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Capital reallocation under climate policy uncertainty

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Non-technical summary

Research Question

There is widespread awareness that climate policies might tighten in the future in many countries. In the European Union, Member States are negotiating on the terms of the European Green Deal. In the United States, a federal price has not yet been put on carbon emissions yet, but could be adopted. At the same time, climate politics has often been characterized by reversals. In the US, this is exemplified by the temporary exit from the Paris Agreement or the Supreme Court's ruling in the case West Virginia vs. Environmental Protection Agency (EPA), which limits the EPA's options to regulate greenhouse gas emissions. In the EU, the energy crisis in the wake of the Russian invasion of Ukraine has created additional risks to the ambitious climate policy agenda. This raises the question: What are the economic consequences of climate policy uncertainty?

Contribution

We investigate how climate policy uncertainty affects capital reallocation across broad sectors of the economy and study the role of the financial channel. For our theoretical contribution, we build a dynamic structural model with two production sectors ("green" and "dirty") that differ in their energy intensity of production and thus in the amount of carbon emissions they create. The model features various climate policies such as carbon taxes and financial regulations – whose future path is uncertain – as well as financial frictions. In our empirical contribution, we test the predictions of the theoretical model by employing a news article-based measure of climate policy uncertainty to identify climate policy uncertainty shocks and investigate their consequences for investment and market valuation in a panel of listed US firms.

Results

Our model predicts that climate policy uncertainty shocks (i) lower the market value of the "dirty" sector relative to the "green" sector and (ii) reduce real investment and the capital stock in the "dirty" sector, while real investment in the "green" sector tends to increase. In line with the predictions from the theoretical model, we find that in response to empirical CPU shocks (i) financial markets substantially mark down strongly carbon-emitting listed US firms relative to firms with low carbon emissions, and (ii) substantial investment reallocation takes place, in particular from the manufacturing sector towards services.

Nichttechnische Zusammenfassung

Fragestellung

Die Möglichkeit einer künftigen Verschärfung der Klimapolitik in vielen Ländern ist ein vielbeachtetes Thema. In der EU verhandeln die Mitgliedstaaten die Ausgestaltung des Europäischen Green Deals. In den USA gibt es zwar noch keinen bundesweiten CO_2-Preis, er könnte aber eingeführt werden. Gleichzeitig war Klimapolitik in der Vergangenheit oft von Kehrtwenden charakterisiert. Beispiele dafür sind der vorrübergehende Ausstieg der USA aus dem Pariser Klimaabkommen oder das Urteil des Obersten Gerichtshofes der USA, welches die Möglichkeit der US-Umweltschutzbehörde einschränkte, Treibhausgasemissionen zu regulieren. Für die klimapolitische Agenda der EU erwachsen aus der Energiekrise im Zuge der russischen Invasion der Ukraine neue Risiken. Es stellt sich die Frage, welche ökonomischen Konsequenzen die Unsicherheit über die Klimapolitik hat.

Beitrag

Wir untersuchen die Effekte klimapolitischer Unsicherheit auf die Kapitalallokation zwischen breiten Wirtschaftssektoren sowie die Rolle des Finanzkanals. Als theoretischen Beitrag erstellen wir ein Modell mit zwei Produktionssektoren („grün“ und „schmutzig“), die sich durch ihre Energieintensität und damit durch ihren CO_2-Ausstoß unterscheiden. Das Modell bildet mehrere klimapolitische Instrumente ab, wie CO_2-Emissionssteuern und Finanzregulierungen – deren zukünftige Ausgestaltung unsicher ist – sowie Finanzfriktionen. Als empirischen Beitrag testen wir die theoretischen Vorhersagen. Dazu verwenden wir ein auf Zeitungsartikeln basierendes Maß für klimapolitische Unsicherheit, um klimapolitische Unsicherheitsschocks zu identifizieren und untersuchen ihren Effekt auf Marktkapitalisierung und Investitionen in einem Panel börsennotierter US-Firmen.

Ergebnisse

Unsere Modellanalyse ergibt, dass klimapolitische Unsicherheitsschocks (CPU-Schocks) (i) den Marktwert der Firmen im „schmutzigen“ Sektor relativ zu denen im „grünen“ Sektor senken und (ii) die realen Investitionen im „schmutzigen“ Sektor mindern, wohingegen Investitionen im „grünen“ Sektor dazu tendieren zu steigen. Im Einklang mit den Aussagen des theoretischen Modells finden wir, dass empirische CPU-Schocks (i) zu einem merklichen Verlust des Börsenwerts „schmutziger“ US-Firmen relativ zu „grünen“ Firmen führen, sowie (ii) zu einer bedeutenden Reallokation von Investitionen, insbesondere weg vom Verarbeitenden Gewerbe und hin zum Dienstleistungssektor.

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Abstract

In a structural dynamic model that incorporates two broad production sectors with different carbon emissions, we find that climate policy uncertainty (CPU) shocks (i) lower the market value of the highly carbon-emitting sector relative to the low carbon-emitting sector, and (ii) reduce real investment and the capital stock in the highly carbon-emitting sector, while real investment in the sector with low carbon emissions tends to fare better. To apply the theoretical predictions to the data, we employ a news article-based measure of climate policy uncertainty to identify CPU shocks as well as quarterly balance sheet data of listed firms in the United States. In line with the predictions from the theoretical model, we find that in response to CPU shocks (i) financial markets markedly revalue strongly carbon-emitting firms relative to firms with low carbon emissions, and (ii) substantial investment reallocation takes place, in particular from the manufacturing sector towards services.

Keywords: Climate policy uncertainty, production factor reallocation, firm-level investment decision, financial market valuation.

JEL classification: E22, E44, Q54, Q58.

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1 Introduction

There is widespread awareness that climate policies might tighten in the future in many countries. In the European Union, Member States are negotiating on the terms of the European Green Deal. In the United States, a federal price has not yet been put on carbon emissions, but could be adopted. At the same time, climate politics has often been characterized by reversals. In the US, this is exemplified by the temporary exit from the Paris Agreement or the Supreme Court's ruling in the case *West Virginia vs. Environmental Protection Agency (EPA)*, which limits the EPA's options to regulate greenhouse gas emissions. In the EU, the energy crisis in the wake of the Russian invasion of Ukraine has created additional risks to the ambitious climate policy agenda. This raises the question: What are the economic consequences of climate policy uncertainty?

In this paper, we study the effects of climate policy uncertainty (CPU) shocks. For this purpose, in the first part of the paper, we develop a dynamic stochastic general equilibrium model. To allow us investigate the allocation effects of climate policy uncertainty within the economy, we incorporate two broad production sectors. The two sectors differ in their energy intensity of production. In our analysis, we assume that the energy intensity of production is closely linked to its associated carbon emissions. Hence, we label the sector with the lower energy intensity "green" and the other one "dirty".

As climate policy comes in many guises, it is not straightforward to derive general statements on the effects of climate policy uncertainty. We meet this challenge by considering various policy tools in the model that can be used for the purpose of climate policy. The first one, a tax on energy use, is akin to a price on carbon emissions. Secondly, we consider financial regulations concerning assets associated with high-emission industries. Climate-related risk provisions or investors' efforts to decarbonize their portfolios can affect the pledgeability of assets of dirty industries and hence their financing costs. Thirdly, we consider a tax on final goods that require, for their production, a large amount of carbon emissions. This represents a simplified form of capturing policies that aim to discourage the use of emission-intensive goods. Formally, we model these policy tools as exogenous processes and CPU shocks as shocks to the standard deviation of these processes.

The main result of the theoretical analysis is that climate policy uncertainty triggers a reallocation of capital from dirty firms to green ones. All CPU shocks considered in the model (i) lower the market value of the more carbon-intensive sector relative to the less carbon-intensive one, and (ii) reduce real investment and the capital stock in the highly carbon-intensive sector. At the same time, in some settings CPU shocks trigger investments and raise the capital stock in the less carbon-intensive sector. Whereas the model predicts significant consequences for the reallocation of capital, the effects of CPU shocks to economy-wide aggregates – such as consumption and GDP – are far more moderate.

Central to the reallocation of capital in the model are balance sheet-constrained financial institutions, which are modeled in the vein of Gertler and Karadi (2013). These institutions finance the capital stock of non-financial firms. In the face of increased climate policy uncertainty, they shift their portfolio towards green assets. CPU shocks to the tax rates on energy or on products with high carbon-emission requirements translate into uncertainty regarding the marginal revenue product of capital in the high-emission industry and hence into uncertainty regarding the return on its assets; the third type of CPU shock directly affects the pledgeability of the assets of the dirty industry. Consequently, in the face of a positive CPU shock, financial institutions demand a climate risk premium on assets from the high-emission industry and the market value of dirty assets relative to green assets declines.

CPU shocks not only cause divestment in the dirty sector: they can also raise investment in the green sector and boost the market value of green assets. This is a particularly robust finding for uncertainty shocks to the collateral value of dirty assets held by financial institutions. This type of shock affects households and firms only indirectly and only mildly dampens economic activity. Thus, rather than shrinking the balance sheet of financial institutions, this shock redirects the funds divested from dirty industries into green assets, funding an increase in real investment in the low-emission sector.

To apply the theoretical predictions to the data, we identify CPU shocks using a news article-based measure of climate policy uncertainty for the United States (Gavriilidis 2021) and investigate the effects of empirical CPU shocks on publicly listed US firms in sectors with different carbon-intensities. Our empirical analysis confirms the predictions of the model. Empirical CPU shocks trigger a relative decline in the average market value of firms in industries that are responsible for a larger amount of carbon emissions, while greener sectors gain. Furthermore, we find that real investment increases in green sectors and falls in dirty ones in response to CPU shocks.

More specifically, we identify CPU shocks by orthogonalizing the measure for climate policy uncertainty with respect to US economic policy uncertainty (Baker, Bloom and Davis 2016), crude oil and natural gas spot prices, as well as macroeconomic and financial uncertainty (Jurado, Ludvigson and Ng 2015). The extracted shocks correspond well to anecdotal episodes in the sample. For instance, shocks are largely positive during the global climate strike in 2019. To zero in on capital reallocation across firms we use US firm-level data. We focus on firms that are characterized as downstream emitters of carbon in the sense that they do not necessarily emit carbon only directly but especially indirectly via very carbon-intensive inputs. In other words, while we exclude coke and petroleum production, mining, and utilities from the sample, we explicitly account for upstream inputs sourced from those sectors (for instance, by sectors such as services, manufacturing, construction, retail trade, etc.). Thus, in order to characterize sectors by their full carbon emission requirement per unit of output, one needs to account for domestic and international input-output linkages. For this purpose we employ the World Input-Output Database and the corresponding environmental accounts.

To investigate capital reallocation between sectors, we split firms into five groups that are ordered by the carbon emissions they require. We find that – in line with the predictions from the theoretical model – in response to CPU shocks (i) financial markets revalue heavily carbon-emitting firms relative to firms with low carbon emission requirements. Whereas in the group of the 20% of firms with the highest carbon emission requirements a firm faces a 2% market valuation loss, in the group of the 20% of firms with the lowest carbon emission requirements firms face a roughly 2% gain in market valuation (expressed relative to an average firm in the market and as the average effect in the current and following quarter of the shock). (ii) In response to the financial market revaluation, firms adjust their real investment decisions. Whereas in the quintile of the highest emitters a firm decreases – relative to an average firm in the market – its quarterly net investment by almost USD 2 million (constant 2019) in response to a CPU shock, a firm in the low-emission quintile increases investment by roughly USD 1.5 million. Overall, the empirical findings confirm the theoretical predictions of substantial capital reallocation toward less carbon-intensive industries – in practice, particularly from the manufacturing sector towards services.

Overall the empirical analysis confirms the model predictions that CPU shocks trigger a capital reallocation from high-emission to low-emission industries that affects both the market values of firms and their real investment activity. Our results imply that not only a higher stringency of climate policies but also greater climate policy uncertainty can reduce the carbon intensity of aggregate production and trigger green investment, thereby aiding the decarbonization of an economy.

Related literature Our theoretical analysis is related to the work of Fried, Novan and Peterman (2022) and Bretschger and Soretz (2022). Fried et al. (2022) analyze the effect of climate policy transition risk in a multi-sector model and find that climate-related policy transition risk reduces firms' investment in fossil capital relative to green capital and results in decarbonization in the aggregate economy. Our analysis of firms' investment decisions corroborates this finding in a setting with infinitely-lived agents in which we model uncertainty in a more standard fashion as the stochastic volatility of exogenous policy tools. Bretschger and Soretz (2022) investigate the theoretical effects of stochastic taxes and subsidies on dirty and green production factors in a one-sector model. Their results suggest that uncertainty regarding taxation of dirty capital incentivizes investors to divest from this input factor. We show, in a setting that allows for the reallocation of resources between sectors, that a similar divestment also takes place even if the capital of the high-emission industry is not directly the target of climate taxes. We add to the analysis of both papers by investigating the effects of uncertainty associated with various different climate policy tools. Importantly, we account for the role of the financial sector in the transmission of CPU shocks, which is key to our results. This allows us to provide novel testable predictions regarding market valuation in response to CPU shocks.

Diluiso, Annicchiarico, Kalkuhl and Minx (2021) and Carattini, Heutel and Melkadze (2021) discuss climate transition risk in very similar DSGE models to ours, including financial frictions as in Gertler and Karadi (2011). While they explore the possibility that macroprudential or monetary policy can mitigate transition risk and stabilize the economy, our analysis presents policy itself as a potential source of uncertainty.

Our theoretical analysis of the effects of CPU shocks builds on the literature on uncertainty shocks in DSGE models. This literature was pioneered by Bloom (2009). Born and Pfeifer (2014) discuss the effects of policy uncertainty and lay out the channels via which uncertainty can affect investment and consumption in a standard medium-scale model. Mikkelsen and Poeschl (2019) and Khalil and Strobel (2021) investigate the effect of uncertainty shocks in models with financial intermediaries.

Our paper also relates to the broader investigation of the effects of climate policy, which has been an active field in recent years. As a result, many researchers have developed innovative models that often feature intricate production networks or international linkages (see e.g. Hassler, Krusell, Olovsson and Reiter (2019); Bukowski and Kowal (2010); Hinterlang, Martin, Röhe, Stähler and Strobel (2021); Varga, Roeger and in 't Veld (2021) and Frankovic (2022)). The literature focuses mainly on the effects of realized policy changes or long-term transition paths. With the focus on CPU, our contribution is complementary to this literature. In comparison, we keep the model rather small so as to be tractable for the higher-order solution required to capture uncertainty shocks, and to facilitate the discussion of the mechanisms at work in the model.

A small body of empirical literature investigates the effects of climate policy uncertainty. Berestycki, Carattini, Dechezleprêtre and Kruse (2022) develop a news-based CPU measure for the OECD and show a decrease of real investment by firms in carbon-intensive and capital-intensive sectors in response to increasing climate policy uncertainty. Our empirical work is complementary to theirs. First, we exclude the obviously most heavy emitters of carbon located in energy and mining sectors or in coke and petroleum production while we do not exclude services sectors. Our genuine interest is in how firms in – and reallocation across– broad sectors of the economy – especially services, manufacturing, and construction – are affected. Second, we account for carbon-emissions embedded in the inputs used for production, such as energy. Furthermore, our focus lies on the US.[1] Despite these differences in design, our investigation comes to the same conclusion regarding the investment response of high-polluting firms. In addition, we show that low-emission firms benefit. Also, we extend the results to the effect of CPU shocks to the market value of low- and high-emission firms. Bouri, Iqbal and Klein (2022) show that higher CPU as measured by Gavriilidis (2021) is positively associated with a better performance of green stocks relative to stocks of dirty companies as captured in selected exchange traded funds (ETFs). Our empirical analysis focuses on the consequences of CPU shocks to granular firm-level variables, while Bouri et al. (2022) study the relation between levels of CPU and prices for ETFs. Our result – that firms in more energy-intensive industries reduce their investment when CPU rises – is consistent with those of Hoang (2022), who shows that heavy-emitter US firms reduce their R&D investment in the face of higher CPU. Noailly, Nowzohour and van den Heuvel (2022) find that a rise in environmental policy uncertainty is related to lower funding for green technology startups. This stands in contrast to our finding that higher climate policy uncertainty raises relative net investment in greener sectors. While Noailly et al. (2022) focus on the role of environmental policy uncertainty for high-risk green investment, we study the role of climate policy uncertainty for the reallocation of capital across large firms and broad sectors of the economy.

2 Climate policy uncertainty in a model of differently exposed sectors

We analyze the effect of climate political uncertainty in a two-sector model with energy use and financial frictions. The key difference between the sectors lies in the energy intensity of their production: dirty industries are more energy-intensive, green ones less so. In this setting, we consider various avenues for modeling CPU. As a first option, we capture CPU with taxes, whose future rates are uncertain and which are levied on

[1] The results of Berestycki et al. (2022) are likely to reflect mostly the effect on European firms as the Orbis firm-level dataset they use provides a better coverage of European firms than of US firms.

energy use and – in an alternative specification – on consumption goods produced by the sector with a higher energy intensity. In addition, we consider the case that uncertainty regarding climate regulations translates into uncertainty regarding the collateral value of assets in the dirty industries and hence affects the willingness of financial institutions to finance capital spending in dirty industries.

