Do Firm Credit Constraints Impair Climate Policy?*

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Abstract

This paper shows that firm credit constraints impair climate policy. Empirically, firms with tighter credit constraints, measured by their distance-to-default, exhibit a relatively smaller emission reduction after a carbon tax increase. We incorporate this channel into a quantitative DSGE model with endogenous credit constraints and carbon taxes. Credit frictions reduce the optimal investment into emission abatement since shareholders are less likely to receive the payoff from such an investment. We find that carbon taxes consistent with net zero emissions are 24 dollars/ton of carbon larger in the presence of endogenous credit constraints than in an economy without such frictions.

Keywords: Climate Policy, Credit Constraints, Emission Reduction, Corporate Capital Structure, Firm Heterogeneity

JEL Classification: E44, G21, G28, Q58

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1 Introduction

There is a broad consensus that the net zero transition requires large upfront investments into low-emission technologies. Since investment at the firm-level is often debt-financed, this immediately raises the question whether firms' access to credit impairs climate policy. Answering this question is crucial for the design of climate policies, as policymakers need to take potential frictions into account when implementing carbon taxes along the transition to net zero. This paper aims to broaden our understanding of firm credit constraints for the efficacy of climate policy.

Empirically, we document the relevance of firm credit constraints for climate policy in a large international sample of listed firms from 2011 to 2019. We obtain emissions data from ISS-ESG and measure firm credit constraints by the distance-to-default (Merton 1974), which has been identified as a suitable measure of credit constraints by Farre-Mensa and Ljungqvist (2015). To measure climate policy, we employ an annual dataset of country-specific carbon taxes, which is maintained by *OECD Statistics* for 33 countries that jointly accounted for 77% of global emissions in 2019. Employing a standard difference-in-difference approach, we test whether firms with tighter credit constraints, i.e. with a lower distance-to-default, cut their emissions by less than their unconstrained peers in the same industry in response to a carbon tax hike.

We find that a one standard deviation increase of the distance-to-default implies an additional emission reduction by 1.1 percentage points in response to a carbon tax increase by ten USD per ton of carbon dioxide ($/tCO2). This effect is sizable, given that the full-sample standard deviation of emission growth is 0.9 percentage points. The effect is particularly strong in the manufacturing sector, where the effect amounts to around 2.7 percentage points, and for firms with lower capital intensities.[1] The effect is robust to including firm control variables such as profitability, size or age, and their interactions with carbon tax increases. This alleviates concerns that our empirical specification in fact picks up a differential emission reduction response by younger and smaller firms.

To assess the macroeconomic relevance of firm credit constraints in the context of climate policy, we incorporate this channel into a quantitative DSGE model with endogenous credit constraints, firm investment, and emission abatement. Manufacturing firms generate carbon emissions as a by-product of their production and are subject to carbon taxes. Manufacturers can either invest in physical capital or in emission abatement. The possibility of emission abatement allows firms to reduce their carbon tax bill without reducing their production (Heutel 2012).

[1] We define the capital intensities as Property, Plant and Equipment (PPE) over gross revenues. Such firms might be more constrained in their access to credit since they can pledge less physical capital as collateral.

Following the framework of Gomes, Jermann, and Schmid (2016), firms finance their investment either by issuing defaultable debt to households or by receiving an equity transfer from firm owners. Firm owners are more impatient than households and issue debt to front-load dividends, which is conceptually similar to short-termism. However, firms expose themselves to default risk when issuing debt: they are subject to uninsurable idiosyncratic productivity shocks and default on their debt if production revenues net of carbon taxes fall short of repayment obligations. Corporate default entails a cost which is borne by creditors and fully reflected in borrowing conditions, i.e. the price of corporate debt. Under their optimal capital structure, firms issue debt until the marginal default cost equals the benefits of additional debt issuance. These benefits are given by the relative impatience of firm owners vis-a-vis debt owners, which is the key credit friction in our model and gives rise to endogenous credit constraints.

Credit constraints have direct implications for manufacturing firms' investment choices. While optimal abatement increases in the expected carbon tax, it also takes into account that firm owners do not receive the payoff from abatement in the case of default. All else equal, the benefits of acquiring abatement goods are lower if credit constraints are tight, which reduces abatement in equilibrium. The crucial difference to related models building on Heutel (2012) lies in our assumption that investment in abatement goods is chosen one period in advance rather than contemporaneously.[2] Importantly, corporate short-termism is not detrimental to climate policy objectives in itself, for example by inducing firms to stick to conventional technologies that generate large short term payoffs (coal plants) rather than undertaking high upfront investments into technologies that are more profitable in the longer term (renewable energy). Instead, short-termism manifests itself in high firm default probabilities that makes investment generally less attractive. This is conceptually related to the classical debt overhang problem (Myers 1977).

As a next step, we calibrate a quantitative version of our model to the data. Technology and climate policy parameters are set to standard values in the literature. Parameters concerning credit frictions are calibrated to match key empirical regularities of corporate default risk and credit constraints, such as the distance-to-default, leverage ratio, and recovery rate on corporate debt. The model can replicate the (untargeted) pro-cyclicality of distance-to-default that has been documented empirically (Gilchrist and Zakrajšek 2012) and implies an empirically plausible (untargeted) corporate default rate of 0.8%. The model is furthermore able to reconcile key (untargeted) dynamics of firm risk-taking and default risk over the business cycle.

[2] In models where the abatement effort is a contemporaneous choice, it is not directly affected by credit constraints, see for example Carattini, Melkadze, and Heutel (2023).

In the model, tight credit constraints are associated with a low distance-to-default, which provides a direct link to our empirical analysis. We exploit this link to further corroborate the external validity of our calibration. Specifically, we compare the effect of an unanticipated and permanent carbon tax increase by 10$/tCO2 on a counterfactual economy that is free of default risk. Emissions decline by 11.7% in the risk-free economy, while the emission reduction is only 11.1% in the baseline economy with default risk. The (untargeted) differential is slightly smaller but of similar magnitude to our empirical results. This shows that our model with credit frictions captures the interaction between credit constraints and climate policy reasonably well and that our model's quantitative predictions are conservative.

Equipped with this quantitative version of our model, we assess the macroeconomic relevance of endogenous credit constraints in the context of climate policy. For our main policy experiment, we compare our baseline economy to a counterfactual economy without default risk and credit constraints. The full-abatement tax is 300$/tCO2 in the risk-free economy, while it is 324$/tCO2 in the baseline economy, i.e it amounts to almost ten percent of the necessary carbon tax. The quantitative relevance of credit constraints is robust to changes in technology parameters.

Endogenous credit constraints associated with short-termism place macroeconomically relevant restrictions on the conduct of climate policy in the transition to net zero. This can be illustrated by subjecting the baseline and counterfactual economies to the same carbon tax path. We impose a linear increase of carbon taxes from zero in 2010 to 300$/tCO2 in 2050. This terminal tax would implement net zero emissions in the risk-free economy, in line with the Paris Agreement, but would not suffice to implement net zero emissions in the baseline model. If this carbon tax path would be implemented, cumulated carbon emissions would be 41 gigatons larger by 2050. This difference is quite substantial given that global carbon emissions amounted to 33 gigatons in 2022.[3]

In contrast to credit supply driven constraints to investment in low emission technologies, our analysis highlights the role of credit demand, i.e. firm-driven credit constraints. As a consequence, policies that aim at fostering the supply of credit to low emission firms are not able to overcome these credit constraints. In fact, green credit easing policies might even exacerbate such credit constraints by increasing investors willingness to pay for corporate debt. Instead, policies that address short-termism associated with corporate borrowing endogenously reduce credit constraint and effectively support climate policy.

[3]Naturally, the carbon tax consistent with net zero also depends on a variety of technological characteristics from which our representative agent model abstracts, in particular heterogeneities between and within different production sectors. We argue that firm-driven credit constraints have to be taken into account irrespective of other technological constraints.

Related Literature There is a growing body of research studying the interactions between credit constraints and emission reductions, often identified through shocks to bank credit supply. Goetz (2019) shows that a shock to the debt financing cost increases firms' abatement activities. Xu and Kim (2021) show that credit constrained firms are less likely to engage in pollution abatement, which is consistent with our empirical findings for climate policy. Accetturo et al. (2023) demonstrate that firms increase their green investment when experiencing a positive credit supply shock. Kacperczyk and Peydro (2022) focus on the credit supply of banks committing to carbon reduction targets set by the so called "Science Based Targets Initiative". They find that high emission firms in relationship with committed banks experience a smaller inflow of credit, but do not significantly improve their climate performance.

A second strand of literature focuses on credit constraints and emission reduction at the firm level in response to regulatory changes. Fang, Hsu, and Tsou (2023) study the role of financial constraints for pollution abatement in the context of regulatory uncertainty. Mueller and Sfrappini (2022) show that banks allocate credit away from banks in response to an increase in climate policy salience after the Paris Agreement. Döttling and Lam (2024) use high-frequency identified monetary policy shocks and find that firms reduce their emissions in response to interest rate hikes, while emission intensities slightly increase over the medium term, which is consistent with the notion that tighter credit constraints - due to restrictive monetary policy - induces firms to forgo investment into abatement technologies. Closely related to our empirical analysis is De Haas et al. (2024), who show that both credit constraints and weak corporate management are associated with higher firm emissions. Specifically, for a large sample of firms in emerging markets, removing credit constraints would reduce emissions by 4.5%. This effect size is of similar magnitude to our results.

Our paper is also related to the recent literature that studies credit constraints, investment and endogenous climate policy in a joint framework. Analytically tractable results are provided by Döttling and Rola-Janicka (2022), Heider and Inderst (2022) and Haas and Kempa (2023). While our analysis delivers novel analytical results, we also contribute to the quantitative E-DSGE literature by explicitly introducing credit frictions into firms' abatement decision. Our framework is related to Carattini, Melkadze, and Heutel (2023), who discuss the macroeconomic effects of asset stranding and to Giovanardi and Kaldorf (2023), who add bank capital regulation to an E-DSGE model with corporate financing frictions. Iovino, Martin, and Sauvagnat (2023) provide an analysis of asset-based borrowing constraints in a general equilibrium model with heterogeneous firms and corporate taxation. Campiglio, Spiganti, and Wiskich (2023) add financial constraints to a directed technical change model and study the interactions between experience effects and the financing of new low-emission technologies. Using a model of external financing constraints that is tailored to small firms, Schuldt and Lessmann (2023) show that relaxing firm-level credit constraints has positive side effects on climate policies. Our paper contributes to this literature by demonstrating that credit frictions have a negative effect on emission abatement through a debt overhang channel that appears to be particularly suitable to study large firms, consistent with our empirical approach.

Outline This paper is structured as follows. Our data and the main empirical results are presented in Section 2. Our augmented DSGE model is introduced in Section 3. The model's calibration and quantitative predictions are discussed in Section 4. We illustrate the key mechanism through which credit frictions impair climate policy in Section 5. Section 6 concludes.

2 Credit Constraints and Climate Policy in the Data

In this section, we first outline how we measure climate policy, credit constraints and carbon emissions. We then discuss our empirical specification and results.

2.1 Data

Measuring Climate Policy A key empirical challenge lies in the measurement of climate policies, which encompasses a large variety of different policies, such as emission trading systems, direct taxation, or mandatory industry standards. To align our empirical analysis as closely as possible to our macroeconomic model, we use a country-specific measure of carbon tax stringency, provided by *OECD Statistics*. Data are available for 27 OECD member countries as well as Brazil, China, India, Indonesia, Russia and South Africa at annual frequency.

The key advantage of this dataset is that carbon taxes can be readily compared across countries. The carbon taxation index ranges from 0 (no policy in place) to 6 (most stringent). Here, the index value of 6 is assigned to country-year observations above the 90th percentile of the distribution over all countries from 1990-2020 (see Section 2.2 in Kruse et al. 2022 for a detailed description). Index values between 1 and 5 correspond to 10\$/tCO2 intervals. An increase of the index by one point, thus, corresponds to an increase of approximately 10\$/tCO2.[4] The index passes a battery of plausibility checks and is, for example, negatively correlated with country-wide emission-to-GDP ratios. For details on the scope of

[4] Note that the index does not capture an increase in the *scope* of carbon policies, for example by requiring more firms to participate in a cap-and-trade scheme.

the dataset and its construction, we refer to Kruse et al. (2022). Appendix A.1 shows the country-specific time series of carbon tax shocks (Figure A.1) and the evolution of carbon tax levels (Figure A.2) over our sample period.

Measuring Carbon Emissions We obtain firm-level emissions data from *Institutional Shareholder Services* (ISS). The dataset contains annual information on firm-level greenhouse gas (GHG) emissions, differentiating between scope 1 (direct emissions from operations of affiliates that are owned or controlled by the company) and scope 2 (emissions from the consumption of electricity, heat or steam) emissions. We use scope total emissions in our analysis, defined as the sum of scope 1 and scope 2 emissions. Throughout the analysis, we do not take Scope 3 emissions into account, since these refer to activities outside the direct control of the firm. GHGs are defined according to the GHG Procotol, a collaborative accounting standard by the World Resources Institute and the World Business Council on Sustainable Development. Emissions data are either reported or estimated by ISS. Figure A.3 in Appendix A.2 shows how carbon emissions vary across countries and time. In each country, the median emission growth hovers around zero, but sharply declines in 2016 and 2017 after the Paris Agreement was signed. Table A.1 provides summary statistics across countries and sectors. When pooling all observations over time, the distribution of emission growth over firms is fairly symmetric around zero.

Measuring Credit Constraints and other Firm Characteristics Data on credit constraints and firm financial characteristics is from Compustat North America and Global, which assembles data on securities and firm-level accounting information. For credit constraints, the empirical corporate finance literature has often used various definitions of leverage and profitability, computed from accounting data, as indicator for binding credit constraints. However, as demonstrated by Farre-Mensa and Ljungqvist (2015), firms classified as constrained by indicators based on accounting ratios do not behave as if they were actually credit constrained. Specifically, Farre-Mensa and Ljungqvist (2015) use business tax reductions, which incentivize corporate debt issuance due to the tax deductability of interest expenses, as exogenous shock to the optimal capital structure trade-off. They show that firms classified as constrained according to several commonly used indicators do not behave differently from firms classified as unconstrained.

Therefore, we measure credit constraints by the *distance-to-default (D2D)* proposed by Merton (1974) which passes the plausibility tests for measures of credit constraints proposed by Farre-Mensa and Ljungqvist (2015). Since computing the distance-to-default requires equity and balance sheet data, this naturally restricts our sample to listed firms. We compute the distance-to-default for each firm and year closely following the methodology outlined in Gilchrist and Zakrajšek (2012). Figure A.4 in Appendix A.3 shows the evolution of the country-specific average distance-to-default over time, with a full sample average of around eight and a substantial dispersion across countries. Table A.2 contains summary statistics across countries and sectors. Perhaps surprisingly, there are no significant differences in distance-to-default among sectors.

While matching emissions data obtained from ISS with credit constraints data from Compustat and the carbon taxation index is conceptually straightforward, we have to make an assumption on the relevance of country-specific carbon policy for multi-country firms. In cases where there are multiple subsidiaries of a given firm in the firm-level dataset, we use its primary location in Compustat, i.e. the country of its headquarters, as the matching entity. Implicitly, our baseline specification assumes that firms respond to the climate policy in their primary location.[5] Lastly, we exclude financial firms (SIC-codes between 60 and 67, or 69) and public administration (SIC-codes between 90 to 99). To ensure that our results remain unaffected by the global Corona pandemic, we end our datasets in 2019. The final data sample consists of 18,882 firms annually spanning from 2012 to 2019, and 97,913 firms × year observations.

