sold to the final-good firm ($k = \{c, d\}$).
The composition of varieties in each sector changes over time because of firms' entry. Therefore, the intermediate good in each sector Y_t^k is defined over a fixed continuum of firms Ω^k. At each period t, only a subset $\Omega_t^k = N_t^k$ is available, where N_t^k denotes the number of firms in sector k at a given period t, which is determined endogenously.
The aggregation of varieties in the sector $k = \{c, d\}$ is given by:

$$Y_t^k = \int_{\Omega^k} \left((y_{jt}^k)^{\frac{\varepsilon^k-1}{\varepsilon^k}}\right)^{\frac{\varepsilon^k}{\varepsilon^k-1}} dj \tag{5}$$

where ε^c and ε^d respectively denote the elasticity of substitution between varieties. The intensity

of the monopolistic competition in the variety market in each sector k is driven by $\frac{\varepsilon^k}{\varepsilon^k-1}$.
The intermediate good firm in each sector k buys varieties y_t^k at price p_t^k. The price index in each sector reads as:

$$P_t^k = \int_{\Omega^k} \left((p_{jt}^k)^{1-\varepsilon^k} \right)^{\frac{1}{1-\varepsilon^k}} dj \tag{6}$$

The profit maximization, combined with (3) yields the following intermediate demand functions, respectively for clean and dirty inputs:

$$y_t^c = \omega \left(\frac{p_t^c}{P_t^c} \right)^{-\varepsilon^c} \left(\frac{P_t^c}{P_t} \right)^{-\varepsilon} Y_t, \qquad y_t^d = (1-\omega) \left(\frac{p_t^d}{P_t^d} \right)^{-\varepsilon^d} \left(\frac{P_t^d}{P_t} \right)^{-\varepsilon} Y_t \tag{7}$$

4.1.3 Producing varieties: A backward-induction process

I now turn to the description of firms producing varieties j in each sector $k = \{c, d\}$.
In each sector, firms have to pay a sunk cost to enter the market. Once entering the market, they start producing varieties using sector-specific labor, obtained from a perfectly competitive market. In the first step, firms decide whether to enter the market or not, comparing the costs (sunk cost) and benefits (flow of future discounted profits) of doing so. This determines the number of varieties in each sector. As each firm produces one variety only (monopolistic competition), the number of varieties in each period is identical to the number of producers.
In the second step, after entering the market, they maximize their operational profit, taking into account the demand function (7) each producer faces.
Their optimization program can be solved backward. I start by presenting profit maximization and I then describe the firms' entry.

Profit maximization Once entered into the market, variety-producing firms j in sector k = {c, d} produce with the following technology:

$$y_{jt}^k = [1 - \Gamma(M_t)] l_{P,jt}^k \tag{8}$$

The production of varieties requires sector-specific labor $l_{P,t}^k$ which is supplied by households, and remunerated at sector-specific wage w_t^k.
The production function is negatively altered by an environmental externality. It stems from a stock of pollutant emissions generated by the production of the dirty input. $\Gamma(.)$ is an increasing

and convex function of the stock of pollution. This damage function writes as:

$$\Gamma(M_t) = a + bM_t + cM_t^2 \tag{9}$$

where a, b, and c are calibrated following Nordhaus (2018).

The law of motion of the pollutant stock is given by:

$$M_t = \gamma M_{t-1} + \int_0^{N_t^d} e_{jt} dj + E^* \tag{10}$$

γ is the decay rate of pollution, $\int_0^{N_t^d} e_{jt}$ is the total emission from residents, generated by variety-producing firms in the dirty sector. E^* denotes the pollution from the rest of the world.

Emissions are proportional to the output produced by the dirty firm and can be abated. Denoting φ the constant level of emission per unit of dirty output and μ_{jt} the abatement level chosen by the firm, individual emissions are defined by:

$$e_{jt} = (1 - \mu_{jt})\varphi y_{jt}^d \tag{11}$$

Abating emissions is costly, and the abatement cost, paid in units of the final good and denoted Z_t, is an increasing function of the quantity abated. Following the E-DSGE literature (see Heutel (2012) for a seminal contribution), I model abatement cost as:

$$Z_{jt} = \theta_1 \mu_{jt}^{\theta_2} y_{jt}^d \tag{12}$$

where θ_1 and θ_2 are two positive parameters.

The real profit of the dirty firm in the pre-tax steady state writes as:

$$\pi_{jt}^d = p_{jt}^d y_{jt}^d - Z_{jt} - w_t^d l_{P,jt}^d \tag{13}$$

While in the post-tax steady state, dirty firms have to pay the carbon tax τ, and their profit becomes:

$$\pi_{jt}^{d*} = p_{jt}^{d*} y_{jt}^{d*} - \tau e_{jt}^* - Z_{jt}^* - w_t^{d*} l_{P,jt}^{d*} \tag{14}$$

Variety-producing firms choose the monopolistic price they set and the optimal abatement level to maximize profit, taking the technology constraint (8) and the demand it faces (7) as given.

The cost-minimization problem yields the following first-order condition on abatement:

$$\tau \varphi y_{jt}^{d} = \theta_1 \theta_2 \mu_{jt}^{\theta_2 - 1} y_{jt}^{d} \tag{15}$$

It is straightforward that in the pre-tax steady state, when $\tau = 0$, firms will not abate emissions. Indeed, (15) states that firms will abate emissions up to the point where the marginal gain of doing so (the left-hand-side) equalizes its marginal cost (right-hand-side). In the *laissez-faire* economy, emissions are costless, and firms are not incentivized to reduce them. It follows that, in this scenario, $\mu_{jt} = Z_{jt} = 0 \;\; \forall t$. In contrast, in the post-tax steady state, emissions are costly and firms have incentives to abate: $\mu_{jt}^{*} > 0$ and $Z_{jt}^{*} > 0$.

The optimality condition on price setting yields the standard condition in the pre-tax steady state:

$$p_{jt}^{d} = \frac{\varepsilon^{d}}{\varepsilon^{d} - 1} \frac{w_t^{d}}{[1 - \Gamma(M_t)]} \tag{16}$$

And, in the post-tax steady state, the marginal cost of dirty firms includes the carbon tax and abatement costs, yielding:

$$p_{jt}^{d*} = \frac{\varepsilon^{d}}{\varepsilon^{d} - 1} \left((1 - \mu_{jt}^{*}) \tau \varphi + \theta_1 (\mu_{jt}^{*})^{\theta_2} + \frac{w_t^{d*}}{[1 - \Gamma(M_t^{*})]} \right) \tag{17}$$

I now turn to the description of variety-producing firms in the clean sector. They do not pollute and therefore do not incur pollution-related costs. Profit in the clean sector is thus given by:

$$\pi_{jt}^{c} = p_{jt}^{c} y_{jt}^{c} - w_t^{c} l_{P,jt}^{c} \tag{18}$$

The expression of their profit is the same in the post-tax steady state since clean variety-producing firms do not pay the carbon tax.

As for the dirty sector, firms producing clean varieties set their price to maximize this profit, subject to the technology constraint (8) and the demand they face (7). The pricing decision yields:

$$p_{jt}^{c} = \frac{\varepsilon^{c}}{\varepsilon^{c} - 1} \frac{w_t^{d}}{[1 - \Gamma(M_t)]} \tag{19}$$

Equations (16), (17) and (19) show that $\frac{\varepsilon^k}{\varepsilon^k - 1}$ is the markup charged by monostically competitives firms. It is a negative function of the substitutability between each variety in a given sector.

Entry Decision I endogenize firms' entry following Bilbiie et al. (2012). To enter the clean or the dirty market, prospective entrants must pay a sunk cost that is imputed in terms of labor. They then obtain a monopolistic position on their product. After paying the sunk cost in period t, the new entrants start producing at period *t+1*, introducing a one-period time-to-build lag.
At each period, the variety-producing sector $k = \{c, d\}$ comprises a mass N_t^k of producing firms and prospective entrants $N_{E,t}^k$. In addition, firms might exit the market with exogenous probability δ, which is symmetric across sectors.
Consequently, the number of producing firms in each sector $k = \{c, d\}$ is given by:

$$N_t^k = (1-\delta)(N_{t-1}^k + N_{E,t-1}^k) \tag{20}$$

Firms decide to enter (or, equivalently, households decide to finance the entry cost) by comparing the cost and benefits of entering the market. On the one hand, prospective entrants have to pay the innovation cost of F_E labor units. On the other hand, producing yields a stream of profits. A prospective entrant thus computes the expected post-entry value v_{jt}^k, given by the present discounted value of its expected stream of profit:

$$v_{jt}^k = \mathbb{E}_t \left\{ \sum_{s=t+1}^{\infty} \Lambda_{t,s} \pi_{jt}^k \right\} \tag{21}$$

Where $\Lambda_{t,s}$ denotes the households' stochastic discount factor, derived in Section 4.2 (Equation (37)).

Prospective entrants j in sector $k = \{c, d\}$, demand labor $L_{E,jt}^k$ to enter, remunerated at wage w_t^k. Due perfect substitution of worked hours within a given sector, the within-sector wage is the same for workers in producing firms and workers in innovating firms.

The free-entry condition indicates that entry occurs up to the point where the firm's value, denoted v_{jt}^k equalizes the entry cost. Labor $L_{E,t}^k$ being remunerated at wage w_t^k, the total cost of firm creation is $w_t^K F_E$.
The free-entry condition is thus:

$$v_t^k = w_t^k F_E \tag{22}$$

In each sector k, total labor demand for the creation of $N_{E,t}^k$ firms is given by:

$$L_{E,t}^k = F_E N_{E,t}^k \tag{23}$$

Symmetric Equilibrium For all firms j in a given sector k, the wage is the same because hours worked are perfectly substitutable within each sector. If applicable, the cost of climate policy is the same for all firms in the dirty sector. The marginal cost across firms in a given sector is therefore same. They thus charge the same price, as shown by (19) and (16). In addition, all firms in a given sector face the same demand function (7). Therefore, within-sector, firms are symmetric and the equilibrium prices, quantities produced, quantities abated, and profits are identical across firms within a sector.
It follows, for $k = \{c, d\}$:

$$P_t^k = \left(N_t^k\right)^{\frac{1}{1-\varepsilon^k}} p_t^k \tag{24}$$

$$Y_t^k = N_t^k y_t^k \tag{25}$$

$$E_t = \int_0^{N_t^d} e_{jt} dj = N_t^d e_t \tag{26}$$

4.2 Households

A continuum of households of length unity populates the economy. Each household consumes, works, receives a lump-sum tax T_t, and holds shares x_t^k in two mutual funds of firms, one for each sector k = {c, d}. From this shareholding, the household receives dividend income, which is the value of selling its initial share position (the profit realized by each firm π_t^k plus the price of claim to future profit v_t^k). At each period t, the household buys shares in a mutual fund of $N_t^k + N_{E,t}^k$ firms at price v_t^k. Due to an exogenous probability of exit, at *t+1*, only $(1 - \delta)$ of these firms will produce and pay a dividend.
Besides, due to climate policy uncertainty, households expect that the government might introduce a carbon tax in the next period with probability p, directly altering the profit function of the dirty variety-producing firms (comparing (13) with (14)).
At each period, household members derive utility from consumption C_t and supply labor L_t^k in each sector k, providing disutility but a wage income w_t^k.

The discounted expected utility is given by:

$$U_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \kappa \frac{\left(\left[(L_t^d)^{1+\rho_L} + (L_t^c)^{1+\rho_L} \right]^{\frac{1}{1+\rho_L}} \right)^{1+\Phi}}{1+\Phi} \right] \tag{27}$$

where $\mathbb{E}$ is the rational expectations operator, $\beta \in (0, 1)$ denotes the discount factor, κ weights the disutility of working and Φ is the inverse of the Frisch elasticity.

$L_t \equiv \left[(L_t^d)^{1+\rho_L} + (L_t^c)^{1+\rho_L}\right]^{\frac{1}{1+\rho_L}}$ is the bundle of hours worked in period t, either supplied in the dirty (L_t^d) or in the clean (L_t^c) sector. If strictly positive, the parameter ρ_L introduces imperfect labor substitutability between sectors.

The representative household chooses the sequences $\{C_t, L_t^k, x_{t+1}^k\}_{k=\{c,d\}}$, taking into account the probability that the government will introduce a carbon tax in the next period, to maximize (27) subject to the following budget constraint:

$$C_t + \sum_k v_t^k (N_t^k + N_{E,t}^k) x_{t+1}^k = \sum_k w_t^k L_t^k + \sum_k (\pi_t^k + v_t^k) N_t^k x_t^k \tag{28}$$

If a tax is implemented, households receive lump-sum transfers from the government and the budget constraint becomes:

$$C_t^* + \sum_k v_t^{k*} (N_t^{k*} + N_{E,t}^{k*}) x_{t+1}^{k*} = \sum_k w_t^{k*} L_t^{k*} + \sum_k (\pi_t^{k*} + v_t^{k*}) N_t^{k*} x_t^{k*} + T_t^* \tag{29}$$

In the pre-tax steady state, the problem of the household is:

$$V_t = \max_{C_t, L_t^c, L_t^d, x_{t+1}^c, x_{t+1}^d} \left\{ \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \kappa \frac{\left(\left[(L_t^d)^{1+\rho_L} + (L_t^c)^{1+\rho_L} \right)^{\frac{1}{1+\rho_L}} \right)^{1+\Phi}}{1+\Phi} \right] + \beta \left[p W_{t+1} + (1-p) V_{t+1} \right] \right\} \tag{30}$$

subject to the budget constraint (28).

In the pre-tax steady state, the value function of the household is a weighted average of the value function if the government introduces a carbon tax, W_{t+1} (i.e. the economy moves to the post-tax steady state) and the continuation value if the government does not introduce a carbon tax (meaning that the economy remains in the pre-tax steady state next period), V_{t+1}. The post-tax steady state is absorbing: the introduction of a carbon tax levies all uncertainty, and the economy will remain in the post-tax steady state at all following periods. Therefore, the continuation value in the post-tax steady state is:

$$W_t = \max_{C_t^*, L_t^{c*}, L_t^{d*}, x_{t+1}^{c*}, x_{t+1}^{d*}} \left\{ \left[\frac{(C_t^*)^{1-\sigma}}{1-\sigma} - \kappa \frac{\left(\left[(L_t^{d*})^{1+\rho_L} + (L_t^{c*})^{1+\rho_L} \right)^{\frac{1}{1+\rho_L}} \right)^{1+\Phi}}{1+\Phi} \right] + \beta W_{t+1} \right\} \tag{31}$$

subject to the budget constraint (29).

In the pre-tax steady state, the optimization problem on labor and consumption yields the following standard first-order conditions, with λ_t denoting the marginal utility of consumption:

$$C_t^{-\sigma} = \lambda_t \tag{32}$$

$$L_t^{\Phi-\rho_L}(L_t^k)^{\rho_L} = w_t^k \lambda_t \tag{33}$$

Combining (32) with (33), we get:

$$L_t^{\Phi-\rho_L}(L_t^k)^{\rho_L} = w_t^k C_t^{-\sigma} \tag{34}$$

Solving the optimality condition for x_{t+1}^k and replacing N_{t+1}^k by the values given in (20) yields the Euler equation for shareholdings:

$$v_t^k = \beta(1-\delta)\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma}\Big((1-p)(v_{t+1}^k + \pi_{t+1}^k) + p(v_{t+1}^{k*} + \pi_{t+1}^{k*})\Big) \tag{35}$$

And, in the post-tax steady state, when there is no uncertainty anymore, we have:

$$v_t^{k*} = \beta(1-\delta)\left(\frac{C_{t+1}^*}{C_t^*}\right)^{-\sigma}(v_{t+1}^{k*} + \pi_{t+1}^{k*}) \tag{36}$$

The household's stochastic factor is therefore given by:

$$\Lambda_{t,s} = \left(\frac{C_{t+s}}{C_t}\right)^{-\sigma}(\beta(1-\delta))^s \tag{37}$$

4.3 Government

In the pre-tax steady state, the economy is decentralized and the government does not intervene. However, if it introduces a climate policy (post-tax steady state), the government simply transfers revenues of the carbon tax τ in a lump-sum manner to the households. The public budget constraint thus takes the following form:

$$T_t^* = \tau(N_t^d)^* e_t^* \tag{38}$$

4.4 Market clearing

Following Bilbiie et al. (2012), in each sector $k = \{c, d\}$, labor demand emanates for two motives: production purposes ($L^k_{P,t} = N^k_t l^k_{P,t}$) and sunk entry cost ($L^k_{E,t} = F_E N^k_{E,t}$). Labor market clearing imposes that, in each sector k, labor supply (from households, provided by the optimality condition (34)) equalizes labor demand (from producing firms and prospective entrants), yielding:

$$L^k_t = L^k_{P,t} + L^k_{E,t} = N^k_t \frac{y^k_t}{[1 - \Gamma(M_t)]} + N^k_{E,t} F_E = \frac{Y^k_t}{[1 - \Gamma(M_t)]} + N^k_{E,t} F_E \tag{39}$$

Aggregating the household's budget constraint (29) yields the following market clearing on the final good market:

$$Y_t = C_t \tag{40}$$

In the post-tax steady state, where firms in the dirty sectors abate their emissions, the market clearing condition is given by:

$$Y^*_t = C^*_t + N^{d*}_t Z^*_t \tag{41}$$

5 Calibration

This section describes the calibration of the parameters of the baseline model, where time is measured in quarters. I calibrate the parameters to match some features of the U.S. economy, where there is no climate taxation policy ($\tau = 0$) but policy risk ($p > 0$). One can divide the parameters into three categories: standard real business cycle (RBC) parameters, firm entry and exit parameters, and parameters related to climate externality.

Table 2 presents the calibrated values[17].

[17] I conduct a set of sensitivity analyses varying some of these parameter values. The results are reported in Appendix I.