2.1 The model

The agents in the model are households, financial intermediaries and two non-financial firm sectors. The non-financial sectors feature goods producers, retailers and capital producers. Energy is exogenously provided and used by the goods producers of each sector as an input factor in production.

2.1.1 Households

The representative household i consumes, supplies labor and saves in bank deposits. The utility function of the household reads

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{(C_{i,t} - hC_{i,t-1})^{1-\sigma_c}}{1-\sigma_c} - \chi \frac{(L_{i,t})^{1+\sigma_l}}{1+\sigma_l} \right], \tag{1}$$

where $C_{i,t}$ is consumption by household i and $L_{i,t}$ is its supply of labor. Parameter h governs habit formation in consumption, σ_c is the coefficient of relative risk aversion, σ_l is the inverse of the Frisch elasticity, and β is the discount factor.

The household's budget constraint is

$$C_{i,t} + D_{i,t} = R_{t-1} D_{i,t-1} + \frac{W_{i,t}}{P_t} L_{i,t} + T_t, \tag{2}$$

where R_t is the real interest rate on the household's bank deposits, $D_{i,t}$. $W_{i,t}$ is the nominal wage set by household i, P_t is the consumer price index, and $T_{i,t}$ summarizes the net income from transfers, taxes and firms' profits. In equilibrium, all households are identical in their consumption and deposits ($\forall i : C_{i,t} = C_t$ and $D_{i,t} = D_t$).

$$\beta E_t \Lambda_{t+1} R_t = 1 \tag{3}$$

where $\Lambda_t = \frac{\lambda_t}{\lambda_{t-1}}$ denotes the households' stochastic discount factor, and $\lambda_t = (C_t - hC_{t-1})^{-\sigma_c} - \beta h E_t (C_{t+1} - hC_t)^{-\sigma_c}$ is the marginal utility of consumption.

Different types of labor are bundled according to the Dixit-Stiglitz aggregator

$$L_t = \left(\int_0^1 (L_{i,t})^{\frac{\epsilon_w - 1}{\epsilon_w}} di \right)^{\frac{\epsilon_w}{\epsilon_w - 1}}, \tag{4}$$

where L_t is the aggregate labor demand and ϵ_w is the elasticity of substitution across differentiated labor inputs within the production of each sector. Across sectors, we assume that there are no restrictions to labor mobility so that the wage equalizes across sectors. L_t is used as a factor input by cost-minimizing firms. This implies that household i faces the labor demand function

$$L_{i,t} = \left(\frac{W_{i,t}}{W_t} \right)^{-\epsilon_w} L_t, \tag{5}$$

where W_t is aggregate wage index,

$$W_t = \left(\int_0^1 (W_{i,t})^{1-\epsilon_w} di \right)^{\frac{1}{1-\epsilon_w}}. \tag{6}$$

Households set wages with a markup over their marginal rate of substitution between consumption and leisure, $MRS_{i,t} = \chi \frac{(L_{i,t})^{\sigma_l}}{\lambda_{c,t}}$. We assume Calvo-type wage setting with a fixed probability, ζ_w, so a household cannot update its wage in any given period. These assumptions result in a standard wage Phillips curve.

2.1.2 Production sectors green and dirty

Firms in the two non-financial sectors (green and dirty, i.e. $k \in G, D$) are comprised of goods-producing firms, retailers and capital producers. In the baseline model, the climate policy-related asymmetry between the two sectors lies in their energy use by goods-producing firms.

Goods-producing firms

Goods-producing firms in sector k act in perfect competition with each other. They produce output, $Y^k_{p,jt}$, using energy, E^k_t, as an input in addition to a capital-labor bundle KL^k_t. Their production follows the CES production technology

$$Y^k_{p,t} = \left[\kappa^k (E^k_t)^{\frac{\iota-1}{\iota}} + (1-\kappa^k)(KL^k_t)^{\frac{\iota-1}{\iota}} \right]^{\frac{\iota}{\iota-1}}, \tag{7}$$

where κ^k is a weight on the energy use in aggregate output in sector k and ι the elasticity of substitution between energy and the capital-labor bundle. The capital-labor bundle of firms of sector k has a standard Cobb-Douglas form

$$KL_t = A_t^k (K_{t-1}^k)^{\alpha_k} (L_t^k)^{1-\alpha_k}, \tag{8}$$

where K_{t-1}^k denotes the capital installed at the end of period $t-1$ and used in production in period t. A_t^k denotes the sector-specific productivity of this bundle. α_k is the output elasticity with respect to capital goods.

In line with the policy of introducing a tax on carbon emissions, we model a tax on energy use in production with the tax rate, τ_t^e. Cost minimization by goods-producing firms gives rise to their energy demand condition

$$(1+\tau_t^e) P_{E,t} = \kappa^k P_{m,t}^k \left(\frac{Y_{p,t}^k}{E_t^k} \right)^{\frac{1}{\iota}}, \tag{9}$$

where $P_{E,t}$ is the relative price of energy (in terms of domestic consumption) and $P_{m,t}^k$ is the output price of sector k.

The first order condition for the firms' labor demand is

$$W_t = \frac{(1-\alpha)(1-\kappa^k)}{L_t^k} P_{m,t}^k {KL_t^k}^{\frac{\iota-1}{\iota}} {Y_{p,t}^k}^{1/\iota}. \tag{10}$$

Whereas wages and the price of energy equalize across sectors, capital input is sector-specific. This gives rise to potentially differing returns on capital, $R_{k,t}^k$. We adopt the assumption by Gertler and Karadi (2011) that goods-producing firms buy capital at the beginning of the period, and re-sell it after using it in production. The demand for capital by final goods producers thus depends on the marginal product of capital and variations in the price of capital

$$R_{k,t}^k = \frac{\frac{\alpha(1-\kappa^k)}{K_{t-1}^k} P_{m,t}^k {KL_t^k}^{\frac{\iota-1}{\iota}} {Y_{p,t}^k}^{1/\iota} + (1-\delta) Q_t^k}{Q_{t-1}^k} \tag{11}$$

with δ being the depreciation rate and Q_t^k being the price of capital.

Capital-producing firms

Capital-producing firms buy the capital used, repair it and build new capital. The new and refurbished capital is then sold again to final goods producers at the price Q_t^k. The production of capital is subject to investment adjustment costs, which create a dynamic investment decision for capital goods producers. This setting gives rise to the investment

Euler equation

$$Q_t^k = 1 + \phi_K \left(\frac{I_t^k}{I_{t-1}^k} - 1 \right) \frac{I_t^k}{I_{t-1}^k} + \frac{\phi_K}{2} \left(\frac{I_t^k}{I_{t-1}^k} - 1 \right)^2 - \beta \phi_K E_t \left[\Lambda_{t+1}^k \left(\frac{I_{t+1}^k}{I_t^k} - 1 \right) \left(\frac{I_{t+1}^k}{I_t^k} \right)^2 \right]. \tag{12}$$

Retailers and the aggregate price level

Goods-producing firms in sector k sell their output goods to sector-k retailers, which bundle the goods, and sell them as final goods. Retailers are in monopolistic competition and set their prices with a markup over their marginal costs. They face price rigidities à la Calvo (1983) with the probability of not being able to reset the price in any given period denoted by ζ.

Goods market aggregation and carbon emission taxes on final goods

The households' consumption basket is composed of goods produced in sector G (green), C_t^G and in sector D (dirty), C_t^D

$$C_t = \left[\mu_G (C_t^G)^{\frac{\Theta-1}{\Theta}} (1-\mu_G)(C_t^D)^{\frac{\Theta-1}{\Theta}} \right]^{\frac{\Theta}{\Theta-1}}, \tag{13}$$

where μ^G is a consumption weight and Θ is the elasticity of substitution between the different consumption goods types. The corresponding price index reads

$$P_t = \left[\mu_G (P_t^G)^{1-\Theta} (1-\mu_G)((1+\tau_t)P_t^D)^{1-\Theta} \right]^{\frac{1}{1-\Theta}}. \tag{14}$$

Here, τ_t is a consumption tax on goods produced with a higher energy intensity.

2.1.3 Financial sector

Our model features a balance sheet-constrained banking sector in the vein of Gertler and Karadi (2013). Banks fund themselves with deposits by households and extend loans to firms in both sectors – green and dirty – financing their capital stocks. The differences in climate-related risks give rise to different pledgeabilities (or collateral values) of capital assets from the green and dirty sector. Additionally, there is the possibility that climate policy manifests itself in the form of variations in the pledgeability of non-green assets.

More formally, bank j maximizes its value function, V_{jt}, subject to a balance sheet constraint and an incentive constraint

$$V_{jt} = \max_{\{K_{j,t}^G\},\{K_{j,t}^D\}} \quad \beta E_t \Lambda_{t+1} [(1-\theta)N_{j,t+1} + \theta V_{j,t+1}]$$

$$
\begin{aligned}
s.t. \qquad Q_t^G K_{jt}^G + Q_t^D K_{jt}^D &= N_{jt} + D_{jt} \\
V_{jt} &\geq \lambda_G Q_t^G K_{jt}^G + \lambda_{D,t} Q_t^D K_{jt}^D.
\end{aligned}
$$

Λ_t is the stochastic discount factor of households, $N_{j,t}$ is the bank's net worth, and parameter θ is the survival probability of banks. $K_{j,t}^G$ and $K_{j,t}^D$ are claims on the capital stock of the green and the dirty sector, respectively. Q_t^G and Q_t^D are the real prices of capital of firms in the respective sector. D_{jt} are the deposits. λ_G and $\lambda_{D,t}$ govern the divertability of the respective assets for banks. Throughout all exercises in this paper, we make the assumption that the incentive constraint is always binding.

We consider the notion that uncertainty regarding climate policy can affect the pledgeability of assets from the dirty sector. To capture this, we allow for exogenous variations in $\lambda_{D,t}$ that follow an AR(1) process with stochastic volatility (see section 2.1.5). This specification captures in particular uncertainty regarding financial regulations on climate-related risk provisions, as outlined above. It can, however, be interpreted more broadly, as it also reflects the attempt by investors to decarbonize their portfolio and to avoid unsustainable assets. This type of climate-related uncertainty can also translate into uncertainty regarding the pledgeability of dirty assets.

Additionally, the law of motion of net worth is

$$
N_{jt} = (R_{kt}^G - R_{t-1}) Q_{t-1}^G K_{j,t-1}^G + (R_{kt}^D - R_{t-1}) Q_{t-1}^D K_{j,t-1}^D + R_{t-1} N_{j,t-1},
$$

where R_{kt}^G and R_{kt}^D are the real returns on capital of firms in sector A, and R_t is the return on deposits.

To solve for the banks' optimization problem, we guess that the value function is linear in capital claims on both sectors and net worth

$$
V_{jt} = \nu_{kjt}^G Q_t^G K_{jt}^G + \nu_{kjt}^D Q_t^D K_{jt}^D + \nu_{njt} N_{jt}.
$$

As is demonstrated in Appendix B.1, verifying this guess shows that the shadow values of holding assets and equity are tied to the respective (excess) returns

$$
\begin{aligned}
\nu_{kjt}^G &= \beta E_t \Omega_{j,t+1}^G (R_{k,t+1}^G - R_t), \\
\nu_{kjt}^D &= \beta E_t \Omega_{j,t+1}^G (R_{k,t+1}^D - R_t), \\
\nu_{njt} &= \beta E_t \Omega_{j,t+1}^G R_t,
\end{aligned}
$$

where $\Omega_{j,t}^G \equiv \Lambda_t^G ((1-\theta) + \theta(1+\mu_{jt})\nu_{njt})$ is the stochastic discount factor of banks, which incorporates the households' stochastic discount factor as well as the limited expected life span of banks and the tightness of constraint. For aggregation, we assume an equilibrium in which all banks are symmetric (i.e. $\forall j : \nu^G_{kjt} = \nu^G_{bt}, \nu^D_{kjt} = \nu^D_{bt}, \nu_{njt} = \nu_{nt}, \Omega^G_{jt} = \Omega^G_t$).

2.1.4 Fiscal and monetary authority

In our modeling of the fiscal sector, we confine ourselves to the aspect of climate-related taxes on products from the dirty sector and on energy. The revenues generated this way are distributed to households via a lump-sum tax.[2] The budget constraint of the fiscal authority thus simply reads

$$\tau^D_t P^D_t Y^D_t + \tau^E_t P^E_t E_t = T_t. \tag{15}$$

The central bank sets the short-term nominal interest rate following the Taylor-type rule

$$R_{n,t} = (R_{n,t-1})^\rho \left(\left(\frac{\Pi_t}{\Pi}\right)^{\phi_\pi} \left(\frac{Y_t}{Y}\right)^{\phi_y} \right)^{(1-\rho)}, \tag{16}$$

where $R_{n,t} = R_t E_t[\Pi_{t+1}]$. Parameter ρ is the degree of interest rate smoothing. ϕ_π and ϕ_y govern, respectively, the feedback of the policy rule to inflation and output.

2.1.5 Climate policy uncertainty

In our model, we incorporate climate policy uncertainty by modeling taxes, whose future path is uncertain, and by uncertainty regarding the pledgeability (collateral value) of assets from companies in the dirty sector.

The tax rates for goods with a relatively large carbon footprint and for energy follow exogenous auto-regressive processes with stochastic volatility

$$\tau^D_t = \rho_{\tau^D} \tau^D_{t-1} + \sigma^{\tau^D}_t \epsilon^{\tau^D}_t, \tag{17}$$

$$\tau^e_t = \rho_{\tau^e} \tau^e_{t-1} + \sigma^{\tau^e}_t \epsilon^{\tau^e}_t. \tag{18}$$

Parameters ρ_{τ^D} and ρ_{τ^e} govern the persistence of the exogenous tax rate processes. $\sigma^{\tau^D}_t$ and $\sigma^{\tau^e}_t$, which represent the volatilities of the processes, themselves follow exogenous, stochastic processes

$$\sigma^{\tau^D}_t = \rho_{U,\tau^D} \sigma^{\tau^D}_{t-1} + \sigma^{U,\tau^D} \epsilon^{U,\tau^D}_t, \tag{19}$$

$$\sigma^{\tau^e}_t = \rho_{U,\tau^e} \sigma^{\tau^e}_{t-1} + \sigma^{U,\tau^e} \epsilon^{U,\tau^e}_t. \tag{20}$$

[2] Redistribution schemes of this kind have been the subject of political debate in Germany, for example (see e.g. van der Ploeg, Rezai and Tovar Reanos 2022).

ρ_{U,τ^D} and ρ_{U,τ^e} are persistence parameters, and σ^{U,τ^D} and σ^{U,τ^e} are the standard deviations of the volatility process.

We assume that ϵ_t^{τ}, $\epsilon_t^{\tau^e}$, $\epsilon_t^{U,\tau}$, and ϵ_t^{U,τ^e} are normally distributed. This implies that a decrease in tax rates is deemed as likely by agents in the model as an increase. In reality, in the long run, the ongoing change in climate conditions will likely force governments to tighten their climate policies, rather than to loosen them. Nonetheless, in the recent past, US climate politics has been characterized by reversals, such as the exit from the Paris Agreement or the Supreme Court's ruling in the case *West Virginia vs. Environmental Protection Agency (EPA)* that limits the EPA's power to regulate carbon emissions in the power sector. With this in mind, we deem the assumption of symmetric up- and downside risks to be an acceptable simplification for the analysis of short-run dynamics.

In the same way, uncertainty over variations in the collateral value (or pledgeability) of capital of the dirty sector can be captured by modeling the pledgeability of dirty sector capital as a time-varying exogenous process (λ_t^D) with stochastic volatility ($\sigma_t^{\lambda,D}$)

$$\lambda_t^D = \rho_\lambda \lambda_{t-1}^D + \sigma_{\lambda,t}^D \epsilon_t^{\lambda,D}, \tag{21}$$

$$\sigma_{\lambda,t}^D = \rho_{\sigma_\lambda} \sigma_{\lambda,t-1}^D + \epsilon_t^{\sigma_\lambda,D}. \tag{22}$$

This separately modelled shock captures the fact that not only carbon taxes, but also regulatory changes that directly address the pledgeability of dirty assets on the balance sheet of banks, may be a source of political uncertainty.