2.2 Empirical Strategy and Results

In our main specification, we test whether firm credit constraints, measured by their distance-to-default, affect the pass-through of carbon taxes to emission growth at the firm level. We use the relative change of firm j's emissions (in tCO2) from year *t-1* to t ($\Delta log(Emi)_{j,t} \equiv \log(Emi_{j,t}) - \log(Emi_{j,t-1})$) as dependent variable. We regress this on changes to the (country-specific) carbon taxes. To test the role of credit constraints, we interact carbon tax changes with firm j's distance-to-default in the previous year:

$$\begin{aligned}\Delta \log(Emi)_{j,t} = \beta_0 + &\beta_1 \cdot \mathrm{D2D}_{j,t-1} \times \Delta\mathrm{Tax}_{c(j),t} + \beta_2 \cdot \mathrm{D2D}_{j,t-1} + \beta_3 \cdot \Delta\mathrm{Tax}_{c(j),t} \\ &+ \beta_4 \cdot X_{j,t-1} + \chi_c + \tau_t + \epsilon_{j,t}\ . \qquad (1)\end{aligned}$$

We use the lagged distance-to-default $D2D_{j,t-1}$ as a measure of firm credit constraints, since the current distance-to-default might be affected by the change climate policy and can, thus, not reasonably assumed to be exogenous. $\Delta Tax_{c,t}$

[5] Since the firms in our sample are large, it is reasonable to assume that many of them are multinational firms. These firms have the opportunity to shift carbon intensive activities abroad in response to climate policy shocks in their headquarters (see also Bartram, Hou, and Kim 2022). To alleviate this concern, we show in Appendix B.3 that our results are also robust to restricting the firm sample to the Utilities sector. Such firms are predominately active in single countries and, thus, less susceptible to shifting operations abroad.

measures the tax increase from *t-1* to t at country-level, i.e. $\Delta Tax_{c,t} \equiv Tax_{c,t} - Tax_{c,t-1}$. $X_{j,t-1}$ is a vector of firm controls at time *t-1*, which contains firm size (measured by *log(Assets)*), firm age (*young*, which is a dummy equal to 1 if firm age is less than five years and zero otherwise), and profitability (measured by *EBIT/Revenues*). Table A.3 presents descriptive statistics for all variables used in the main analysis.

The coefficient of interest is β_1 on the interaction term $D2D_{j,t-1} \times \Delta Tax_{c,t}$, measuring the extent to which firms' credit constraints affect the pass-through of carbon taxes to emission growth. The identification assumption on the interaction term is that unconstrained firms (with higher distance-to-default) provide a counterfactual for constrained firms in the absence of a change in carbon taxes. Importantly, we do not have to assume that the change in climate policy is exogenous with respect to aggregate credit constraints, but only require that changes in climate policy are not endogenous with respect to differences between treatment and control group.[6] Throughout all specifications, we include year fixed effects to capture global events during the sample period such as the Paris Agreement in December 2015. Furthermore, we add country fixed effects χ_c since countries differ substantially in their level of carbon taxes, as we show in Appendix A.1. By adding sector-by-year fixed effects in the baseline specification, we compare constrained to unconstrained firms within sectors, since there is substantial sectoral heterogeneity in production technologies, particularly in their emission intensities. Standard errors are clustered at the country level in all specifications, which is the treatment level of the carbon tax shock.

The baseline results are shown in Table 1. Using all sectors, column (1) indicates that firms with tighter credit constraints respond less to a carbon tax increase. Quantitatively, a one standard deviation increase of the distance-to-default, which is 5.5 in the full sample (Table A.2), is associated with an additional emission reduction by 1.1 percentage points. This effect is sizable compared to the cross-sectional variation in emission growth rates at the firm level which is 0.91% in the full sample (Table A.1). The coefficient on distance-to-default reported in the second row indicates that firms with a high distance-to-default generally experience a larger growth of emissions. This is not surprising since emissions are strongly correlated with revenues and firms with a faster revenue growth tend to be less credit constrained, i.e. to have a high distance-to-default. Naturally, it is hard to interpret β_2 as causal, since loose credit constraints also enable firms to expand their business activities.

The coefficients on firm-specific control variables are significant across almost all specifications. Emissions grow more slowly in large firms, which tend to be

[6] In Appendix B.1, we provide further evidence that tight aggregate credit constraints do not predict climate policy changes at country level.

Table 1: **Carbon Taxes and Credit Constraints**

VARIABLES	(1) $\Delta log(Emi)_{j,t}$	(2) $\Delta log(Emi)_{j,t}$	(3) $\Delta log(Emi)_{j,t}$	(4) $\Delta log(Emi)_{j,t}$	(5) $\Delta log(Emi)_{j,t}$	(6) $\Delta log(Emi)_{j,t}$	(7) $\Delta log(Emi)_{j,t}$	(8) $\Delta log(Emi)_{j,t}$	(9) $\Delta log(Emi)_{j,t}$
$D2D_{j,t-1} \times \Delta Tax_{c(j),t}$	-0.002**	0.002	-0.004*	-0.005**	0.001	-0.006**	-0.005***	-0.001	-0.008***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$D2D_{j,t-1}$	0.005**	0.006**	0.005***	0.006**	0.006***	0.005*	0.006***	0.007***	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$\Delta Tax_{c(j),t}$	-0.017	-0.078***	0.019	0.020	-0.054*	0.049**	0.018	-0.042*	0.061***
	(0.011)	(0.017)	(0.012)	(0.021)	(0.028)	(0.019)	(0.014)	(0.023)	(0.022)
$Log(Assets)_{j,t-1}$	-0.022*	-0.024	-0.021***	-0.028*	-0.037*	-0.021**	-0.034**	-0.047*	-0.027**
	(0.011)	(0.016)	(0.007)	(0.014)	(0.019)	(0.009)	(0.016)	(0.023)	(0.012)
$Young_{j,t-1}$	-0.021***	-0.030*	-0.015	-0.024***	-0.053**	0.000	-0.019**	-0.053***	0.021
	(0.006)	(0.017)	(0.014)	(0.009)	(0.021)	(0.018)	(0.009)	(0.014)	(0.014)
$EBIT/Revenues_{j,t-1}$	-0.096***	-0.153***	-0.053	-0.060***	-0.081**	-0.041	-0.063***	-0.080**	-0.039
	(0.020)	(0.028)	(0.032)	(0.020)	(0.035)	(0.029)	(0.020)	(0.036)	(0.030)
Constant	0.185*	0.232	0.150**	0.237*	0.357*	0.140**	0.287**	0.449**	0.181*
	(0.096)	(0.154)	(0.057)	(0.120)	(0.186)	(0.068)	(0.140)	(0.219)	(0.100)
Observations	40,109	21,597	18,481	24,125	13,617	10,492	23,984	13,397	10,215
R-squared	0.024	0.033	0.028	0.019	0.031	0.015	0.110	0.157	0.167
Industry-by-year FE	SIC-group	SIC-group	SIC-group	NO	NO	NO	4-digit SIC	4-digit SIC	4-digit SIC
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sectors	All	All	All	Manuf	Manuf	Manuf	Manuf	Manuf	Manuf
Capital Intensity	All	High	Low	All	High	Low	All	High	Low
Year FE	NO	NO	NO	YES	YES	YES	NO	NO	NO

Notes: This table reports the results of estimating Equation (1). Column (1) refers to the full sample and column (2)-(3) provide the results of total carbon emissions in sub-samples firms with a high and low capital intensity, obtained from a median split within each industry. Column (4)-(9) report the results of total emissions exclusively in manufacturing sectors. Regressions are estimated at the firm-year level. $\Delta Tax_{c,t}$ is the difference in country-level tax taxes from $t-1$ to t. $D2D_{j,t-1} \times \Delta Tax_{c,t}$ is the interaction between $D2D_{j,t-1}$ and $\Delta Tax_{c,t}$. The regressions control for firm size ($Log(Assets)_{j,t-1}$), age ($Young_{j,t-1}$) and profitability ($EBIT/Revenues_{j,t-1}$), all lagged by one year. We include country fixed effects in all specifications, year fixed effects in column (4)-(6) and industry $\times$ year fixed effects in column (1)-(3),where the industries are measured by sectors, and column (7)-(9), where the industries are measured by the most granular 4 digit SIC. Standard errors, clustered at the country level, are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

closer to their optimal size. Younger and more profitable firms tend to be more capable of adjust their manufacturing process towards less emission intensive technologies, holding their size and credit constraint fixed. In Appendix B.2, we augment our baseline specification by interacting firm-level controls with the carbon tax shock to ensure that β_1 does not pick up effects that are in fact associated with firm age, size, and profitability, which are naturally correlated with distance-to-default.[7] The coefficient β_1 remains highly significant, and its size even slightly increases.

It is also instructive to re-estimate our baseline specification on different sectors. As shown in the lower panel of Table A.1, the manufacturing sector dominates our sample and, more generally, plays a crucial role for climate policy for three reasons. First, manufacturing processes are often carbon-intensive and contribute significantly to overall carbon emissions. By adopting less emission intensive production technology, the manufacturing sector can have a substantial impact on the success of the transition. Second, manufacturing sectors are at the forefront of developing new technologies that are essential for the net zero transition (Shi, Zhou, and Meinerding 2023). Third, firms in the model presented in Section 3 are best interpreted as manufacturing firms.

Columns (4) to (9) show the results for the manufacturing sector. Generally, the effect of tighter credit constraints on emission growth is much stronger in the manufacturing sectors, see column (4). In a more stringent specification, we replace year fixed effects τ_t by industry $\times$ year fixed effects $(\delta_i \cdot \tau_t)$, where industries are defined according to four-digit SIC codes. In this way, we account for industry-specific time-variation, such as commodity price movements. As column (7) shows, the coefficient size remains almost unchanged, but it is even significant at the 1%-level. Estimating the baseline specifications on sub-samples according to their capital intensities also yields slightly more pronounced effects within the manufacturing sector and especially when controlling for industry $\times$ year fixed effects. Lastly, in Appendix B.4, we show that firms do not respond to future climate policy tightenings, i.e. there are no significant anticipation effects and that emission growth only changes on impact, i.e. an increase in the level of carbon taxes has a permanent effect on the emission level but not on emission growth.

3 Model

Time is discrete and denoted by $t = 1, 2, ...$ In order to align our results as closely as possible to our empirical results, each period corresponds to one year. The

[7] Kim (2023), Lanteri and Rampini (2023) and Capelle et al. (2023) document that emission intensities vary across firm age and size. Younger and smaller firms might therefore respond differently to climate policy for other reasons than tight credit constraints.

model features a representative household, final good firms, capital good firms and manufacturing firms. While final and investment good firms primarily add macroeconomically plausible general equilibrium dynamics to the model, manufacturers are at the heart of the economic mechanism that we have presented in Section 2. Emissions, climate policy, and credit frictions enter the model at the stage of manufacturers.

Households and Banks The representative household has standard preferences over consumption and labor $u(c_t, n_t, \Delta\mathcal{T}_t) = \log(c_t) - \frac{\omega_N}{1+\gamma_N} n_t^{1+\gamma_N} - \gamma_t(\Delta\mathcal{T}_t)^2$, where $\Delta\mathcal{T}_t$ are global temperature increase since pre-industrial times. Households save in the form of bank deposits that earn the real interest rate r_t. We denote their time-preference parameter by β, which pins down the (steady state) real interest rate in equilibrium. The real wage is denoted by w_t. Solving their maximization problem yields standard intra- and inter-temporal optimality conditions.[8] In the following, $\Lambda_{t,t+1} \equiv \beta \frac{c_{t+1}^{-1}}{c_t^{-1}}$ denotes the representative household's stochastic discount factor.

Banks collect deposits d_{t+1} from households that promise to pay $(1 + r_t)d_{t+1}$ units of the consumption good in the next period and invest the proceeds into corporate debt l_{t+1}. The (realized) per-unit payoff from holding corporate debt is denoted by $\mathcal{R}_t$. Following Cúrdia and Woodford (2011), we impose that banks have to repay their depositors in expectations: $(1 + r_t)d_{t+1} = \mathbb{E}_t[\mathcal{R}_{t+1}]l_{t+1}$. Solving the representative banks' profit maximization problem yields the debt pricing condition:

$$q(\overline{m}_{t+1}) = \frac{1}{1+r_t}\mathbb{E}_t[\mathcal{R}_{t+1}] \ . \tag{2}$$

Final and Investment Good Firms *Final good firms* are perfectly competitive and use labor n_t and a homogeneous intermediate good z_t to produce the final good y_t, using a Cobb-Douglas production function

$$y_t = A_t z_t^{\theta} n_t^{1-\theta} \ , \tag{3}$$

where A_t is an exogenous TFP shock. Let the price of the intermediate good be denoted by p_t^Z. Solving their profit maximization problem yields standard demand functions for labor n_t and the intermediate good z_t that are shown in detail in Appendix C.

Investment good firms transform $\left(1 + \frac{\psi_K}{2}(\frac{I_t}{I_{t-1}})\right)$ units of the final good into one unit of capital goods, which they sell to manufacturing firms at price p_t^K. Here I_t denotes aggregate investment from risky and safe manufacturers. The profit

[8] We provide a full list of equilibrium conditions in Appendix C.

maximization problem yields the first-order condition for the supply of capital goods:

$$p_t^K = 1 + \frac{\psi_K}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2 + \psi_K\left(\frac{I_t}{I_{t-1}} - 1\right)\frac{I_t}{I_{t-1}} - \mathbb{E}_t\left[\Lambda_{t,t+1}\psi_K\left(\frac{I_{t+1}}{I_t} - 1\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right] . \quad (4)$$

Manufacturing Firms: Technology The manufacturing production technology is linear in capital k_t and subject to an uninsurable idiosyncratic productivity shock ($z_t = m_t k_t$). We assume that m_t is i.i.d. across firms and time and follows a log-normal distribution with standard deviation ς. We normalize its mean to $-\frac{\varsigma^2}{2}$, which ensures that expected productivity equals one.

During the production process, manufacturers generate emissions e_t. They are proportional to production z_t, consistent with empirical evidence presented in Zhang (2023). Emissions are taxed at rate τ_t and manufacturers can reduce their tax bill by either reducing their investment or by choosing a cleaner but less efficient technology.[9]

Following the E-DSGE literature (Heutel 2012), we model such a technology choice as the option to invest in an abatement good. Specifically, firms can transform $\frac{\alpha_0}{1+\alpha_1} a_{t+1}^{\alpha_1}$ units of the final good in period t into one unit of the abatement good $a_{t+1} \in [0, 1]$ that reduces emissions in the next period. Modeling the costs associated with the net zero transition in terms of an abatement good is a convenient way to model firm heterogeneity in the decision to switch towards clean technologies. In fact, a_t can be interpreted as the share of firms using an emission-free technology.