Table 2: Calibration

Parameter	Value	Description
RBC parameters		
β	0.99	Discount factor
σ	2	Risk aversion
κ	11.549	Disutility of labor
Φ	1	Inverse of the Frisch elasticity of labor
ρ_L	1	Elasticity labor hours clean and dirty
ω	0.7	Share green firms
ε	3	Elasticity of substitution green and brown sector
ε^c	7	Elasticity of substitution clean sector
ε^d	7	Elasticity of substitution dirty sector
Endogenous entry parameters		
δ	0.025	Exit rate
F_E	0.022	Cost of innovation
Environmental parameters		
φ	0.45	Emissions per unit of output
γ	0.9965	Decay rate of pollution
θ_1	0.8	Abatement cost parameter
θ_2	2.7	Abatement cost parameter
E^*	0.402	Emissions from ROW
a	-0.026	Damage function parameter
b	3.6613e-5	Damage function parameter
c	1.4812e-8	Damage function parameter
p	0.0342	Probability that the gov. introduces a carbon tax
τ	0.225	Magnitude of the carbon tax

The discount factor $\beta = 0.99$, and the inverse of the Frisch elasticity of labor $\Phi = 1$ are standard values in the RBC literature. The risk aversion parameter $\sigma = 2$ is also standard and in line with Stern (2008) and Weitzman (2007). ρ_L, the parameter measuring the elasticity of labor hours between the clean and dirty sectors is set at 1, based on the estimate of Horvath (2000) with U.S. data and used in the E-DSGE literature (e.g. Carattini et al., 2023). As usual in the RBC literature, the parameter weighting the labor disutility is set to target the total hours of work in the steady state as 1/3. The elasticity of substitution between clean and dirty sectors, measured by ε, is set to 3, relying on the estimate of Papageorgiou et al. (2017) for the substitution between clean and dirty non-energy sectors. The value of the within-sector elasticity of substitution ε^c and ε^d is based on Carvalho and Nechio (2016) for the within-sector elasticity of substitutions between varieties, and set at 7. The share of clean input in the production of the final firm, ω, is set at 0.7 following Carattini et al. (2023).

Regarding the parameters related to endogenous entry, I follow Bilbiie et al. (2012) and set the exit rate δ at 0.025 by quarter, implying that 10% of firms exit the market each year, a finding corroborated by Bernard et al. (2010). I set the entry cost F_E consistently with the fact that in the U.S., between 2013 and 2020, Research and Development expenditure roughly amounts to 3% of the GDP (World Bank).

Finally, the environmental parameters are calibrated following the literature on Environmental DSGE, based on the most recent version of the DICE model (Nordhaus, 2018). I set the emissions per unit of output $\varphi = 0.45$ as in Annicchiarico and Di Dio (2015), based on World Bank data for the U.S. The decay rate of pollution γ and the parameters of the damage function are set following Carattini et al. (2023). I then rescale these damage function parameters to target a steady-state level of pollution of 1172 Gigatons of carbon as in Carattini et al. (2023). It results that in the baseline steady state, the damage is 3.7% of output, which aligns with Carattini et al. (2023)'s findings. The pollution generated by the rest of the world is constant and set to capture the fact that the U.S. is responsible for one-fifth of global emissions. The abatement cost parameters, θ_1 and θ_2 are borrowed from Heutel (2012).
The value of p, the probability that the government introduces a carbon tax in the next quarter, is *per se* inobservable. I calibrate it following Fried et al. (2021), which uses the internal carbon prices imposed by firms to reduce their emissions. Their methodology uncovers that, according to stakeholders, there is a 75% probability that the government will introduce a carbon tax within the next 10 years. It corresponds to a 3.42% probability that it introduces it in the next quarter. If introduced, I assume that the carbon tax would lower the emissions by 20% after the transition to the post-tax steady state, aligning with the target advocated by policymakers, for example, by the American Clean Energy and Security Act of 2009. Therefore, to calibrate τ, I simulate this post-tax steady state, where a certain tax is enforced without uncertainty, resulting in total emissions that are 20% lower than those in the steady state characterized by uncertainty and no carbon tax. I convert the resulting value ($\tau = 0.225$ in abstract model units) using a back-of-the-enveloppe calculation[18] and find that it corresponds to a \$48.4 per ton of CO_2 emissions. The resulting value also aligns with policy proposals and with Fried et al. (2021) model's assumption on the future value of the potential carbon tax.

6 Quantitative results

This section evaluates the consequences of climate policy uncertainty over several dimensions. In subsection 6.1, I conduct a steady-state comparison analysis capturing the long-run effects of living in an economy characterized by climate policy uncertainty. In subsection 6.2, I analyze the effects of climate policy uncertainty during the transition to a low-carbon economy.

[18] To do so, I use the same methodology as in Carattini et al. (2023)

I conduct these exercises by solving the model for four steady states. I first simulate an economy without climate policy and where there is no climate policy uncertainty. In this "Non-uncertain" steady state, agents never expect that the government will introduce a climate policy in the future ($p_1 = \tau_1 = 0$). Second, I investigate the effects of climate policy uncertainty by simulating the "Uncertain" steady state. This scenario corresponds to the baseline calibration and represents the U.S. economy. The economy is in a pre-tax steady state where there is no climate policy ($\tau_2 = 0$) but, each quarter, entrepreneurs expect that the government can introduce it next period ($p_2 = 0.0342$). Third, I evaluate the consequences of implementing a clear and certain climate policy by simulating the "Policy" steady-state, where there is a carbon tax reducing emissions by 20% compared to the Uncertain steady state. Following Fried et al. (2021), I consider that this "post-tax" steady state is an absorbing state. Once introduced, there is no uncertainty anymore, and the government will never repeal the carbon tax. Therefore, in this case, we have $p_3 = 1$ and $\tau_3 > 0$. Finally, I simulate a fourth steady state where there is a climate policy ($p_4 = 1$) whose magnitude is mean-preserving compared to the uncertain steady state ($\tau_4 = \tau_3 \times p_2$)[19]. This "Mean-preserving" scenario can therefore be interpreted as a sensitivity exercise of the "Policy" scenario with a lower carbon tax set at a level equal to the expectation of the potential future carbon tax simulated in the "Uncertain" steady state.

6.1 Long-run costs of climate policy uncertainty

In this section, I discuss the long-run effects of climate policy uncertainty through a comparison of steady states. At the end of the section, I conduct a dynamic analysis to understand the transition path from one steady state to another.

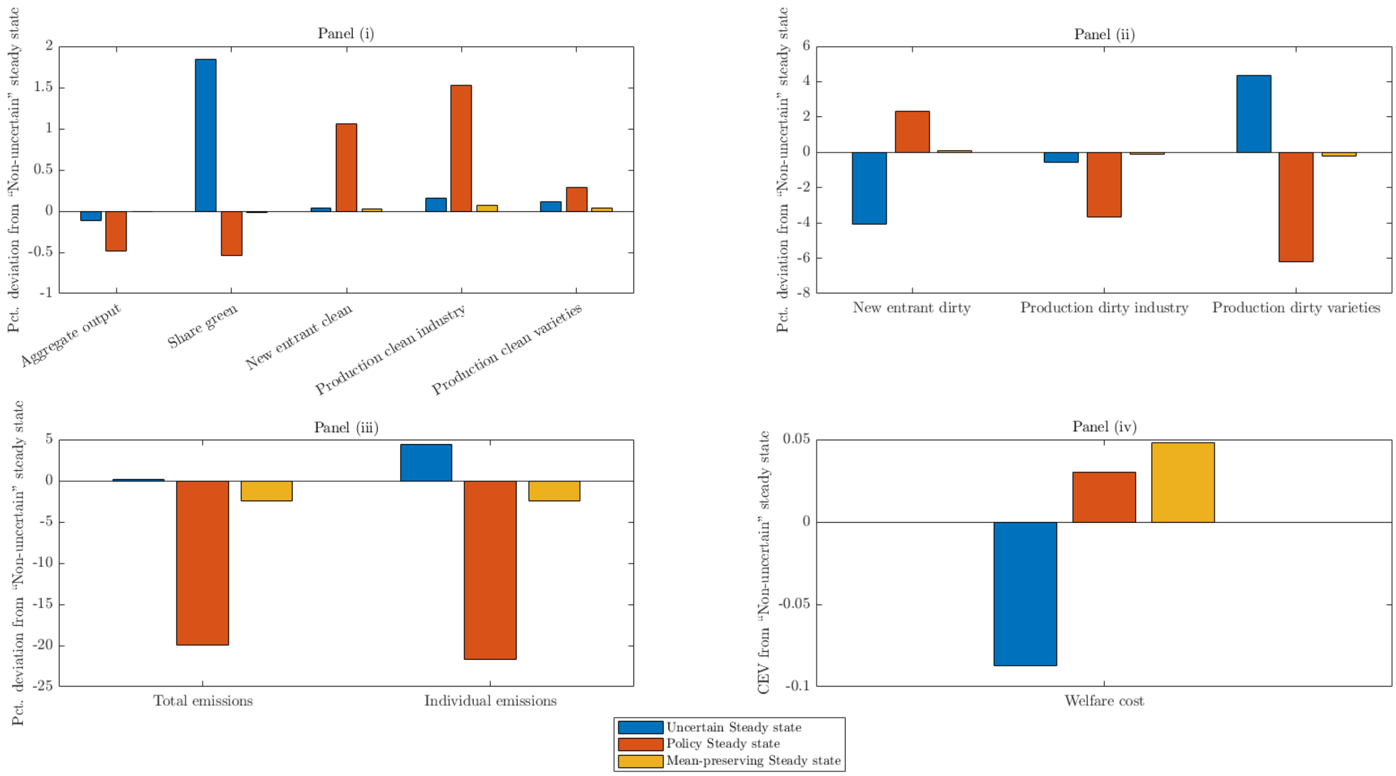
Steady state analysis I evaluate the long-run costs of CPU through a comparative steady-state analysis. To disentangle between the effects of a realized climate policy and the effects of uncertainty surrounding its potential implementation, I start from a situation where there is no climate policy nor climate policy uncertainty ("Non-uncertain" steady state). This scenario serves as a benchmark to then analyze successively the effect of climate policy uncertainty and the effects of climate policy itself comparing this scenario with the "Uncertain" and the "Policy" steady states, respectively.

Figure 5 reports the percentage change for key variables in the 'policy", the "Uncertain"

[19] Concretely, in the "Uncertain" scenario, there is a 75% probability that the future carbon tax will set a 48.4$ per ton of CO_2 in 10 years and a 25% probability that there is no carbon tax emissions in 10 years. In the "Mean-preserving" scenario, there is a 100% probability that the carbon tax is set at 36.3$ per ton ($0.75 \times 48.4 + 0.25 \times 0$).

and the "mean-preserving policy" steady states relative to the "Non-uncertain" steady state[20].

Figure 5: Deterministic steady state, percentage changes relative to the "Non-uncertain" steady state



NOTE: This figure shows the percentage change relative to the Non-uncertain steady state of selected variables for the various scenarios considered. The welfare cost is expressed in compensating consumption variation relative to the Non-uncertain steady state (CEV stands for Consumption-Equivalent Variation). A positive (negative) number represents an amelioration (deterioration) of welfare in a given steady state compared to the Non-uncertain steady state.

The blue bars show that a world with climate policy uncertainty is characterized by lower output and a higher share of green firms than a world with no uncertainty (Panel (i)). Besides, it reduces entry into the dirty sector (Panel (ii)). The rationale is as follows. The introduction of a carbon tax lowers the profit of dirty firms by increasing their marginal cost. Therefore, accounting for the probability of this introduction triggers a decrease in the value of dirty firms, as shown by the Euler equation for shareholdings (Equation 35). In this context, entrepreneurs' incentives to invest in dirty firms' entry are lower, decreasing the number of entrants and producing firms in this sector. However, as the climate policy is not effective, operating firms do not face additional marginal costs and do not need to reduce their production. Through monopolistic competition, the contraction of the extensive margin of production (reduction in the number of entrants) is

[20] I report in Appendix G a table displaying these results.

associated with an expansion of the intensive one (production per incumbent varieties) (Panel (ii)). In this scenario, the production of dirty varieties is almost 5% higher than in a world without climate policy uncertainty, leading to higher individual emissions (Panel (iii)). This expansion of the intensive margin being higher than the contraction along the extensive one, total emissions are higher in this scenario (Panel (iii)). Consequently, the presence of climate policy uncertainty has detrimental effects on environmental outcomes, through an increase in the pollution stock and climate damage. This theoretical result rationalizes the empirical finding of Lemoine (2017) according to which the uncertainty surrounding the implementation of the U.S. cap-and-trade bill in April 2010 led to an increase in greenhouse gas emissions.

In comparison, the orange bars show that the certain implementation of a carbon tax allows reducing both total and individual emissions (Panel (iii)), at the cost of a higher decrease in output than in the "Uncertain" steady state (Panel (i)). Panel (ii) displays that in this scenario, in opposition to the "Uncertain" case, the adjustment in the polluting sector is realized along the intensive margin of production, through a lower per-variety production since the climate policy directly affects upwards the marginal cost. This contraction of the intensive margin is associated with an expansion of the extensive one, through a mechanism that I will detail below. The higher number of producers in the dirty sector mitigates the drop in the production at the industry level and, on aggregate, the recession induced by the carbon tax is lower in my simulation compared to the E-DSGE literature abstracting from endogenous entry[21] (Panel (i)). This result is induced by the firm-entry mechanism, generating an additional margin of adjustment and aligns with Shapiro and Metcalf (2023)'s findings. It is also consistent with the medium- and long-run effects of climate policy obtained by Annicchiarico et al. (2018) in an endogenous entry set-up with oligopolistic competition. Finally, through an endogenous growth model, Peretto (2008) also shows that the introduction of a climate policy triggers an increase in the number of producing firms associated with a decrease in the per-firm production. It should be noted that the effects of climate policy on climate damage ($\Gamma(M_t)$), which are not reported here, are negligible. The 20% reduction in total emission between the "Non-Uncertain" and the "Policy" steady state translates to only a 0.27 percentage point decrease in climate damage. This limited impact arises from the global scope of the pollution stock, which incorporates emissions from the rest of the world, along with its low decay rate, capturing the persistent nature of the pollution stock.

To sum up, climate policy uncertainty discourages entry into the dirty sector, triggering a contraction of the extensive margin of production. Conversely, when a clear climate policy is implemented, the adjustment is realized through the shrinking of the intensive margin. Overall, a clear climate policy has environmental benefits while uncertainty surrounding it triggers environmental

[21] As a comparison, Annicchiarico and Di Dio (2015) show that the introduction of a carbon tax reducing emissions by 20% generates a 2.4% reduction in output.

costs. The decrease in output is higher in the "Policy" steady state, potentially indicating that climate policy-making triggers more important economic costs than uncertainty toward climate policy. However, the yellow bars show that implementing a climate policy with no uncertainty but the same taxation level as the one expected in the "Uncertain" steady state only has a negligible effect on economic activity (Panel (i)) while it enables a reduction in total emissions (Panel (iii)). Therefore, for the same expected level of carbon tax, a clear climate policy has lower economic costs than uncertainty about it and drives environmental benefits.

I dig deeper into the costs of climate policy by quantifying the normative implications of these results. To this end, I compute the welfare costs of the different scenarios. As it is common in the DSGE literature, I measure welfare cost in consumption-equivalent units. For each scenario, I compute the percentage increase in the discounted quarterly consumption that the representative consumer would need to be indifferent between living under a given scenario and the one characterized by the absence of climate policy and no uncertainty. Panel (iv) shows that living in a world characterized by uncertainty toward future climate policy is costly in terms of welfare. This result aligns with Fried et al. (2021). In contrast, living in both policies' steady state triggers an improvement in welfare: the representative consumer living in the policy steady state (resp. mean-preserving steady state) would require a 3% (resp. 4.8%) increase in discounted quarterly consumption to be indifferent between living in this scenario and in the *laissez-faire* scenario. Therefore, a carbon tax can be welfare-improving while uncertainty around it deteriorates welfare.

The dynamic costs of climate policy uncertainty To better understand the mechanisms through which climate policy and uncertainty around it affect the equilibrium of the economy, I now present the transition dynamics from one steady state to the other when starting from the "Non-uncertain" steady state without climate policy nor climate policy risk ($\tau = p = 0$). I first assume that the government introduces a carbon tax in quarter 5, and I plot the transition dynamics to the "Policy" steady state. In that case, τ goes from 0 to \$48.4 per ton of CO_2 emissions[22]. Second, I assume that, at the beginning of quarter 5, agents start to believe that the government might introduce a carbon tax next quarter. The level of the carbon tax is also the one presented in Section 5. I plot the transition dynamics to the "Uncertainty" scenario, where p goes from 0 to 0.0342. Appendix H reports the transition dynamics under both cases. The simulations are conducted using a perfect foresight set-up, where agents discover the shocks in period 5.
The introduction of a carbon tax directly affects downwards the profit of the dirty sector. Emissions are now costly and these firms face additional costs through an increase in abatement efforts up to the value where abatement costs equalize abatement benefits (Eq. (15)). It leads to a decrease

[22] As a reminder, this value allows reducing emissions by 20% between the "Uncertain" and the "Policy" steady states.

in per-firm production, resulting in a decrease in their demand for labor, pushing down the wage offered in the dirty sector. These lower start-up production costs incentive entry into the dirty sector, which immediately increases before converging to its new steady state. It explains why climate policy triggers a contraction of the intensive margin of activity and an expansion of the extensive one.

The transition dynamics to the "Uncertainty" scenario present a different pattern. In this case, the future profit in this sector is now subject to uncertainty, disincentivizing households to finance entry in this sector. As the number of entrants decreases, and because of the exogenous exit rate, the number of producers in this sector decreases (Eq. (20)). Through monopolistic competition, a lower number of competitors triggers an increase in per-variety production, generating a higher demand for labor by dirty incumbents. Because the carbon tax is not effective, dirty firms do not have any incentives to abate emissions, and abatement effort remains constant and null. Therefore, the absence of abatement efforts combined with the increase in the production of dirty varieties generates an increase in individual emissions, increasing slightly total emissions, while total emissions decrease when a carbon tax is effectively implemented.