2.2 Calibration

In our stylized setup, we consider the case of equally sized sectors, i.e. $\mu^G = 0.5$. The green and dirty sectors differ in their energy intensity in production. In the baseline calibration, we assume that the green sector is less energy-intensive, with $\kappa^G = 0.05$ and $\kappa^D = 0.38$. Given a low elasticity of substitution of energy and non-energy inputs in production of $\iota = 0.1$, and output levels in both sectors that are normalized to 1, this implies that the steady state cost share of energy in production of the dirty sector is 6.2% and thus 22 percent higher than in the green sector. The implied energy share for the aggregate economy is broadly consistent with the calibrated energy share in Hassler et al. (2019), who set the energy share to 5.5%. Moreover, calibrating the short-run elasticity of substitution between energy and non-energy inputs in production at close to a rather low value of around 0.1 is in line with insights from the literature studying the interrelation between oil markets and the macroeconomy (for a discussion, see e.g. Khalil 2022). The notion of a very low substitutability of energy and capital/labor inputs is confirmed by

Table 1: Calibration

Symbol	Parameter	Value
μ^G	Preference for green goods	0.5
Θ	Elast. of substit. between A-goods, B-goods and energy	0.44
κ_G	Share of energy in production in green sector	0.05
κ_D	Share of energy in production in dirty sector	0.38
ι	Elast. of substit. between energy and capital-labor bundle	0.1
σ_c	Coefficient of relative risk aversion	2
σ_l	Inverse Frisch elasticity	1
β	Discount factor	0.995
h	Habit formation	0.8
ϕ_K	Capital adjustment cost	10
α	Capital share in cap.-labor bundle	0.36
δ	Depreciation rate	0.025
ζ	Price Calvo parameter	0.75
ζ_w	Wage Calvo parameter	0.75
ϵ	Elasticity of goods demand within sectors	6
ϵ_w	Elasticity of labor demand	6
LEV	Leverage rate	10
θ	Survival rate of banks	0.95
$R_b^k - R_d$	Spread of G- and D-assets returns over deposit rate	25 bp
ρ	Taylor rule: interest rate smoothing	0.8
ϕ_π	Taylor rule: inflation coefficient	2
ϕ_y	Taylor rule: output coefficient	0.125
$\rho_\tau, \rho_{\tau^e}, \rho_\lambda$	Persistence of carbon tax shocks	0.99
ρ_λ	Persistence of collateral value shock	0.99
$\rho_{\sigma_\tau}, \rho_{\sigma_\tau^e}, \rho_{\sigma_\lambda}$	Persistence of climate policy uncertainty shock	0.95

Hassler, Krusell and Olovsson (2021). In an estimated model of input-saving technical change, their posterior mean of this parameter is even lower at 0.02.

We set the households' elasticity of substitution between green and dirty goods to $\Theta = 0.44$. This reflects the estimate for the elasticity of substitution between tradables and non-tradables by Stockman and Tesar (1995). The distinction between tradables and non-tradables is closely associated with the distinction between manufactured goods and services (see, e.g. Khalil 2022), which guides our empirical analysis due to the markedly higher energy intensity of production in the manufacturing sector.

To reflect the fact that changes in taxes and financial regulations are usually designed to be long-lasting, we set the persistence parameters ρ_τ^D, ρ_{τ^e}, and ρ_λ^D to 0.99. The persistence parameters of shocks to the standard deviations of the climate-related tax rates and the pledgeability of dirty assets, $\rho_{\sigma_\tau^D}$, $\rho_{\sigma_\tau^e}$, and $\rho_{\sigma_\lambda^D}$ are set to 0.95. This matches the autocorrelation of the news-based CPU measure by Gavriilidis (2021) purged of effects of a number of control variables.[3] In steady state, we set the standard deviation of the climate tax on products from the dirty sector to 1%. For the standard deviation of the tax rate on energy use, we opt for 10%. This reflects that CPU is, to a large degree, centered around questions of energy efficiency, the design of energy markets or the use of fossil

[3]In particular, we obtain the residuals by regressing the log of the CPU measure on economic policy uncertainty, macroeconomic and financial uncertainty as well as on gas and oil prices and compute the autocorrelation of the series of accumulated residuals.

energy sources. In addition, the price of emission allowances in the EU, which have to be bought by energy-producing firms has often been rather volatile. We set the standard deviation of the pledgeability of dirty assets such that CPU shock to the product tax rate and the CPU shock to the dirty assets' pledgeability both trigger a decline in the dirty sector's capital stock of the same magnitude.

The calibration of the financial parameters is largely guided by Gertler and Karadi (2011), whose framework we adopt. One exception is the steady state leverage ratio, LEV. The higher this is, the stronger are the effects of uncertainty shocks, as with a higher LEV, smaller variations in asset prices can wipe out the financial intermediaries' net worth. $LEV = 10$ is higher than the value of 4 chosen by Gertler and Karadi (2011), but smaller than the average leverage ratio of banks in the US.[4] The quarterly steady state spread of assets over deposits is set to 25 bps.

In the calibration of the rest of the parameters, we largely stick to values commonly adopted in the literature. For the household sector, we choose a coefficient of relative risk aversion $\sigma_c = 2$, and an inverse of the Frisch elasticity $\sigma_l = 1$. The discount factor $\beta = 0.995$ implies that the annualized real interest rate on deposits is 2% in steady state. $h = 0.8$ implies a persistent habit formation in consumption. ϕ_K, the parameter governing investment adjustment costs, is set to 10. Likewise, the elasticity of substitution between varieties of goods produced in one sector, $\epsilon = 6$, and between varieties of labor, $\epsilon_w = 6$, fall within the range of values commonly adopted in the literature. $\delta = 0.025$ and ζ and ζ_w denote the probabilities for each firm and each union to adjust their prices or wages, respectively, in any given period. The value of 0.75 implies an average duration for prices and wages of one year. The central bank's Taylor rule features substantial interest rate smoothing ($\rho = 0.8$), as usually diagnosed in the context of estimations of structural models.[5] $\phi_\pi = 2$ and $\phi_y = 0.125$ are standard values for the feedback coefficients.

2.3 Consequences of climate policy uncertainty shocks

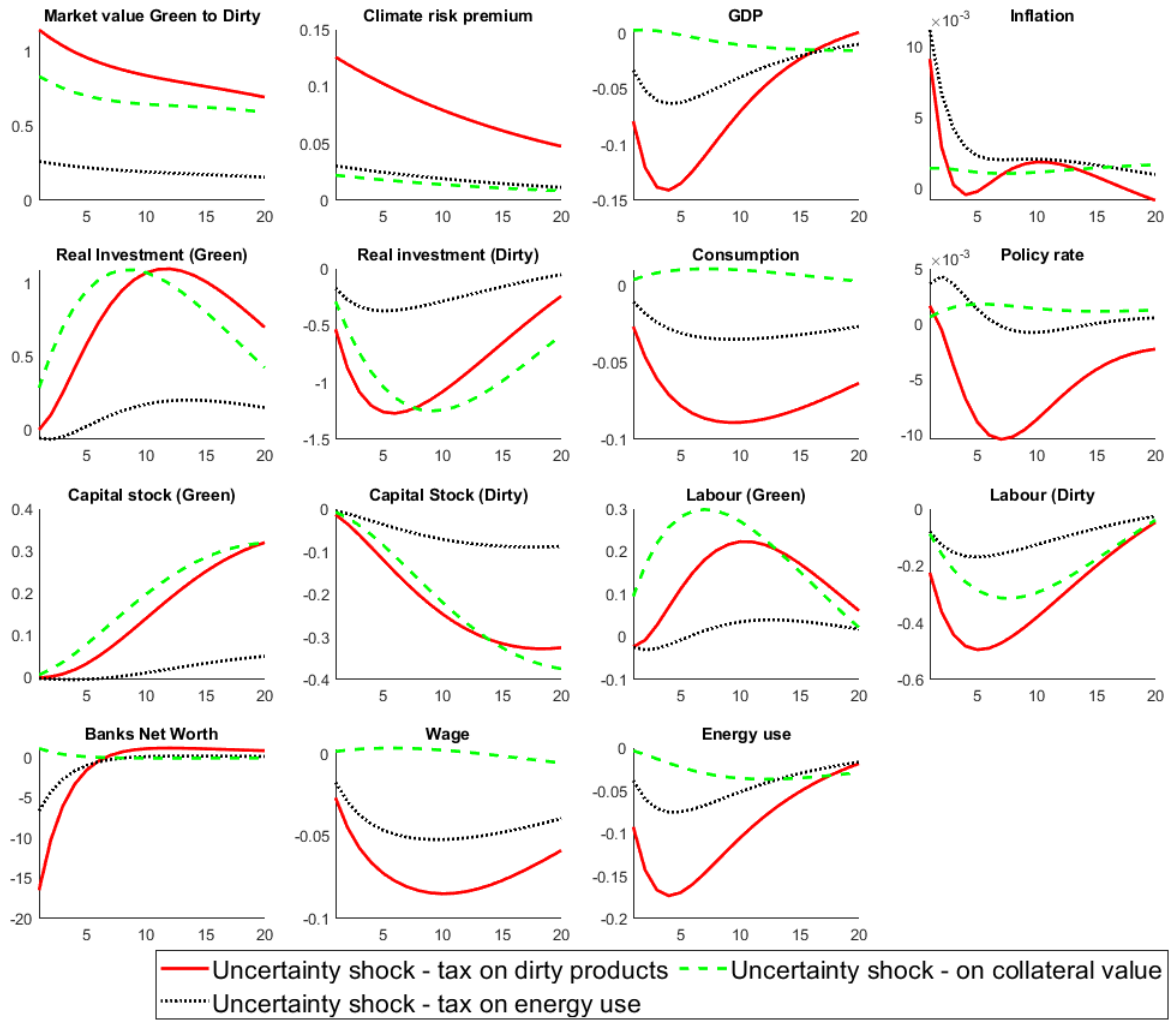
Climate policy can take many different forms. In this section, we discuss the effects of the different climate policy uncertainty shocks embedded in the model.[6] Figure 1 displays the effects of uncertainty shocks to a tax on products from the dirty sector (red), on the energy tax rate (black-dotted) and on the collateral value of assets from the dirty sector (green-dashed). The size of the shock is set to four standard deviations so as to match

[4] See Board of Governors of the Federal Reserve System (2022).

[5] See e.g. Smets and Wouters (2007) or, in more recent estimations on US data, Kulish, Morley and Robinson (2017) or Boehl and Strobel (2020).

[6] The uncertainty shocks are simulated using the non-linear moving average toolkit by Lan and Meyer-Gohde (2013).

Figure 1: Effects of a climate policy uncertainty shock



Note: The figure presents theoretical impulse responses to a shock with the size of 4 standard deviations. y-axis in percent.

the identified CPU shocks associated with the climate strikes in 2019 (see section 3). However, as a precise calibration of the standard deviation of climate policy measures in the model is fraught with difficulties, we focus less on the quantitative implications of CPU shocks in the model and more on the conceptual insights.

2.3.1 Capital reallocation

One key result of our analysis is that for all types of CPU shocks considered, financial institutions respond to an increase in climate policy uncertainty by shifting their portfolio to assets of the green sector. In optimum, financial institutions balance the return on assets with the limit that is placed on their asset holdings by the pledgeability parameters, λ^G and λ_t^D, in the incentive constraint. In the case of both carbon taxes, uncertainty shocks affect the marginal revenue product of capital and translate into uncertainty over the return on the assets of dirty firms. With the third type of CPU shock, the collateral value becomes uncertain. As a consequence, in all cases risk-averse banks require a climate risk premium on the yield of assets from the dirty, energy-intensive industries and divest from that sector. This lowers the price of dirty assets, reduces lending to – and investment by – firms in the energy-intensive sector. The market value of green assets outperforms the value of dirty assets.[7]

CPU shocks not only cause divestment in the dirty sector; they can also raise investment in the green sector and boost the market value of green assets. Generally, the response of green investment is driven by two counteracting types of forces: those that support a contraction of real investment, and those that support a shift of funds from the dirty to the green sector. In the case of CPU shocks to climate-related tax rates, the increase in uncertainty can weigh on aggregate demand as risk-averse households raise their precautionary savings and hold back on spending. At the same time, firms, which may not be able to adjust their prices in future periods due to price stickiness, raise their prices when uncertainty increases in order to lower the probability of being stuck with a negative markup. These forces dampen firms' sales and production, reducing their demand for capital. The CPU shocks to the climate-related tax rates also have a detrimental effect on banks' balance sheets. As the returns, particularly that of dirty assets, become more uncertain, risk-averse banks place a lower value on their assets. The price of these assets falls and so does the net worth of banks, forcing them – via the incentive constraint (Eq. 15) – to further reduce their overall asset holdings. This shrinks their capacities to fund capital expenditures in the non-financial sectors. On the other hand, banks that divest from the dirty sector seek to re-invest their funds in the green sector, thus supporting investment in that sector.

In the case of a positive CPU shock to the collateral value of dirty assets, the portfolio reallocation towards green asset is predominant. There is no general decline in aggregate activity and asset prices, and no broad contraction of bank lending to firms. Instead, the decline in banks' dirty asset holdings is balanced by an expansion in the holdings of green assets. The price of green assets increases and even raises the net worth of banks. The

[7]We provide more details on the effects of CPU shocks to banking sector variables in Appendix B.1. The reallocation of capital in this model is similar to the international portfolio shift towards relatively safe US dollar assets due to higher trade policy uncertainty in Khalil and Strobel (2021). In that paper, the safe asset property of USD assets motivates an ex-ante asymmetry in the pledgeability of USD assets and non-USD assets. In contrast, the reallocation of capital following CPU shocks in our model is due to the asymmetric exposure of green and dirty assets to climate policy uncertainty across sectors.

changed composition on the asset side of banks' balance sheet is mirrored by an increase in real investment in the green non-financial sector and a fall in dirty real investment. Labor input follows the same pattern due to the changes in the marginal productivity of labor induced by the capital movements. The effect on aggregate consumption, GDP and inflation is muted.

CPU shocks to climate-related tax rates have a more immediate impact on the composition of final goods demand and on the composition of the factors used in production. Both the uncertainty shocks to the carbon tax rate on dirty products and the uncertainty shocks to the tax on energy use lower aggregate consumption and trigger a decline in aggregate output. On impact, this lowers the investment response in the green sector. However, subsequently, the influx of funds from the banking sector lifts investment in the green sector such that the capital stock sees a marked increase. The reallocation of labor between sectors follows the reallocation of capital, with labor input in the green sector rising after a brief initial dip. The decline in consumption lowers the reservation wage of workers and, in equilibrium, the real wage. However, the standard deviation of the tax rate on energy use is higher than that of the tax rate on dirty products, and the uncertainty shock to the latter has a stronger impact on consumption, investment and prices. The reason is that product taxes directly affect consumer prices and thus the nominal stochastic discount factor of households, which households, firms and banks use to price the risk of future income streams. In the case of uncertainty regarding the cost of the energy input, the effects on consumption are cushioned by internal decisions by the firm to substitute inputs.

At this point, it is worth highlighting how our results relate to those of other papers in the literature that investigate the effects of climate transition risk. Previous work explores the effects of risks that come with gradual adjustment paths of carbon emissions or an unresolved ambiguity regarding the impositin of a future carbon tax (Diluiso et al. 2021; Carattini et al. 2021; Fried et al. 2022). In contrast, we model CPU shocks as second-order shocks, borrowing from the macroeconomic literature on uncertainty shocks (see e.g. Bloom, 2009) and accounting for channels that have previously been discussed in this literature, such as precautionary savings, precautionary markups or the role of risk for asset prices. This choice is motivated by the observation that in the short run, many climate policy scenarios are possible – including reversals in the stringency of climate measures.

Fried et al. (2022) also discuss risk associated with climate policy. They find that this risk of a carbon tax being imposed in the future on fuel lowers the share of dirty capital in production. In their model, they abstract from financial frictions. We corroborate the finding in our model, which relies on financial channels as our main mechanism. The considerations of financial intermediaries on reducing their holdings of dirty assets that are exposed to climate policy are essential for our main results, as shown in section 2.3.3.

2.3.2 Macroeconomic consequences

Importantly, while our analysis suggests that climate policy uncertainty can have sizable reallocation effects between sectors, the consequences for macroeconomic aggregates are smaller. The decline in GDP is at least one magnitude smaller than the response of investment at the sectoral level. Likewise, though we simulate shocks that have sizeable effects on asset values and sectoral investment streams, consumer price inflation only shows a very weak response. The lower responsiveness of macroeconomic aggregates to the CPU shock compared to sectoral variables is robust to a removal of the financial sector from the model.