Manufacturing Firms: Credit Frictions Manufacturing firms are managed on behalf of impatient firm owners, who have a subjective discount factor $\widetilde{\beta} < \beta$ that is smaller than the household discount factor.[10] As customary in the literature, we assume that the representative firm owner and the representative

[9]We do not allow firms to move their emission intensive activities abroad and also assume that each firms' emissions are public knowledge. While these simplifications allow us to cleanly assess the relevance of credit constraints, there is recent empirical and theoretical work along these lines: Bartram, Hou, and Kim (2022) show that financially constrained firms respond to a tightening of climate policy in California by shifting their production to other states. Similarly, Berg, Ma, and Streitz (2023) show that large public firms sell emission-intensive assets after the Paris Agreement to other firms that are lower levels of public scrutiny. Cartellier, Tankov, and Zerbib (2023) endogeneize emission disclosures at the firm level and Frankovic and Kolb (2024) demonstrate that imperfect emission disclosure negatively affects the conduct of climate policy. Carbon leakage and imperfect emission disclosure further impair the efficacy of climate policy.

[10]The relative impatience for firm owners vis-a-vis debt holders is conceptually related to short-termism. However, different from traditional theories of short-termism, there is no information asymmetry or agency friction between firm owners and firm managers in our model. Instead, short-termism induces firms to increase current dividends by issuing debt, which reduces expected future dividends due to the possibility of default.

households perfectly share their income risk and define the firm owner sdf by $\widetilde{\Lambda}_{t,t+1} \equiv \widetilde{\beta}\frac{c_{t+1}^{-1}}{c_t^{-1}}$. They finance their investment with defaultable long-term debt or with equity, which is modeled as a transfer from firm owners. Debt l_t is long-term and we assume that a share χ of all outstanding debt matures each period. The repayment obligation coming into period t is, therefore, given by χl_t. We take a standard ability-to-repay approach and assume that a firm defaults if after-tax revenues are insufficient to cover the repayment obligation. This is equivalent to assuming that firms can not raise outside equity to repay their creditors. The threshold productivity level $\overline{m}_t$ below which a firm defaults is given by

$$\overline{m}_t \equiv \frac{\chi l_t}{(p_t^Z - \tau_t(1-a_t))k_t} \tag{5}$$

Equation (5) implies that the default threshold $\overline{m}_t$ increases in response to a surprise carbon tax hike in period t. This makes repayment less likely, since a firm needs to draw a higher productivity level in order to be able to repay: unanticipated carbon tax shocks increase the firm default rate on impact. However, the efficacy of carbon taxes depends on manufacturing firms' willingness to exert abatement effort a_{t+1} going into the next period. The optimal abatement effort in turn depends on the carbon tax next period τ_{t+1} and on the threshold productivity level $\overline{m}_{t+1}$ that is relevant next period, as we shall see next.

Manufacturing Firms: Maximization Problem To maintain tractability, we follow Gomes, Jermann, and Schmid (2016) in assuming that a defaulting firm is restructured immediately, such that it re-enters the debt market in the default period. This facilitates aggregation into a representative firm. Dividends in period t can be written as

$$\begin{aligned} div_t =& \mathbb{1}\{m_t > \overline{m}_t\} \cdot \Big(\big(p_t^Z - \tau_t(1-a_t)\big) z_t - \chi l_t \Big) \\ & - p_t^K i_t - \frac{\alpha_0}{1+\alpha_1} \big(a_{t+1}\big)^{1+\alpha_1} + q(\overline{m}_{t+1}) \Big(l_{t+1} - (1-\chi) l_t \Big) \, . \end{aligned} \tag{6}$$

The term in the first line of (6) reflects the after-tax production revenues $\big(p_t^Z - \tau_t(1-a_t)\big)z_t$, net of debt repayment χl_t, in the repayment case where the productivity draw m_t exceeds the default threshold $\overline{m}_t$. The second line of (6) contains all investment and financing activity in period t that is relevant for period $t+1$. Due to the assumption of immediate restructuring, a firm can invest in capital, exert abatement effort and change its net debt position $l_{t+1} - (1-\chi)l_t$ irrespective of its productivity draw.

When changing its debt position, firms are subject to a debt pricing condition that follows from the assumption that all debt is fairly priced by banks. It is helpful to introduce two definitions related to firm default. The expected profitability of a defaulting firm is denoted by $G(\overline{m}_{t+1}) \equiv \int_0^{\overline{m}_{t+1}} mdF(m)$ and the default probability by $F(\overline{m}_{t+1}) \equiv \int_0^{\overline{m}_{t+1}} dF(m)$. Using these definitions, the debt payoff in $t+1$ is a random variable and can be written:

$$\mathcal{R}_{t+1} = \chi\left(1 - F(\overline{m}_{t+1}) + \frac{G(\overline{m}_{t+1})}{\overline{m}_{t+1}} - F(\overline{m}_{t+1})\varphi\right) + (1-\chi)q(\overline{m}_{t+2}) \,. \tag{7}$$

The first term of (7) reflects the expected payoff from the share χ of maturing debt. With probability $1 - F(\overline{m}_{t+1})$, the firm repays. With probability $F(\overline{m}_{t+1})$, the firm defaults and banks pay the restructuring cost φ. The expected payoff from seizing firm revenues $\int_0^{\overline{m}_{t+1}} mk_{t+1}(p^Z_{t+1} - (1-a_{t+1})\tau_{t+1})dF(m)$ is distributed equally among the holders of maturing debt χl_{t+1}. This yields the expression $\frac{G(\overline{m}_{t+1})}{\overline{m}_{t+1}}$. The second term is the rollover share $(1-\chi)$ of outstanding debt, valued at next period's market price $q(\overline{m}_{t+2})$. Combining the debt payoff with the pricing condition (2), the capital structure choice $\overline{m}_{t+1}$ is linked to the debt price in period t.

After plugging in the law of motion for capital $i_t = k_{t+1} - (1-\delta_K)k_t$, we can reduce the firm maximization problem to a two-period consideration:

$$\begin{aligned}
\max_{a_{t+1},k_{t+1},l_{t+1},\overline{m}_{t+1}} \; & -p^K_t k_{t+1} - \frac{\alpha_0}{1+\alpha_1}\left(a_{t+1}\right)^{1+\alpha_1} + q(\overline{m}_{t+1})\Big(l_{t+1} - (1-\chi)l_t\Big) + \\
& \mathbb{E}_t\Bigg[\widetilde{\Lambda}_{t,t+1} \cdot \Bigg\{\int_{\overline{m}_{t+1}}^{\infty} (p^Z_{t+1} - \tau_{t+1}(1-a_{t+1}))m_{t+1}k_{t+1} - \chi \cdot l_{t+1} dF(m_{t+1}) \\
& + p^K_{t+1}(1-\delta_K)k_{t+1} + q(\overline{m}_{t+2})\Big(l_{t+2} - (1-\chi)l_{t+1}\Big)\Bigg\}\Bigg] \,, \\
& \text{s.t. (5) and (2)}
\end{aligned} \tag{8}$$

Solving the firm maximization problem, we obtain the following first-order conditions

$$\alpha_0 a^{\alpha_1}_{t+1} - \mu_t \mathbb{E}_t\left[\frac{\tau_{t+1}\overline{m}_{t+1}}{(p^Z_{t+1} - \tau_{t+1}(1-a_{t+1}))}\right] = \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}\Big\{\big(1 - G(\overline{m}_{t+1})\big)\tau_{t+1}k_{t+1}\Big\}\right] \,, \tag{9}$$

$$\begin{aligned}
& p^K_t - \mu_t \frac{\overline{m}_{t+1}}{k_{t+1}} = \\
& \quad \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}\Big\{(1-\delta_K)p^K_{t+1} + \big(1 - G(\overline{m}_{t+1})\big)\Big(p^Z_{t+1} - (1-a_{t+1})\tau_{t+1}\Big)\Big\}\right] \,,
\end{aligned} \tag{10}$$

$$q(\overline{m}_{t+1}) - \mu_t \frac{\overline{m}_{t+1}}{l_{t+1}} = \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}\Big\{\chi(1 - F(\overline{m}_{t+1})) + (1-\chi)q(\overline{m}_{t+2})\Big\}\right] \,, \tag{11}$$

$$\begin{aligned}
& -\mu_t - q'(\overline{m}_{t+1})\Big(l_{t+1} - (1-\chi)l_t\Big) = \\
& \quad \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}\Big\{\Big(l_{t+2} - (1-\chi)l_{t+1}\Big)q'(\overline{m}_{t+2})\frac{\partial \overline{m}_{t+2}}{\partial \overline{m}_{t+1}}\Big\}\right] \,.
\end{aligned} \tag{12}$$

Here, μ_t denotes the multiplier on the default threshold (5). The optimal abatement effort (9) equates the cost of purchasing one unit of the abatement good, given by its price p_t^A with its benefits: First, abatement reduces next period's default threshold, which increases expected dividends. Second, it further increases next period's dividends by reducing the expected carbon tax burden, which is given by $\big(1 - G(\overline{m}_{t+1})\big)\tau_{t+1}k_{t+1}$. Similarly, the first-order condition for capital (10) balances the cost of purchasing one unit of capital (p_t^K) with the expected after-tax revenue it generates in $t+1$, its re-sale value $(1-\delta_K)p_{t+1}^K$, and its positive effect on the default threshold.

The corporate capital structure is determined according to (11). Issuing debt raises dividends in period t by $q(\overline{m}_{t+1})$ units, which has to equal the expected repayment obligation and a debt roll-over term in period $t+1$. As the LHS of (11) shows, the debt choice also takes into account how an additional unit of debt affects the default threshold. Lastly, (12) links the multiplier on the capital structure choice to the elasticity of the debt price $q'(\overline{m}_{t+1})$, Since debt is long-term, the capital structure choice takes into account that increasing the default risk today is also linked to next period's default risk through the policy function for capital structure $\overline{m}_{t+2}(\overline{m}_{t+1})$. We will illustrate the interactions between credit frictions and firms' abatement effort in a slightly simplified setting in Section 5.

Manufacturing Firms: Additional Variables Before closing the model, we define two additional variables that depend on several endogenous model objects and turn out to be helpful in bringing the model to the data. The model-implied distance-to-default can be expressed using the market value of firm equity going into period $t+1$, which is given by the residual of the market value of assets and the market value of debt $(m_{t+1}p_{t+1}^K k_{t+1} - q(\overline{m}_{t+1})l_{t+1})$. Following the Merton (1974) model, the distance-to-default corresponds to the number of standard deviations that revenues have to fall such that the market value of debt exceeds the market value of assets. The revenue shock realization at which this is the case is given by

$$m_{t+1}^{D2D} = \frac{q(\overline{m}_{t+1})l_{t+1}}{p_t^K k_{t+1}} \,. \tag{13}$$

Due to the i.i.d. assumption on the revenue shock and its normalization to $\mathbb{E}[m_{t+1}] = 1$, we interpret the distance-to-default as the number of standard deviations ς that revenues need to drop from their expected value to the threshold value m_{t+1}^{D2D}. The model-implied distance-to-default, thus, follows as $D2D_t = \frac{1-m_{t+1}^{D2D}}{\varsigma}$.

We can also define the (aggregate) recovery rate per unit of defaulted debt, which corresponds to the realized payoff from holding debt of a defaulting manufacturing firm, relative to the promised payoff χl_t. Since debt holders seize production revenues but have to pay the restructuring cost φ, the recovery rate is given by

$$recov(\overline{m}_{t+1}) = \frac{G(\overline{m}_{t+1})}{F(\overline{m}_{t+1})\overline{m}_{t+1}} - \varphi\ . \tag{14}$$

where the expected productivity conditional on defaulting is given by $\frac{G(\overline{m}_{t+1})}{F(\overline{m}_{t+1})}$.

Resource Constraint and Climate Block The emission tax revenue in period t follows as $\tau_t(1-a_t)z_t$ and is rebated to households in lump sum fashion, such that market clearing on the final goods market requires

$$y_t = c_t + \frac{\alpha_0}{1+\alpha_1} a_t^{1+\alpha_1} + i_t\Big(1 + \frac{\Psi_E}{2}\big(\frac{i_t}{i_{t-1}} - 1\big)^2\Big) + \chi\varphi l_t F(\overline{m}_t)\ . \tag{15}$$

Total emissions in period t are given by $e_t = (1-a_t)z_t$ have a positive effect on the global surface temperature. Following Fernandez-Villaverde, Gillingham, and Scheidegger (2024), we map temperature changes into damages based on the global surface temperature change relative to pre-industrial levels, $\Delta\mathcal{T}_t \equiv \mathcal{T}_t - \mathcal{T}_{1850}$. Specifically, we assume that

$$\Delta\mathcal{T}_t = \Psi_{CCR} E_t\ , \tag{16}$$

where the stock of emissions in any given year is denoted by $E_t \equiv E_{2024} + \sum_{s=2025}^{t} e_s$. Here, E_{2024} corresponds to cumulated emissions up to the last period before the (potential) policy change. The cumulative carbon response Ψ_{CCR} of the surface temperature lies in the range of $0.27° - 0.63°$ per 1,000 GtCO2 emitted. We pick the mid-point of this parameter range $\Psi_{CCR} = 0.45°$ to reconcile the global temperature increases since pre-industrial levels: cumulated global emissions currently amount to $E_{2024} = 2.400$ GtCO2, such that, for our base year 2024, we get $\Delta\mathcal{T}_t = \Psi_{CCR} \cdot \frac{2400}{1000} = 1.1°$C. In the adverse scenario with constant emissions after 2025, cumulated emissions in 2100 would amount to 5.100 GtCO2, implying a global temperature increase of 2.3°.

To map global temperature increases into economic damages, we draw on recent empirical work by Nath, Ramey, and Klenow (2024) and assume that GDP loss can be expressed as $\Delta Y_t = -\gamma_T \Delta\mathcal{T}_t$. They estimate that a global temperature increase by $\Delta\mathcal{T}_t = 3.7°$ is associated with a GDP loss of 7-12%. Again, using the mid-point of 9.5%, we obtain a GDP loss of 5.9% for the mid-point scenario of a 2.3° temperature increase. We impose a quadratic specification on households utility loss from global warming $\mathcal{D}(\Delta\mathcal{T}_t) = \gamma_D(\Delta\mathcal{T}_t)^2$ and inform the parameter γ_D using empirical estimates.[11] Specifically, we map these damages into household

[11] Quadratic loss functions associated with greenhouse gas emissions are commonly used in integrated assessment models, see for example Nordhaus (2008).

utility function using the following relationship:

$$u_{\gamma_D=0}\Big((1-\gamma_T)c_t, n_t, \Delta\mathcal{T}_t\Big) = u_{\gamma_D>0}\Big(c_t, n_t, \Delta\mathcal{T}_t, \cdot\Big) \ ,$$

where we have evaluated all arguments of the utility function under the adverse scenario of no policies. In the Appendix, we show how the welfare analysis is affected by using the parameter bounds that imply a global temperature increase of 1.4° to 3.2°, respectively. Using these bounds together with the upper and lower bounds on the damage intensity, we get a range for damages between 7% $\cdot 1.4/3.7 = 2.7\%$ to 12% $\cdot 3.2/3.7 = 2.7\% = 10.4\%$.

4 Quantitative Analysis

In this section, we present a calibration of our model, discuss its ability to replicate our empirical findings, and quantify the macroeconomic relevance of credit frictions in the context of emission abatement.