Sensitivity These results are influenced by the calibration of the model's deep parameters. Notably, the elasticity of substitution within the dirty sector (ε^d) determines the market power of each variety-producing firm in this sector. It therefore governs variety-producing firms' ability to transfer the tax cost by increasing their monopolistic price. Likewise, in the clean sector, the market power of each variety-producing firm is defined by the within-sector elasticity of substitution (ε^c). The elasticity of substitution between the clean and the dirty sectors (ε) is also important in determining the magnitude of the expansion of the clean sector as the dirty sector shrinks. The elasticity of substitution in labor hours (ρ_L) determines labor reallocation as the relative wages offered by each sector vary. Besides, the magnitude of the Frisch elasticity, which determines how aggregate labor supply varies with wage, is disputed in the literature. I conduct a sensitivity analysis on this parameter, relying on the review offered by Chetty et al. (2011).[23] The stringency of the potential carbon tax (τ) and the probability of its introduction (p) play a crucial role in the magnitude of the variation in the outcomes presented above. I also examine the sensitivity of my results to other parameter values associated with climate variables, notably the steady-state level of the stock of pollution ($\bar{M}$) and the abatement efficiency parameter (θ_1).

Appendix I presents the sensitivity analysis. In each figure, the two first bars display the percentage changes when the parameter of interest is lower than the baseline. The baseline value is reported in the two subsequent bars. The two last bars report the cases when the parameter is higher than

[23] Chetty et al. (2011) emphasize that microeconomic and macroeconomic estimates of the Frisch elasticity of labor supply on aggregate labor hours differ. Notably, they show that microeconomic evidence estimates this elasticity as around 0.82 while macroeconomic studies estimate it at 2.84. I use both values to perform a sensitivity analysis on the *inverse* of the Frisch elasticity.

in the baseline. In each case, I report, in the following order, the percentage change in the value of the variables in the "'Uncertain" steady state compared to the "Non-uncertain" and the percentage change in the "Policy" compared to the "Non-uncertain" steady state. The calibration is made from the "Uncertain" steady-state and adapted given the different values of the parameter of interest[24]. In Figure I.1, I report the sensitivity of the results when varying the likelihood that the government introduces a carbon tax. Figure I.2 displays the sensitivity analysis with respect to the substitution elasticity between the clean and the dirty inputs in the final good's production. Figure I.3 (resp. Figure I.4) conducts the sensitivity analysis by varying the substitution elasticity within the dirty (resp. clean) sector. In Figure I.5, I investigate the effect of the substitution between labor hours in each sector while Figure I.6 reports the sensitivity analysis for the inverse of the Frisch elasticity on labor supply. Figure I.7 analyzes how results are affected if the steady-state level of pollution is set at 800 Gigatons of carbons (GtC) as in Annicchiarico and Di Dio (2015) or at 1520 GtC as in Benmir and Roman (2020). Finally, I report in Figure I.8 the results when θ_1 is set at 0.0334, as in the baseline calibration used in Carattini et al. (2023) and at 10.8 as in the sensitivity exercise conducted by Benmir and Roman (2020)[25]. I analyze the effect of the stringency of the tax target in subsection 7.1.

Summary This analysis drives three main results. First, climate policy uncertainty generates sectoral reallocation, characterized by a lower product creation in the dirty sector but a higher in the clean one. Second, it triggers environmental costs characterized by an increase in emissions. Third, climate policy uncertainty generates macroeconomic costs through lower aggregate output and welfare. These original findings are supported by the empirical evidence reported in Section 3.

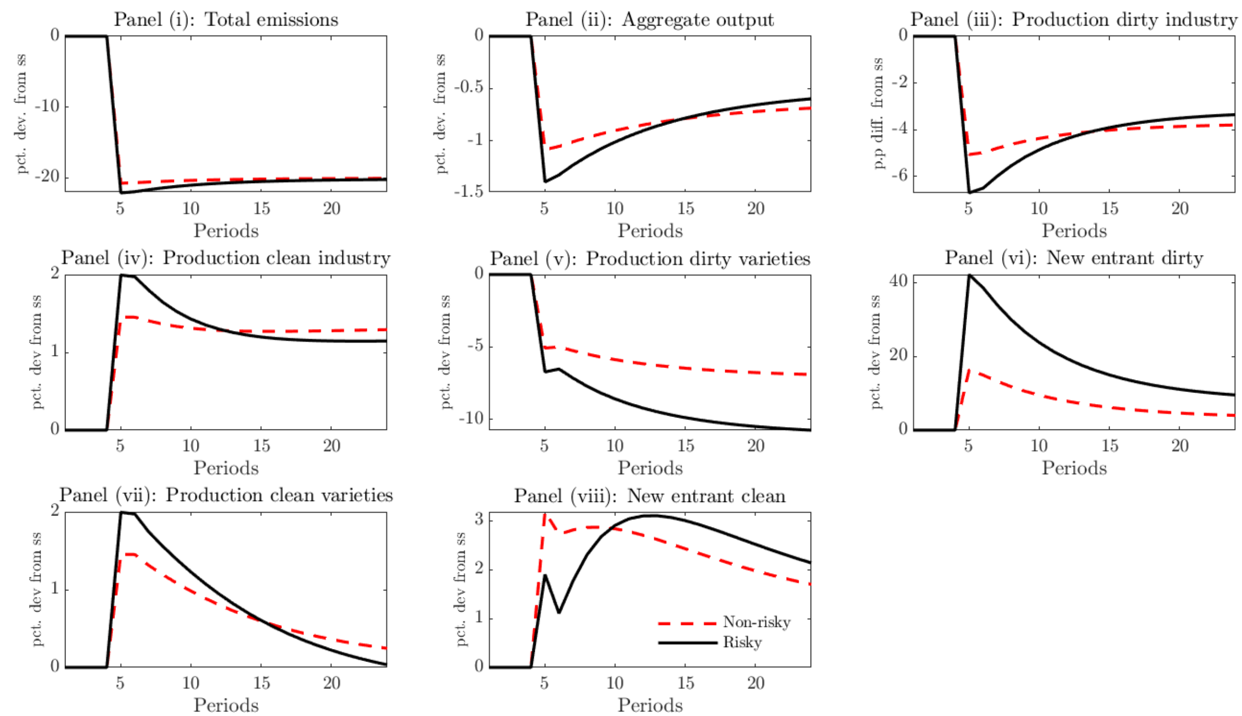
6.2 The cost of climate policy uncertainty during the transition

This section assesses the effects of climate policy uncertainty during the transition to a low-carbon economy. To this end, I assume that the economy starts in a pre-tax steady state and that the government introduces a carbon tax in quarter 5. I compare the transition dynamics starting from two scenarios. First, in the pre-tax steady state, the likelihood that the government will introduce a carbon tax is null ("Non-uncertain" steady state) while in the second case, there is a positive probability that carbon taxation will be introduced next quarter ("Uncertain" steady state). In both cases, the carbon tax implemented is the one reported in Table 2 and targets a 20% reduction of total emissions over the long run. Figure 6 plots the evolution of nine variables during the transition, when the pre-tax steady state is Non-uncertain (red dashed line) and when

[24] The resulting calibrations are available upon request.
[25] The corresponding Tables are available upon request.

it is Uncertain (black solid line). All variables are expressed in percentage deviations from their initial steady states, and time is measured in quarters and reported in the horizontal axis.

Figure 6: Transition to a low-carbon economy with and without CPR



Note: This figure plots the response of selected variables to the introduction of a carbon tax under two scenarios: (1) no uncertainty prior to the introduction and (2) uncertainty related to this introduction in the pre-tax steady state. All variables are reported as percentage deviations from the initial steady state.

The comparison of both lines highlights that even during the transition, where all the uncertainty is solved[26], climate policy uncertainty has economic costs. Panel (ii) shows that the recession triggered by the tax introduction is even more pronounced if the economy starts in the "Uncertain" pre-tax steady state. Following the same carbon tax shock, the decrease in aggregate output is 0.5 percentage points higher in this case. It is due to a more important contraction in the production of the dirty industry (Panel (iii)), that is not compensated by the higher production of the clean sectoral good (Panel (iv)). The contraction in the production in the dirty industry is induced by a contraction in the extensive margin (decrease in y_t^d, Panel (v)), associated with an expansion in the intensive one (increase in N_t^d induced by the increase in $N_{E,t}^d$, Panel (vi)). Starting from the Uncertain steady state, these effects are more pronounced. As presented in the first bar of

[26] I remind here that the post-tax steady state is an absorbing state: once the carbon tax is implemented, the economy will always stays in this steady state.

Figure 5, the per-variety production in the dirty sector is higher in the Uncertain steady state compared to the Non-uncertain one. Therefore, when a carbon tax is implemented, the adjustment of the intensive margin in response to higher marginal cost is accentuated. Through the mechanism presented in the previous section, it leads to higher entry into the dirty sector when the economy starts from the Uncertain steady state. However, the difference in the contraction of the intensive margin is higher than the difference in the expansion of the extensive one, triggering a lower decrease in the production of dirty industry starting from the Uncertain steady state. In the clean sector, the introduction of the carbon tax triggers an expansion of both margins in both scenarios (increase in y_t^c reported in Panel (vii) and increase in $N_{E,t}^c$, Panel (viii)). It triggers an increase in the production of the clean industry (Panel (iv)) that mitigates the drop in aggregate output.

Summary This section shows that climate policy uncertainty has economic costs during the transition to a low-carbon economy, characterized by a higher recession.

7 Robustness and Additional Results: Climate Policy Risk Spreading

After presenting the results of the baseline version of the model, this section investigates how sensitive they are to alternative ways of modeling climate policy uncertainty.

To this end, I extend the model in two avenues, each capturing a different source of risk spreading. First, in the previous simulations, I assume that the magnitude of the carbon tax, if introduced, is perfectly known by the agents. Even though they don't know if the government will introduce it next period, they know that, if this is the case, it will target a 20% reduction in emissions. However, the magnitude of the carbon tax is also subject to uncertainty. I introduce uncertainty on the magnitude of the potential carbon tax in subsection 7.1. Second, if the baseline model considers carbon taxation as the sole instrument to reduce emissions, policy-making (and, therefore, uncertainty around it) has other instruments to meet environmental goals. I extend the baseline model and simulate in subsection 7.2 innovation policy (uncertainty) in the form of subsidies on entry costs in the clean sector[27].

[27] I report in Appendix J the calibration of the model's extensions. The parameters whose calibration is borrowed from existing literature are not reported since they are equal to the values presented in Table 2. I follow the same targets for the calibration of the deep parameters (i.e. κ, F_E, E^*, τ. I rescale a, b and c to target a steady-state level of pollution of 1172 GtC.), and calibrate jointly the other set of parameters related to each extension.

7.1 Uncertainty in the magnitude of the carbon tax

So far, the only source of uncertainty in the model is related to the timing of the potential climate policy. If agents do not know whether or not the government will implement the carbon tax, they perfectly know its magnitude in case of introduction. However, in practice, this magnitude is also subject to uncertainty. While policy-making advocates for a tax reducing the emissions by 20%, it could be argued that this commitment is not perfect and that the future potential carbon tax might be more or less stringent.

To account for it, I perform an additional exercise where I still consider that there is a 75% probability that the State will implement the carbon tax within the next 10 years. However, this carbon tax can target a 10%, a 20% or a 30% decrease in emissions. I assume that these events are equally distributed: with a 25% probability, the future carbon tax will be low, it will be medium with 25% probability, and high with 25% probability (and absent with 25% probability). Therefore, the Euler equation for shareholdings in sector $k \in \{c, d\}$ becomes:

$$v_t^k = \beta(1-\delta)\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma}\left((1-p_1-p_2-p_3)(v_{t+1}^k + \pi_{t+1}^k) + \sum_{i=1}^{3} p_i \left((v_{t+1}^k)^i + (\pi_{t+1}^k)^i\right)\right) \tag{42}$$

where $i = 1$ corresponds to the low-target (10% reduction in emissions), $i = 2$ is the medium-target (20% reduction) and $i = 3$ represents the high-target (30% reduction).

If the tax is implemented, all uncertainty is solved: it cannot be repealed or changed. Therefore, in the post-tax steady state, we have:

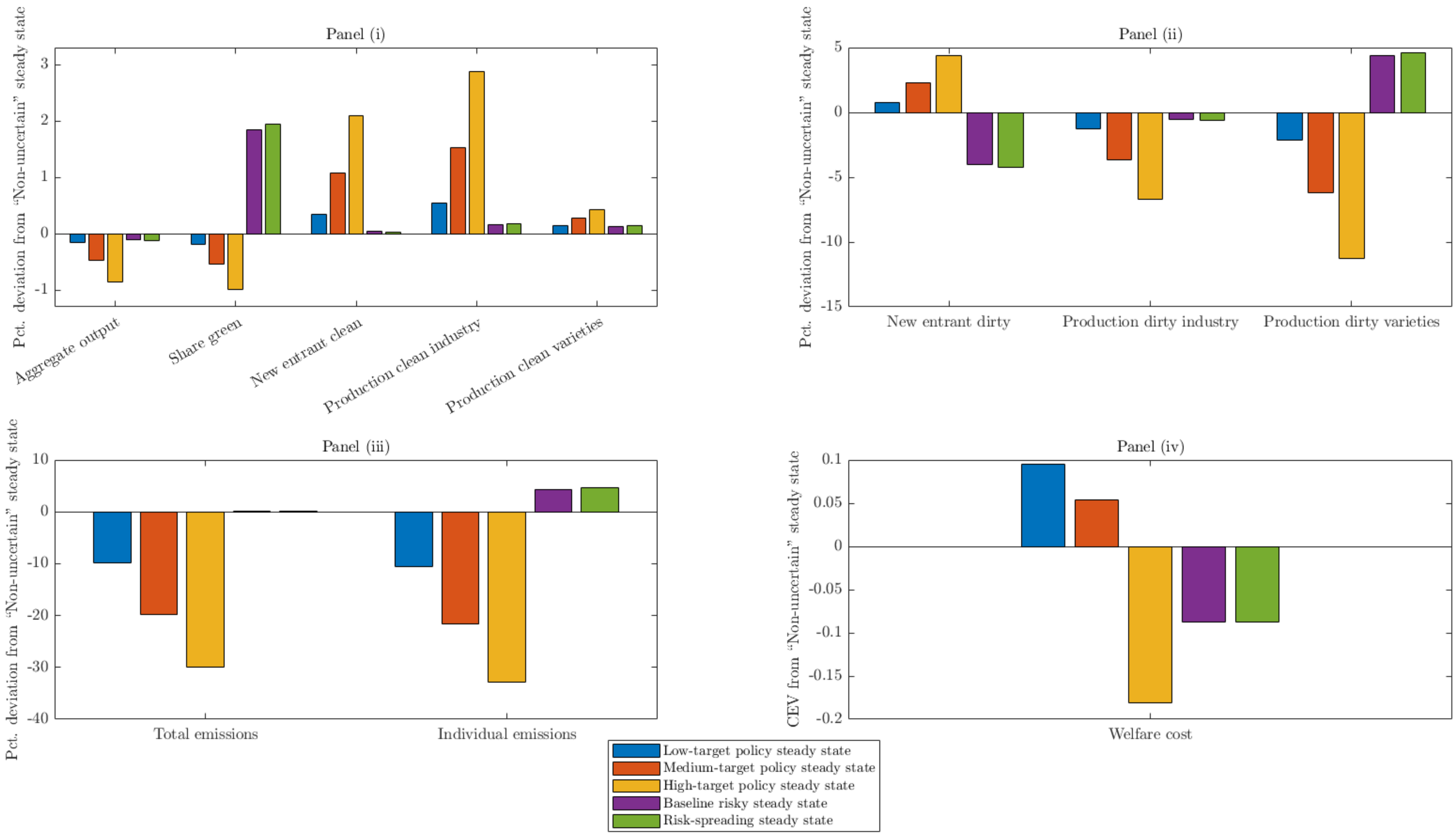
$$(v_t^k)^i = \beta(1-\delta)\left(\frac{C_{t+1}^i}{C_t^i}\right)^{-\sigma}\left((v_{t+1}^k)^i + (\pi_{t+1}^k)^i\right) \tag{43}$$

I compute the level of the tax $\tau^i, i \in \{1, 2, 3\}$ to target the reduction in emissions relative to the pre-tax Uncertain steady state.

Results I report in Figure 7 the percentage variation of the main variables of interest in various scenarios relative to the Non-uncertain steady state[28]. For each variable reported, the three first bars present the scenarios where there is an effective climate policy, with the various targets I consider. The purple bar focuses on the baseline results in the Uncertain steady state reported in Section 6.1 while the green bar reports the results in the "risk-spreading" steady state, where the magnitude of the potential tax is also subject to uncertainty. It is noteworthy that the expected level of the carbon tax is the same in both Uncertain steady states.

[28] I report in Appendix K a table displaying these results.

Figure 7: Deterministic steady state with risk-spreading, percentage changes relative to the non-Uncertain steady state



NOTE: This figure shows the percentage change relative to the Non-uncertain steady state of selected variables for the various scenarios considered. The welfare cost is expressed in compensating consumption variation relative to the Non-uncertain steady state. A positive (negative) number represents an amelioration (deterioration) of welfare in a given steady state compared to the Non-uncertain steady state.