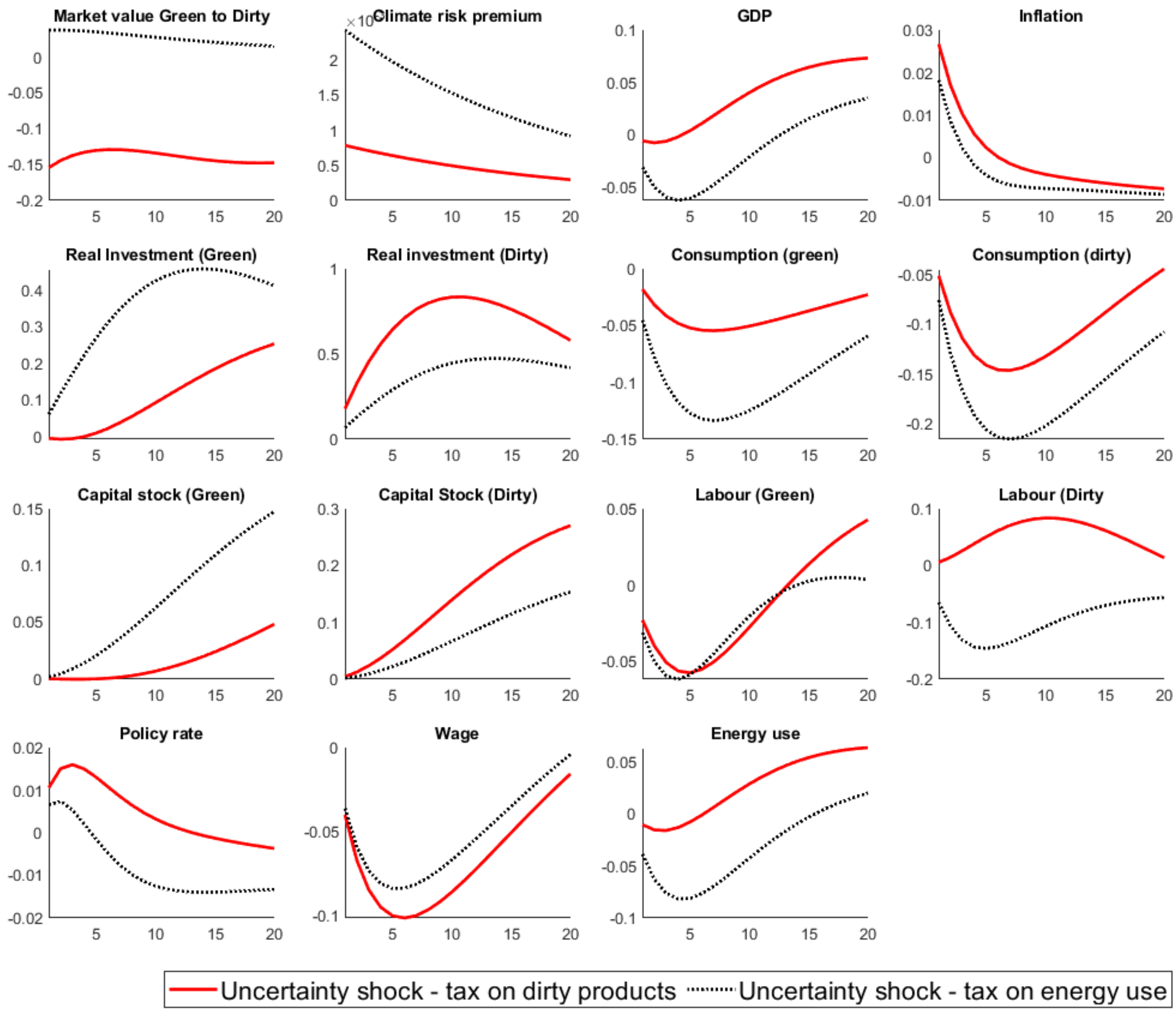
2.3.3 The role of the financial channel

The presence of balance sheet-constrained lenders is key to capital reallocation from the dirty to the green sector. First, it allows us to investigate the effects of an uncertain collateral value of assets from the dirty industries. Second, in the absence of financial frictions, a CPU shock can even raise investment in the dirty sector.

To illustrate this, Figure 2 depicts the effect of uncertainty shocks to climate tax rates in a model without financial frictions. For both the CPU shock to the tax on dirty products and on energy use, investment increases in both sectors in the absence of balance sheet-constrained financial intermediaries. In the case of the uncertainty shock to the tax on dirty products, investment rises by more in the dirty sector.

A rising capital stock in the face of increased uncertainty is well known in the literature and can have different reasons (see e.g. Born and Pfeifer 2014, Caldara, Iacoviello, Molligo, Prestipino and Raffo 2020). In the case where the utility function of households is separable into consumption and leisure, an increase in uncertainty that dampens consumption triggers an increase in hours worked via a wealth effect on the labor supply. The higher labor input in production raises the marginal product of capital, making investment in the physical capital stock more attractive for firms in both sectors. A second reason is embedded in the production function of firms, which features predetermined capital and flexible labor adjustment. Any shock that raises output prices has a direct positive effect on the marginal revenue product of capital. In addition, firms can expand their optimal output by flexibly raising their labor input. Thus, their marginal revenue product of capital rises by more than one to one with the output price, and can be

Figure 2: Effects of a climate policy uncertainty shock (absent financial frictions)



Note: Results from a model without banks and financial frictions. The figure presents theoretical impulse responses to a shock with the size of 4 standard deviations. y-axis in percent.

convex in output prices. An increase in the uncertainty of output prices can therefore make it attractive for firms to expand their capital stock.[8] This applies in the case of a CPU shock to the tax on dirty products, which translates into uncertainty regarding the output prices of firms in the dirty sector.

Figure 2 shows, for the case of CPU shocks to dirty product taxes, that capital is reallocated from the green to the dirty sector and that the market value of green assets falls behind that of dirty assets. Thus, for the transmission of CPU shocks to taxes on dirty products, financial frictions are an essential element for facilitating the reallocation

[8]This is called the Oi-Hartmann-Abel effect (Oi, 1961; Hartman, 1972; Abel, 1983).

of capital towards the green sector that we observe in our empirical analysis.

2.3.4 Sensitivity analysis

Our main results are quite robust, particularly concerning the effects of CPU shocks to the collateral value of dirty assets. In this section, we very briefly discuss the sensitivity of our main results to some changes in calibration. More details are provided in Appendix B.2.

Whereas the effects of CPU shocks to product taxes and to dirty assets' collateral value are robust to the changes in the elasticity of substitution between energy and non-energy inputs in production, the effects of a CPU shock to energy taxes can reverse given sufficiently high values of ι. In that case, firms – particularly in the energy-intensive dirty sector – quickly reduce their energy use and increase their capital input instead. Real investment in the dirty sector rises. Banks finance the transition of the dirty sector to reduce the exposure of their assets to uncertainty on energy taxes. As a result, funds in the green sector dry up. Consequently, relative market values of green to dirty assets and the climate risk premium decrease. However, as mentioned in section 2.2, the notion that the elasticity of substitution between energy and non-energy inputs can be low in the short run is rather common.

Whether green investment increases or decreases in absolute terms after a CPU shock, depends on the calibration of other parameters as well. For instance, given high values for the substitution elasticity of green and dirty goods in consumption, Θ, consumers shift their demand towards green goods in the face of CPU shocks in order to avoid uncertainty regarding their expenditures. This supports production and investment in the green sector. However, if Θ is sufficiently low, this channel is attenuated and investment in the green sector falls on impact. Low values for the elasticity of the capital-labor bundle with respect to capital, α, deepen the decline of aggregate investment for CPU shocks related to taxes, such that real investment in both sectors can drop on impact. Nonetheless, for variations in these parameters, the relative increase in green to dirty investment holds. Similarly, the rise in the market value of green assets over dirty assets and in the climate risk premium are robust. Lastly, the results are qualitatively robust to changes in κ^G and κ^D, which determine the energy intensiveness of production in the respective sectors.

3 Empirical evidence

We test our theoretical predictions in a firm-level dataset of listed firms in the US based on the following empirical strategy: First, to identify climate policy uncertainty shocks, we extract orthogonalized innovations from a news article-based climate policy uncertainty measure (Gavriilidis 2021). Second, we categorize firms into green and dirty based on direct and indirect use of carbon-emitting intermediate inputs (especially energy). The categorization takes into account domestic and international input-output linkages to capture all carbon emissions required to produce one unit of a firm's final goods. Third, we study heterogeneity across low- and high-emission firms in the impact on firms' stock market valuations and real investment decisions in response to climate policy uncertainty shocks.

3.1 Identifying climate policy uncertainty shocks

In order to identify shocks to uncertainty in US climate policy, we use the monthly measure of Gavriilidis (2021), who employs the same methodology as Baker et al. (2016). In particular, Gavriilidis (2021) screens articles of eight leading US newspapers for phrases indicating uncertainty over policy, legislation, and regulation in the context of climate-related issues (e.g. global warming, greenhouse, carbon emissions, renewable energy). As we are interested in shocks to climate policy uncertainty that are unrelated to overall economic policy uncertainty as well as macroeconomic uncertainty and conditions in global energy markets, we estimate following regression model

$$\begin{aligned}\Delta \ln cpu_t = \beta_0 + \beta_1 \Delta \ln epu_t + \beta_2 \Delta \ln unc_t^{macro.} + \\ + \beta_3 \Delta \ln unc_t^{finan.} + \beta_4 \Delta \ln p_t^{oil} + \beta_5 \Delta \ln p_t^{gas} + u_t, \quad (23)\end{aligned}$$

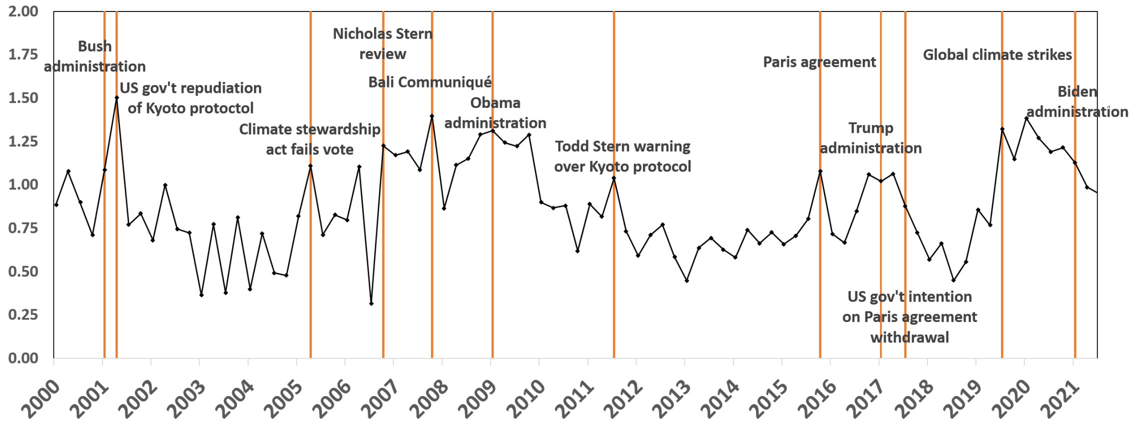
where cpu_t is climate policy uncertainty, epu_t is economic policy uncertainty, $unc_t^{macro.}$ and $unc_t^{finan.}$ measure macroeconomic and financial uncertainty, and p_t^{oil} and p_t^{gas} are prices for crude oil and natural gas.

We extract climate policy uncertainty shocks cpu_t^{ϵ} as the fitted residuals in regression (23). We use, at a monthly frequency, the economic policy uncertainty index of Baker et al. (2016) to measure epu_t. $unc_t^{macro.}$ and $unc_t^{finan.}$ are measured by the corresponding estimates of Jurado et al. (2015) and Ludvigson, Ma and Ng (2021). p_t^{oil} is the spot price for West Texas Intermediate crude oil and p_t^{gas} is the natural gas spot price (Henry Hub).[9] As the analysis in section 3.3 is based on quarterly data, we convert the monthly shock series into a quarterly series by using a simple average.

For data from 2000Q1 to 2021Q4, Figure 3 shows the cumulative impact of climate

[9]All data sources are described in Appendix C.1. As a robustness exercise – employing the measure of Engle, Giglio, Kelly, Lee and Stroebel 2020 – we also control for climate policy news, which leads to a very similar shock series (see Figure D.7 in the Appendix) but has the disadvantage of limited data availability for the time span under consideration.

Figure 3: Cumulative effects of climate policy uncertainty shocks to climate policy uncertainty



Note: The series is normalized to start at 1 in 1999Q4.

policy uncertainty shocks to climate policy uncertainty and adds selected events related to climate policy in the US and globally. The identified CPU shocks resonate quite well with historically interesting events surrounding the context of US climate policy. For instance, the beginning of the Bush administration and especially the repudiation of the Kyoto protocol imposed positive climate policy uncertainty shocks, likely indicating that the announcements of the Bush administration made the path of US climate policy more uncertain. In October 2007 – as another example – the "Stern review" was published, leading to intensified debate over future climate policy around the globe. At the end of 2015, CPU spiked with the announcement of the Paris agreement, which clarified global policy goals in terms of greenhouse emission reductions but was less clear on concrete implications for national and international climate policies. Interestingly, the first years of the Trump administration are marked by a number of negative climate policy uncertainty shocks, possibly indicating that the (then more deregulatory) path of US policy with respect to climate and environmental concerns was not perceived as uncertain.[10] The global climate strikes in 2019, which were unrelated to concrete US climate policy actions, triggered a large positive shock to CPU.

3.2 Classifying US sectors by their carbon emissions

To categorize firms into "more greenish" and "more dirty" firms in terms of carbon emissions we employ environmental account estimates of Román, Corsatea, Amores, Neuwahl, Velázquez Afonso, Rueda-Cantuche, Arto and Lindner (2019) in combination with the World Input-Output Database (WIOD) (Timmer, Los, Stehrer and de Vries,

[10]Notwithstanding this, uncertainty on US trade policy increased substantially under the Trump administration. See Caldara et al. (2020) and Khalil and Strobel (2021).

2013; Stehrer, de Vries, Los, Dietzenbacher and Timmer, 2014). These datasets allows us to characterize US sectors by their carbon emission requirements. In particular, because we have information on domestic and international input-output linkages, the dataset not only provides carbon intensities – i.e. carbon emissions of a sector per one unit of gross sector output – but also enables us to infer carbon emission requirements taking into account that sectors source inputs from other – potentially heavily carbon-emitting sectors (in particular energy).

More specifically, assume a number of N countries and M sectors (in particular $N = 43$ and $M = 56$ in the most recent WIOD release for the years 2000-2014). In our input-output framework, we then have

$$A * x + c = x, \tag{24}$$

$$x = L * c. \tag{25}$$

where the coefficient matrix A has dimension $(NM) \times (NM)$, and the gross output vector x as well as the final consumption vector c have dimension $(NM \times 1)$. In this system, $L = (I - A)^{-1}$ is the Leontief inverse with dimension $(NM) \times (NM)$.

Given the $(NM \times 1)$ vector of carbon emissions (in tonnes) in every sector $carbon^{emm}$, we obtain the $(NM \times 1)$ vector of carbon intensities $CO2_{int}$ – i.e. carbon emitted by sector i per one unit of output of sector i – as

$$CO2_{int} = CO2_{emm} \oslash x, \tag{26}$$

where $\oslash$ indicates pair-wise division. It is straightforward to compute a $(NM \times 1)$ vector of carbon emission requirements $CO2_{req}$ – i.e. the total carbon emissions required to produce one unit of gross output of sector i – as

$$CO2_{req} = L * CO2'_{int}. \tag{27}$$

The vector $CO2_{req}$ summarizes carbon emission requirements for all sectors in the N countries of the WIOD database, but we are ultimate interested only in US sectors.

3.3 Evidence based on firm-level data

In our panel regression we employ quarterly firm-level data for the US, provided by Compustat. The data set included listed firms and provided balance sheet information.

Table 2: Descriptive statistics: Compustat dataset averages 2000Q1-2019Q4.

	CO2 Req	CO2 Int	Market Val.	Sales	Invest.	Largest 2-digit NAICS categories
1	0.13	0.01	2660	505	2.1	Information, Wholesale Trade, Professional/Scientific
2	0.20	0.05	2058	544	3.6	Professional/Scientific, Real Estate, Retail Trade
3	0.27	0.06	2453	361	1.7	Manufacturing, Hospitality, Support Services
4	0.42	0.05	2015	245	1.4	Manufacturing, Construction
5	0.79	0.34	2935	499	4.3	Manufacturing (Durables- and Nondurables)

Note: All balance sheet figures are in (const. 2019) USD millions. Carbon emission requirements and intensity are in tonnes of carbon (per one unit of ouput in const. mil. produced). All measures are group averages.

In our benchmark analysis we exclude sectors with particularly high carbon emissions, such as utilities, mining, and coke/petroleum production. The main reason is that we aim to focus on capital reallocation across broad economic sectors (such as services, manufacturing, construction) that emit carbon especially indirectly by sourcing energy. Moreover, we exclude financial services to avoid spurious results in assessing the financial channel at the firm level.

We match each firm in the dataset with the categorization of carbon emission requirements at the sector level from equation (27). If a company belongs to more than one sector, we take simple averages. We restrict the start of the panel to 2000Q1 (given the availability of our CPU measure) and the end to 2019Q4 (before the Covid-19 pandemic). We order all firms according to the average total carbon emission requirement (per one unit of output) of their sector to obtain five categories of $GreenCat$.

Table 2 shows that the five groups differ substantially in their required carbon emissions. While the group with the lowest emissions takes a value of 0.13 tonnes of carbon per USD 1 million of output produced, the largest emitters require 0.79 tonnes. Moreover, the table shows that carbon emissions are heavily tilted towards manufacturing, whereas services require relatively little emissions.

For other firm characteristics, the five groups do not vary that substantially. For instance, the groups are similar in terms of average market value and sales – despite some differences, such as lower sales in group 3 and 4 compared to group 1, 2 and 5. With regard to investment the statistics are more mixed. Investment is lowest on average in group 4, indicating that investment is not necessarily tilted towards the sectors with higher emissions.

To gauge the impact of climate policy uncertainty on capital reallocation, we estimate the following panel regression

$$x_{i,t} = \kappa_i + \sum_{l=t}^{t-(T-1)} \beta_{a,l} cpu_l^{\varepsilon} + \sum_{l=t}^{t-(T-1)} \beta_{b,l} cpu_l^{\varepsilon} * \text{GreenCat}_i + v_{i,t}, \tag{28}$$

where $x_{i,t}$ is – measured in deviations from a common path of all firms (business cycle)

– (1) the log of the current market value of a firm i or (2) net investment (in const. 2019 USD millions) of a firm i. The market value of a firm is measured as outstanding shares times market price of the share, while net investment is measured as the change in the reported value of a company's property, plant, and equipment normalized by the implicit price deflator of US gross private domestic investment (provided by the Bureau of Economic Analysis). $v_{i,t}$ is an i.i.d. error term and κ_i captures firm-fixed effects. We set $T = 2$. $GreenCat_i$ is the firm's category in terms of total carbon emission requirements, as described above.