4.1 Calibration

First, we show how we parameterize the model presented in Section 3. Parameters governing household preferences and the technology of manufacturing firms are set to standard values. The annual time discount factor of households is set to $\beta = 0.99$, implying a risk-free rate of one percent. Setting the curvature of labor supply disutility to $\gamma_N = 1$ implies a Frisch labor elasticity of one, while the weight $\omega_N = 8$ ensures that labor supply equals $n^{SS} = 0.33$ in the deterministic steady state.

The next group of parameters affects technology and the closely related emission block of our model. We set the capital depreciation rate to $\delta_K = 0.08$ and the investment adjustment cost parameter to $\psi_K = 10$, which are typical values in RBC models. Following Heutel (2012), the abatement cost function is parameterized to be consistent with Nordhaus (2008): we set $\alpha_1 = 0.075$ and $\alpha_2 = 1.6$, which delivers an abatement cost-to-GDP ratio of 4.3% under full abatement. The annual emission decay parameter is fixed at $\delta_E = 0.986$, which implies a half-life of 50 years for atmospheric carbon dioxide. Under our abatement cost function, full abatement is reached for a carbon tax of 330\$/tCO2. This carbon tax implies that the resources spent on emission abatement are 4.8% of GDP.[12]

[12] We map the carbon tax in the model into a price in \$/tCO2 using world GDP (y^{world} = 105 trillion USD in 2022, at PPP, see IMF 2022) and world emissions ($e^{world} = 33$ gigatons in 2022). Absent carbon taxes, the model implies a GDP of $y^{model} = 0.6361$ and emissions of $e^{model} = 2.2243$. The carbon price in \$/tCO2 associated with a given tax τ_t is thus given by $\frac{y^{\text{world}}/y^{\text{model}}}{e^{\text{world}}/e^{\text{model}}}\tau_t$.

Table 2: Baseline Calibration

Parameter	Value	Source/Target
Households		
Household discount factor β	0.99	Standard
Labor disutility curvature γ_N	1	Standard
Labor disutility weight ω_N	8	Labor supply $n^{SS} = 0.33$
Technology		
Cobb-Douglas coefficient θ	1/3	Capital share
Inv. adj. parameter ψ_K	10	Standard
Capital depreciation rate δ_K	0.08	Standard
Abatement cost parameter α_1	0.075	Abatement/GDP ratio 4.3%
Abatement cost parameter α_2	1.6	Heutel (2012)
Emission decay δ_E	0.986	Heutel (2012)
Financial Markets		
Firm owner discount factor $\widetilde{\beta}$	0.983	Distance-to-Default 3.95
St. dev. firm productivity ς	0.18	Leverage ratio 30%
Debt maturity parameter χ	0.2	5-year average maturity
Restructuring costs φ	0.25	Recovery rate 69%
Shocks		
Persistence TFP ρ_A	0.95	Standard
TFP shock st. dev. σ_A	0.02	Standard

The last set of parameters is related to credit frictions. We set $\chi = 0.2$ to obtain an average debt maturity of five years. We then jointly calibrate the standard deviation of the idiosyncratic productivity shock $\varsigma = 0.18$, the restructuring cost $\varphi = 0.25$, and the annual firm owner discount factor $\widetilde{\beta} = 0.983$ to match the recovery rate on debt, the distance-to-default, and firm leverage. We set the carbon tax to zero when computing model-implied moments.

The data moment for the recovery rate is based on a publicly available dataset from the World Bank Doing Business archive and based on the methodology proposed by Djankov et al. (2008). We collect the recovery rate ("cents on the dollar") for all countries in our sample from 2012 until 2019 and compute a simple average over time and across countries to obtain a target moment of 69%. We target a leverage ratio of 25% which corresponds to the full sample mean of our firm sample (see Table A.3). In order to keep our macro model comparable to our micro approach in the data, we choose to target a distance-to-default of 3.95, which corresponds to the 25% percentile of the distance-to-default in our sample, both for the manufacturing sector and the full sample (see Table A.2). The model-implied distance-to-default is strongly pro-cyclical, consistent with empirical evidence pre-

Table 3: Model Fit

Moment	Model	Data
Targeted Moments		
Distance to default	-38	-40
Leverage (%)	29	26
Recovery rate (%)	81	82
Untargeted Moments		
Corporate default rate (%)	0.83	1.7
Relative vol. consumption $\sigma(c)/\sigma(y)$	0.83	0.88
Relative vol. leverage $\sigma(lev)/\sigma(y)$	0.50	0.93
Relative vol. D2D $\sigma(D2D)/\sigma(y)$	0.50	0.86
D2D-GDP $cor(y, F(\overline{m}))$	0.57	0.42

Notes: All model-implied moments are computed based on a second-order approximation around the deterministic steady state. All moments are expressed in relative deviations from their steady state value. All data moments are based on real data and de-trended using an HP-filter with smoothing parameter of 6.25.

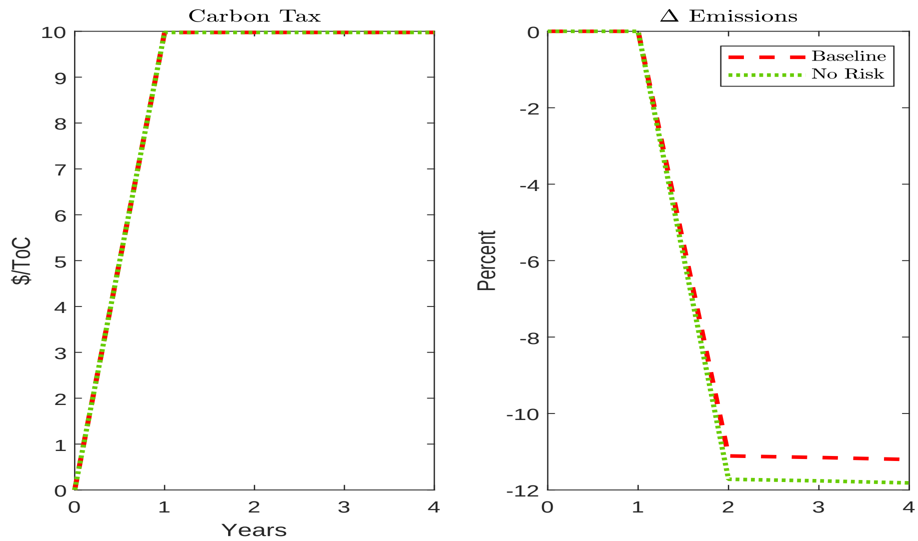
sented in Gilchrist and Zakrajšek (2012).[13] Our baseline parameterization implies a default rate of 0.83%.

4.2 Model Validity: Carbon Taxes and Credit Constraints

As a next step, we demonstrate that our calibrated model implies a reasonable impairment of the pass-through of carbon taxes to the abatement effort. In the data, a one-standard deviation increase in the distance-to-default (5.5) corresponds to a 1.1 percentage point smaller emission reduction. We exploit this cross-sectional heterogeneity in the distance-to-default to corroborate the validity of our model. While we have used the 25% percentile of the distance to default (3.95) as calibration target, the 75% quantile of the distance-to-default is 9.90 (see Table A.2), i.e. firms in the upper quartile of the distribution are essentially free of default risk. We therefore solve a version of the model without default risk by eliminating the borrowing motif in the manufacturing sector. This is obtained by setting $\widetilde{\beta} = \beta$. We provide a full list of equilibrium conditions for this simplified case in Appendix C.2. Since the interquartile range is quite close to the full sample

[13] The model-implied cyclicality of the distance-to-default is $\text{cor}(\widehat{y}, D2D) = 0.57$ when the model is solved with a second-order approximation around the deterministic steady state. Both variables are de-trended using an HP-filter with parameter 6.25.

Figure 1: Effect of Permanent Carbon Tax Shock



Notes: This figure displays the dynamic effects of an unanticipated and permanent carbon tax increase. We solve the model under perfect foresight, assuming that all uncertainty about the carbon tax is revealed immediately once the shock hits.

standard deviation, a 10\$/tCO2 carbon tax increase should imply an emission reduction that is around one percentage point larger in the model without default risk than in the baseline model.

Therefore, we subject the baseline model with risky and the simplified model with safe firms to an unanticipated and permanent carbon tax increase, starting from an initial level of zero to 10\$/tCO2. We assume that carbon taxes remain constant after the increase, such that we can solve the model by perfect foresight.[14] The upper row of Figure 1 shows that an increase in carbon taxes has a positive effect on the abatement share, such that emissions decline. Comparing the baseline (dashed red line) to the safe economy (dotted green lines), we observe that credit frictions imply a smaller increase of the abatement share. This translates into an emission reduction of 11.73% after one year for the no risk economy and an emission reduction of 11.13% for the economy with severe credit frictions. The differential of 0.6% is slightly smaller but of similar magnitude as the effect in the data. Since we did not target this differential in our calibration, this shows that our model can replicate the interaction between credit constraints and climate policy reasonably well. Furthermore, since the model-implied emission reduction

[14] We solve for the transition dynamics numerically using Dynare. Due to the very large persistence of emissions, we simulate the economy for 2000 periods, which ensures that the new steady state is reached eventually.

is slightly smaller than in the data, the model provides a conservative prediction of the climate policy implications of firm credit constraints, to which we turn next.

4.3 Climate Policy Implications

We use the model to study the impact of credit frictions on climate policy outcomes. By reducing the return on the abatement, climate policy has to implement a carbon tax of 324\$/tCO2 tax to achieve full abatement in the baseline economy. In contrast, full abatement ($a_t = 1$) is reached under a 300\$/tCO2 tax in the economy without credit frictions. The difference of 24\$/tCO2 illustrates that credit frictions at the firm level have a macroeconomically relevant effect on the conduct of climate policy.

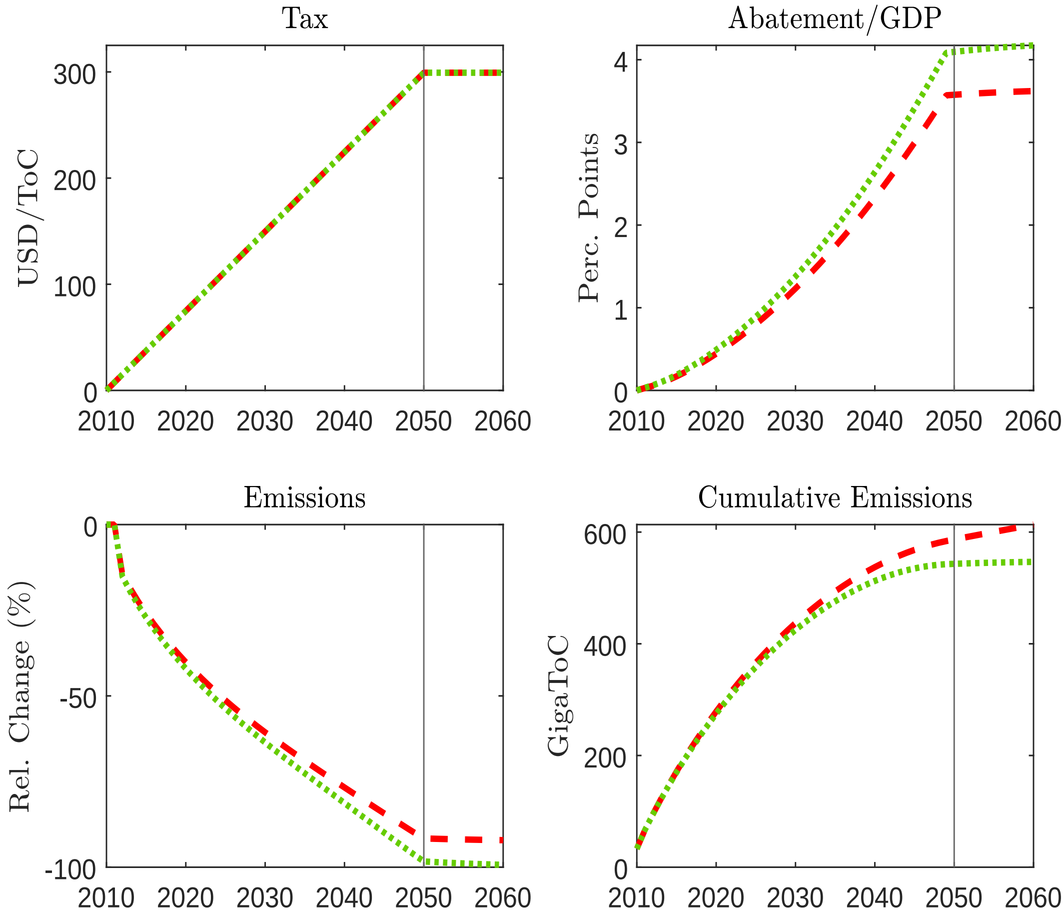
The macroeconomic relevance of credit frictions can also be illustrated by comparing the effects of the same tax path across different model specifications. Specifically, we assume that carbon taxes are increased linearly from zero to 300\$/tCO2 over forty years. This would implement net zero emissions in the risk-free economy. Consistent with our firm panel, we interpret 2010 the start date such that net zero would be achieved in 2050 under this tax path, which is in line with climate policy goals set out in the Paris Agreement. We also compute the effect of such an *oblivious tax path* - which does not take the climate policy impairment associated with credit constraints into account - in our baseline model with endogenous credit constraints.

Figure 2 displays the results. The *oblivious tax path* induces an abatement share of 92% in the baseline economy with credit frictions, which translates into around 3.5% of GDP being spent on abatement. In contrast, the abatement/GDP ratio is slightly above 4% in the risk-free economy. Consequently, the emission reduction relative to the base year 2010 is always slightly smaller. The lower right panel shows that cumulated emissions in 2050 are 41 gigatons larger in the economy with credit frictions. To put these numbers into perspective, note that global carbon emissions amount to 33 gigatons in 2022.[15]

In Table 4, we perform a number of comparative statics exercises with respect to key model parameters related to financial frictions. In the third column, we further decrease the firm owner discount factor to $\widetilde{\beta} = 0.98$. This increases the optimal leverage and default rate, while the distance-to-default declines to 3.87. Compared to the baseline in the first column, the effect on financial markets appear quite modest but this degree of additional short-termism increases the net zero consistent tax by another 10\$/tCO2. Cumulated emissions would be 55 gi-

[15] Almost the same number obtains if we focus on the credit-constrained baseline economy, but compare the *oblivious tax path* to a tax path that linearly increases to 324\$/tCO2, which induces full abatement in in the economy with credit frictions, until 2050. Under this more ambitious tax path, emissions would be 40 gigatons smaller in the baseline economy.

Figure 2: Credit Constraints and the Net Zero Transition



Notes: This figure displays the dynamic effects of an unanticipated shift onto a linear carbon tax path in 2010. The tax path implies net zero emissions in 2050 (vertical black line) in the risk-free economy. The dotted green line refers to the risk-free economy while the dashed red line reflects the baseline case with credit frictions. We solve the model under perfect foresight, assuming that all uncertainty about the carbon tax is revealed immediately.

gatons larger under the linear carbon tax path that reaches 300\$/tCO2 in 2050. By contrast, reducing the debt restructuring cost to $\varphi = 0.15$ or increasing the standard deviation of idiosyncratic productivity shocks to $\varsigma = 0.2$ also induces risk-taking in the manufacturing sector, but the impairment of climate policy is very small in this case. This suggests that short-termism is the quantitatively relevant driver of credit constraints as far as the efficacy of climate policy is concerned.