Comparing the three first bars in Panel (i) shows that a more stringent carbon tax leads to a higher output contraction, as the production of the dirty industry is more heavily affected as the tax target is higher (Panel (ii)). Through substitution effect, the decrease in the demand for the dirty sectoral good triggers an expansion in the clean industry (Panel (i)). However, because of imperfect subtitution, this surge in the demand for clean input does not compensate for the decrease in the dirty one, resulting in a lower aggregate output as the tax target increases. The contraction of the dirty industry is mainly due to a shrinking of the intensive margin of production. With higher marginal costs and lower profits, individual producers reduce their production of dirty varieties (Panel (ii)). In the clean sector, however, both margins expand with the tax target. Through the between-sectors substitution effect, a more stringent carbon tax is associated with a higher demand for the clean industry, inducing a higher number of firms, and each firm produces more (Panel (i)). Besides, as expected, a more stringent carbon tax has environmental benefits identified by lower individual and aggregate emissions (Panel (iii)).

Comparing the purple and green bars reveals that additional uncertainty related to the magnitude of the potential future carbon tax triggers additional costs. Compared to the baseline case, where the only source of uncertainty comes from the timing of the implementation of climate policy, the risk-spreading case displays a lower decrease in output (Panel (i)) and a higher increase in total emissions (Panel (iii)). However, these additional costs are of small magnitude, suggesting that the costs of climate policy uncertainty are primarily driven by uncertainty related to the *timing* and not the *magnitude* of climate policies. It is noteworthy, however, that in this simulation, the probabilities of the introduction of the future taxes are equally distributed and set such that, on expectation, the magnitude of the future tax is equal under both scenarios reported in the purple and green bars.

7.2 Uncertainty in other climate policies

The baseline model focuses on carbon taxation as the sole instrument to tackle greenhouse gas emissions reduction. In August 2022, the President of the United States Joe Biden ratified the Inflation Reduction Act whose explicit goal is, according to the White House, to "*build a new clean energy economy, powered by American innovators, American workers, and American manufacturers, that will (...) cut the pollution that is fueling the climate crisis (...).*"[29] Concretely, this law provides \$370 billion in investments to support private investment in clean energy, tax provisions and \$11.7 billion to support issuing new loans and grant programs favoring the transition to a low-carbon economy.

[29] https://www.whitehouse.gov/cleanenergy/inflation-reduction-act-guidebook/ (last accessed, May 6, 2024).

Even though this law has been signed and is well-documented, there is still uncertainty surrounding it[30]. To take into account this additional source of uncertainty stemming from another climate policy, I extend the model to include subsidies on the clean sector's entry cost, at gross rate $\tau^e < 1$, as in Chugh and Ghironi (2011). Denoting x_t^{subsidy} the value of variable x_t if the policy is in place, the effective entry cost in the clean sector in terms of labor becomes $\tau^e F_E (w_t^c)^{\text{subsidy}}$ and the free-entry condition (Eq. 22) is thus given by:

$$(v_t^c)^{\text{subsidy}} = (w_t^c)^{\text{subsidy}} F_E \tau^e \tag{44}$$

In the pre-tax steady state, this policy is not enforced yet but agents expect that it could be in the future with probability p^{subsidy}. Additionally, they expect that a carbon tax can be implemented with probability p^{tax} and that both policies can be implemented with probability $p^{\text{both}} = p^{\text{subsidy}} \times p^{\text{tax}}$. Therefore, the Euler equation for shareholdings in the clean sector (Eq. 35) rewrites:

$$v_t^c = \beta(1-\delta)\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma}\left((1 - p^{\text{tax}} - p^{\text{subsidy}} - p^{\text{both}})(v_{t+1}^c + \pi_{t+1}^c) + \sum_{i=\{\text{tax,subsidy,both}\}} p^i \left((v_{t+1}^c)^i + (\pi_{t+1}^c)^i\right)\right) \tag{45}$$

It is worth noticing that in the "*tax*" case, uncertainty affects the marginal cost of dirty firms, while in the "*subsidy*" case, it affects the fixed (sunk) cost in the clean sector.

In terms of calibration, I assume that the introduction of this policy is more likely than the introduction of the carbon tax. The probability of carbon taxation introduction is unchanged compared to the baseline model and reflects a 75% probability that the government might introduce it within 10 years. To account for the strongest commitment regarding innovation policy, I set p^{subsidy} such that there is a 75% probability that the government introduces it in the next 2 years, yielding $p^{\text{subsidy}} = 0.1591$ at a quarterly frequency. The probability that both policies are implemented is simply the product of the probability that each event occurs. I rely on the guidebook detailing the concrete actions related to the Inflation Reduction Act and set the innovation subsidies τ^e at 6%, in line with the Investment Tax Credit for Energy Property, the Clean Electricity Investment Tax Credit or the Advanced Energy Project Credit.

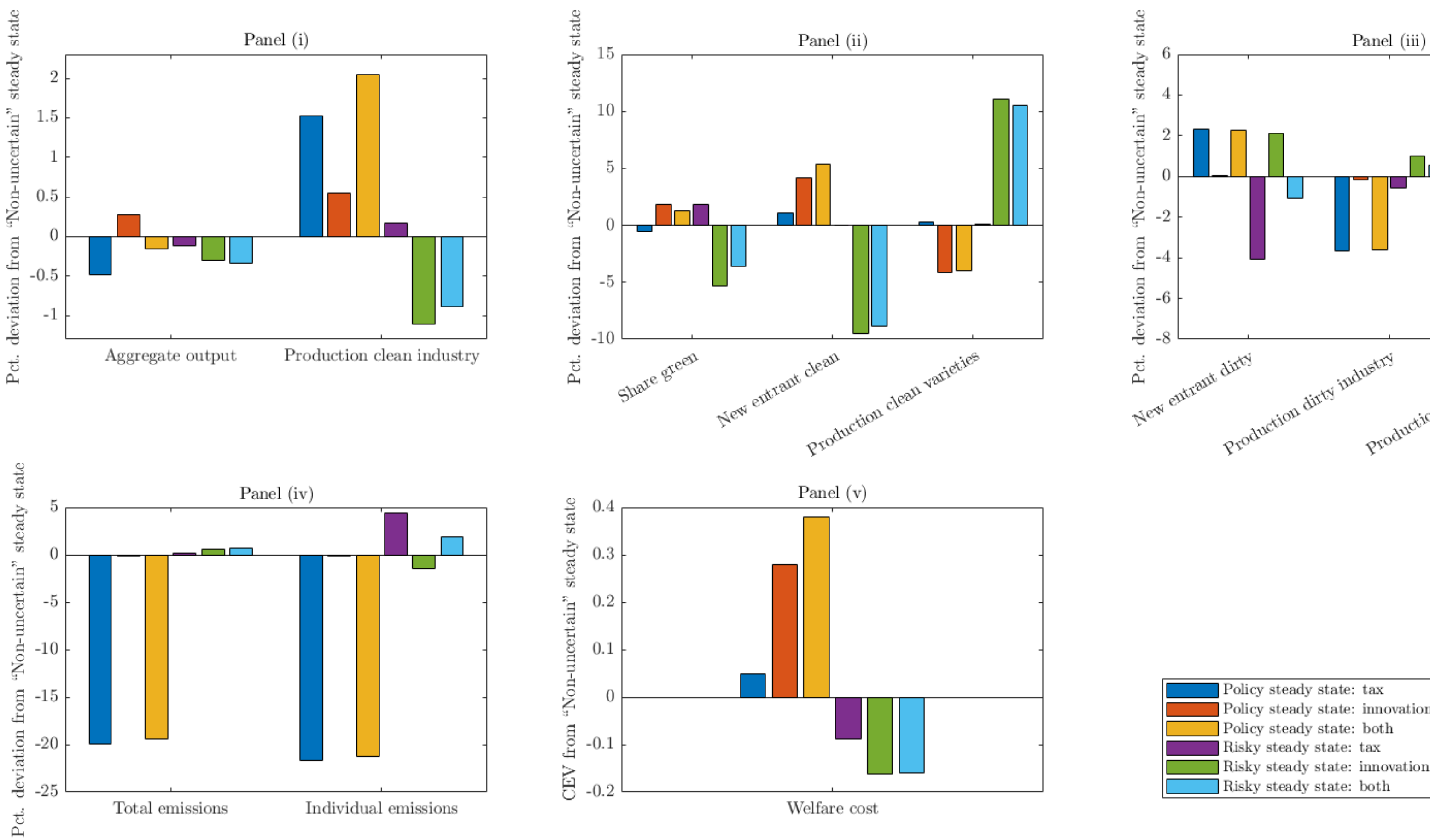
[30] As an illustration, the guidebook detailing the actions specifies: "*Nothing contained in this document constitutes formal guidance from the U.S. government on any law, program, policy, application process, or funding eligibility*" (https://www.whitehouse.gov/wp-content/uploads/2022/12/Inflation-Reduction-Act-Guidebook.pdf (last accessed, May 6, 2024))

Results To assess the effect of uncertainty in other climate policies, I simulate the model under several scenarios. First, the "Non-uncertain" steady state, with no climate policy nor climate policy uncertainty. In the "Policy" steady state, I allow the policy-making toolbox to vary and include either only a carbon tax, only a subsidy for clean producers' entry, or both. I also simulate three "Uncertain" steady states, where I assume that agents are uncertain either on the introduction of a carbon tax, the introduction of subsidy, or both. The baseline calibration relies on the Uncertain steady state. Concretely, I run three sets of calibrations depending on the uncertain policy (either only the carbon tax, only the innovation policy, or both) and use this calibration for simulating the corresponding Policy steady state[31]. When there is uncertainty surrounding the potential introduction of a carbon tax, its magnitude targets a 20% reduction if the carbon tax is in place. The calibration of the Non-uncertain steady state is the same as in the baseline case, presented in Table 2.

For each scenario I simulate, I compute the percentage change of the main variables of interest relative to the "Non-uncertain" steady state and report the results in Figure 8[32].

[31] The resulting calibrations are available upon request.
[32] I report in Appendix L a table displaying these results.

Figure 8: Deterministic steady state with innovation policy, percentage changes relative no-Uncertain steady state



NOTE: This figure shows the percentage change relative to the Non-uncertain steady state of selected variables for the various scenarios considered. The welfare cost is expressed in compensating consumption variation relative to the Non-uncertain steady state. A positive (negative) number represents an amelioration (deterioration) of welfare in a given steady state compared to the Non-uncertain steady state.

I first focus on the “Policy” cases (three first bars). In Panel (iv), the three first bars show that all the climate policies simulated allow reducing total emissions. If the carbon tax specifically targets a 20% reduction in emissions, a 6% subsidy of the clean sector’s entry cost provides a 0.15% reduction in emissions, without altering aggregate output which even increases (Panel (i), orange bar). Indeed, in this scenario, the contraction of the dirty industry is lower than when the government levies a carbon tax on dirty firms’ emissions since it does not directly affect their marginal cost. As a result, the production of dirty variety-producing firms only decreases by 0.18% (Panel (iii), orange bar). The contraction of the production in the dirty industry is mainly driven by a between-sector subsitution effect. Through the subsidy, the number of entrants in the clean sector increases by more than 4%, ensuring more competitivity in this sector, lowering the price charged by variety-producing firms, and making the clean input more competitive compared to the dirty one (Panel (iii), orange bar). It results an increase in aggregate output of about 3% (Panel (i), orange bar), associated with welfare gains (Panel (v), orange bar). However, the reduction in total emissions, induced by the slight contraction of the intensive margin in the dirty sector, is negligible and below the 20% target (Panel (iv), orange bar). Therefore, this policy instrument, if used alone, does not allow the economy to meet environmental goals. The yellow bar shows that the combination of a carbon tax and a subsidy on clean innovation triggers a 19% reduction in emissions relative to the Non-uncertain steady state (Panel (iv)), at lower economic and welfare costs than the sole implementation of a carbon tax (respectively, Panel (i) and Panel (v)).

Turning to the “Uncertain” cases, the three last bars show the costs of climate policy uncertainty and the cost of risk spreading. Panel (i) reports that, while the introduction of a subsidy leads to a higher output relative to the Non-uncertain steady state (orange bar), uncertainty surrounding this introduction leads to a contraction in aggregate output (green bar). In this scenario, the number of clean entrants and, therefore, of clean firms, is lower even though the introduction of this policy would benefit them (Panel (ii), green bar). This result aligns with the “wait-and-see” behavior documented by the literature in the presence of uncertainty. In the future, if this policy is indeed adopted, the entry cost in the clean sector would be 6% lower. Therefore, forward-looking and optimizing agents reduce entry in this sector when the policy is still uncertain, and increase innovation in the dirty sector (the number of dirty entrants is almost 4% higher in this scenario relative to the Non-uncertain steady state, Panel (iii), green bar). As a consequence, this sector becomes more competitive, as evidenced by the lower per-variety production (which is associated with lower prices). This contraction of the intensive margin is less important than the expansion of the extensive one (Panel (iii), green bars). On aggregate, total emissions slightly increase (Panel (iv)). Therefore, in line with the previous results, uncertainty on innovation policy leads to environmental costs, on top of economic costs characterized by lower output and welfare costs.

Summary Purple and green bars confirm the results obtained in the previous sections of this paper: uncertainty surrounding future climate policy, in the form of a potential tax or a potential subsidy for clean innovation, triggers an increase in total emissions and pollution stock, leading to higher climate damage and environmental costs. In addition, it generates economic costs, through a contraction in output and it is welfare-deteriorating (Panel (v)). Blue bars show that when the risk spreads, and that there are two sources of climate policy uncertainty, these costs are even more important. While the introduction of both instruments reported in yellow bars delivered the highest benefits, uncertainty related to the introduction of these two instruments triggers the highest costs. The contraction in aggregate output, the increase in total emissions, and the welfare costs are the most important in this scenario.

8 Conclusions

This paper investigates the effects of Climate Policy Uncertainty (CPU) on sectoral reallocations and their subsequent economic and environmental consequences.
To this end, I first empirically establish the interactions between climate policy uncertainty and sectoral reallocations. Using a VAR model, I estimate the impact of a CPU shock using an index of CPU alongside four time series that capture the responses of economic activity, patenting activity, and CO_2 emissions. Then, the core of the paper develops a Dynamic General Equilibrium model to examine how CPU affects economic and environmental outcomes. The model features two sectors (a "dirty" sector that pollutes, and a "clean" that does not but is affected by the climate externality) and sector-specific firm's entry. I assume that the economy begins in a pre-tax steady state, and in each period, agents anticipate the potential implementation of a carbon tax in the future.

The findings of this paper reveal significant outcomes. First, climate policy uncertainty discourages entry into the dirty sector while promoting entry into the clean one, resulting in sectoral reallocations. Second, in an economy characterized by CPU, emissions are higher compared to a scenario with either a clear climate policy or no uncertainty. Third, both in the long run and during the transition to a low-carbon economy, output is lower in the presence of CPU. Fourth, living in an economy with uncertain climate policy negatively impacts welfare. The robustness analysis of risk spreading confirms and reinforces these results. I show that the costs of climate policy uncertainty are amplified when the magnitude of the potential climate policy (on top of its timing) is also subject to uncertainty. These costs further increase with the number of uncertain climate policies. The empirical analysis corroborates these findings, showing that CPU shocks lead to a contraction in GDP. I identify shifts in patenting activity, evidenced by a sustained increase in clean patent applications, while the total number of patent applications and those for dirty patents both decrease. The VAR analysis further highlights the environmental impact of CPU, revealing an immediate surge in CO_2 emissions.

In terms of policy recommendations, this paper underscores the environmental, economic, and welfare costs associated with the lack of commitment in climate policy-making. For future research, a valuable extension of this framework could involve incorporating search and matching frictions in the labor markets to quantify how these sectoral reallocations affect sector-specific and overall unemployment.

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Appendix

A Details on the construction of the CPU Index

To measure climate policy uncertainty, the empirical part uses the index built by Gavriilidis (2021).

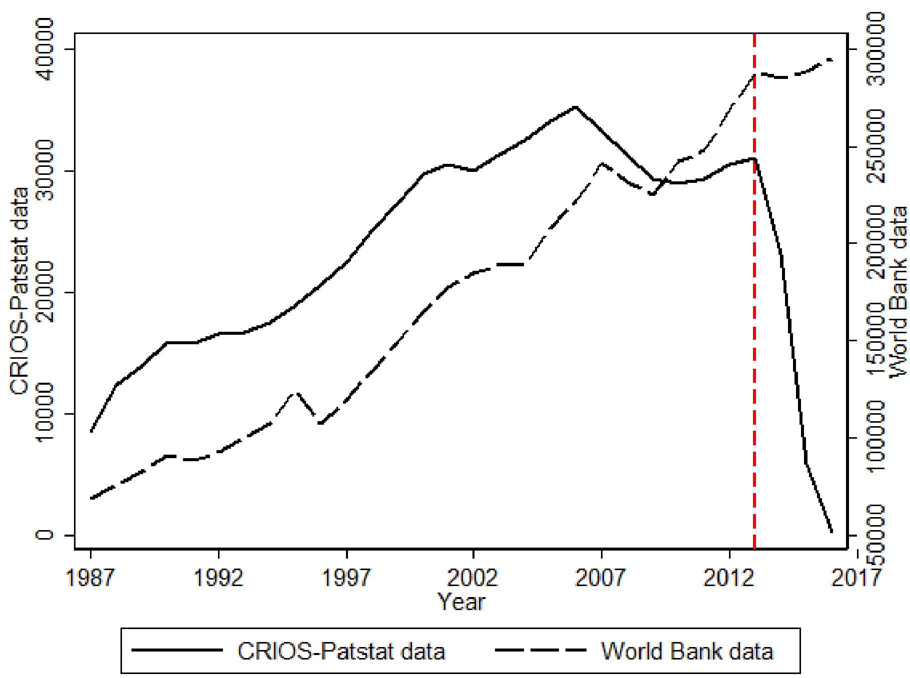
Following the methodology of Baker et al. (2016), it counts the frequency of newspaper articles that contain terms related to the following trio of topics: (1) Climate (2) Policy (3) Uncertainty. The lexicon used for the first topic includes: "carbon dioxide", "climate", "climate risk", "greenhouse gas emissions", "greenhouse", "CO_2", "emissions", "global warming", "climate change", "green energy", "renewable energy", "environmental", for the second topic, he considers: "regulation", "legislation", "White House", "Congress", "EPA", "law", "policy"; while the third topic contains the following terms: "uncertain", "uncertainty".