Regression (28) directly maps to the theoretical predictions of section 2.3. Thus, our empirical hypothesis is that (i) CPU shocks lower the market value of the more carbon-intensive sector relative to the less carbon-intensive sector and (ii) CPU shocks lower real investment of the more carbon-intensive sector relative to the less carbon-intensive sector.

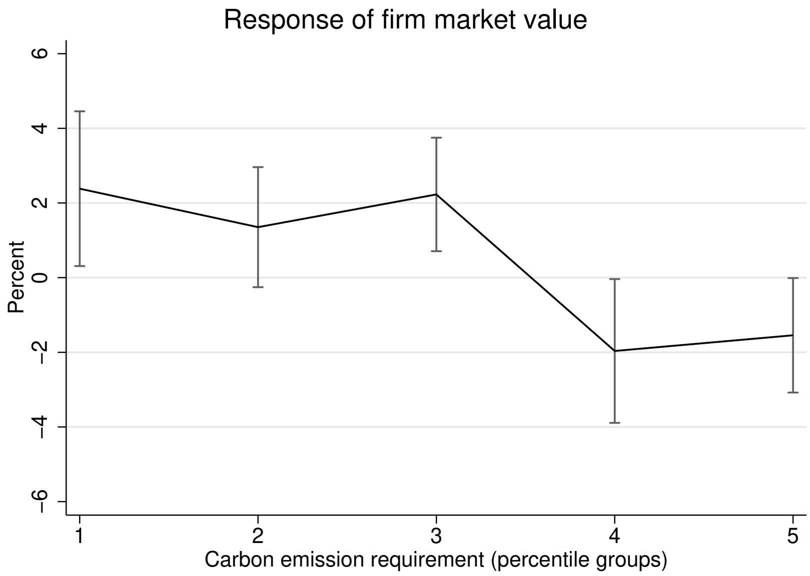
3.4 Results

Figure 4 plots the results for the response of firms' market value to increasing climate policy uncertainty for different levels of carbon emissions. Note that carbon emissions capture direct emissions and indirect emissions caused by input-output linkages. Firms are categorized into five groups (GreenCat), where 1 indicates the low-emission firms and 5 the high-emission firms. For each group Figure 4 shows the marginal effect of an identified CPU shock (expressed as the average effect in the current and following quarter of the shock).

The results indicate that climate policy uncertainty shocks induce substantial firm revaluation in the face of climate policy uncertainty shocks. While an average firm in the group of the 20% of firms with the highest carbon emission requirements in the sample faces a roughly 2% market valuation loss in response to an average CPU shock, an average firm in the group of 20% of firms with the lowest carbon emission requirements faces an average 2% gain in market value. This indicates that especially services sector firms gain in market value while especially highly-emitting manufacturing firms are devalued.

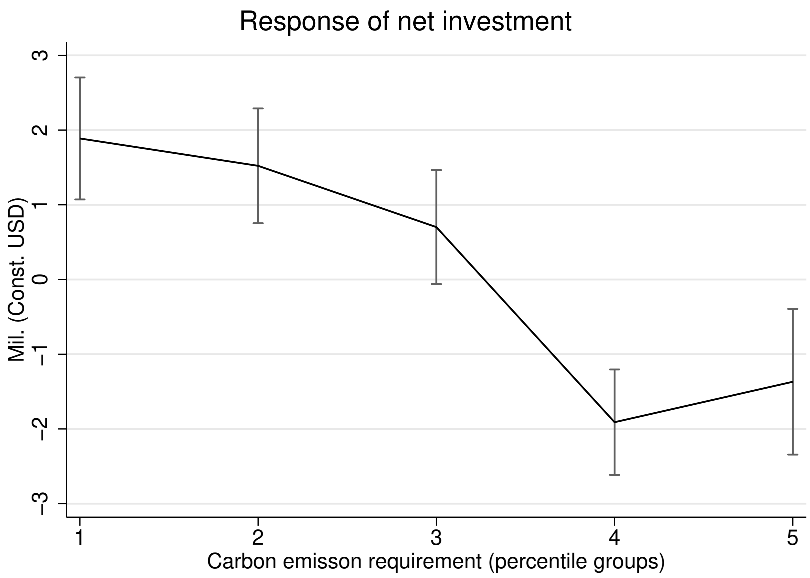
In response to CPU shocks that affect firms' valuation, firms also adjust their real investment decisions. Figure 5 shows the response of net investment to climate policy uncertainty shocks across differently emitting firms. While an average firm in the group of firms with the highest carbon emission requirements lowers its quarterly net investment by around USD 1.5 million (constant 2019) USD in response to a CPU shock, an average firm in the quintile with the lowest carbon emission requirements increases investment by almost USD 2 million.

Figure 4: Current market value response to climate policy uncertainty shocks for different levels of required carbon emissions



Note: 1 represents low carbon-emission requirements while 5 represents high carbon-emission requirements. Confidence intervals at the 90%-level. Expressed as the average effect in the current and following quarter of the shock. Sample period: 2000Q1-2019Q4. # of firms=11,445. # of observations: 349,214.

Figure 5: Net investment response to climate policy uncertainty shocks for different levels of required carbon emissions



Note: 1 represents low carbon-emission requirements while 5 represents high carbon-emission requirements. Confidence intervals at the 90%-level. Expressed as the average effect in the current and following quarter of the shock. Sample period: 2000Q1-2019Q4. Observations with an absolute value of quarterly net investment above USD 500 million are excluded from the sample. # of firms=10,394. # of observations: 331,454.

These results are important as they indicate that there is substantial reallocation within the economy, especially from the manufacturing sectors, which are more strongly represented in the high-emission groups, towards the services sectors. Moreover, the findings suggest decarbonization of the aggregate economy under climate policy uncertainty as production factors are reallocated to the cleaner sectors of the economy.

3.4.1 The response of aggregate consumption, investment and GDP to climate policy uncertainty shocks

Our theoretical exercise highlights that the consequences of CPU shocks for the reallocation of capital are substantial – which is confirmed in the empirical exercise – but that the effects of CPU shocks to economy-wide aggregates are far more moderate. As a sanity check for our theoretical exercise, it is instructive to see how climate policy uncertainty shocks affect consumption, investment and GDP in the data. In particular, we estimate

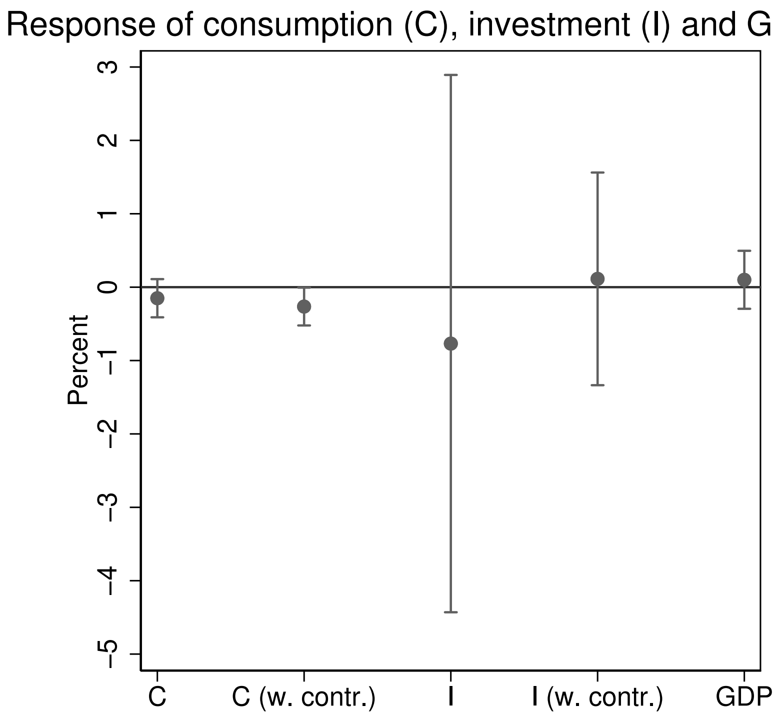
$$x_t = \kappa + x_{t-1} + \sum_{l=t}^{t-(T-1)} \beta_l cpu_l^{\varepsilon} + \gamma_t + \upsilon_t, \tag{29}$$

where x_t is (i) aggregate real consumption (in logs), (ii) aggregate real investment (in logs), or (iii) real GDP (in logs). υ_t is an i.i.d error term and κ a constant. We set $T = 2$. γ_t is a vector of controls that includes, in the case of regression (i), current and lagged values of aggregate investment and aggregate profits (both in logs), and, in the case of regression (ii), current and lagged values of aggregate consumption and aggregate profits (both in logs). We estimate separate regressions excluding and including the control vector γ_t. To avoid spurious results we exclude the Great Recession period (2008 Q3 to 2009 Q4).[11] Figure 6 shows the results. Each chart reports the average of the effects in the current and following quarter of the shock.

In line with the theoretical predictions, we find small responses of consumption, investment and GDP. The responses of investment and GDP are in fact not different from zero. In the specification including controls, we find a statistically significant negative consumption response.

[11] In the benchmark firm-level analysis we did not exclude the Great Recession observations. In the panel estimation this is less of an issue as the left-hand-side observation is measured in deviation from an average firm. This accounts for fluctuations in the business cycle more generally. However, we repeated the firm-level regressions excluding the observations from 2008 Q3 until 2009 Q2 and obtain very similar results compared to the benchmark (see Appendix D).

Figure 6: Responses of aggregate consumption, investment and GDP to climate policy uncertainty shocks



Note: Average response (first two quarters) of US real consumption, US real investment, and US real GDP to a climate policy uncertainty shock. Confidence intervals at the 90% level. "w. contr." indicates that control variables (other than lagged dependent variables) are included. Sample period: 2000Q1-2019Q4. Excluding left-hand-side observations from 2008Q3 to 2009Q2.

3.4.2 Controlling for climate-related first-moment shocks

As a robustness check we run a similar regression as (28), but instead of categorizing firms into five groups we directly include the sector-specific required carbon emissions in the regressions. Moreover, we add a measure of climate policy news (Engle et al. 2020) – in first differences of logs – to additionally control for shifts in climate policy news. This measure aims at capturing climate news, for instance related to weather events (such as floods, hurricanes or droughts), planet-wide consequences of global warming (such as higher sea levels), and coverage about regulations. Although it implicitly aims at capturing changes in climate-related risk, one can interpret these shocks as first-moment shocks, as the knowledge (or the news) about consequences of climate change and/or climate policies increases. At minimum, including the measure allows us to control for the possibility that our innovations capturing climate policy uncertainty shocks are contaminated by climate-related news.[12]

[12]In Appendix D we also demonstrate that our extracted CPU shock series remains very similar when we additionally include the measure of Engle et al. (2020) in the orthogonalization procedure.

Table 3: Controlling for first-moment effects of climate-related events

Net investment:

	CPU (1)	Climate change news (2)
carbon em. req.	-2.83**	11.28***
	(-2.36)	(4.08)
N	299551	299551

Market value:

	CPU (1)	Climate change news(2)
carbon em. req.	-3.51*	3.92
	(-2.16)	(-1.26)
N	296970	296970

Note: t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 reports the results. The evidence hints at important differences in the transmission of climate policy uncertainty and climate policy news. The results for the response of climate policy uncertainty remain robust and are similar compared to the findings discussed above. The coefficient of net investment for climate policy news is – in contrast to the sign of policy uncertainty shocks – significantly positive. This suggests that actual climate-related news raises investment in the high-emission sectors. This can be related to actual disruptions to physical capital due to climate-related events. It could also be the case that climate-related news leads to energy-efficient or low-emission investment in the dirtier sectors of the economy. Our approach does not allow us to distinguish between green investment and dirty investment within sectors. Thus, we cannot interpret the implications of this finding for decarbonization.

4 Conclusion

This paper argues that an increase in climate policy uncertainty triggers a reallocation of capital from carbon-intensive industries to industries with a lower carbon intensity in their production. We consider various forms of modeling CPU shocks and cast them in a dynamic general equilibrium model. In this setting, we show that an increase in climate policy uncertainty favors the market value of green over dirty assets, lowers real investment by firms in carbon-intensive industries and tends to raise real investment by green firms. The key mechanism in our model relies on the notion that financial institutions seek to avoid uncertainty. Thus, as a consequence of CPU shocks, they have a motive to divest from dirty industries and to invest in green industries.

To test the theoretical prediction of the model, we sort US industries by the carbon emission-content of their products, accounting for the carbon intensity of their upstream industries. We show that identified CPU shocks reduce the average market value of firms in industries with a higher carbon intensity in production and lowers their physical investment. This mostly affects manufacturing sectors. At the same time, we show that real investment activity and the market value of green industries profit from higher climate policy uncertainty.

Our analysis suggests that not only realized climate policy measures benefit the environment. Also the mere uncertainty surrounding future climate policies reduces carbon emissions by scaring investors out of investments in carbon-intensive industries.

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A Appendix to the theoretical model

A.1 Financial sector

The banking sector is modeled in the vein of Gertler and Karadi (2013). Banks fund themselves with deposits by households and extend loans to firms in both the green and the dirty sector to finance their capital stock. Bank j maximizes its value function, V_{jt}, subject to a balance sheet constraint and an incentive constraint

$$V_{jt} = \max_{\{K^G_{j,t}\},\{K^D_{j,t}\}} \quad \beta E_t \Lambda_{t+1}[(1-\theta)N_{j,t+1} + \theta V_{j,t+1}]$$

$$\begin{aligned} s.t. \qquad Q^G_t K^G_{jt} + Q^D_t K^D_{jt} &= N_{jt} + D_{jt} \\ V_{jt} &\geq \lambda_G Q^G_t K^G_{jt} + \lambda_{D,t} Q^D_t K^D_{jt}. \end{aligned}$$

Λ_t is the stochastic discount factor of households, $N_{j,t}$ is bank j's net worth, and parameter θ is the survival probability of banks. $K^G_{j,t}$ and $K^D_{j,t}$ are claims on the capital stock of the green and the dirty sector, respectively. Q^G_t and Q^D_t are the real prices of capital of firms in the respective sector. D_{jt} are the deposits. Parameters λ_G and $\lambda_{D,t}$ govern the divertability of the respective assets for banks.[13] We consider possible time-variation in the latter to allow for uncertainty about $\lambda_{D,t}$. Additionally, the law of motion of net worth is

$$N_{jt} = (R^G_{kt} - R_{t-1})Q^G_{t-1}K^G_{j,t-1} + (R^D_{kt} - R_{t-1})Q^D_{t-1}K^D_{j,t-1} + R_{t-1}N_{j,t-1},$$

where R^G_{kt} and R^D_{kt} are the real returns on capital of firms in sector A, and R_t is the return of deposits.

Guessing that the value function is linear in capital claims on both sectors and net worth yields

$$V_{jt} = \nu^G_{kjt} Q^G_t K^G_{jt} + \nu^D_{kjt} Q^D_t K^D_{jt} + \nu_{njt} N_{jt}.$$

The Lagrangian function for the optimization problem of the bank reads

$$\mathcal{L} = (1+\mu_{jt})(\nu^G_{kjt} Q^G_t K^G_{jt} + \nu^D_{kjt} Q^D_t K^D_{jt} + \nu_{njt} N_{jt}) - \mu_{jt}(\lambda_G Q^G_t K^G_{jt} + \lambda_{D,t} Q^D_t K^D_{jt})$$

[13]Throughout all exercises in this paper, we make the assumption that the incentive constraint is always binding.