Table 4: Comparative Statics: Carbon Taxes and Credit Constraints

	Baseline	Risk-Free	$\widetilde{\beta} = 0.98$	$\varphi = 0.15$	$\varsigma = 0.2$
Transition					
Leverage Ratio (%)	29	NA	30	30	28
Recovery Rate (%)	69	NA	69	80	69
D2D	3.95	∞	3.87	3.89	3.61
Default Rate (%)	0.82	0	1.22	1.47	0.92
Climate Policy Implications					
Net Zero Tax ($/tCO2)	324	300	334	324	325
Δ Cum. Emissions (2050, in gigatons)	41	0	55	40	43

Notes: The transition paths are based on a linearly increasing carbon tax from zero to 300$/tCO2, which is consistent with full abatement in the risk-free economy.

5 Illustrating the Mechanism

In the last section, we analytically illustrate how credit frictions impair climate policy in a slightly simplified version of our model. Motivated by the quantitative results in Table 4, we focus on the role of short-termism which gives rise to endogenous credit constraints.

Simplifying the Model We consider the case without aggregate risk ($\Lambda_{t,t+1} = \beta$), one-period debt ($\chi = 1$) and full capital depreciation ($\delta_K = 1$). Plugging $\chi = 1$ into (12) reveals that the multiplier on the default threshold reduces to $\mu_t = -q'(\overline{m}_{t+1})l_{t+1}$ since $\frac{\partial \overline{m}_{t+2}}{\partial \overline{m}_{t+1}} = 0$ in the case of one-period debt. We further simplify the exposition by assuming that all output is lost in the case of default but that there are no debt restructuring costs ($\varphi = 0$). In this case, the debt price schedule is given by the discounted repayment probability:

$$q(\overline{m}_{t+1}) = \beta\big(1 - F(\overline{m}_{t+1})\big) \ . \tag{17}$$

The first-order condition for abatement simplifies to

$$\alpha_0 a_{t+1}^{\alpha_1} + q'(\overline{m}_{t+1})\overline{m}_{t+1}^2 \mathbb{E}_t[\tau_{t+1}]k_{t+1} = \widetilde{\beta}\big(1 - G(\overline{m}_{t+1})\big)\mathbb{E}_t[\tau_{t+1}]k_{t+1} \ . \tag{18}$$

Investment depends on the after-tax price $\widetilde{p}_{t+1}^Z \equiv p_{t+1}^Z - (1 - a_{t+1})\mathbb{E}_t[\tau_{t+1}]$:

$$p_t^K + q'(\overline{m}_{t+1})\overline{m}_{t+1}^2 \widetilde{p}_{t+1}^Z = \widetilde{\beta}\big(1 - G(\overline{m}_{t+1})\big)\widetilde{p}_{t+1}^Z \ . \tag{19}$$

The first-order condition for loans reduces to:

$$q(\overline{m}_{t+1}) + q'(\overline{m}_{t+1})\overline{m}_{t+1} = \widetilde{\beta}\big(1 - F(\overline{m}_{t+1})\big) \ . \tag{20}$$

We can use the simplified debt price schedule (17) and its derivative $q'(\overline{m}_{t+1}) = -\beta f(\overline{m}_{t+1})$ to express the first-order condition for debt issuance in terms of the relative impatience of firm owners and households:

$$\big(\beta - \widetilde{\beta}\big)\big(1 - F(\overline{m}_{t+1})\big) = \beta f(\overline{m}_{t+1})\overline{m}_{t+1} \ . \tag{21}$$

Equation (20) pins down the equilibrium capital structure choice by equating the relative impatience of firm owners to marginal default risk. An increase in the relative impatience of firm owners unambiguously increases the risk choice $\overline{m}_{t+1}$ (Giovanardi et al. 2023). To see this, it is convenient to express marginal default risk by the hazard rate of the revenue shock.[16] The severity of credit frictions is linked to the degree of short-termism $\beta - \widetilde{\beta}$ and is positively related to firm default risk $F(\overline{m}_{t+1})$ and negatively related to the debt price $q(\overline{m}_{t+1})$. The case of risk-free firms is nested in this model by setting $\widetilde{\beta} = \beta$ and implies $\overline{m}_{t+1} = 0$.

Climate Policy Implications To relate credit frictions to the abatement effort, we re-arrange the first-order condition for abatement (18) as

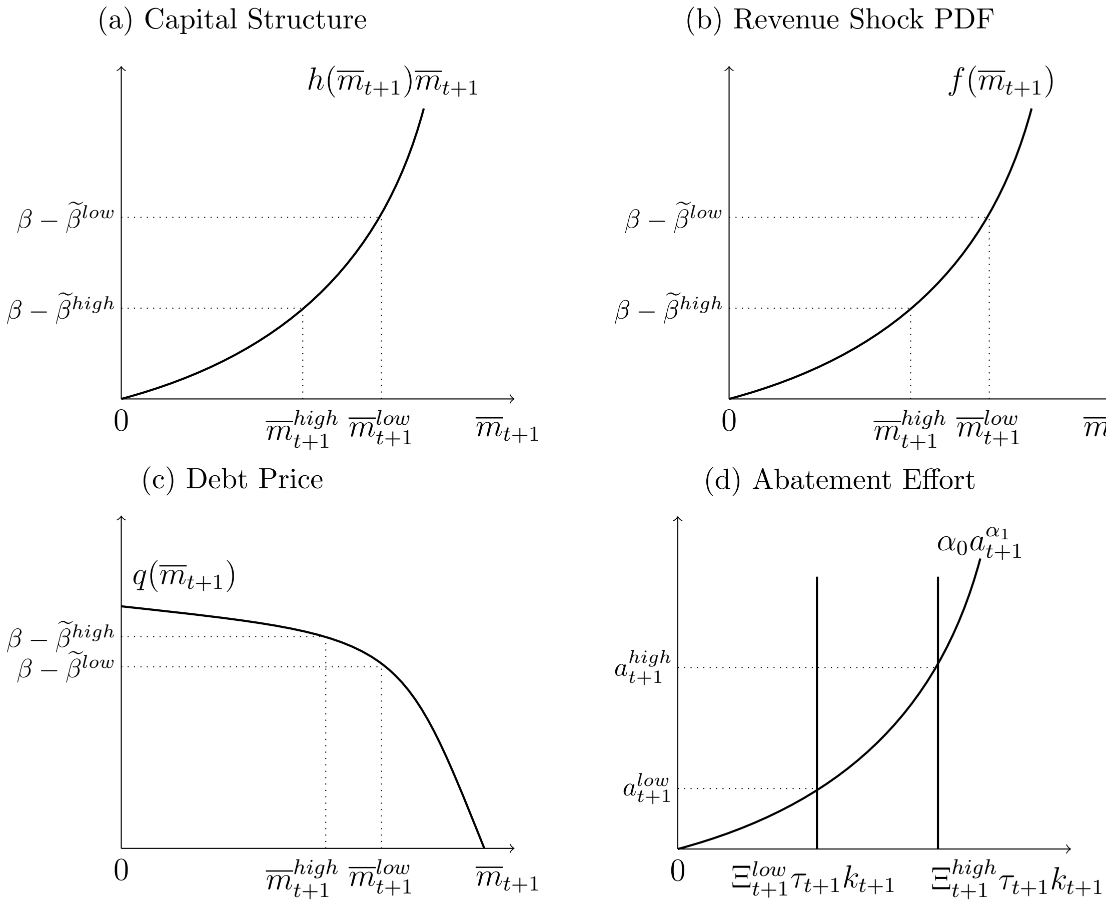
$$\alpha_0 a_{t+1}^{\alpha_1} = \underbrace{\Big(\widetilde{\beta}\big(1 - G(\overline{m}_{t+1})\big) + \beta f(\overline{m}_{t+1})\overline{m}_{t+1}^2\Big)}_{\equiv \Xi_{t+1}} \mathbb{E}_t[\tau_{t+1}]k_{t+1} \tag{22}$$

The abatement effort increases in the expected carbon tax $\mathbb{E}_t[\tau_{t+1}]$ and the capital choice k_{t+1}. Credit frictions drive a impairment term Ξ_{t+1} into this optimality condition. Without short-termism ($\widetilde{\beta} = \beta$), the impairment term is irrelevant for the abatement choice ($\Xi_{t+1} = \beta$). With credit frictions, the first part of the impairment term $\widetilde{\beta}\big(1-G(\overline{m}_{t+1})\big)$ is smaller than one since firms receive the payoff from purchasing one unit of the abatement good in fewer states in period $t+1$. The second term is positive since a higher abatement effort increases the debt price by reducing the default probability, which consequently increases dividends in period t. Under all reasonable parameterizations, the first effect dominates, i.e. a tightening of credit frictions (a decrease in $\widetilde{\beta}$) reduces the optimal abatement effort. The impairment is particularly strong if Ξ_{t+1} is small, i.e. when $\widetilde{\beta}$ is low.

We provide an illustration of the key mechanism in Figure 3, where we consider two economies that differ in the degree of short-termism. With more patient firm

[16] The hazard rate is defined as $h(\overline{m}_{t+1}) \equiv \frac{f(\overline{m}_{t+1})}{1-F(\overline{m}_{t+1})}$. Since the log-normal distribution satisfies a monotone hazard rate condition of the form $\frac{\partial(h(m)m)}{\partial m} > 0$. We can re-arrange (21) to $\beta - \widetilde{\beta} = \beta h(\overline{m}_{t+1})\overline{m}_{t+1}$, which immediately shows the result.

Figure 3: Credit Frictions, Capital Structure, and Abatement Effort



owners, the optimal default threshold and the associated default frequency is lower than in the case of more impatient firm owners ($\widetilde{\beta}^{low} < \widetilde{\beta}^{high}$). This is shown in the top left and top right panel, respectively. The default probability is given by the integral of the revenue shock pdf from zero until $\overline{m}_{t+1}^{high}$ and $\overline{m}_{t+1}^{low}$, respectively. With a large β, relative impatience is small and the threshold revenue level is very low. In this case, the equilibrium debt price is large, as shown in the bottom left panel. Lastly, the bottom right panel of Figure 3 shows how the severity of credit frictions affects abatement in equilibrium. The payoff from increasing abatement effort is *smaller* in the economy with β^{low}, consistent with the numerical results reported in Table 4.

Discussion The effect of short-termism on the debt price is closely related to our empirical strategy. In Section 2, we proxy the tightness of credit constraints by the distance-to-default. As illustrated by Farre-Mensa and Ljungqvist (2015), credit constraints can be interpreted as tight if the debt price schedule is very sensitive to an additional unit of debt issuance. The bottom left panel of Figure 3 illustrates that the debt price schedule steepens as the capital structure choice increases. This follows from the monotone hazard rate assumption on the revenue shock's pdf: for very low values of $\overline{m}_{t+1}$, a marginal increase in the capital structure choice only adds few additional default states and the debt price only deteriorates slightly. If relative impatience increases, firms choose a higher default threshold and, thereby, move into the steeper part of the debt price schedule. Notably, the tightness of credit constraints follows endogenously from structural model parameters related to short-termism by firm owners and not from exogenous restrictions placed on the availability of funds.

This observation has implications for the design of credit polices that - at first glance - complement carbon taxes in the policy mix to achieve net zero emissions. Our model demonstrates that credit policies can potentially be detrimental to achieving climate policy objectives. Credit easing can be interpreted as a ceteris paribus increase in the debt price associated with an increase in debt-holders' discount rate β. This endogenously tightens credit constraints further and undermines the efficacy of climate policy through carbon taxes. It should be stressed that this result is an implication from a model tailored to large firms that are able to borrow against their cash-flows and could also issue equity to finance their investment. While this appears to be an empirically plausible model for the firms in our empirical analysis, smaller and potentially more innovative firms might benefit from such credit policies.

6 Conclusion

In this paper, we demonstrate that firm credit constraints impair the efficacy of climate policies as measured by emission growth at the firm level. Using a cross-country dataset of emissions and credit constraints of publicly traded firms, we show that firms with tight credit constraints, measured by their distance-to-default, experience a smaller emission reduction than unconstrained firms in the same industry. These effects are particularly strong in the manufacturing sector and for firms with a low capital intensity. Such firms experience an emission reduction which is around 1.1 percentage point smaller after a carbon tax increase of 10\$/tCO2, compared to their unconstrained peers. This points towards financial barriers to the adoption of clean technologies.

Incorporating this channel into a DSGE model with endogenous credit constraints, we show that carbon taxes are less effective in an economy with credit frictions but otherwise identical structural parameters. We calibrate the model to match key characteristics of firm credit frictions and use it to assess the macroeconomic relevance of credit constraints for climate policy. The tax associated with full abatement is almost 24$/tCO2 larger in an economy with credit constraints than in a counterfactual risk-free economy. Achieving net zero emissions requires a more stringent climate policy. Ignoring that firm credit constraints impair the effectiveness can have potentially severe consequences: our model predicts that cumulated global emissions in 2050 would be around 40 gigatons larger, which appears to be substantial - given that global emissions amount to 33 gigatons in 2022.

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A Data

A.1 Carbon Taxation

Figure A.1 shows how the carbon tax varies over time for the largest 28 countries in our sample. We do not specifically show the data for Slovenia, Slovakia, Ireland, Czech Republic and Hungary since we have at most 100 firm by year observations in those countries. The majority of countries in our sample did not change their carbon taxation between 2012 and 2019. We observe carbon tax changes in Canada, Denmark, France, Japan, Portugal, Spain, Switzerland and the United Kingdom. Most of those changes are tax hikes, although our sample also includes three tax decreases. As Figure A.2 suggests, there is considerable cross-country heterogeneity in the level of carbon taxes in our sample. Some countries like Finland, Norway, Sweden and Switzerland have permanently high carbon tax levels, countries like France, Japan, Denmark, Poland and the United Kingdom experience intermediate tax levels. The remaining countries have carbon taxes close to zero throughout the sample period.