He uses the following U.S. newspapers: *Boston Globe*, *Chicago Tribune*, *Los Angeles Times*, *Miami Herald*, *New York Times*, *Tampa Bay Times*, *USA Today* and the *Wall Street Journal.*

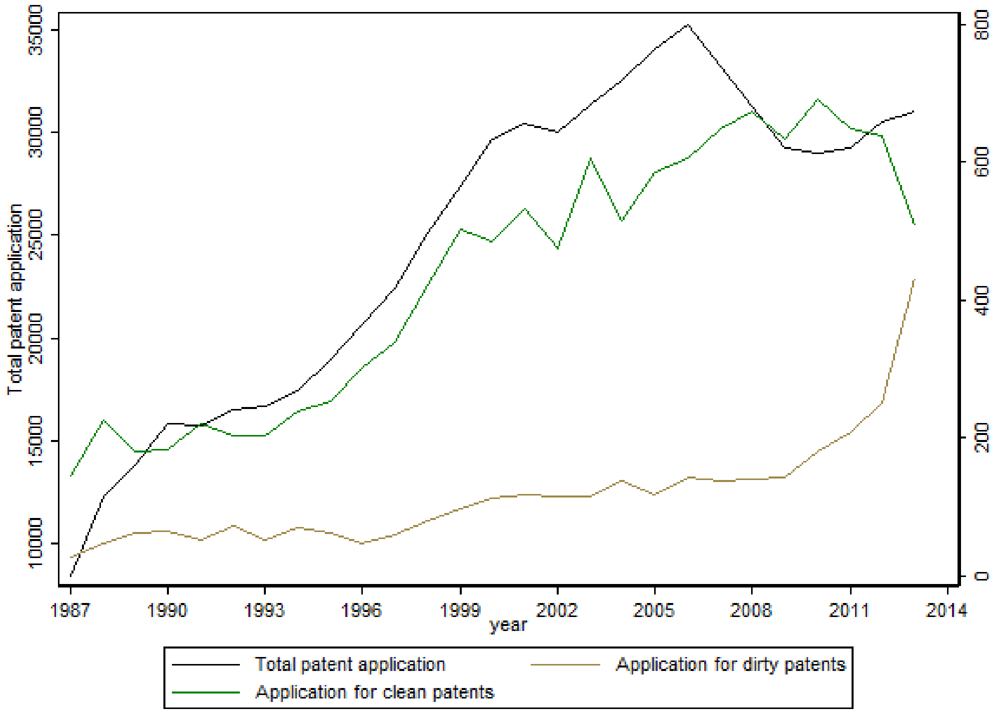
The count of this index is made at a monthly frequency, between 1987M4 and 2021M3.

B Evolution of the number of patent applications in the USA: Explanation of the sample restriction

This Figure illustrates my rationale for restricting the sample. After 2013Q4, indicated using the vertical red dashed line, the CRIOS-Patstat data (solid line) exhibit a sharp decrease in the number of patent applications which diverges from the upward trend shown by World Bank data (dashed line). I interpret this divergence as indicative of measurement errors toward the end of the sample and, therefore, exclude the last two years to ensure unbiased estimation. Between 1987 and 2013Q4, the discrepancy between the numbers provided by the CRIOS-Patstat and the World Bank databases can be explained as follows. First, the CRIOS-PatStat database only uses patents filed at the European Patent Office while the World Bank accounts *all* the applications from U.S. residents. Second, among the applications provided by the CRIOS-PatStat database, I only select those submitted by a company. Third, to avoid multiple counts of the same patent, I retain only the earliest application date for a given patent. It leads to a lower count of patent applications in the USA than the one provided by the World Bank.

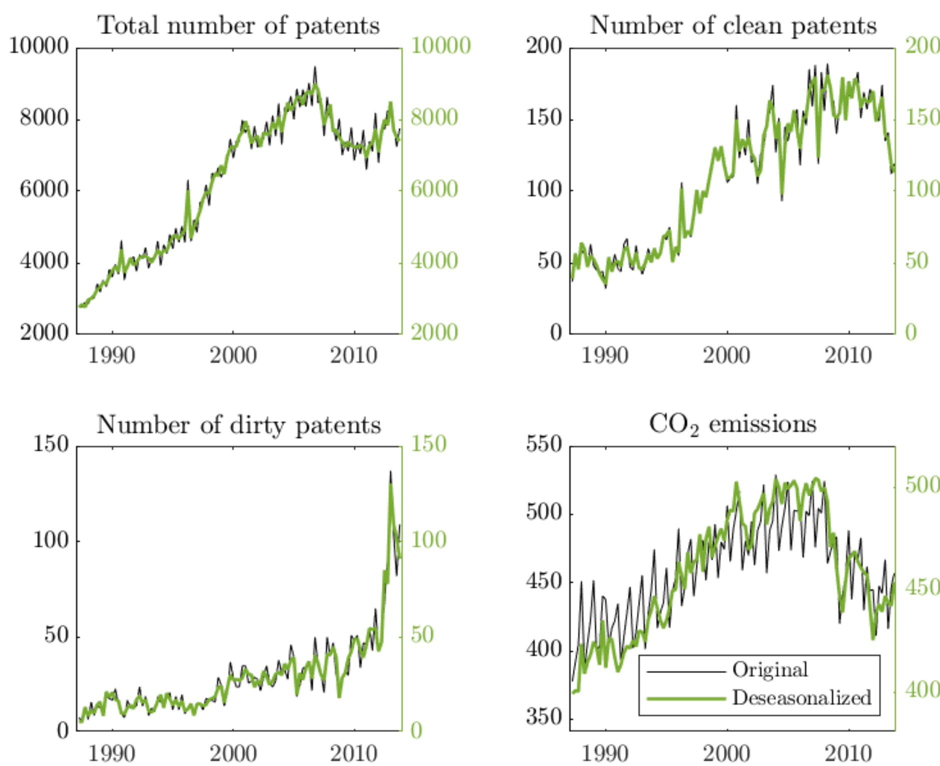


C Evolution of the number of patents in the USA (1987 - 2013)

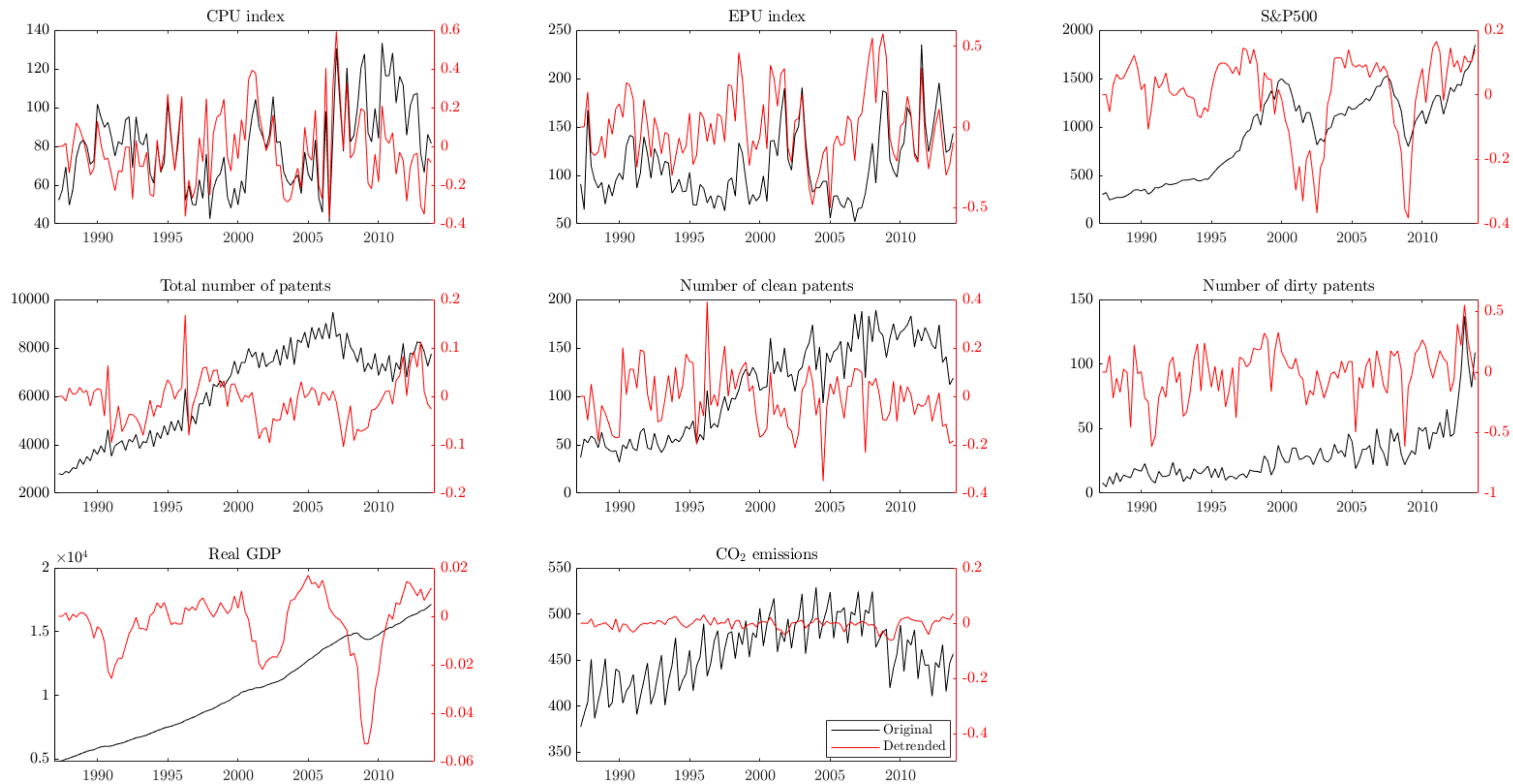


D Representation of the series used in the VAR

D.1 Deseasonalized series



D.2 Detrended series

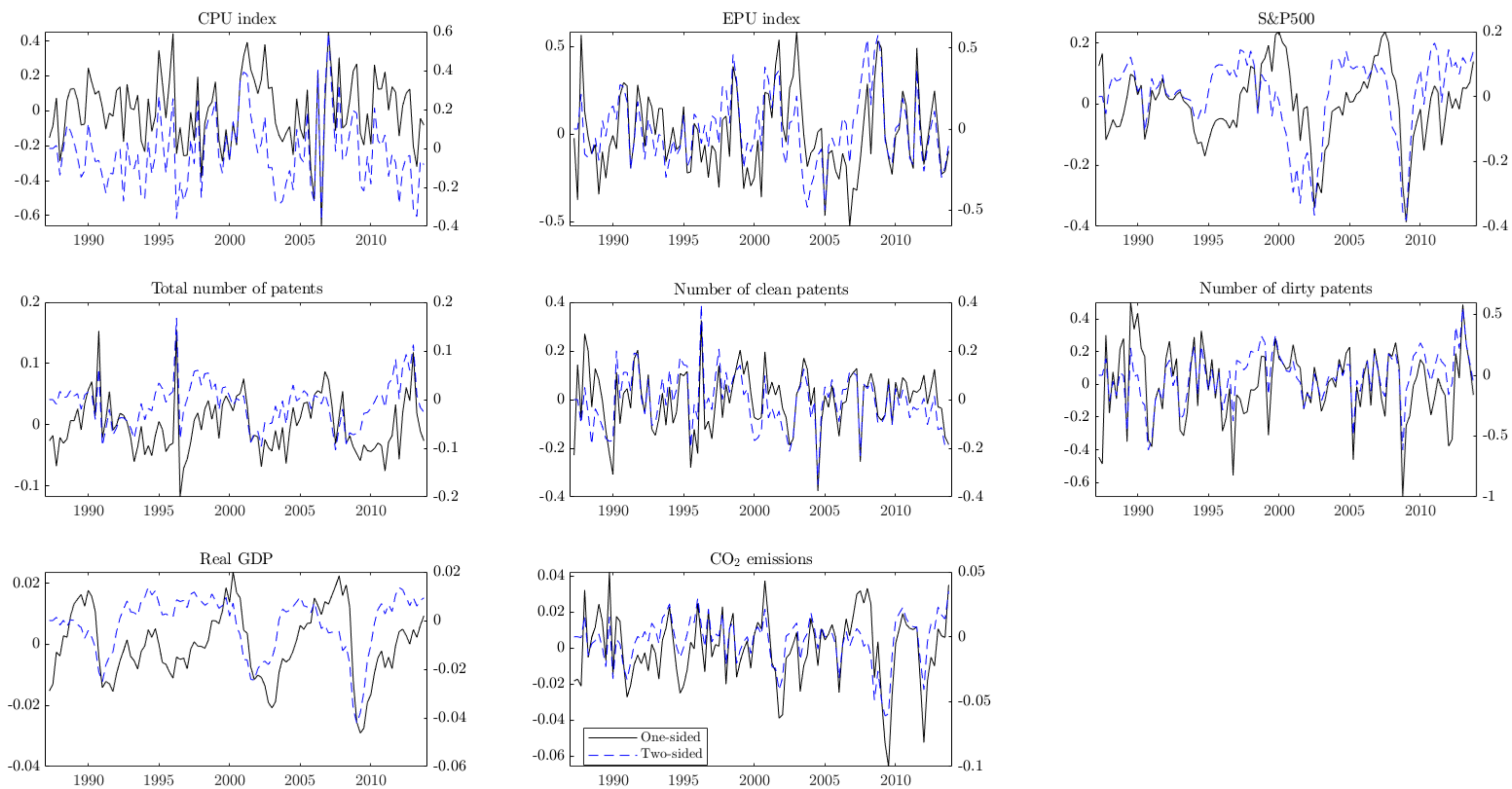


E Robustness: Detrending the series using a two-sided HP filter

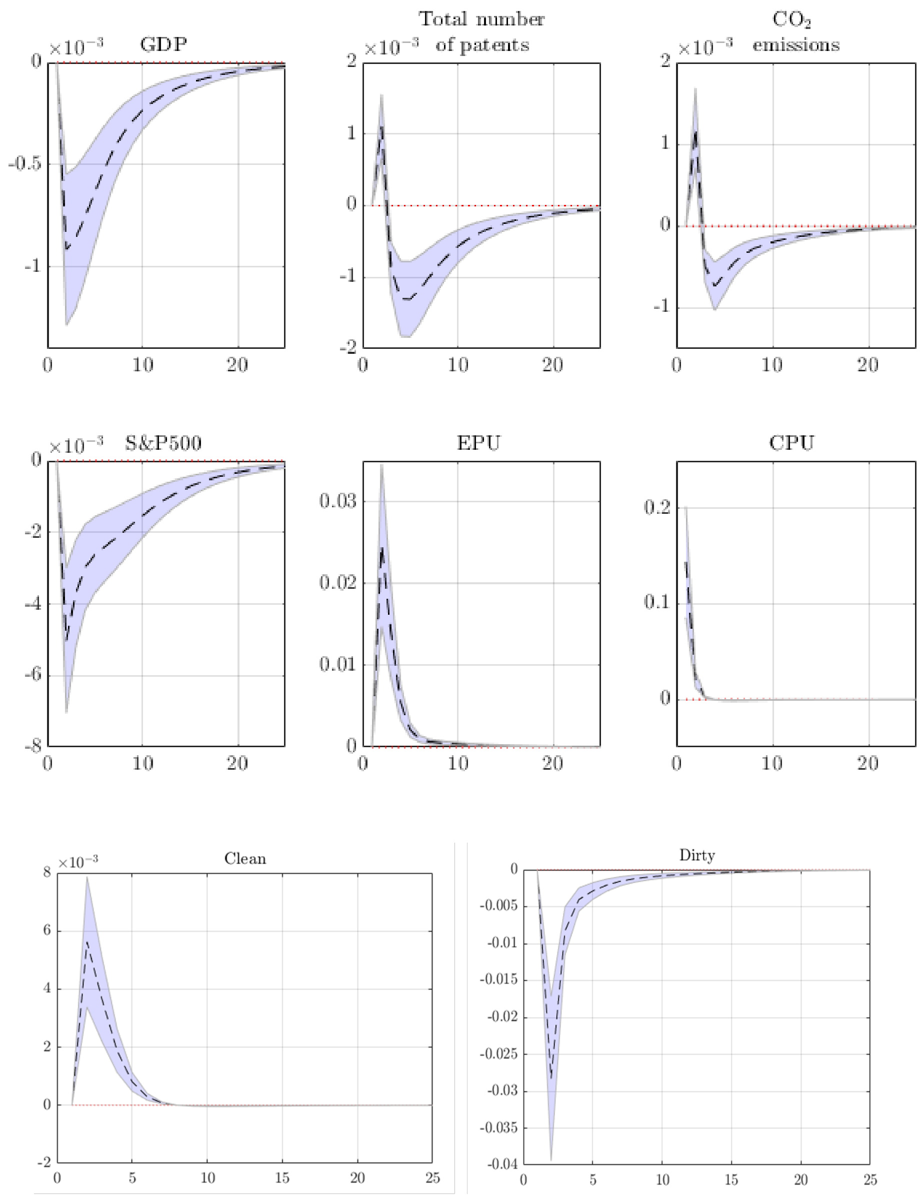
The main specification is estimated using time series detrended through a one-sided HP filter, that uses only past and present information to estimate the trend. An alternative approach consists of detrending the time series relying on a two-sided HP filter that also incorporates future observations, which is more distortive regarding the backward-looking nature of VAR models. Figure E.1 displays the time series detrended using a one-sided HP filter (black line), which is employed in the main specification, alongside the detrended series obtained from the two-sided HP filter (blue line). This comparison evidences that the resulting detrended series differ based on the filter selected. Subsequently, I report the IRF when variables are detrended using the two-sided HP filter.