Hence, the first order conditions for holdings of domestic and foreign bonds as well as for the Lagrangian multiplier, μ_{jt}, are

$$\nu^G_{kjt} = \lambda_G \frac{\mu_{jt}}{1+\mu_{jt}}$$

$$\nu^D_{kjt} = \lambda_{D,t} \frac{\mu_{jt}}{1+\mu_{jt}}$$

$$\nu^G_{kjt} Q^G_t K^G_{jt} + \nu^D_{kjt} Q^D_t K^D_{jt} + \nu_{njt} N_{jt} = \lambda_G Q^G_t K^G_{jt} + \lambda_{D,t} Q^D_{b,t} K^D_{jt}$$

The demand for domestic bonds by domestic banks can be obtained by rearranging the incentive constraint

$$Q^G_t K^G_{jt} = \frac{\nu^D_{kjt} - \lambda_D}{\lambda_G - \nu^G_{kjt}} Q^D_t K^D_{jt} + \frac{\nu_{njt}}{\lambda_G - \nu^G_{kjt}} N_{jt}$$

The value function can be written solely as a function of N_{jt} by substituting out the assets using the foregoing equation

$$\begin{aligned}
V_{jt} \quad &= \nu^G_{kjt} Q^G_t K^G_{jt} + \nu^D_{kjt} Q^D_t K^D_{jt} + \nu_{njt} N_{jt} \\
\Leftrightarrow V_{jt} \quad &= \left[\nu^G_{kjt} \frac{\nu^D_{kjt} - \lambda_{D,t}}{\lambda_G - \nu^G_{kjt}} + \nu^D_{kjt} \right] Q^D_t K^D_{jt} + \left[\nu^G_{kjt} \frac{\nu_{njt}}{\lambda_G - \nu^G_{kjt}} + \nu_{njt} \right] N_{jt} \\
\Leftrightarrow V_{jt} \quad &= \left[\nu^G_{kjt} \frac{\nu_{njt}}{\lambda_G - \nu^G_{kjt}} + \nu_{njt} \right] N_{jt} \\
\Leftrightarrow V_{jt} \quad &= \left[\frac{\lambda_G \nu_{njt}}{\lambda_G - \nu^G_{kjt}} \right] N_{jt} \\
\Leftrightarrow V_{jt} \quad &= \left[\frac{\lambda_G \nu_{njt}}{\lambda_G - \lambda_G \frac{\mu_{jt}}{1+\mu_{jt}}} \right] N_{jt} \\
\Leftrightarrow V_{jt} \quad &= (1+\mu_{jt}) \nu_{njt} N_{jt}
\end{aligned}$$

Defining $\Omega_{j,t} \equiv \Lambda_t((1-\theta) + \theta(1+\mu_{jt})\nu_{njt})$, plugging this expression of the value function into the Bellman equation, and using the law of motion of net worth yields

$$V_{jt} = \nu_{kjt}^G Q_t^G K_{jt}^G + \nu_{kjt}^D Q_t^D K_{jt}^D + \nu_{njt} N_{jt}$$

$$= \beta E_t \Lambda_{t+1}[(1-\theta)N_{j,t+1} + \theta V_{j,t+1}]$$

$$= \beta E_t \Lambda_{t+1}[(1-\theta)N_{j,t+1} + \theta(1+\mu_{j,t+1})\nu_{nj,t+1} N_{j,t+1}]$$

$$= \beta E_t[\Omega_{t+1}((R_{k,t+1}^G - R_t)Q_t^G K_{j,t}^G + (R_{k,t+1}^D - R_t)Q_t^D K_{j,t}^D + R_t N_{j,t})].$$

Applying the method of undetermined coefficients results in

$$\begin{aligned}
\nu_{kjt}^G &= \beta E_t \Omega_{j,t+1}(R_{k,t+1}^G - R_t), \\
\nu_{kjt}^D &= \beta E_t \Omega_{j,t+1}(R_{k,t+1}^G - R_t), \\
\nu_{njt} &= \beta E_t \Omega_{j,t+1} R_t.
\end{aligned}$$

For aggregation, we assume an equilibrium in which all banks are symmetric (i.e. $\forall j$: $\nu_{kjt}^G = \nu_{kt}^G, \nu_{kjt}^D = \nu_{kt}^D, \nu_{njt} = \nu_{nt}, \Omega_{jt}^A = \Omega_t^A$).

A.2 The full set of model equations

A.2.1 Households

$$1 = \beta E_t[\tfrac{i_t}{\Pi_{t+1}} \Lambda_{t+1}] \tag{A.1}$$

$$\Lambda_t = \tfrac{\lambda_t}{\lambda_{t-1}} \tag{A.2}$$

$$\lambda_t = (C_t - hC_{t-1})^{-\sigma_c} - \beta h(E_t[C_{t+1}] - hC_t)^{-\sigma_c} \tag{A.3}$$

i_t is the short-term nominal interest rate set by the central bank, Π_t consumer price inflation, and $\beta\Lambda_t$ the stochastic discount factor of households. λ_t is the marginal utility of consumption, with h and σ_c being the degree of habit formation and the coefficient of relative risk aversion.

A.2.2 Wage setting

Optimal wage setting implies the following first order conditions

$$1 = \frac{\epsilon_w}{\epsilon_w - 1}\frac{Z1_{w,t}}{Z2_{w,t}} \tag{A.4}$$

$$Z1_{w,t} = \left(\frac{W_t}{W_t^*}\right)^{\epsilon_w(1+\sigma_l)} \chi \frac{(L_t)^{1+\sigma_l}}{\lambda_t} + \beta\zeta_w E_t\left[\left(\frac{W_{t+1}^*}{W_t^*}\Pi_{t+1}\right)^{\epsilon_w(1+\sigma_l)} Z1_{w,t+1}\right] \tag{A.5}$$

$$Z2_{w,t} = (W_t^*)^{1-\epsilon_w}(W_t)^{\epsilon_w} L_t + \beta\zeta_w E_t\left[\left(\frac{W_{t+1}^*}{W_t^*}\Pi_{t+1}\right)^{\epsilon_w - 1} Z2_{w,t+1}\right] \tag{A.6}$$

W_t is the real wage and W_t^* is the optimal real wage. $Z1_{w,t}$ and $Z2_{w,t}$ are auxiliary variables, which allow for a recursive formulation of the wage Phillips curve. ϵ_w is the elasticity of substitution between varieties of labor, χ the weight on the disutility of labor in the households' preferences, σ_l the inverse of the Frisch elasticity, and ζ_w the probability that a union updates its price in any given period. The dynamics of the aggregate wage index and wage dispersion, $\Delta_{w,t}$, are captured by

$$1 = \zeta_w\left(\frac{W_t}{W_{t-1}}\Pi_t\right)^{\epsilon_w-1} + (1-\zeta_w)\left(\frac{W_t}{W_t^*}\right)^{\epsilon_w-1} \tag{A.7}$$

$$\Delta_{w,t} = \zeta_w\Delta_{w,t-1}\left(\frac{W_t}{W_{t-1}}\Pi_t\right)^{\epsilon_w} + (1-\zeta_w)\left(\frac{W_t^*}{W_t}\right)^{-\epsilon_w} \tag{A.8}$$

$$L_t = L_{f,t}\Delta_{w,t} \tag{A.9}$$

$$L_{f,t} = L_{f,t}^A + L_{f,t}^B. \tag{A.10}$$

L_t is the labor supplied by households. $L_{f,t}^A$ and $L_{f,t}^B$ are the amounts of labor employed by firms in sectors A and B. L_t and L_{ft} differ due to wage dispersion.

A.2.3 Production, price setting, capital goods and goods market clearing

Goods-producing firms in the green and dirty sector (sectors G and D) produce their output, $Y_{p,jt}^k$, using energy, E_t^k, and a capital-labor bundle $KL_{p,t}^k$, as inputs. Their production follows the CES production technology

$$Y_{p,t}^k = \left[\kappa^k(E_t^k)^{\frac{\iota-1}{\iota}} + (1-\kappa^k)(KL_{p,t}^k)^{\frac{\iota-1}{\iota}}\right]^{\frac{\iota}{\iota-1}}, \tag{A.11}$$

κ^k is the steady-state ratio of energy use in aggregate output in sector k and ι the elasticity of substitution between energy and the capital-labor bundle. The capital-labor bundle of firms of sector k has a standard Cobb-Douglas form

$$KL_{p,t} = A_t^k(K_{t-1}^k)^{\alpha_k}(L_t^k)^{1-\alpha_k}, \tag{A.12}$$

where K_{t-1}^k denotes the capital installed at the end of period $t-1$ and used in production in period t. A_t^k denotes the sector-specific productivity of this bundle. α_k is the output elasticity with respect to capital goods.

In line with the policy of introducing a tax on carbon emissions, we model a tax on energy use in production with the tax rate, τ_t^e. Cost minimization by goods-producing firms gives rise to their energy demand condition

$$(1+\tau_t^e)P_{E,t} = \kappa^k P_{m,t}^k \left(\frac{Y_{p,t}^k}{E_t^k}\right)^{\frac{1}{\iota}}, \tag{A.13}$$

where $P_{E,t}$ is the relative price of energy (in terms of domestic consumption) and $P_{m,t}^k$ is the output price of sector k.

The first order condition for the firms' labor demand is

$$W_t = \frac{(1-\alpha)(1-\kappa^k)}{L_t^k} P_{m,t}^k KL_{p,t}^{k\ \frac{\iota-1}{\iota}} Y_{p,t}^{k\ 1/\iota}, \tag{A.14}$$

Whereas wages and the price of energy equalize across sectors, capital input is sector-specific. This gives rise to potentially differing returns to capital, $R_{k,t}^k$. We adopt the assumption by Gertler and Karadi (2011) that goods-producing firms buy capital at the beginning of the period, and re-sell it after using it in production. Demand for capital by final goods producers thus depends on the marginal product of capital and variations in the price of capital

$$R_{k,t}^k = \frac{\frac{\alpha(1-\kappa^k)}{K_{t-1}^k} P_{m,t}^k KL_{p,t}^{k\ \frac{\iota-1}{\iota}} Y_{p,t}^{k\ 1/\iota} + (1-\delta)Q_t^k}{Q_{t-1}^k} \tag{A.15}$$

with δ being the depreciation rate and Q_t^k being the price of capital.

Capital-producing firms

Capital-producing firms buy the used capital, repair it and build new capital. The new and refurbished capital is then sold again to final goods producers at price Q_t^k. The production of capital is subject to investment adjustment costs, which create a dynamic investment decision for capital goods producers. This setting gives rise to the investment Euler equation

$$Q_t^k = 1 + \phi_K \left(\frac{I_t^k}{I_{t-1}^k} - 1\right)\frac{I_t^k}{I_{t-1}^k} + \frac{\phi_K}{2}\left(\frac{I_t^k}{I_{t-1}^k} - 1\right)^2 - \beta\phi_K E_t\left[\Lambda_{t+1}^k \left(\frac{I_{t+1}^k}{I_t^k} - 1\right)\left(\frac{I_{t+1}^k}{I_t^k}\right)^2\right] \tag{A.16}$$

Retailers

Sector-k retailers buy the output of producing firms of their sector at price $P^k_{m,t}$, which therefore constitutes the marginal cost of retailers. They are in monopolistic competition and set their prices with a markup over their marginal costs. They face price rigidities à la Calvo (1983), with the probability of not being able to reset the price in any given period being ζ. The first order condition for the optimally set price, $P^{*,A}_t$, can be derived as

$$\sum_{l=0}^{\infty}(\beta\zeta)^l E_t \left\{ \frac{\lambda_{t+l}}{\lambda_t} \left(\frac{P^k_t}{P^k_{t+l}} \right)^{-\epsilon} Y^k_{p,t+l} \left[\frac{P^{*,k}_t}{P^k_{t+l}} - \frac{\epsilon}{\epsilon-1} MC^k_{t+l} \right] \right\} = 0.$$

Retailers in sector k set their optimal prices according to

$$p^{*,k}_t = \tfrac{\epsilon}{\epsilon-1} \tfrac{Z^k_{2,t}}{Z^k_{1,t}}. \tag{A.17}$$

Here, $p^{*,k}_t$ is the optimal price relative to the overall price level in a given sector. The superscript A, A stands for prices related to goods produced in A and sold in A, A, B for goods produced in A and sold in B, B, A for goods produced in B and sold in A, and B, B for goods produced in B and sold in B. $Z1_t$ and $Z2_t$ are auxiliary variables to facilitate recursive price Phillips curves with Calvo pricing.

$$Z^k_{1,t} = Y^k_{p,t} + \beta\zeta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} (\Pi^k_{t+1})^{\epsilon-1} Z^k_{1,t+1} \right\} \tag{A.18}$$

$$Z^k_{2,t} = Y^k_{p,t} MC^k_t + \beta\zeta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} (\Pi^k_{t+1})^{\epsilon} Z^k_{2,t+1} \right\} \tag{A.19}$$

Π^k stand for the rate of change in prices in the respective sectors. ϵ is the elasticity of substitution between varieties of goods and ζ is the probability that a firm can update its price in any given period. The dynamics of the inflation rates and the respective price dispersion measures, Δ^k_t, are

$$1 = (1-\zeta)(p^{*,k}_t)^{1-\epsilon} + \zeta(\Pi^k_t)^{\epsilon-1} \tag{A.20}$$

$$\Delta^k_t = \zeta\Delta^k_{t-1}(\Pi^k_t)^{\epsilon} + (1-\zeta)\left(\frac{1-\zeta(\Pi^k_t)^{\epsilon-1}}{(1-\zeta)} \right)^{\frac{\epsilon}{\epsilon-1}} \tag{A.21}$$

Accounting for price dispersion, the production of final goods in either sector equals the demand for these goods

$$Y^k_{p,t} = Y^k_t \Delta^k_t. \tag{A.22}$$

Sector-k output is used for consumption and investment.

$$Y^k_t = C^k_t + I^k_t \tag{A.23}$$

Consumption basket and consumer prices

The households' consumption basket is composed of energy consumption, E^C_t, and core consumption of goods produced in the green sector, C^G_t , and in the dirty sector, C^D_t

$$C_t = \left[\kappa^E (E^C_t)^{\frac{\Theta-1}{\Theta}} + (1-\kappa^k)\mu_G (C^G_t)^{\frac{\Theta-1}{\Theta}} (1-\kappa^k)(1-\mu_G)(C^D_t)^{\frac{\Theta-1}{\Theta}}\right]^{\frac{\Theta}{\Theta-1}}. \tag{A.24}$$

κ^E and μ^G are consumption weights and Θ is the elasticity of substitution between energy and the different consumption good types. The consumer price index reads

$$P_t = \left[\kappa^E (P^E_{C,t})^{1-\Theta} + (1-\kappa^k)\mu_G (P^G_t)^{1-\Theta} (1-\kappa^k)(1-\mu_G)((1+\tau_t)P^D_t)^{1-\Theta}\right]^{\frac{1}{1-\Theta}}. \tag{A.25}$$

τ_t is a consumption tax on goods produced with a higher energy intensity.

Households' demand for core consumption goods and energy depends on relative prices.

$$C^G_t = (1-\kappa^E)\mu^G (p^G_t)^{-\Theta} C_t \tag{A.26}$$

$$C^D_t = (1-\kappa^E)(1-\mu^G)((1+\tau_t)p^D_t)^{-\Theta} C_t, \tag{A.27}$$

$$E^C_t = \kappa^E ((1+\tau^e_t)p^E_{C,t})^{-\Theta} C_t. \tag{A.28}$$

The CPI and the development of relative prices are linked via

$$\Pi_t = \Pi^G_t \frac{\frac{P^G_{t-1}}{P_{t-1}}}{\frac{P^G_t}{P_t}}, \tag{A.29}$$

$$\Pi_t = \Pi^G_t \frac{\frac{(1+\tau_{t-1})P^G_{t-1}}{P_{t-1}}}{\frac{(1+\tau_t)P^G_t}{P_t}}, \tag{A.30}$$

$$\Pi_t = \Pi^E_{C,t} \frac{\frac{(1+\tau^e_{t-1})P^E_{C,t-1}}{P_{t-1}}}{\frac{(1+\tau^e_t)P^E_{C,t}}{P_t}}. \tag{A.31}$$

For simplicity, we assume that energy is provided to firms and households at fixed real prices, $P_t^E = P^E$ and $P_{C,t}^E = P_C^E$.

A.2.4 Financial sector

The banking sector is modeled in the vein of Gertler and Karadi (2011, 2013). Banks fund themselves with deposits by households and invest in capital assets of both the green and the dirty sector. The aggregate bank balance sheets read

$$Q_t^G K_t^G + Q_t^D K_t^D = N_t + D_t, \tag{A.32}$$

where N_t and D_t are the banks' net worth and their deposits. The banks' net worth evolves according to

$$N_t = (R_{kt}^G - R_{d,t-1})Q_{t-1}^G K_{t-1}^G + (R_{kt}^D - R_{d,t-1})Q_{t-1}^D K_{t-1}^D + R_{d,t-1}N_{t-1}$$

R_{kt}^G and R_{kt}^D are the real return on capital of the respective sectors. R_{dt} is the return on bank deposits.

The bankers' optimization problem, discussed in the main body of the text, gives rise to the following first order conditions for optimal asset holdings

$$\nu_{kt}^G = \lambda_G \frac{\mu_t}{1+\mu_t}, \tag{A.33}$$

$$\nu_{kt}^G = \lambda_{D,t} \frac{\mu_t}{1+\mu_t}, \tag{A.34}$$

The parameters λ_G and $\lambda_{D,t}$ govern the divertability of the respective assets for banks. ν_t^G and ν_t^D are the shadow values of the asset holdings for banks. μ_t is the Lagrangian multiplier of the incentive constraint. The rearranged first order condition for the multiplier is

$$Q_t^G K_t^G = \frac{\nu_{kt}^D - \lambda_{D,t}}{\lambda_G - \nu_{kt}^G} Q_t^D K_t^D + \frac{\nu_{nt}}{\lambda_G - \nu_{kt}^G} N_t. \tag{A.35}$$

ν_{nt} is the shadow value for the bank of an additional unit of net worth. The shadow values of asset holdings and net worth are related to the spreads in the following way

$$\nu_{kt}^G = \beta E_t \Omega_{t+1}(R_{k,t+1}^G - R_{d,t}), \tag{A.36}$$

$$\nu_{kt}^D = \beta E_t \Omega_{t+1}(R_{k,t+1}^D - R_{d,t}), \tag{A.37}$$

$$\nu_{nt} = \beta E_t \Omega_{t+1} R_{d,t}, \tag{A.38}$$

where we have defined

$$\Omega_t \equiv \Lambda_t((1-\theta) + \theta(1+\mu_t)\nu_{nt}). \tag{A.39}$$

Note that there is a turnover of bankers in the financial sector. Therefore, one can distinguish between the net worth of new and old bankers, $N_{o,t}$ and $N_{n,t}$, respectively.

$$N_{o,t} = \theta(R^G_{kt}Q^G_{t-1}K^G_{t-1} + R^D_{kt}Q^D_{t-1}K^D_{t-1} - R_{d,t-1}D_{t-1}), \tag{A.40}$$

$$N_{n,t} = \omega(Q^G_{t-1}K^G_{t-1} + Q^D_{t-1}K^D_{t-1}). \tag{A.41}$$

where ω is set such that the initial wealth of banks entering the banking sector offsets the wealth that exits with banks that leave the sector.