Figure A.1: **Carbon Tax Shocks over Time**

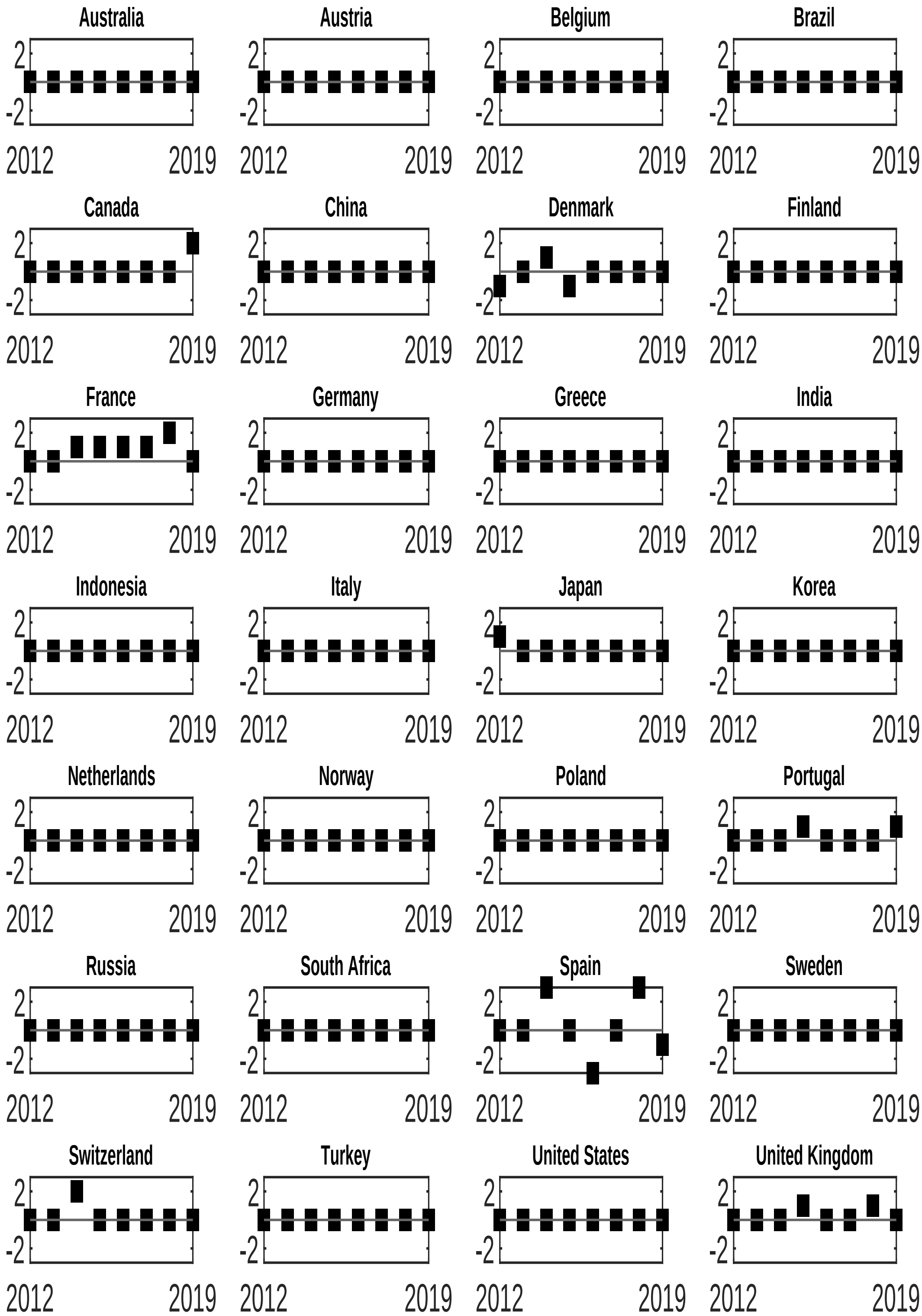
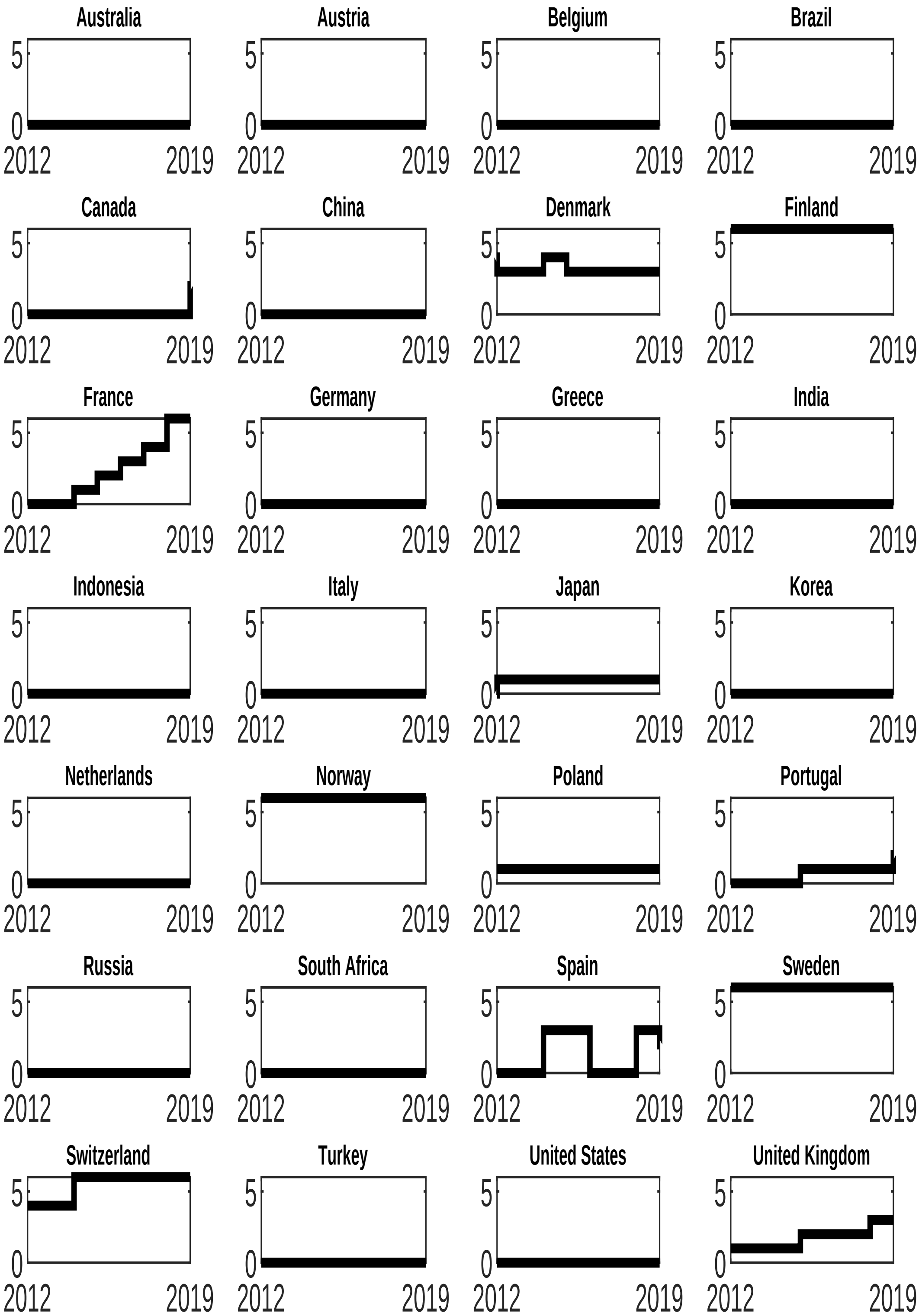


Figure A.2: **Carbon Taxes over Time**



A.2 Emission Growth

Figure A.3 shows emission growth at the country level. For each country and year, we compute the median emission growth (defined as its log difference) over all firms. In most countries, emission growth is positive in most years, with the notable exception being 2017. The pronounced emission reduction relative to 2016 can reasonably be associated with the Paris Agreement which was signed in December 2015 and came into force in 2016. This pattern points towards using year fixed effects in our empirical specifications.

Figure A.3: **Emission Growth over Time**

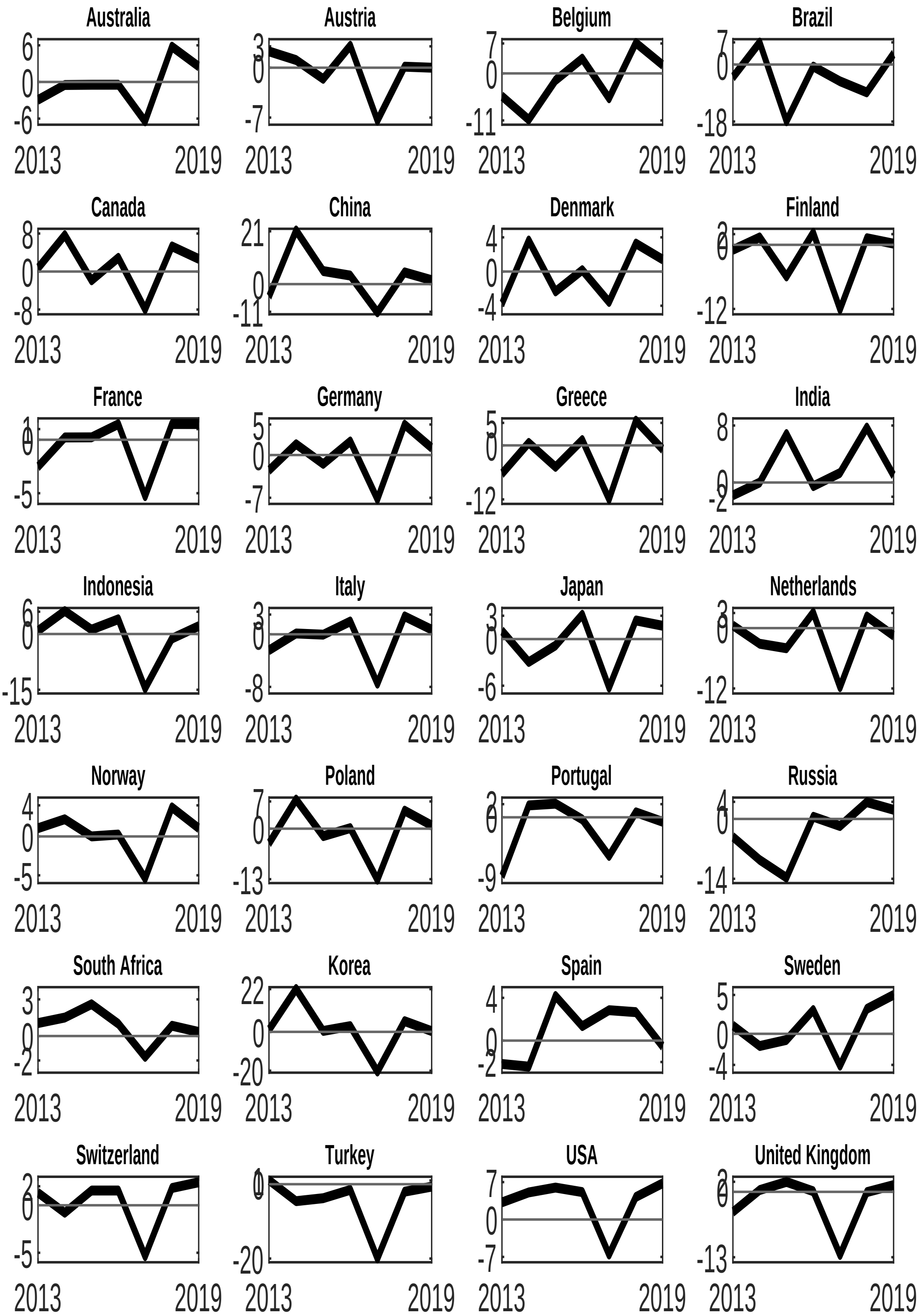


Table A.1: **Emission Growth (%): Summary Statistics**

	N	**Mean**	**SD**	**P25**	**P50**	**P75**
Panel A: Summary Statistics of Emission Growth across Countries						
Australia	2154	-0.49	1.15	-43.22	-0.46	43.59
Austria	241	-1.40	0.76	-25.27	-0.35	23.07
Belgium	380	2.33	1.00	-27.53	0.83	36.65
Brazil	778	2.91	1.21	-44.06	-2.07	45.32
Canada	1590	-0.05	0.93	-30.77	0.01	32.31
China	14080	-0.19	0.94	-40.29	0.00	40.26
Denmark	378	-2.45	0.88	-38.38	-3.40	31.57
Finland	637	-0.59	0.88	-31.42	-2.06	25.77
France	1797	-1.24	0.91	-28.42	0.07	24.54
Germany	1827	-0.44	0.83	-27.73	0.04	27.18
Greece	517	-4.34	0.94	-36.50	-0.87	32.49
India	4642	1.88	1.03	-33.52	0.66	38.05
Indonesia	1771	-1.36	0.99	-36.33	-0.67	32.49
Italy	723	-2.53	0.90	-27.39	-0.55	23.06
Japan	16545	0.03	0.77	-22.41	0.23	22.03
Netherlands	448	0.33	0.91	-26.80	-0.14	31.74
Norway	636	-0.91	1.13	-43.19	-1.11	36.78
Poland	1318	0.00	0.92	-32.82	0.03	30.04
Portugal	172	2.10	0.93	-29.66	0.47	27.47
Russia	529	-0.70	1.04	-31.64	1.06	42.44
South Africa	735	0.76	0.80	-17.66	0.66	19.34
South Korea	6359	0.30	0.92	-37.10	0.46	36.90
Spain	534	3.02	0.94	-31.75	1.78	33.97
Sweden	1433	-0.36	1.12	-45.30	-0.60	39.59
Switzerland	825	-0.78	0.95	-25.41	0.04	24.79
Turkey	1031	1.30	1.00	-36.34	0.57	34.75
USA	12535	-0.28	0.86	-31.32	0.02	31.42
United Kingdom	3479	0.57	0.93	-30.37	0.00	29.58
Panel B: Summary Statistics of Emission Growth across Sectors						
Mining	3258	-0.60	1.14	-43.47	0.60	44.13
Construction	2569	-0.13	0.91	-28.52	0.51	30.43
Manufacturing	41641	0.02	0.87	-31.03	0.04	30.72
Transportation & public utilities	6810	-1.12	0.96	-28.04	0.01	26.15
Wholesale trade	3577	0.35	1.18	-34.98	-0.19	37.58
Retail trade	4504	0.81	0.81	-26.93	-0.03	27.33
Services	11836	-0.62	0.89	-35.99	-0.50	34.04
Full sample	74729	0.00	0.91	-31.46	0.03	31.33

A.3 Distance-to-Default across Countries and Sectors

Figure A.4 shows the country-specific median distance-to-default over time. In Table A.2, we show descriptive statistics of distance-to-default across countries and sectors. Panel A and B refer to countries and industries, respectively. In both cases, the sub-sample size N refers to the number of firm by year observations. The minimum and maximum values of 0.66 and 20 are imposed on the iterative algorithm used to compute the distance-to-default. There are only modest differences in terms of key quantiles, mean and standard deviations across industries. In contrast, the cross-country variation is fairly large. We thus include country fixed effects in all specifications to capture within country variations. Summary statistics for firm-specific control variables are given in Table A.3. All variables are winsorized at the 1st and 99th percentiles.