See next page

Figure E.1

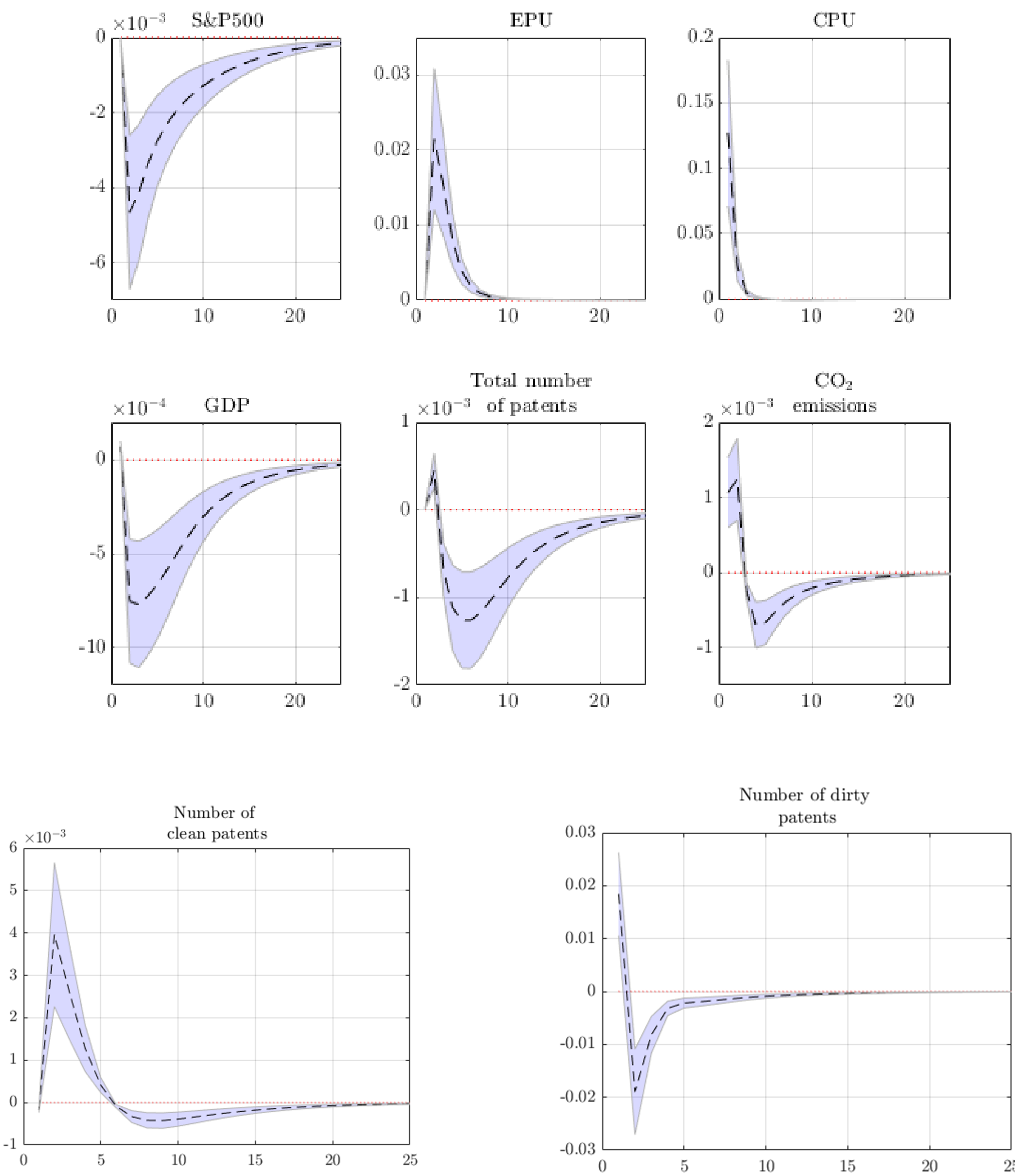


CPU index
EPU index
S&P500
Total number of patents
Number of clean patents
Number of dirty patents
Real GDP
CO_2 emissions
One-sided
Two-sided



NOTE: The CPU index is ordered in the last position and is orthogonalized to the overall EPU shocks. Black dashed lines are mean responses of the endogenous variables to a one-standard-deviation increase in the innovation to CPU. Blue-shaded areas represent 68 percent error bands. The estimation is conducted between 1987Q2 and 2013Q4. The series are detrended using a two-sided HP filter.

F Robustness: Alternative Ordering



NOTE: The CPU index is ordered in the third position, after the S&P500 index and the EPU index. Black dashed lines are mean responses of the endogenous variables to a one-standard-deviation increase in the innovation to CPU. Blue-shaded areas represent 68 percent error bands. The estimation is conducted between 1987Q2 and 2013Q4.

G Deterministic steady state, percentage changes relative to the "Non-uncertain" steady state

	Uncertain steady state	Policy steady state	Mean-preserving policy steady state
Aggregate output ($\Delta\bar{Y}$)[1]	-0.116	-0.487	-0.006
Share green ($\Delta\frac{\bar{N}^c}{\bar{N}^c+\bar{N}^d}$)	1.844	-0.541	-0.02
Total emissions ($\Delta\bar{E}$)	0.132	-19.895	-2.404
New entrant clean[2] ($\bar{N}^c$)	0.036	1.061	0.029
Production clean industry ($\Delta\bar{Y}^c$)	0.162	1.528	0.068
Production clean varieties ($\Delta\bar{y}^c$)	0.119	0.285	0.035
New entrant dirty[2] ($\Delta\bar{N}^d$)	-4.057	2.304	0.075
Production dirty industry ($\Delta\bar{Y}^d$)	-0.557	-3.659	-0.125
Production dirty varieties ($\Delta\bar{y}^d$)	4.366	-6.186	-0.212
Individual emissions[3] ($\Delta\bar{e}$)	4.366	-21.699	-2.477
Welfare cost (CEV)	-0.087	0.03	0.048

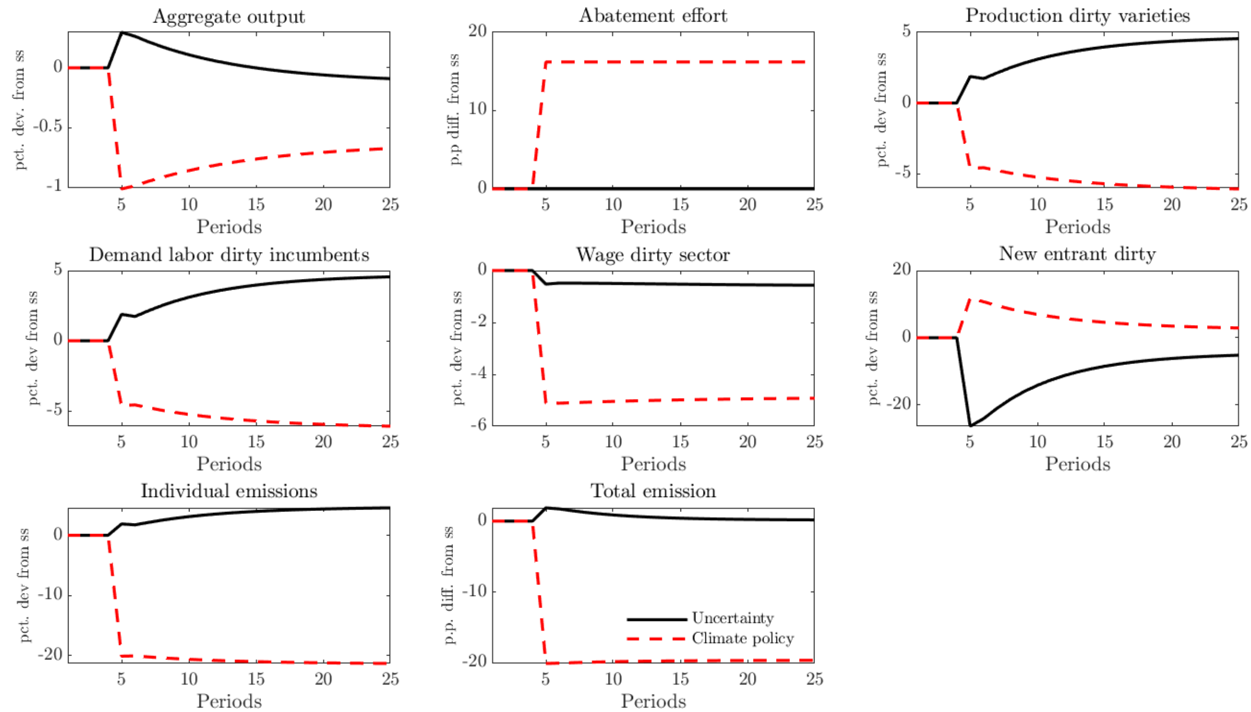
NOTE: This table shows the percentage change relative to the Non-uncertain steady state of selected variables. The welfare cost is expressed in compensating consumption variation relative to the Non-uncertain steady state. A positive (negative) number represents an amelioration (deterioration) of welfare in a given steady state compared to the Non-uncertain steady state. In the first column, I report the percentage change of the Policy steady state compared to the Non-uncertain steady state. The second column reports the percentage change of the Uncertain steady state compared to the Non-uncertain steady state. Finally, the third column reports the percentage change of the Mean-preserving policy steady state compared to the Non-uncertain steady state.

[1] I denote $\bar{X}$ the steady state of variable X and Δ its percentage change relative to its value in the "Non-uncertain" steady state.

[2] From (20), the number of producing from is proportional to the number of new entrants and the steady state. Their percentage change from one steady state to the other is therefore identical ($\Delta\bar{N}^k = \Delta\bar{N}^k_E$, for $k = \{c, d\}$)

[3] In the absence of climate policy, from (11), individual emissions are proportional to the production of the dirty varieties. Their percentage change from one steady state to the other is therefore identical ($\Delta\bar{y}^d = \Delta\bar{e}$, when $\bar{\mu} = 0$)

H Transition dynamics from one steady state to the other

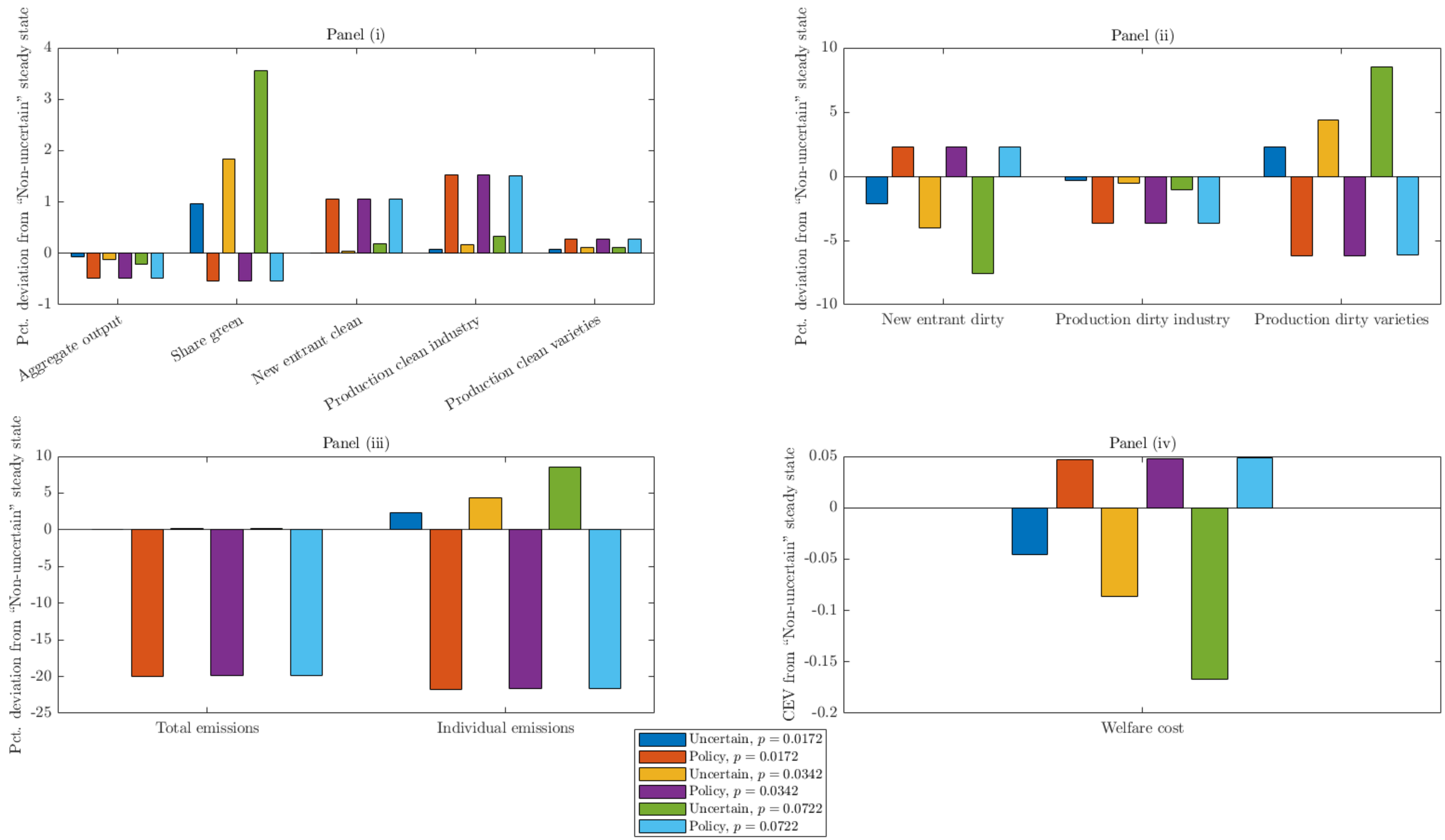


NOTE: This figure plots the response of selected variables, starting from the Non-uncertain steady state, under two scenarios: (1) uncertainty towards future climate policy emerges and (2) the climate policy is effectively set. All variables are reported as percentage deviations from the initial steady state, except abatement effort, which is expressed in percentage point difference.