A.2.5 Fiscal and monetary authority

In our modeling of the fiscal sector, we confine ourselves to the aspect of climate related taxes on products of the dirty sector and on (fossil) energy. The revenues generated in this way are distributed to households via a lump-sum tax. The budget constraint of the fiscal authority reads

$$\tau^B_t P^B_t Y^B_t + \tau^E_t P^E_t E_t = T_t. \tag{A.42}$$

The central bank sets the short-term nominal interest rate following the Taylor-type rule

$$R_{n,t} = (R_{n,t-1})^{\rho} \left(\left(\frac{\Pi_t}{\Pi}\right)^{\phi_\pi} \left(\frac{Y_t}{Y}\right)^{\phi_y} \right)^{(1-\rho)}, \tag{A.43}$$

where $R_{n,t} = R_t E_t[\Pi_{t+1}]$. Parameter ρ is the degree of interest rate smoothing. ϕ_π and ϕ_y govern the feedback of the policy rule to inflation and output, respectively.

A.2.6 Climate policy uncertainty

We capture climate policy uncertainty by modeling taxes on energy and dirty goods, whose future path is uncertain. Tax rates follow exogenous autoregressive processes with stochastic volatility

$$\tau_t = \rho_\tau \tau_{t-1} + \sigma^\tau_t \epsilon^\tau_t, \tag{A.44}$$

$$\tau^e_t = \rho_{\tau^e} \tau^e_{t-1} + \sigma^{\tau^e}_t \epsilon^{\tau^e}_t. \tag{A.45}$$

Parameters ρ_τ and ρ_{τ^e} govern the persistence of the exogenous tax rate processes. σ_t^τ and $\sigma_t^{\tau^e}$, the volatilities of the processes, themselves follow exogenous, stochastic processes

$$\sigma_t^\tau = \rho_{U,\tau}\sigma_{t-1}^\tau + \sigma^{U,\tau}\epsilon_t^{U,\tau}, \tag{A.46}$$

$$\sigma_t^{\tau^e} = \rho_{U,\tau^e}\sigma_{t-1}^{\tau^e} + \sigma^{U,\tau^e}\epsilon_t^{U,\tau^e}. \tag{A.47}$$

$\rho_{U,\tau}$ and ρ_{U,τ^e} are persistence parameters and $\sigma^{U,\tau}$ and σ^{U,τ^e} are the standard deviations of the volatility process. ϵ_t^τ, $\epsilon_t^{\tau^e}$, $\epsilon_t^{U,\tau}$, and ϵ_t^{U,τ^e} are normally distributed.

B Further model results

This section contains some additional results of our model analysis.

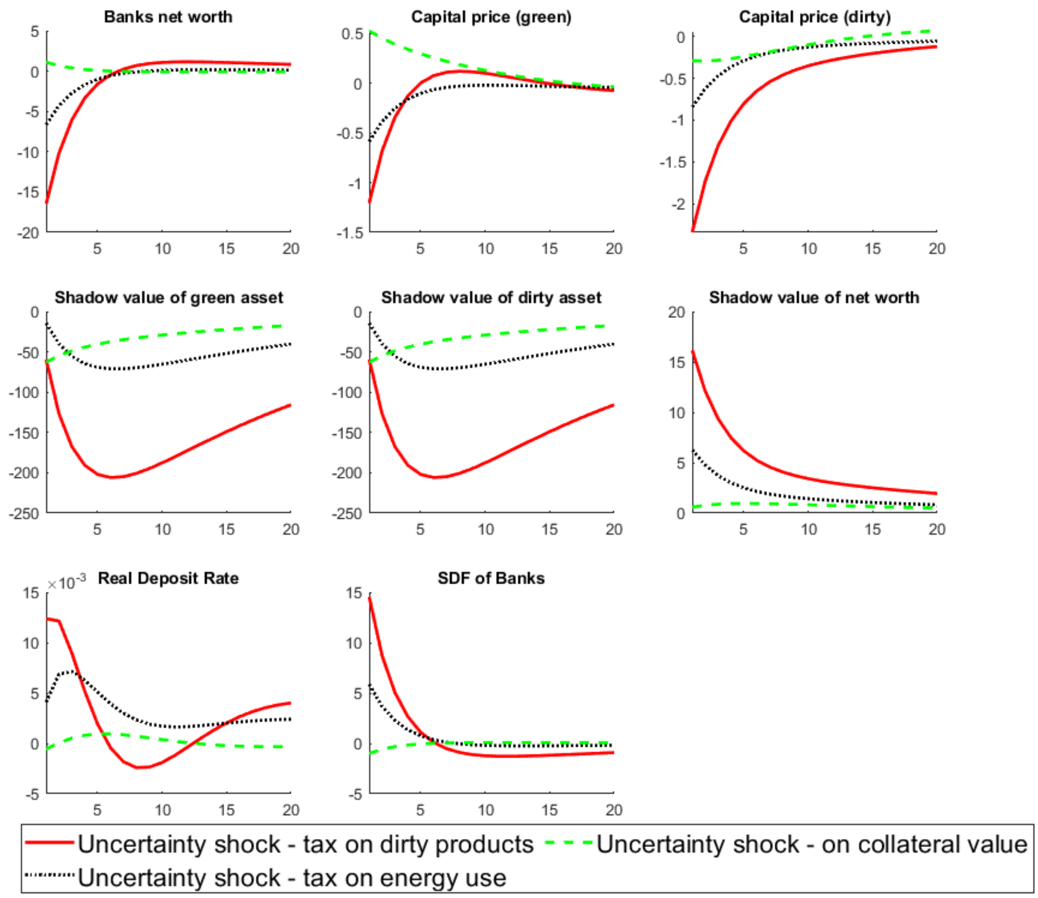
B.1 Financial sector dynamics

Figure B.1 shows that, after the CPU shock to taxes on dirty products as well as after CPU shocks to energy taxes, the ensuing uncertainty raises the real deposit rate. Note that, as shown in the main body of the text, these taxes raise the real deposit rate. With their funding costs rising, the balance sheet-constrained banks reduce the size of their balance sheets and sell assets. The price of capital in both sectors declines, reducing the net worth of banks overproportionally.

The decline in asset prices is amplified via a second important channel through which uncertainty affects the banking sector. This channel relies on the fact that banks are owned by households and inherit their risk-aversion. As uncertainty raises the deposit rate and reduces the net worth of banks via their balance sheet, the value that banks attribute to an additional unit of net worth, $\nu_{n,t}$, increases and so does their stochastic discount factor, Ω_t. Thus, the decline in asset prices following the tax-related CPU shock causes losses for the banks at times in which banks are in need of more net worth. Consequently, risk-averse banks place a lower marginal value on their asset holdings ($\nu_{k,t}^G$ and $\nu_{k,t}^D$), amplifying the decrease in their demand for assets, particularly for assets from the dirty sector, which carry a higher risk for their portfolio.

In the case of the uncertainty shock to the collateral value of dirty assets, the mechanism is different. Here, banks increase their overall holdings of assets and build up their net worth. Still, to avoid the uncertainty associated with the dirty assets' collateral value, they shift their portfolio towards green assets and reduce their holdings of dirty assets. This is a setting, in which the bank fares rather well at times in which the stochastic discount factor declines. Thus, this type of uncertainty also lowers the marginal values

Figure B.1: Effects of a climate policy uncertainty shock



Note: The figure presents theoretical impulse responses to a shock with the size of 4 standard deviations. y-axis in percent.

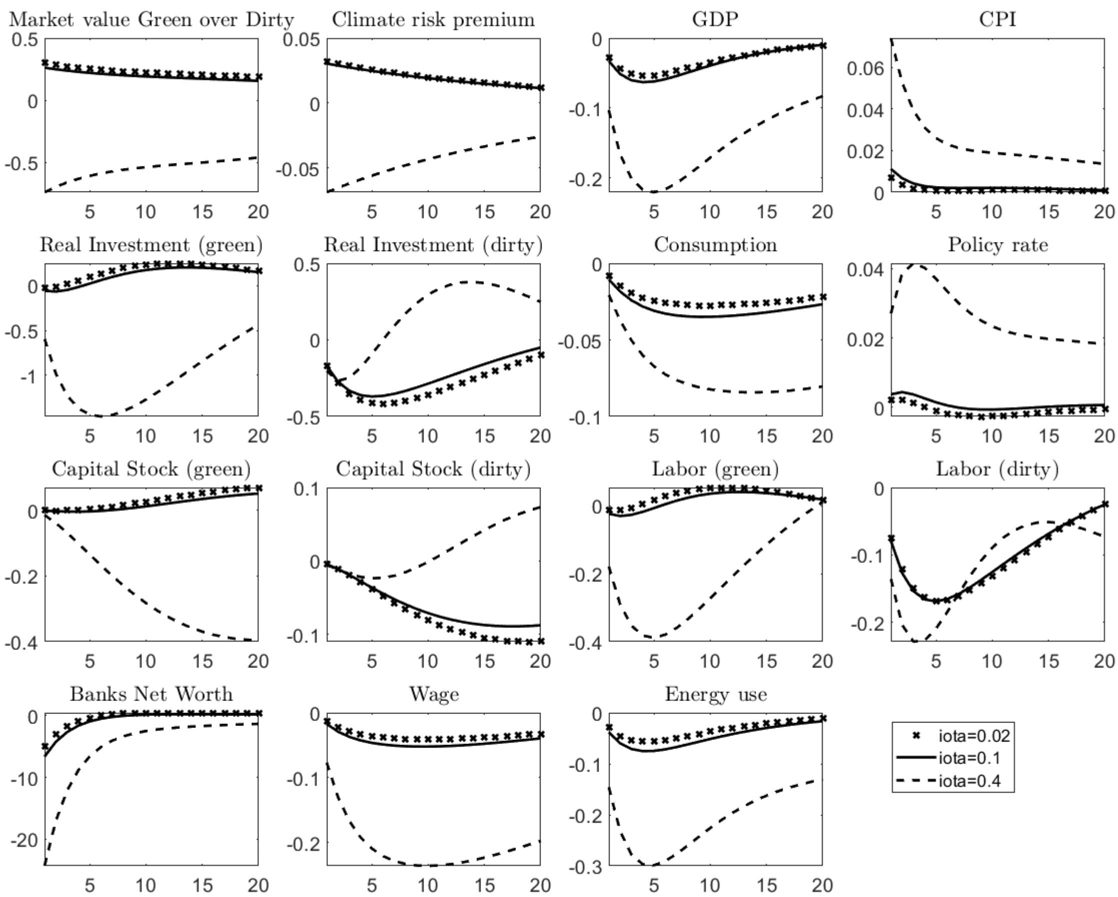
that risk-averse banks place on their asset holdings.

B.2 Sensitivity analysis

Fried et al. (2022) show that capital flows between sectors in the face of climate transition risk may change with the substitutability of energy and non-energy inputs in production. In our case, the main effects of CPU shocks to product taxes on dirty goods and of CPU shocks to the assets pledgeability are robust to changes in the substitution elasticity, ι. The effects of CPU shocks to energy taxes, however, are sensitive to this parameter.

The short-run elasticity of substitution between energy and capital/labor inputs in production, ι, matters for the transmission of CPU shocks to the energy tax rate. In the

Figure B.2: Effects of an uncertainty shock to the tax rate on energy for different values of the elasticity of substitution of inputs in production



Note: The figure presents theoretical impulse responses to a shock with the size of 4 standard deviations. y-axis in percent.

case that it is low – as in the baseline calibration – firms in the dirty sector cannot quickly reduce their energy use and are stuck with increased uncertainty regarding their cost of production. In turn, the return on assets in the dirty sector becomes more uncertain, inducing banks to withdraw their financing. Investment in the dirty sector declines.

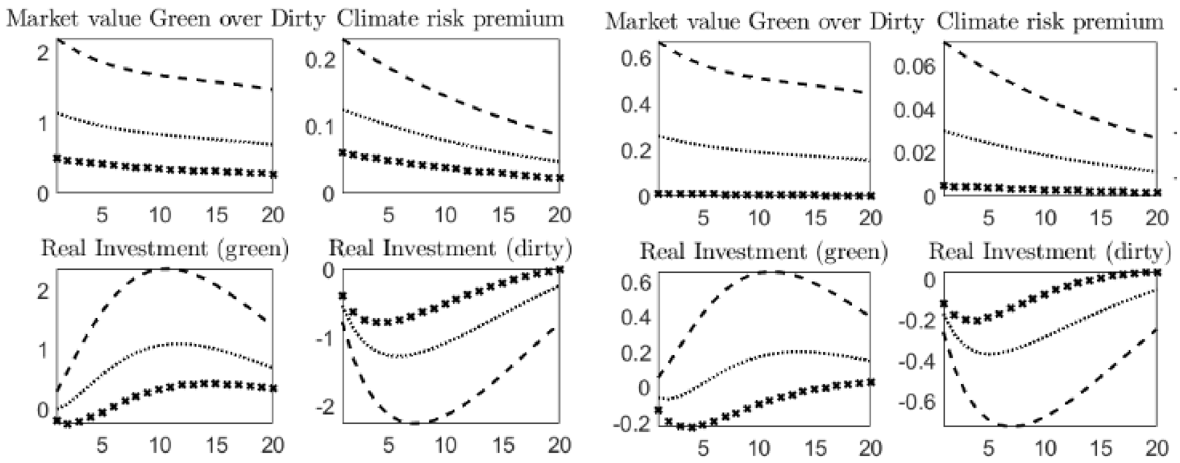
However, for sufficiently high values of ι the effects of the CPU shock on the energy tax reverses. Figure B.2 shows that, for $\iota = 0.4$, firms quickly reduce their energy use. In turn, firms, particularly those in the energy-intensive dirty sector, increase their demand for capital. Real investment in the dirty sector rises. Banks finance the transition of the dirty sector to reduce their assets' exposure to uncertainty on energy taxes. As a result, funds in the green sector dry up. Consequently, the relative market value of green to dirty assets and the climate risk premium decrease. For a high ι, the ensuing dynamics after a CPU shock to energy taxes can be quite sharp. The precautionary motive of households and firms to hold back spending or to raise prices become more prominent. This leads to a stronger fall in consumption and to a stronger increase in inflation than in the case of a low short-run elasticity of substitution for inputs in production. With CPI rising faster, the central bank raises its policy rate by more, which weighs more heavily on investment and consumption than in the baseline case.

Our choice of a low value of ι in the baseline calibration (ι=0.1) is in line with insights from the literature on the role of oil for the macroeconomy (see e.g. Khalil 2022). The notion of a very low substitutability of energy and capital/labor inputs is confirmed by Hassler et al. (2021). In an estimated model of input-saving technical change, their posterior mean of this parameter is even lower, at 0.02. In addition, the result of our empirical analysis – which is that climate policy uncertainty shocks result in a reallocation of real investment from dirty towards green industries – supports the notion that the calibration of a low ι captures the more relevant case.

For higher values of the elasticity of substitution of green and dirty goods in the households consumption basket, Θ, the reallocation of capital from the dirty to the green sector becomes more pronounced. (see Figure B.3, dashed line). As uncertainty hits the dirty sector and translates into uncertainty about product prices, households allocate their spending to the less uncertain green goods. With demand concentrated on green goods, this stimulates investment in the green sector. Conversely, when Θ is lower (crossed line), this channel is attenuated. This holds for the case of a CPU shock to dirty product taxes (left-hand panels) as well as for a CPU shock to energy taxes (right-hand panels).