Figure A.4: **Distance-to-Default over Time**

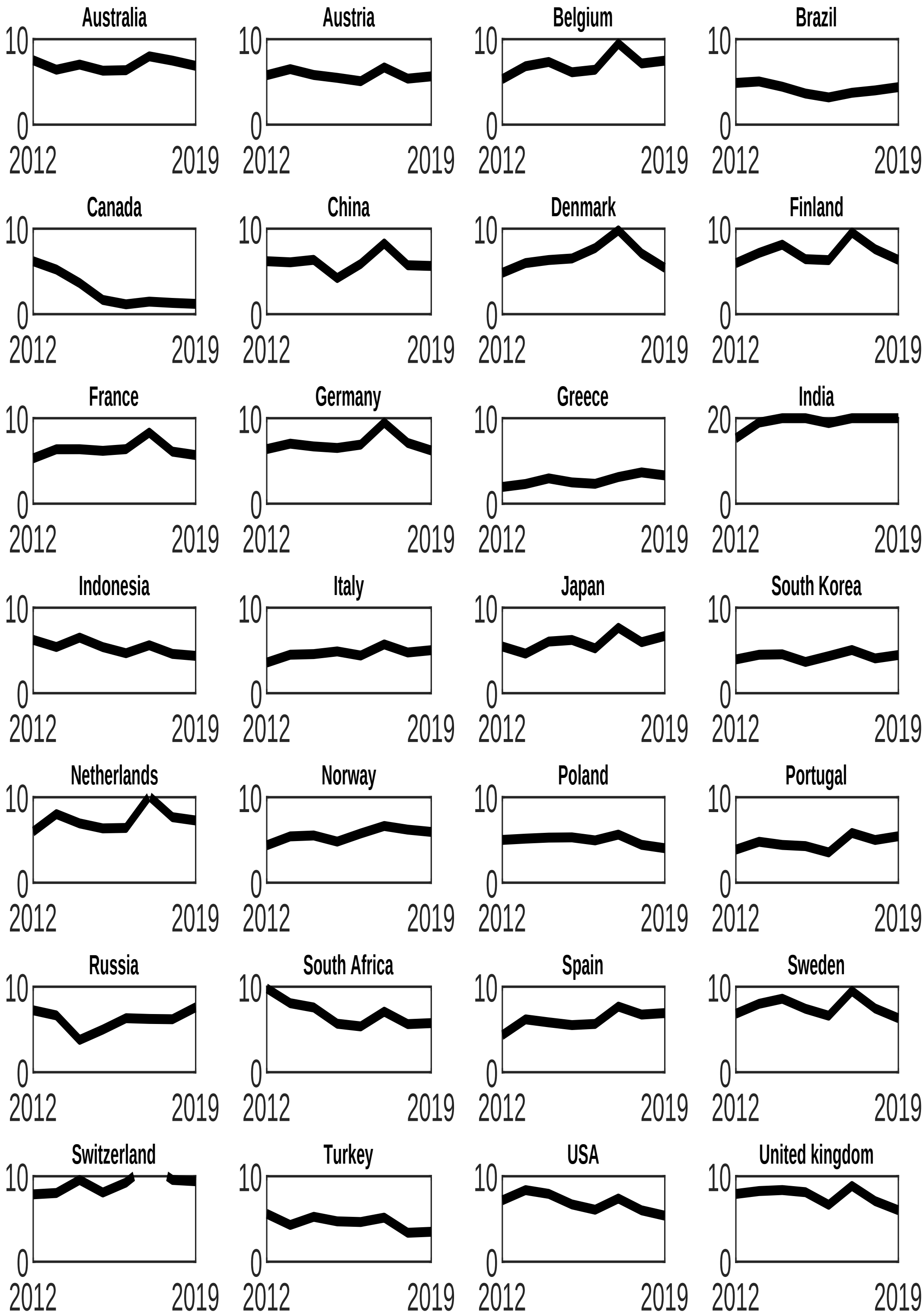


Table A.2: **Distance-to-Default: Summary Statistics**

	N	**Mean**	**SD**	**P25**	**P50**	**P75**
Panel A: Summary Statistics of D2D across Countries						
Australia	1584	8.53	5.8	4.32	6.89	11.01
Austria	268	7.29	4.42	4.57	5.93	8.20
Belgium	363	8.24	4.77	4.89	7.08	10.21
Brazil	747	5.24	4.13	2.58	4.12	6.76
Canada	1291	14.32	8.04	8.63	14.32	20.00
China	14420	7.95	5.61	4.01	5.85	9.77
Denmark	348	8.09	5.74	4.04	6.08	10.57
Finland	446	7.99	4.32	4.98	7.08	9.94
France	1742	7.53	4.45	4.60	6.34	9.07
Germany	1547	8.49	5.53	4.65	6.66	10.23
Greece	433	4.50	5.16	1.36	2.66	4.98
India	190	15.15	6.48	10.19	20.00	20.00
Indonesia	1724	8.75	6.93	3.19	5.47	15.74
Italy	646	5.74	3.45	3.48	4.82	7.15
Japan	14309	7.54	4.95	4.05	6.03	9.37
Netherlands	319	8.11	4.94	4.43	7.26	10.43
Norway	608	6.94	5.42	3.41	5.43	8.33
Poland	1064	6.21	4.60	3.29	4.92	7.46
Portugal	134	5.16	3.93	1.87	4.60	7.01
Russia	425	8.15	6.12	3.49	6.01	11.45
South Africa	688	8.29	5.12	4.57	7.05	10.99
South Korea	5364	6.04	4.95	3.01	4.32	6.77
Spain	474	7.50	5.16	3.99	5.92	9.68
Sweden	848	9.20	5.80	4.86	7.48	11.60
Switzerland	798	10.11	5.386	6.06	8.97	13.43
Turkey	1170	6.23	4.97	3.10	4.46	7.27
USA	8779	10.42	6.50	5.18	8.40	20.00
United Kingdom	2551	9.58	5.77	5.21	7.80	12.95
Manufacturing Sector	28538	7.84	5.48	3.93	5.94	9.88
Full Sample	47378	7.86	5.50	3.95	6.01	9.90

Table A.3: **Summary Statistics of Control Variables**

Variables	**N**	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**
Log(Assets)	79068	9.00	2.93	2.38	7.06	8.94	11.02	16.02
Young	80266	0.56	0.50	0.00	0.00	1.00	1.00	1.00
EBIT/Revenues	93218	0.02	0.70	-5.79	0.05	0.10	0.18	0.63
Capital Intensity	93267	0.61	1.08	0.00	0.12	0.27	0.58	7.28
Leverage	84495	0.24	0.24	0.00	0.04	0.17	0.38	1.00

B Additional Empirical Results

B.1 Exogeneity of Carbon Policy Shocks

A potential threat to our identification assumption is the endogeneity of carbon tax changes with respect to firm credit constraints. Policymakers might defer carbon tax hikes if the economy would otherwise experience financial distress (Döttling and Rola-Janicka 2022). We test whether the probability of a carbon tax increase depends on *aggregate* credit constraints in country c in the previous year:

$$\text{Prob}(\text{Tax}_{c,t} \neq \text{Tax}_{c,t-1}) = \beta_0 + \beta_1 \cdot \text{D2D}_{c,t-1} + \beta_2 \cdot X_{c,t-1} + \epsilon_{c,t} \ . \tag{23}$$

Here $\text{D2D}_{c,t-1}$ refers to the aggregate distance-to-default in country c, where we use both median and average distance-to-default across firms in each country and year. The vector $X_{c,t-1}$ contains typical control variables including GDP growth, inflation rate, short-term and long-term interest rates, public debt-to-GDP ratio and unemployment rate.[17] We do not add country fixed effects, since we would loose observations in all countries without carbon tax changes. Standard errors are clustered at country level. The coefficient of interest is β_1: if it is different from zero, aggregate credit constraints would predict the probability of a tax change. We specify Equation (23) as a Probit-model, but find similar results in a Logit-model. The results in Table B.1 show that aggregate credit constraints do not predict climate policy, irrespective of using the mean or median to aggregate firms within each country.

[17] We collect the public debt-to-GDP ratio from IMF Data Mapper. All the other control variables in are obtained from OECD statistics.

Table B.1: **Credit Constraints and Carbon Tax Shocks at Country Level**

VARIABLES	(1) Prob($\text{Tax}_{c,t} \neq \text{Tax}_{c,t-1}$)	(2) Prob($\text{Tax}_{c,t} \neq \text{Tax}_{c,t-1}$)
Mean D2D$(j, t-1)$	-0.015	
	(0.017)	
Median D2D$(j, t-1)$		-0.009
		(0.018)
Country-Controls	✓	✓
Observations	158	158
Pseudo R-squared	0.0544	0.0539

Notes: This table reports the results of estimating Equation (23). Column (1) refers to the mean of *D2D* for each country and column (2) is for the median of *D2D*. Regressions are estimated at the country-year level. The regressions control for GDP growth, inflation rate, short-term and long-term interest rates, public debt-to-GDP ratio and unemployment rate, all lagged by one year. Standard errors, clustered at the country level, are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

B.2 Refining Treatment and Control Groups

In this section, we present the results of adding interaction terms between firm level control variables and the carbon tax shock. If the tightness of credit constraints is correlated with firm size, age, and profitability, the key coefficient in our baseline specification might actually pick up heterogeneous responses of smaller, younger, or more profitable firms. To mitigate such concern, we estimate

$$\begin{aligned}\Delta \log(Emi)_{j,t} = \beta_0 + &\beta_1 \cdot \text{D2D}_{j,t-1} + \beta_2 \cdot \Delta\text{Tax}_{c,t} + \beta_3 \cdot \text{D2D}_{j,t-1} \times \Delta\text{Tax}_{c,t} \\ &+ \beta_4 \cdot X_{j,t-1} + \beta_5 \cdot X_{j,t-1} \times \Delta\text{Tax}_{c,t} + \chi_c + \tau_t + \epsilon_{j,t} \ . \end{aligned} \tag{24}$$

Table B.2 displays the results. Compared to the baseline results in Table 1, the coefficient on the interaction term $D2D_{j,t-1} \times \Delta\, Tax_{c(j),t}$ is even slightly larger and remains highly significant.

Table B.2: **Adding Interaction between Controls and Carbon Tax Shock**

VARIABLES	(1) $\Delta log(Emi)_{j,t}$	(2) $\Delta log(Emi)_{j,t}$	(3) $\Delta log(Emi)_{j,t}$	(4) $\Delta log(Emi)_{j,t}$	(5) $\Delta log(Emi)_{j,t}$	(6) $\Delta log(Emi)_{j,t}$	(7) $\Delta log(Emi)_{j,t}$	(8) $\Delta log(Emi)_{j,t}$	(9) $\Delta log(Emi)_{j,t}$
$D2D_{j,t-1} \times \Delta Tax_{c(j),t}$	-0.002**	0.002	-0.003*	-0.006***	-0.000	-0.007***	-0.006***	-0.002	-0.009***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$D2D_{j,t-1}$	0.005**	0.005**	0.005***	0.006**	0.006***	0.005**	0.006***	0.007**	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$\Delta Tax_{c(j),t}$	-0.052**	-0.089**	-0.024	-0.025	-0.101	0.012	-0.022	-0.074	-0.002
	(0.025)	(0.032)	(0.019)	(0.036)	(0.066)	(0.028)	(0.028)	(0.049)	(0.034)
$Log(Assets)_{j,t-1}$	-0.022*	-0.024	-0.021***	-0.028*	-0.037*	-0.021**	-0.034**	-0.048**	-0.026**
	(0.011)	(0.017)	(0.007)	(0.014)	(0.019)	(0.009)	(0.016)	(0.023)	(0.012)
$Young_{j,t-1}$	-0.021***	-0.030*	-0.015	-0.024***	-0.053**	-0.000	-0.019**	-0.053***	0.020
	(0.006)	(0.017)	(0.014)	(0.009)	(0.021)	(0.018)	(0.008)	(0.014)	(0.014)
$EBIT/Revenues_{j,t-1}$	-0.096***	-0.153***	-0.052	-0.060***	-0.083**	-0.041	-0.064***	-0.082**	-0.038
	(0.020)	(0.028)	(0.032)	(0.020)	(0.035)	(0.029)	(0.019)	(0.035)	(0.031)
$Log(Assets)_{j,t-1} \times \Delta Tax_{c(j),t}$	0.003	0.001	0.004**	0.008*	0.009	0.007*	0.008**	0.009	0.012**
	(0.002)	(0.002)	(0.002)	(0.005)	(0.006)	(0.004)	(0.004)	(0.007)	(0.005)
$Young_{j,t-1} \times \Delta Tax_{c(j),t}$	0.029	0.018	0.032	-0.000	0.016	-0.012	-0.016	-0.009	-0.020
	(0.023)	(0.025)	(0.025)	(0.022)	(0.039)	(0.034)	(0.030)	(0.033)	(0.054)
$EBIT/Revenues_{j,t-1} \times \Delta Tax_{c(j),t}$	0.014***	0.010	0.019	0.019***	0.024***	-0.000	0.022***	0.028***	0.002
	(0.003)	(0.010)	(0.030)	(0.006)	(0.008)	(0.011)	(0.008)	(0.008)	(0.017)
Constant	0.185*	0.232	0.149**	0.237*	0.360*	0.138*	0.287**	0.453**	0.177*
	(0.096)	(0.155)	(0.057)	(0.120)	(0.185)	(0.068)	(0.140)	(0.218)	(0.099)
Observations	40,109	21,597	18,481	24,125	13,617	10,492	23,984	13,397	10,215
R-squared	0.024	0.033	0.028	0.020	0.032	0.015	0.111	0.158	0.167
Industry-by-year FE	SIC-group	SIC-group	SIC-group	NO	NO	NO	4-digit SIC	4-digit SIC	4-digit SIC
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sectors	All	All	All	Manuf	Manuf	Manuf	Manuf	Manuf	Manuf
Capital Intensity	All	High	Low	All	High	Low	All	High	Low
Year FE	NO	NO	NO	YES	YES	YES	NO	NO	NO

Notes: This table reports the results adding interactions between baseline controls and carbon tax shock as additional controls. Regressions are estimated at the firm-year level. The regressions control for firm size ($Log(Assets)_{j,t-1}$), age ($Young_{j,t-1}$), profitability ($EBIT/Revenues_{j,t-1}$) and their interactions with carbon policy shock, all lagged by one year. We include country fixed effects in all specifications, year fixed effects in column (4)-(6) and industry × year fixed effects in column (1)-(3),where the industries are measured by sectors, and column (7)-(9), where the industries are measured by the most granular 4 digit SIC. Standard errors, clustered at the country level, are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

B.3 Robustness: Utilities

Throughout the analysis, we assume that companies respond to carbon tax increases in their country of incorporation. Since firms in our sample are large, it is reasonable to assume that they generate a part of their emissions abroad. Such emissions would not respond directly to changes in domestic climate policy. To address this concern, Table B.3 shows that our baseline results also hold in the sector "Transportation and public utilities". These companies are usually not multinational and should mostly respond to domestic policies. The coefficient on the interaction term $D2D_{j,t-1} \times \Delta Tax_{c(j),t}$ is negative and highly significant, also when including industry $\times$ year fixed effects at the four-digit SIC level.

Table B.3: Carbon Taxes and Credit Constraints: Utility Sector

VARIABLES	(1) $\Delta log(Emi)_{j,t}$	(2) $\Delta log(Emi)_{j,t}$
$D2D_{j,t-1} \times \Delta Tax_{c(j),t}$	-0.004***	-0.003***
	(0.001)	(0.001)
$D2D_{j,t-1}$	0.000	-0.000
	(0.001)	(0.001)
$\Delta Tax_{c(j),t}$	-0.004	-0.023
	(0.022)	(0.023)
Controls	✓	✓
Observations	3,237	3,233
R-squared	0.033	0.076
Industry-by-year FE	NO	YES
Country FE	YES	YES
Year FE	YES	NO
Sample	Transportation & Public Utilities	Transportation & Public Utilities

Notes: This table reports the baseline results in the sector of Transportation and Public Utilities. Regressions are estimated at the firm-year level. The regressions control for firm size ($Log(Assets)_{j,t-1}$), age ($Young_{j,t-1}$), profitability ($EBIT/Revenues_{j,t-1}$), all lagged by one year. We include country fixed effects in all specifications, year fixed effects in column (1) and industry $\times$ year fixed effects in column (2),where the industries are measured by 4 digit SICs. Standard errors, clustered at the country level, are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

B.4 Robustness: Anticipation and Persistence

To test whether emission growth reacts to potentially anticipated climate policy changes in the future, we use changes in the tax policy from period t to $t+1$ and estimate the following specification:

$$\begin{aligned}\Delta \log(Emi)_{j,t} = \beta_0 + &\beta_1 \cdot \mathrm{D2D}_{j,t-1} + \beta_2 \cdot \Delta\mathrm{Tax}_{c,t+1} + \beta_3 \cdot \mathrm{D2D}_{j,t-1} \times \Delta\mathrm{Tax}_{c,t+1} \\ &+ \beta_4 \cdot X_{j,t-1} + \delta_i \cdot \tau_t + \chi_c + \epsilon_{j,t} \ . \end{aligned} \tag{25}$$

Column (1)-(3) shows that emission growth does not respond to future tax increases, neither in full sample nor in sub-samples with high and low capital intensities: a level shift in carbon taxes does not have a permanent effect on emission *growth*.