I Sensitivity analysis

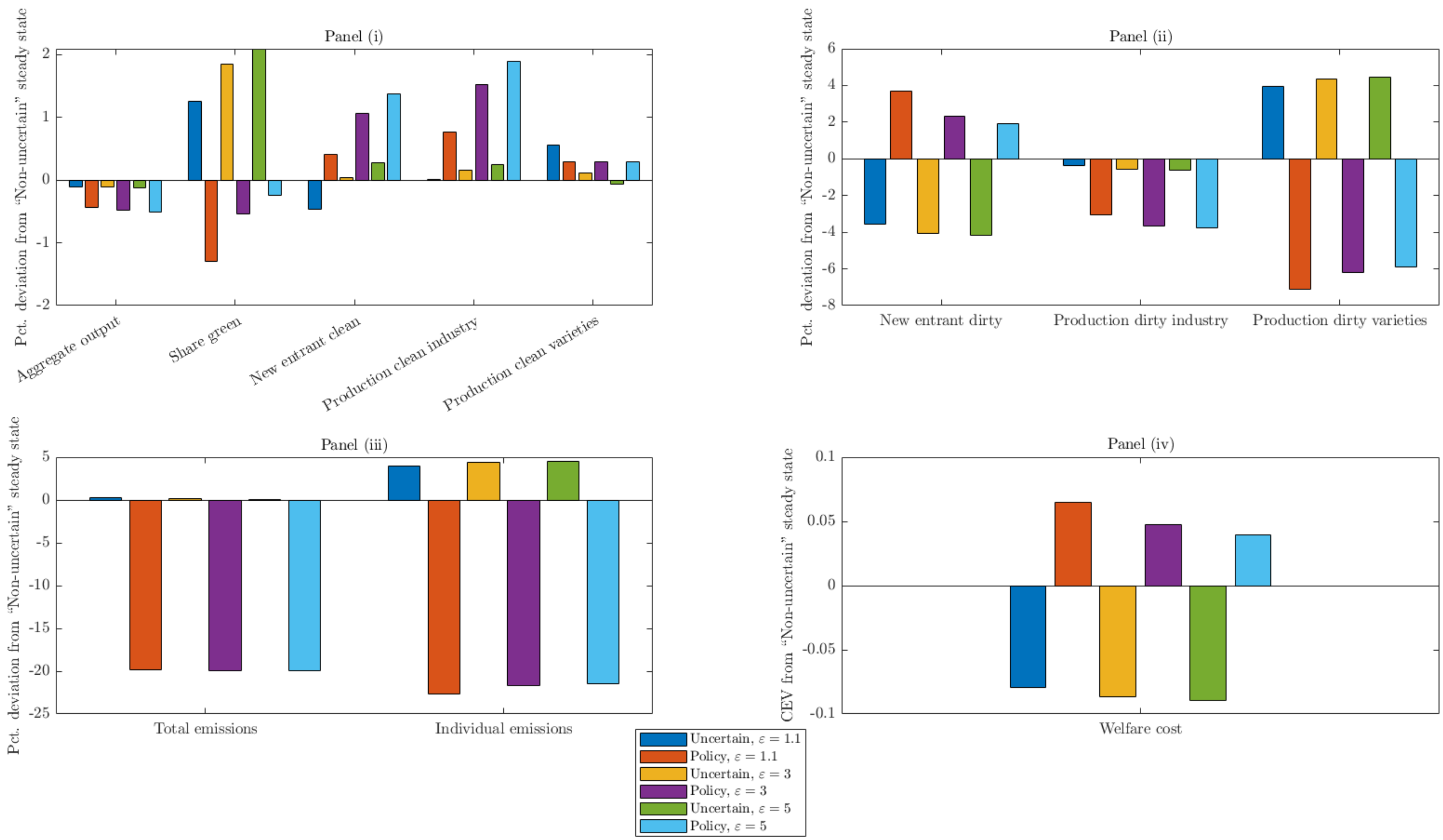
See next page

Figure I.1: Sensitivity Analysis: Probability of carbon tax introduction



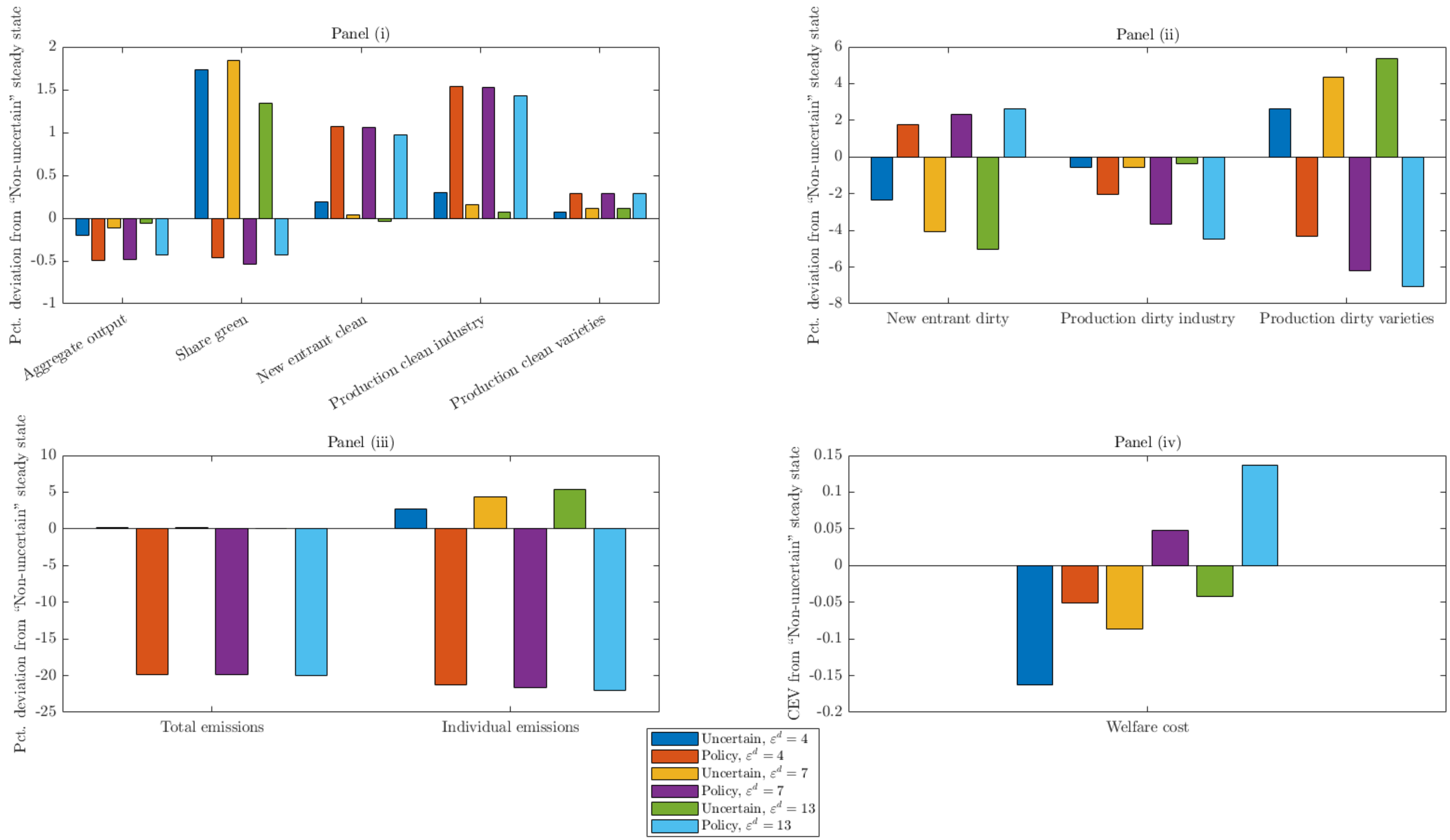
NOTE: This figure shows the percentage change compared to the "Non-uncertain" steady state of selected variables and for different values of p, the probability that the government impedes a carbon tax next period. I report in the two first bars the percentage changes when p is low, and agents expect that there is a 50% probability that the government will introduce the carbon tax within the next 10 years. It corresponds to $p = 0.0172$. The two subsequent bars correspond to the baseline scenario, i.e. $p = 0.0342$, reflecting a 75% probability of introduction in the next 10 years. The two last bar report the values when the probability is high, i.e. there is a 95% probability of introduction ($p = 0.0722$). Then, in each case, the first bar displays the percentage change of the "Uncertain" steady state compared to the "Non-uncertain" case, and the second bar presents the percentage change of the "Policy' steady state compared to the "Non-uncertain" steady state.

Figure I.2: Sensitivity Analysis: Substitution elasticity between clean and dirty sector



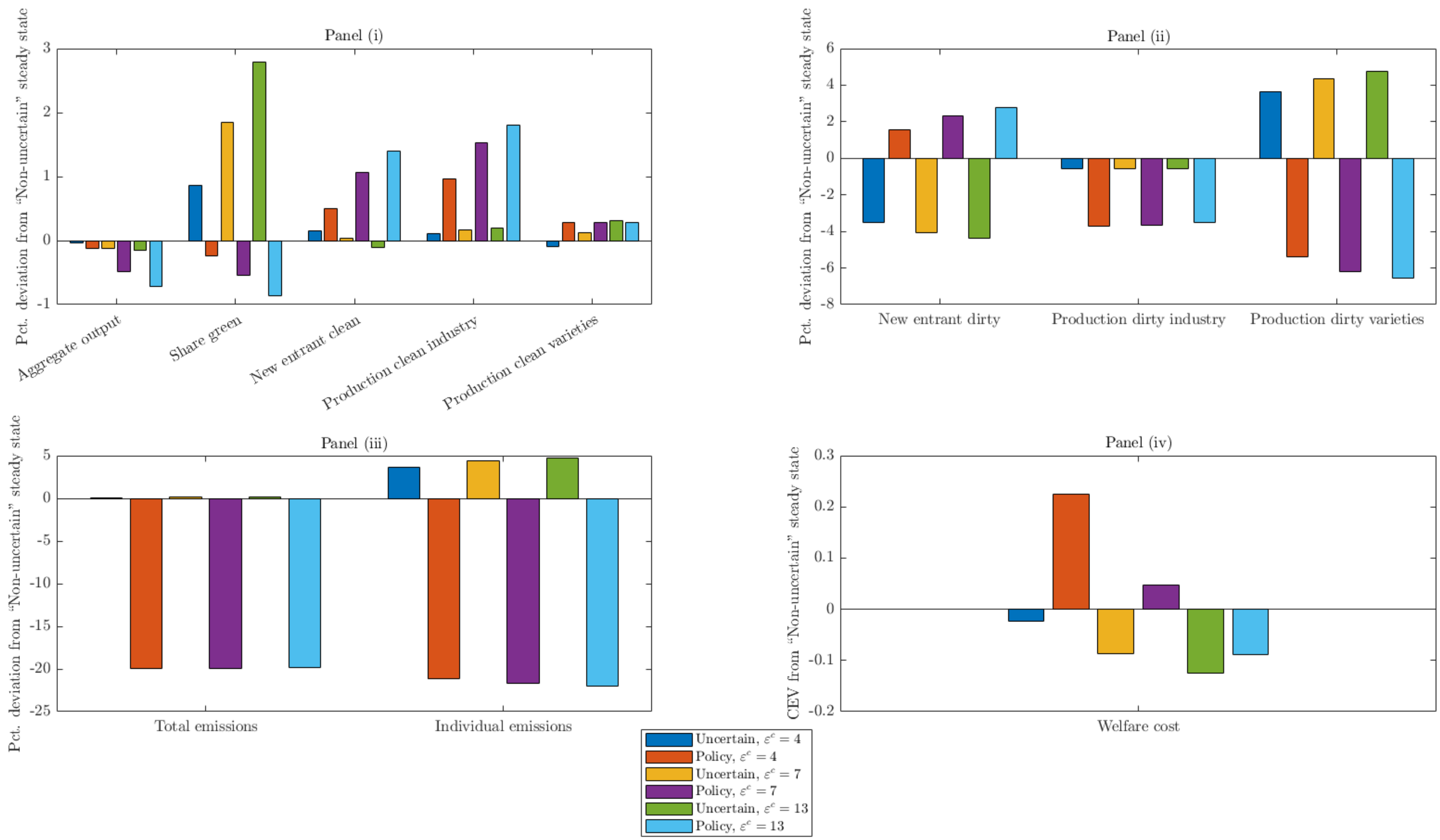
NOTE: This figure shows the percentage change compared to the "Non-uncertain' steady state of selected variables and for different values of ε, the elasticity of substitution between the clean and the dirty sector. I report in the two first bars the percentage changes when ε is low, i.e. $\varepsilon = 1.1$. The two subsequent bars correspond to the baseline scenario, i.e. $\varepsilon = 3$. The two last columns report the values when ε is high, i.e. $\varepsilon = 5$. Then, in each case, the first bar displays the percentage change of the "Uncertain" steady state compared to the "Non-uncertain" case, and the second bar presents the percentage change of the "Policy' steady state compared to the "Non-uncertain" steady state.

Figure I.3: Sensitivity Analysis: Substitution elasticity within dirty varieties



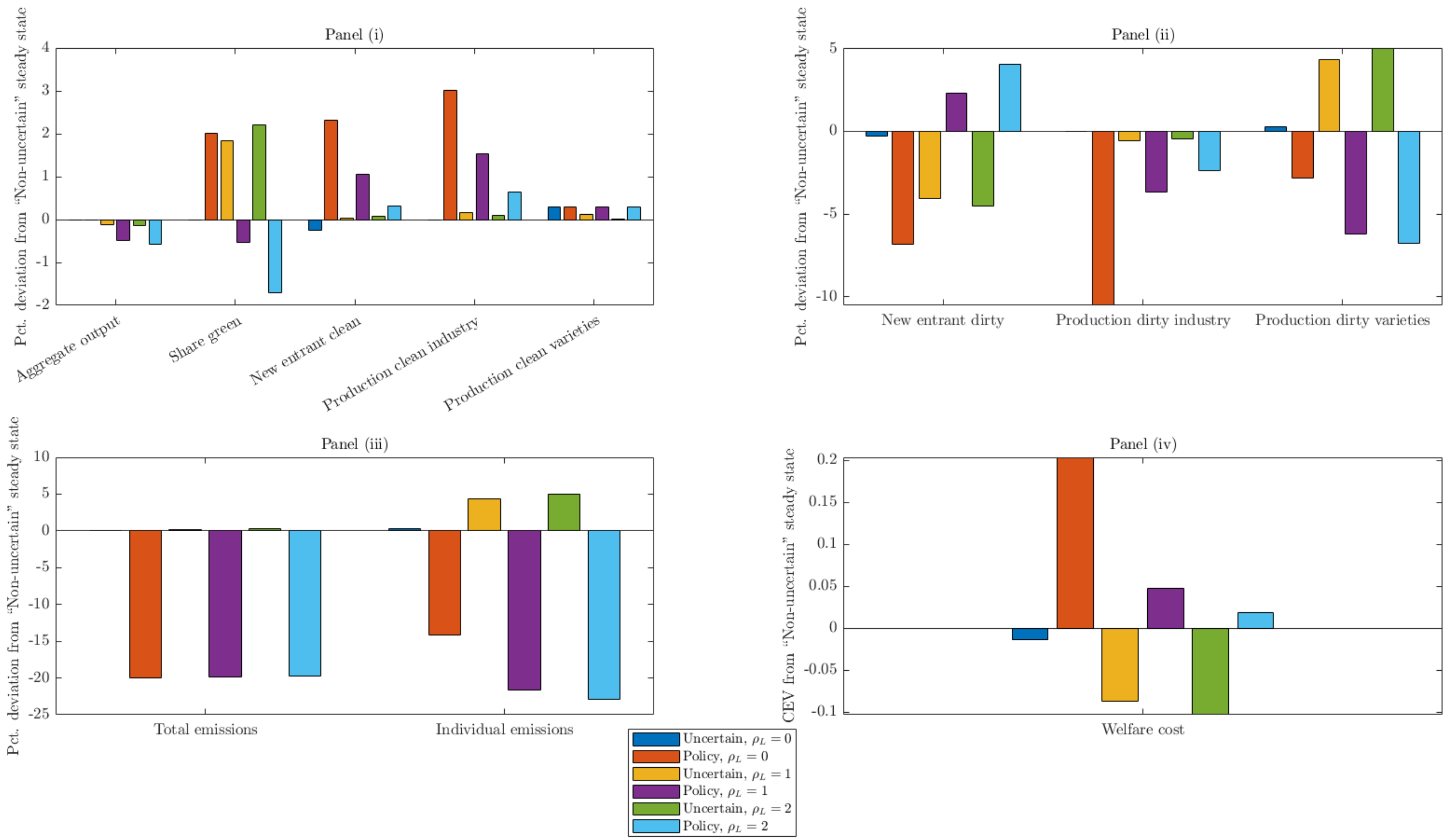
NOTE: This figure shows the percentage change compared to the "Non-uncertain" steady state of selected variables and for different values of ε^d, the elasticity of substitution within the dirty varieties. I report in the two first bars the percentage changes when ε^d is low, i.e. $\varepsilon^d = 4$. The two subsequent bars correspond to the baseline scenario, i.e. $\varepsilon^d = 7$. The two last bars report the values when ε^d is high, i.e. $\varepsilon^d = 13$. Then, in each case, the first bar displays the percentage change of the "Uncertain" steady state compared to the "Non-uncertain" case, and the second bar presents the percentage change of the "Policy' steady state compared to the "Non-uncertain" steady state.

Figure I.4: Sensitivity Analysis: Substitution elasticity within clean varieties



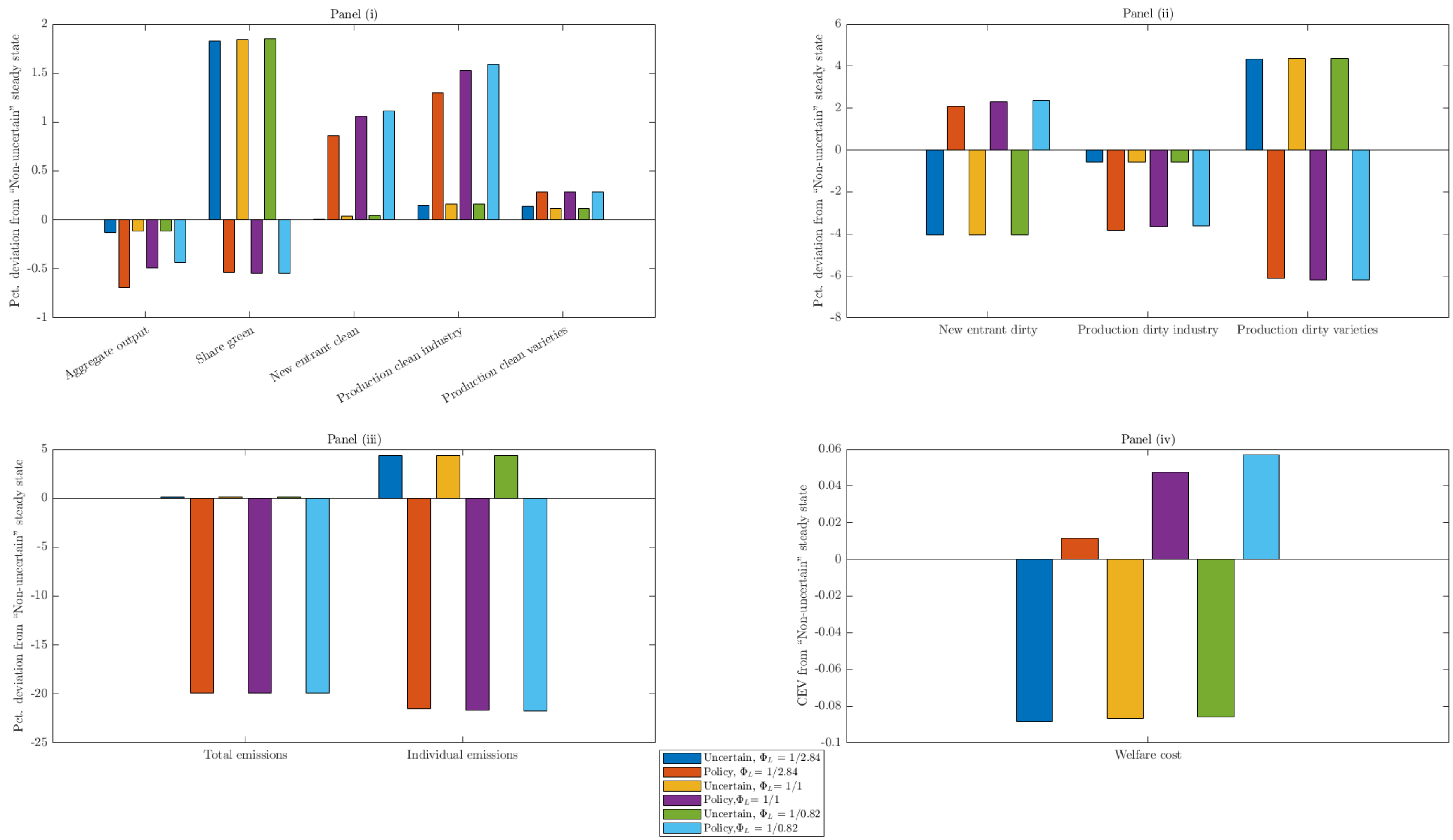
NOTE: This figure shows the percentage change compared to the "Non-uncertain" steady state of selected variables and for different values of ε^c, the elasticity of substitution within the clean varieties. I report in the two first bars the percentage changes when ε^c is low, i.e. $\varepsilon^c = 4$. The two subsequent bars correspond to the baseline scenario, i.e. $\varepsilon^c = 7$. The two last bars report the values when ε^c is high, i.e. $\varepsilon^c = 13$. Then, in each case, the first bar displays the percentage change of the "Uncertain" steady state compared to the "Non-uncertain" case, and the second bar presents the percentage change of the "Policy' steady state compared to the "Non-uncertain" steady state.