Figure B.4 shows that lower values of the elasticity of the capital-labor bundle with respect to capital, α, deepen the decline of aggregate investment in the case of both a CPU shock to dirty product taxes (left-hand panels) and for a CPU shock to energy

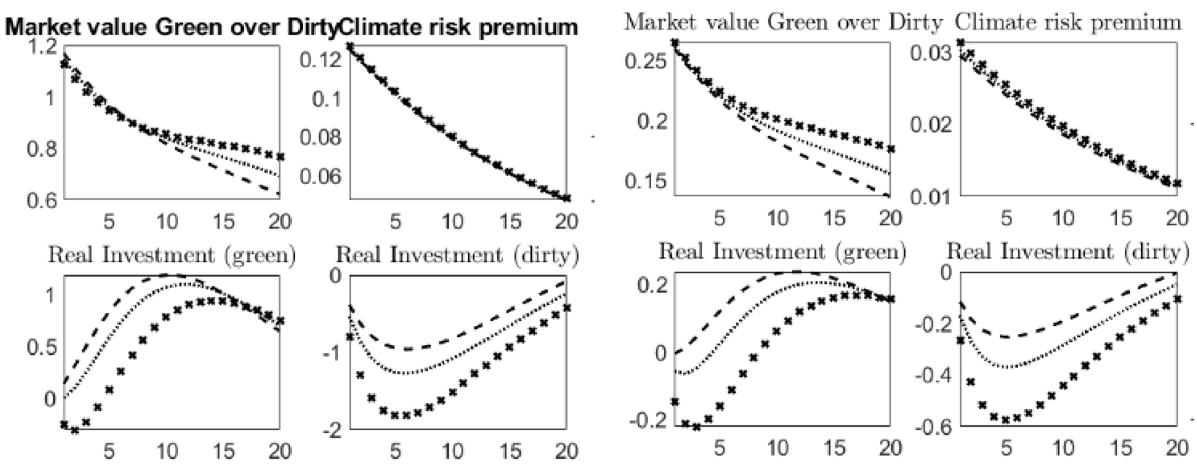
Figure B.3: Effects of climate policy uncertainty shocks: different values of the elasticity of substitution in consumption



Crossed line: $\Theta = 0.2$**, dotted line:** $\Theta = 0.44$**, dashed line:** $\Theta = 0.9$**. Left panels:** Impulse responses to CPU shock to tax rate of dirty products **Right panels:** Impulse responses to CPU shock to tax rate of energy use. Note: The figure presents theoretical impulse responses to a shock with the size of 4 standard deviations. y-axis in percent.

taxes (right-hand panels). As a consequence, for $\alpha = 0.45$, investment in the green sector increases on impact, whereas for $\alpha = 0.25$ it decreases on impact (though by less than in the dirty sector) and gradually recovers thereafter.

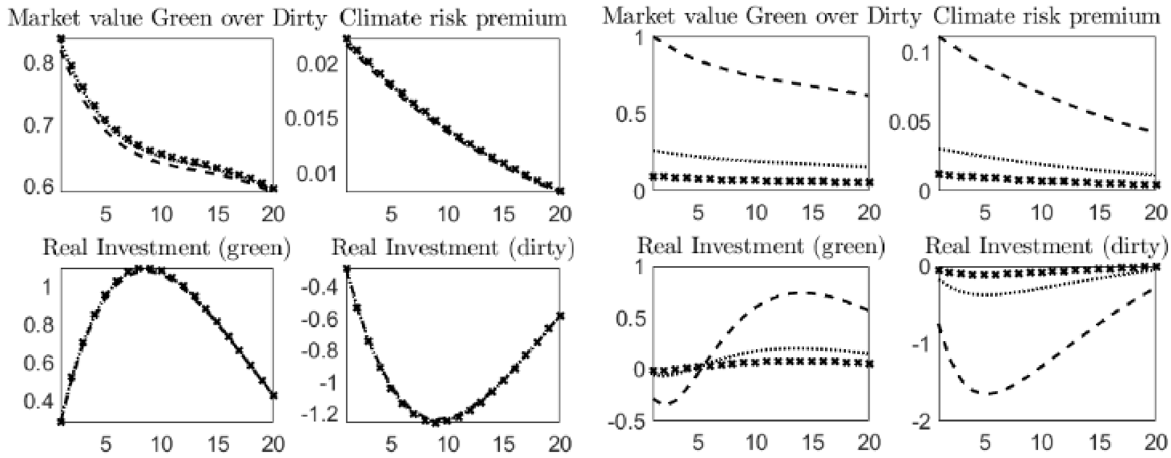
Figure B.4: Effects of climate policy uncertainty shocks: different values of the output elasticity of capital



Crossed line: $\alpha = 0.25$**, dotted line:** $\alpha = 0.36$**, dashed line:** $\alpha = 0.44$**. Left-hand panels:** Impulse responses to CPU shock to tax rate of dirty products. **Right-hand panels:** Impulse responses to CPU shock to tax rate of energy use. Note: The figure presents theoretical impulse responses to a shock with the size of 4 standard deviations. y-axis in percent.

Figure B.5 shows that variations in the share of energy used in production in the green sector, κ^G, do not change the main results qualitatively. The same holds for κ^D. In this figure – as above – we focus on the CPU shocks that are related to taxes. The effects of the CPU shock related to the collateral value are not affected by changes in the parameters discussed.

Figure B.5: Effects of climate policy uncertainty shock: different values of the energy share in production



Crossed line: $\kappa^G = 0.03$**, dotted line:** $\kappa^G = 0.05$**, dashed line:** $\kappa^G = 0.1$. **Left-hand panels:** Impulse responses to CPU shock to tax rate of dirty products. **Right-hand panels:** Impulse responses to CPU shock to tax rate of energy use. Note: The figure presents theoretical impulse responses to a shock with the size of 4 standard deviations. y-axis in percent.

B.3 Allowing for uncertainty about carbon taxes on households' energy consumption

In our baseline model, we focus on energy use by firms. Here, we discuss a model variant, in which households also consume energy.

In this setting, the households' consumption basket is composed of energy consumption, E_t^C, and core consumption of goods produced in sector G, C_t^G, and in sector D, C_t^D,

$$C_t = \left[\kappa^E (E_t^C)^{\frac{\Theta-1}{\Theta}} + (1-\kappa^E)\mu_G (C_t^G)^{\frac{\Theta-1}{\Theta}} (1-\kappa^E)(1-\mu_G)(C_t^D)^{\frac{\Theta-1}{\Theta}}\right]^{\frac{\Theta}{\Theta-1}}, \tag{B.1}$$

where κ^E and μ^G are consumption weights and Θ is the elasticity of substitution between energy and the different consumption good types. The corresponding price index reads

$$P_t = \left[\kappa^E((1+\tau_t^e)P_{C,t}^E)^{1-\Theta} + (1-\kappa^E)\mu_G(P_t^D)^{1-\Theta}(1-\kappa^E)(1-\mu_G)((1+\tau_t)P_t^D)^{1-\Theta}\right]^{\frac{1}{1-\Theta}}. \tag{B.2}$$

Here, τ_t is a consumption tax on goods produced with a higher energy intensity.

The steady state share of energy consumption of households, κ^E, is set to 0.09, which was the relative importance of energy in the US Urban Consumer Price Index in June

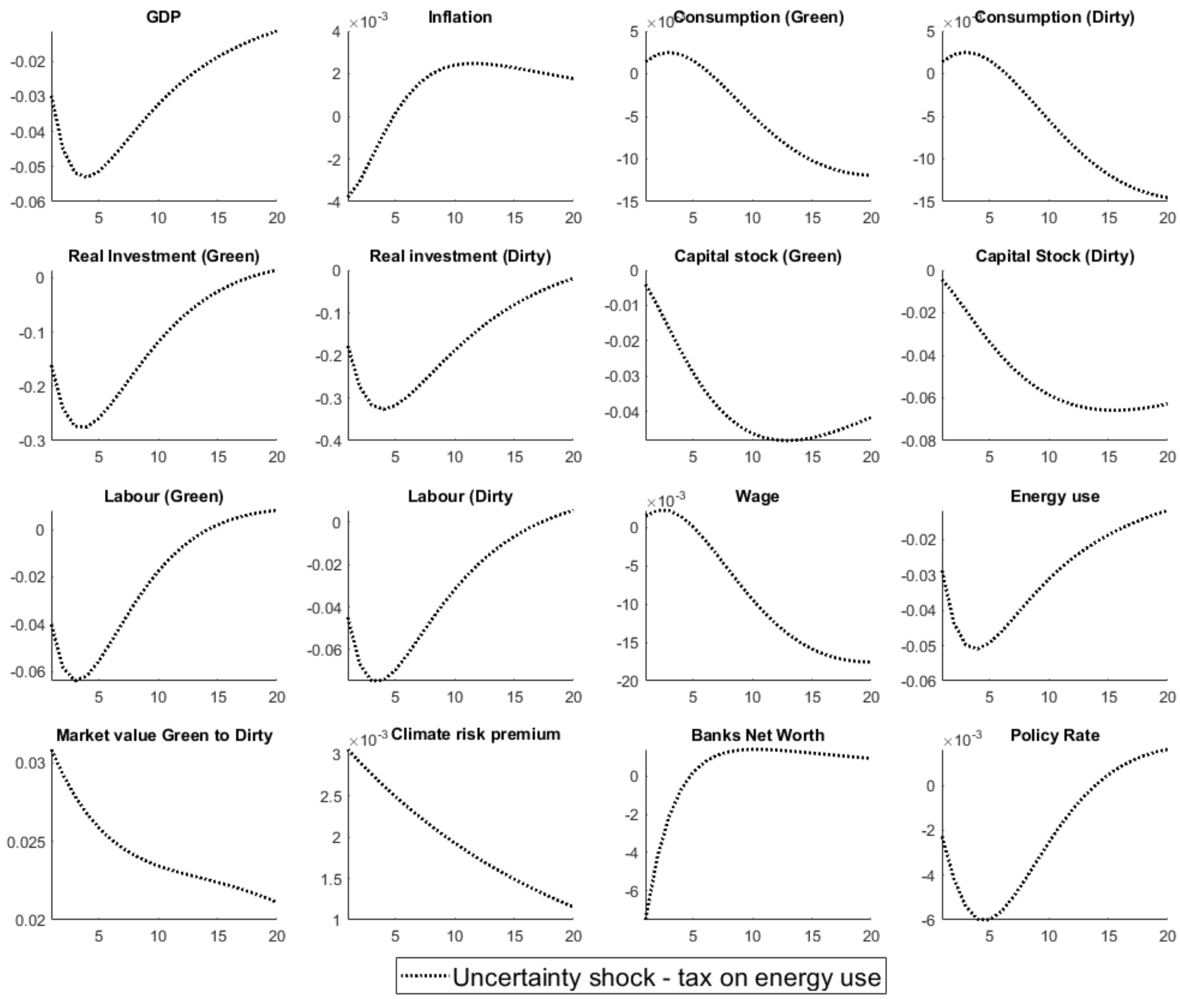
2022.[14] As a simplification, we assume that the households' elasticity of substitution between green-sector and dirty-sector goods is the same as between energy and non-energy goods, namely $\Theta = 0.44$. In the simulations below, we reduce the standard deviation of the tax rate on energy use to one percent to achieve a roughly similar level of divestment as in the baseline simulations.

Figure B.6 shows, for the CPU shock on the energy tax rate, that the effects associated with the reallocation of capital between sectors, such as the climate risk premium and an increase in the relative market value of green assets remain intact. Notably, as the uncertainty shock to the energy tax rate now directly affects agents' nominal stochastic discount factor expenditures, the effects on real activity are amplified. Households now initially shift their expenditures from energy use to core consumption goods (C_t^G and C_t^D). After a few quarters, however, the precautionary savings motive predominates and consumption decreases. Investment is reduced in both sectors. The decrease in aggregate demand lowers inflation.

Any differences in the effects of the CPU shocks to the tax rate of dirty products and on the collateral value of dirty assets compared to the baseline model are negligible.

[14]See https://www.bls.gov/charts/consumer-price-index/consumer-price-index-relative-importance.htm.

Figure B.6: Effects of a climate policy uncertainty shock



Note: The figure presents theoretical impulse responses of the size of 4 standard deviations. y-axis in percent.

C Data description

C.1 Data sources for time series

Time series	Data source
US climate policy uncertainty	Gavriilidis (2021), http://www.policyuncertainty.com
US climate change-related news	Engle et al. (2020), https://sites.google.com/view/stefanogiglio/data-code
US macroeconomic and financial uncertainty	Jurado et al. (2015), https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes
US economic policy uncertainty	Baker et al. (2016), http://www.policyuncertainty.com
West Texas Intermediate Cushing (CME Group) spot prices	Energy Information Administration, Haver Analytics.
Natural gas (Henry Hub) spot prices	Energy Information Administration, Haver Analytics.
Gross private domestic investment (implicit price deflator)	Bureau of Economic Analysis, Fred Economic Data.
Personal consumption expenditure	Bureau of Economic Analysis, Haver Analytics.
Gross private domestic investment	Bureau of Economic Analysis, Haver Analytics.
Corporate profits	Bureau of Economic Analysis, Haver Analytics.
Gross domestic product	Bureau of Economic Analysis, Haver Analytics.

Table C.1: Time series at a monthly frequency

D Further empirical results

Figure D.7: Quarterly climate policy uncertainty shocks

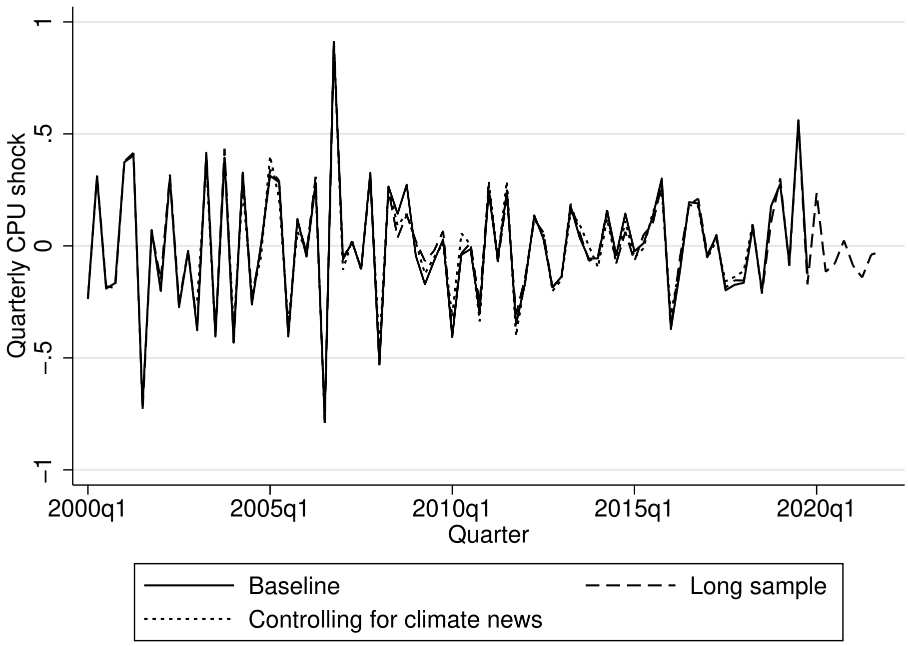
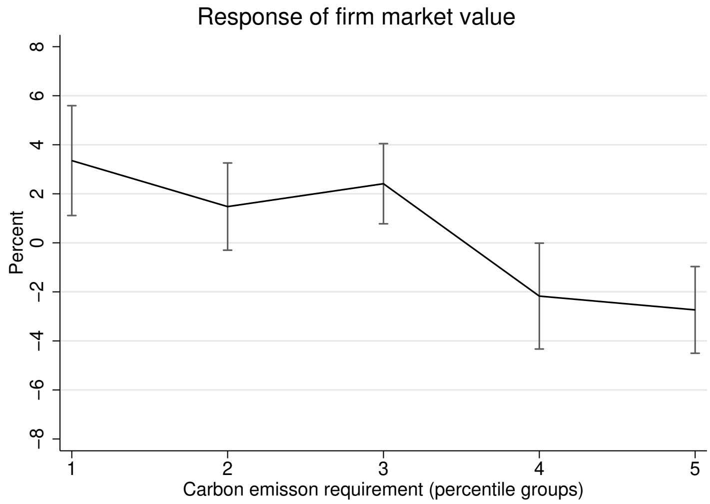
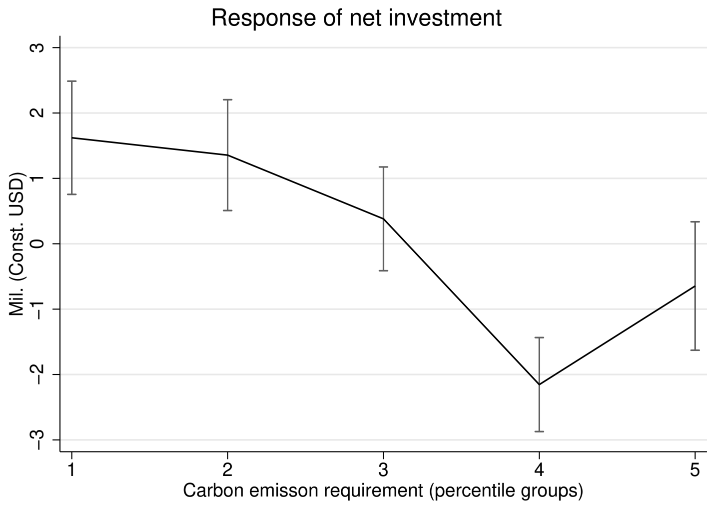


Figure D.8: Current market value response to climate policy uncertainty shocks for different levels of required carbon emissions excluding left-hand-side observations from 2008Q3 to 2009Q2



Note: 1 represents low carbon-emission requirements, while 5 represents high carbon-emission requirements. Confidence intervals at at 90% level. Expressed as the average effect in the current and following quarter of the shock. Sample period: 2000Q1-2019Q4. Excluding left-hand-side observations from 2008Q3 to 2009Q2.

Figure D.9: Net investment response to climate policy uncertainty shocks for different levels required carbon emissions excluding left-hand-side observations from 2008Q3 to 2009Q2.



Note: 1 represents low carbon-emission requirements, while 5 represents high carbon-emission requirements. Confidence intervals at 90% level. Epressed as the average effect in the current and following quarter of the shock. Sample period: 2000Q1-2019Q4. Observations with an absolute value of quarterly net investment above USD 500 million are excluded from the sample. Excluding left-hand-side observations from 2008Q3 to 2009Q2.