Figure I.5: Sensitivity Analysis: Substitution elasticity between labor hours



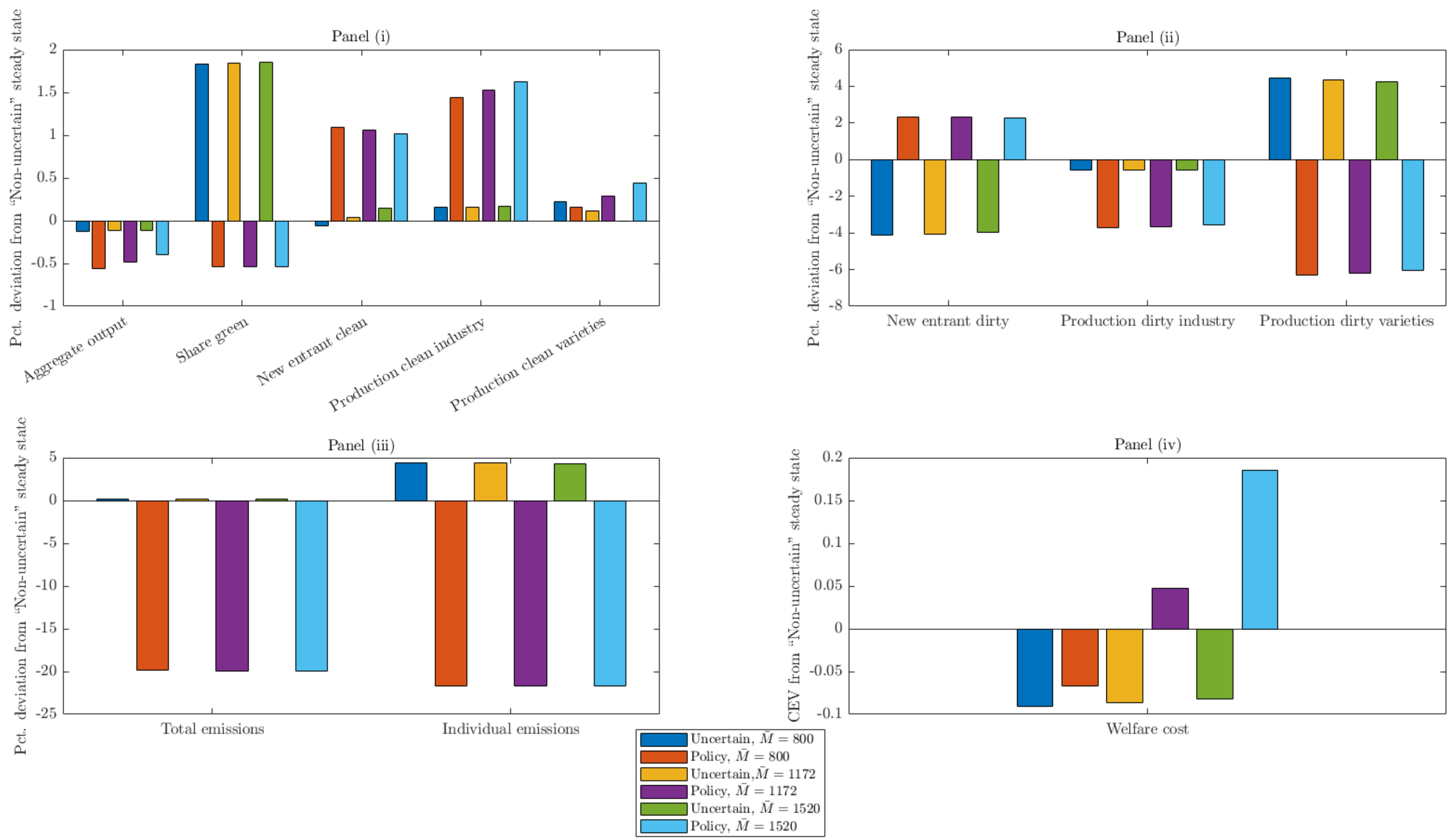
Note: This figure shows the percentage change compared to the "Non-uncertain" steady state of selected variables and for different values of ρ^L, the elasticity of substitution between labor hours in each sector. I report in the two first bars the percentage changes when ρ^L is low, i.e. $\rho^L = 0$. In this case, labor hours are perfectly substitutable. The two subsequent bars correspond to the baseline scenario, i.e. $\rho^L = 1$. The two last bars report the values when ρ^L is high, i.e. $\rho^L = 2$. Then, in each case, the first bar displays the percentage change of the "Uncertain" steady state compared to the "Non-uncertain" case, and the second bar presents the percentage change of the "Policy' steady state compared to the "Non-uncertain" steady state.

Figure I.6: Sensitivity Analysis: Inverse of the Frisch elasticity on labor supply



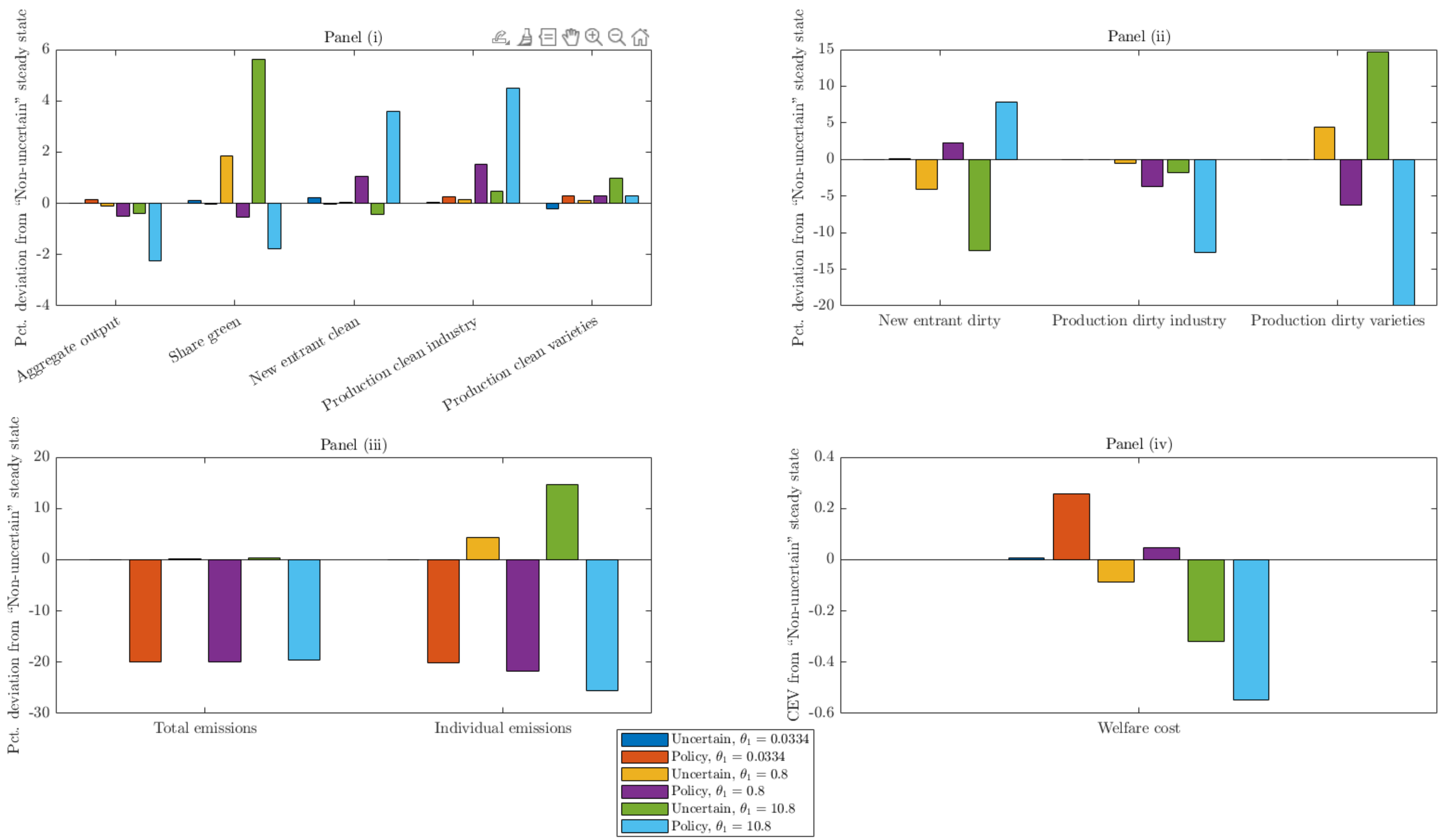
NOTE: This figure shows the percentage change compared to the "Non-uncertain" steady state of selected variables and for different values of ρ^L, the elasticity of substitution between labor hours in each sector. I report in the two first bars the percentage changes when ρ^L is low, i.e. $\frac{1}{\Phi_L} = 2.84$ (corresponding to macroeconomic estimates). In this case, labor hours are perfectly substitutable. The two subsequent bars correspond to the baseline scenario, i.e. $\frac{1}{\Phi_L} = 1$. The two last bars report the values when ρ^L is high, i.e. $\frac{1}{\Phi_L} = 0.82$ (microeconomic estimates). Then, in each case, the first bar displays the percentage change of the "Uncertain" steady state compared to the "Non-uncertain" case, and the second bar presents the percentage change of the "Policy' steady state compared to the "Non-uncertain" steady state.

Figure I.7: Sensitivity Analysis: Steady-state level of pollution stock



Note: This figure shows the percentage change compared to the "Non-uncertain" steady state of selected variables and for different values of $\bar{M}$, the steady-state level of pollution stock. I report in the two first bars the percentage changes when $\bar{M}$ is low, i.e. $\bar{M} = 800$, as in Annicchiarico and Di Dio (2015). The two subsequent bars correspond to the baseline scenario, i.e. $\bar{M} = 1172$. The two last bars report the values when $\bar{M}$ is high, i.e. $\bar{M} = 1520$ as in Benmir and Roman (2020). Then, in each case, the first bar displays the percentage change of the "Uncertain" steady state compared to the "Non-uncertain" case, and the second bar presents the percentage change of the "Policy' steady state compared to the "Non-uncertain" steady state.

Figure I.8: Sensitivity Analysis: Abatement cost



NOTE: This figure shows the percentage change compared to the "Non-uncertain" steady state of selected variables and for different values of θ_1, the abatement cost parameter. I report in the two first bars the percentage changes when θ_1 is low, i.e. $\theta_1 = 0.0334$, as in Carattini et al. (2023). The two subsequent bars correspond to the baseline scenario, i.e. $\theta_1 = 0.8$. The two last bars report the values when θ_1 is high, i.e. $\theta_1 = 10.8$ as in Benmir and Roman (2020). Then, in each case, the first bar displays the percentage change of the "Uncertain" steady state compared to the "Non-uncertain" case, and the second bar presents the percentage change of the "Policy' steady state compared to the "Non-uncertain" steady state.

J Calibration of the model's extensions

Parameter	Value	
	Magnitude tax	Innovation policy
κ	11.548	11.513
F_E	0.022376	0.022327
E^*	0.40195	0.40432
τ_1	0.074275	-
τ_2	0.2251	-
τ_3	0.43457	-
τ	-	0.20818
$p_1 = p_2 = p_3$	-	0.0114
$p^{subsidies}$	-	0.1591
τ^e	-	0.96

K Deterministic steady state with risk-spreading, percentage changes relative to the non-Uncertain steady state

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	Low-target policy steady state	Medium-target policy steady state	High-target policy steady state	Baseline Uncertain steady state	Risk-spreading steady state
Aggregate output ($\Delta\bar{Y}$)[1]	-0.155	-0.483	-0.857	-0.116	-0.121
Share green ($\Delta\frac{\bar{N}^c}{\bar{N}^c+\bar{N}^d}$)	-0.188	-0.541	-0.990	1.844	1.940
Total emissions ($\Delta\bar{E}$)	-9.872	-19.887	-29.900	0.132	0.141
New entrant clean[2] ($\Delta\bar{N}^c$)	0.344	1.069	2.087	0.036	0.032
Production clean industry ($\Delta\bar{Y}^c$)	0.539	1.531	2.871	0.162	0.172
Production clean varieties ($\Delta\bar{y}^c$)	0.137	0.280	0.422	0.119	0.135
New entrant dirty[2] ($\Delta\bar{N}^d$)	0.771	2.311	4.394	-4.057	-4.271
Production dirty industry ($\Delta\bar{Y}^d$)	-1.254	-3.653	-6.680	-0.557	-0.585
Production dirty varieties ($\Delta\bar{y}^d$)	-2.135	-6.188	-11.246	4.366	4.609
Individual emissions[3] ($\Delta\bar{e}$)	-10.562	-21.696	-32.851	4.366	4.609
Welfare cost (CEV)	0.095	0.054	-0.181	-0.087	-0.088

NOTE: This table shows the percentage change relative to the Non-uncertain steady state of selected variables. The welfare cost is expressed in compensating consumption variation relative to the Non-uncertain steady state. A positive (negative) number represents an amelioration (deterioration) of welfare in a given steady state compared to the Non-uncertain steady state. I report in the first column the percentage change of the "low-target" policy steady state compared to the Non-uncertain steady state, where the carbon tax targets a 10%-reduction in emissions. The second column reports the percentage change of the "medium-target" policy steady state compared to the Non-uncertain steady state, where the carbon tax targets a 20%-reduction in emissions. The third column reports the percentage change of the "high-target" policy steady state compared to the Non-uncertain steady state, where the carbon tax targets a 30%-reduction in emissions. The fourth column focuses on the baseline risk steady state explored in Section 6. Finally, the fifth column reports the percentage change of the risk-spreading steady state compared to the Non-uncertain steady state.

[1] I denote $\bar{X}$ the steady state of variable X and Δ its percentage change relative to its value in the "Non-uncertain" steady state.

[2] From (20), the number of producing from is proportional to the number of new entrants and the steady state. Their percentage change from one steady state to the other is therefore identical ($\Delta\bar{N}^k = \Delta\bar{N}^k_E$, for $k = \{c, d\}$)

[3] In the absence of climate policy, from (11), individual emissions are proportional to the production of the dirty varieties. Their percentage change from one steady state to the other is therefore identical ($\Delta\bar{y}^d = \Delta\bar{e}$, when $\bar{\mu} = 0$)

L Deterministic steady state with innovation policy, percentage changes relative no-Uncertain steady state

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	(1) Policy steady state: tax	(2) Policy steady state: subsidy	(3) Policy steady state: both	(4) Uncertain steady state: tax	(5) Uncertain steady state: subsidy	(6) Uncertain steady state: both
Aggregate output ($\Delta\bar{Y}$)[1]	-0.487	0.277	-0.156	-0.116	-0.305	-0.339
Share green ($\Delta\frac{\bar{N}^c}{\bar{N}^c+\bar{N}^d}$)	-0.541	1.806	1.292	1.844	-5.359	-3.656
Total emissions ($\Delta\bar{Y}$)	-19.895	-0.153	-19.416	0.132	0.630	0.730
New entrant clean[2] ($\Delta\bar{N}^c$)	1.062	4.205	5.315	0.036	-9.460	-8.912
Production clean industry ($\Delta\bar{Y}^c$)	1.528	0.545	2.040	0.162	-1.114	-0.895
Production clean varieties ($\Delta\bar{y}^c$)	0.284	-4.172	-3.942	0.119	11.042	10.507
New entrant dirty[2] ($\Delta\bar{N}^d$)	2.305	0.026	2.280	-4.058	2.127	-1.100
Production dirty industry ($\Delta\bar{Y}^d$)	-3.659	-0.149	-3.610	-0.557	0.983	0.545
Production dirty varieties ($\Delta\bar{y}^d$)	-6.187	-0.179	-6.112	4.366	-1.466	1.851
Individual emissions[3] ($\Delta\bar{e}$)	-21.700	-0.179	-21.212	4.366	-1.466	1.851
Welfare cost (CEV)	0.048	0.279	0.380	-0.087	-0.163	-0.160

NOTE: This table shows the percentage change relative to the Non-uncertain steady state of selected variables. The welfare cost is expressed in compensating consumption variation relative to the Non-uncertain steady state. A positive (negative) number represents an amelioration (deterioration) of welfare in a given steady state compared to the Non-uncertain steady state. I report in three first columns the percentage change of the policy steady state compared to the Non-uncertain steady state, where the policy tools are, in the following order: only a carbon tax, only entry subsidy for the clean sector, and both.. The three last columns report the percentage change of the Uncertain steady state compared to the Non-uncertain steady state, where uncertainty is, on the following order, on the carbon tax only, on the innovation subsidy only, and on both policies.

[1] I denote $\bar{X}$ the steady state of variable X and Δ its percentage change relative to its value in the "Non-uncertain" steady state.

[2] From (20), the number of producing from is proportional to the number of new entrants and the steady state. Their percentage change from one steady state to the other is therefore identical ($\Delta\bar{N}^k = \Delta\bar{N}^k_E$, for $k = \{c, d\}$)

[3] In the absence of climate policy, from (11), individual emissions are proportional to the production of the dirty varieties. Their percentage change from one steady state to the other is therefore identical ($\Delta\bar{y}^d = \Delta\bar{e}$, when $\bar{\mu} = 0$)