We also test whether carbon tax shocks have a long-lived effect on emission growth at the firm level. To do so, we consider leads of firm-level emission growth $\Delta \log(Emi)_{j,t+1}$ on the LHS:

$$\begin{aligned}\Delta \log(Emi)_{j,t+1} = \beta_0 + &\beta_1 \cdot \mathrm{D2D}_{j,t-1} + \beta_2 \cdot \Delta\mathrm{Tax}_{c,t} + \beta_3 \cdot \mathrm{D2D}_{j,t-1} \times \Delta\mathrm{Tax}_{c,t} \\ &+ \beta_4 \cdot X_{j,t-1} + \delta_i \cdot \tau_t + \chi_c + \epsilon_{j,t} \ . \end{aligned} \tag{26}$$

As columns (4)-(6) in Table B.4 indicate, the effect on emission growth is short-lived. At the firm level, carbon tax increases induce a permanent shift in the level of emissions, but have no effect on their growth rate. We will make use of the short-lived nature of the effect and the lack of anticipation effects in our modeling choices in Section 3.

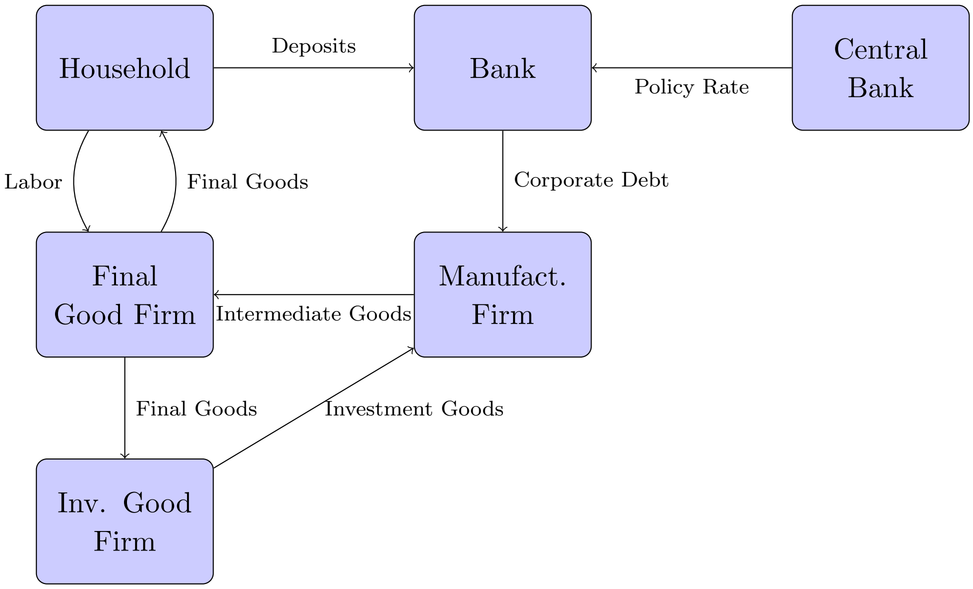
Table B.4: **Anticipation and Persistence**

VARIABLES	Anticipation			Persistence		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta log(Emi)_{j,t}$	$\Delta log(Emi)_{j,t}$	$\Delta log(Emi)_{j,t}$	$\Delta log(Emi)_{j,t+1}$	$\Delta log(Emi)_{j,t+1}$	$\Delta log(Emi)_{j,t+1}$
$D2D_{j,t-1} \times \Delta Tax_{c(j),t+1}$	0.001	0.000	0.000			
	(0.001)	(0.002)	(0.001)			
$D2D_{j,t-1}$	0.005***	0.006***	0.005***			
	(0.001)	(0.001)	(0.001)			
$\Delta Tax_{c(j),t+1}$	0.014	0.034	0.004			
	(0.014)	(0.023)	(0.015)			
$D2D_{j,t-1} \times \Delta Tax_{c(j),t}$				0.000	-0.001	0.000
				(0.001)	(0.002)	(0.001)
$D2D_{j,t-1}$				-0.000	-0.000	-0.001
				(0.001)	(0.001)	(0.001)
$\Delta Tax_{c(j),t}$				0.013	0.028	0.006
				(0.011)	(0.020)	(0.009)
Controls	✓	✓	✓	✓	✓	✓
Observations	40,111	21,597	18,483	35,766	19,094	16,648
R-squared	0.023	0.032	0.027	0.031	0.032	0.040
Industry-by-year FE	Sector	Sector	Sector	Sector	Sector	Sector
Country FE	YES	YES	YES	YES	YES	YES
Sectors	All	All	All	All	All	All
Capital Intensity	All	High	Low	All	High	Low

Notes: This table reports the results of estimating the anticipation and persistence effects. Column (1)-(3) record the results of Equation (25) and column (4)-(6) for Equation (26) in full sample and sub-samples firms with a high and low capital intensity, obtained from a median split within each industry. Regressions are estimated at the firm-year level. $\Delta Tax_{c(j),t}$ is the difference in country-level taxes from $t-1$ to t, while $\Delta Tax_{c(j),t+1}$ is the difference in country-level taxes from t to $t+1$. The regressions control for firm size ($Log(Assets)_{j,t-1}$), age ($Young_{j,t-1}$) and profitability ($EBIT/Revenues_{j,t-1}$), all lagged by one year. We include industry-year fixed effects and country fixed effects in all specifications. Standard errors, clustered at the country level, are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

C Model Appendix

Figure C.1: Model Structure



This section contains supplementary information on our macroeconomic model. Its stylized structure is illustrated in Figure C.1. We then present additional details on the maximization problem of final, investment and manufacturing good firms.

Final good firms The price of the final good is normalized to one, such that the (static) maximization problem yields the following first order conditions:

$$w_t = (1-\theta)\frac{y_t}{n_t} \,, \tag{C.1}$$

$$p_t^Z = \theta\frac{y_t}{z_t} \,. \tag{C.2}$$

Investment good firms Taken the price p_t^K as given, the profit maximization problem is given by

$$\max_{\{i_s\}_{s=0}^{\infty}} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \Lambda_{t,t+s} \left\{ p_{t+s}^K i_{t+s} - \left(1 + \frac{\psi_K}{2} \left(\frac{i_{t+s}}{i_{t+s-1}} - 1 \right)^2 \right) i_{t+s} \right\} \right]$$

and yields the first-order condition (4).

Manufacturing firm The Lagrangian associated with the maximization problem reads

$$
\begin{aligned}
\mathcal{L}_t = & -p_t^K k_{t+1} - \frac{\alpha_0}{1+\alpha_1}\left(a_{t+1}\right)^{1+\alpha_1} + q(\overline{m}_{t+1})\Big(l_{t+1} - (1-\chi)l_t\Big) \\
& + \mathbb{E}_t\Bigg[\widetilde{\Lambda}_{t,t+1}\cdot\Bigg\{\int_{\overline{m}_{t+1}}^{\infty}\big(p_{t+1}^Z - \tau_{t+1}(1-a_{t+1})\big)m_{t+1}k_{t+1} - \chi\cdot l_{t+1}dF(m_{t+1}) \\
& \quad + p_{t+1}^K(1-\delta_K)k_{t+1} + q(\overline{m}_{t+2})\Big(l_{t+2} - (1-\chi)l_{t+1}\Big)\Bigg\}\Bigg] + \\
& + \mu_t\left(\overline{m}_{t+1} - \frac{\chi l_{t+1}}{(p_{t+1}^Z - \tau_{t+1}(1-a_{t+1}))k_{t+1}}\right)
\end{aligned}
$$

Differentiating with respect to a_{t+1}, k_{t+1}, l_{t+1}, $\overline{m}_{t+1}$ and the multiplier λ_t yields equations (C.9) - (C.13). Following Gomes, Jermann, and Schmid (2016), the slope of the policy function for risk $\frac{\partial \overline{m}_{t+2}}{\partial \overline{m}_{t+1}}$ is obtained by differentiating the first order condition with respect to $\overline{m}_{t+1}$. Further differentiating (C.11) with respect to the default threshold, we express the Lagrangian multiplier λ_t as follows:

$$
\lambda_t = \frac{l_{t+1}}{\overline{m}_{t+1}}q(\overline{m}_{t+1}) - \widetilde{\Lambda}_{t,t+1}\frac{l_{t+1}}{\overline{m}_{t+1}}\left[\chi(1-F(\overline{m}_{t+1})) + (1-\chi)q(\overline{m}_{t+2})\right] .
$$

This condition can be used to back out the slope of the policy function and, thereby, pins down loan demand and the default threshold.

C.1 Baseline Model: Full System of Equations

The equilibrium is characterized by the following system of 15 equations. Household optimality:

$$w_t = \omega_N n_t^{\gamma_N} c_t \ , \tag{C.3}$$

$$1 = \mathbb{E}_t\left[\Lambda_{t,t+1}(1+r_t)\right] \ , \tag{C.4}$$

Final good producers:

$$y_t = z_t^{\theta} n_t^{1-\theta} \ , \tag{C.5}$$

$$(1-\theta)y_t = p_t^Z z_t \ , \tag{C.6}$$

$$\theta y_t = w_t n_t \ . \tag{C.7}$$

Investment good supply:

$$p_t^K = 1 + \frac{\psi_K}{2}\left(\frac{i_t}{i_{t-1}} - 1\right)^2 + \psi_K\left(\frac{i_t}{i_{t-1}} - 1\right)\frac{i_t}{i_{t-1}} - \mathbb{E}_t\left[\Lambda_{t,t+1}\psi_K\left(\frac{i_{t+1}}{i_t} - 1\right)\left(\frac{i_{t+1}}{i_t}\right)^2\right] \ . \tag{C.8}$$

Manufacturing good firms:

$$\alpha_0 a_{t+1}^{\alpha_1} - \mu_t \mathbb{E}_t[\tau_{t+1}] \frac{\overline{m}_{t+1}}{(p^Z_{t+1} - \tau_{t+1}(1-a_{t+1}))k_{t+1}} = \mathbb{E}_t\Big[\widetilde{\Lambda}_{t,t+1}\Big\{\big(1 - G(\overline{m}_{t+1})\big)\tau_{t+1}\Big\}\Big] \; , \tag{C.9}$$

$$p_t^K + \frac{\alpha_0}{1+\alpha_1}\big(a_{t+1}\big)^{1+\alpha_1} - \mu_t \frac{\overline{m}_{t+1}}{k_{t+1}} = \mathbb{E}_t\Big[\widetilde{\Lambda}_{t,t+1}\Big\{(1-\delta_K)p^K_{t+1} + \big(1 - G(\overline{m}_{t+1})\big)\Big(p^Z_{t+1} - (1-a_{t+1})\tau_{t+1}\Big)\Big\}\Big] \; , \tag{C.10}$$

$$q(\overline{m}_{t+1}) - \mu_t \frac{\overline{m}_{t+1}}{l_{t+1}} = \mathbb{E}_t\Big[\widetilde{\Lambda}_{t,t+1}\Big\{\chi(1 - F(\overline{m}_{t+1})) + (1-\chi)q(\overline{m}_{t+2})\Big\}\Big] \; , \tag{C.11}$$

$$-\mu_t - q'(\overline{m}_{t+1})\Big(l_{t+1} - (1-\chi)l_t\Big) = \mathbb{E}_t\Big[\widetilde{\Lambda}_{t,t+1}\Big\{\Big(l_{t+2} - (1-\chi)l_{t+1}\Big)q'(\overline{m}_{t+2})\frac{\partial \overline{m}_{t+2}}{\partial \overline{m}_{t+1}}\Big\}\Big] \; , \tag{C.12}$$

$$\overline{m}_{t+1} = \frac{\chi l_{t+1}}{(p^Z_{t+1} - \tau_{t+1}(1-a_{t+1}))k_{t+1}} \; , \tag{C.13}$$

$$\lambda_t = \frac{l_{t+1}}{\overline{m}_{t+1}} q(\overline{m}_{t+1}) - \widetilde{\Lambda}_{t,t+1}\frac{l_{t+1}}{\overline{m}_{t+1}}\Big[\chi(1 - F(\overline{m}_{t+1})) + (1-\chi)q(\overline{m}_{t+2})\Big] \; . \tag{C.14}$$

$$i_t = k_{t+1} - (1-\delta_K)k_t \; , \tag{C.15}$$

Corporate debt price:

$$q(\overline{m}_{t+1}) = \mathbb{E}_t\Big[\Lambda_{t,t+1}\Big\{\chi\Big(1 - F(\overline{m}_{t+1}) + \frac{G(\overline{m}_{t+1})}{\overline{m}_{t+1}} - F(\overline{m}_{t+1})\varphi\Big) + (1-\chi)q(\overline{m}_{t+2})\Big\}\Big] \; , \tag{C.16}$$

$$q'(\overline{m}_{t+1}) = \mathbb{E}_t\Big[\Lambda_{t,t+1}\Big\{-\chi\frac{G(\overline{m}_{t+1})}{\overline{m}^2_{t+1}} - \chi\varphi F'(\overline{m}_{t+1}) + (1-\chi)\frac{\partial \overline{m}_{t+2}}{\partial \overline{m}_{t+1}} q'(\overline{m}_{t+2})\Big\}\Big] \; . \tag{C.17}$$

Emission accumulation:

$$\mathcal{E}_t = e_t + \delta_E \mathcal{E}_{t-1} \; , \tag{C.18}$$

Market clearing:

$$y_t = c_t + \frac{\alpha_0}{1+\alpha_1} a_t^{\alpha_1} + i_t\left(1 + \frac{\psi_K}{2}\Big(\frac{i_t}{i_{t-1}} - 1\Big)^2\right) + \chi\varphi l_t F(\overline{m}_t) \; . \tag{C.19}$$

C.2 Safe Manufacturing Firms: Maximization Problem

This section describes the maximization problem of the representative safe manufacturing firm which is nested in our full model as the special case $\widetilde{\beta} = \beta$. All decision variables of these firms with superscript *rf*. Each firm is managed on behalf of a patient firm owner that has the same discount factor β as the household. Therefore, these firms do not have an advantage from issuing debt to households, since debt issuance merely entails a cost due to the possibility of default, but no benefits. The choice variables of safe manufacturing firms are the abatement effort a_{t+1}^{rf} and physical investment i_t^{rf}, which is linked to next period's capital stock of safe manufacturers k_{t+1}^{rf} through the law of motion $i_t^{rf} = k_{t+1}^{rf} - (1-\delta_K)k_t^{rf}$. Furthermore, we can integrate out the idiosyncratic productivity shock to its mean of one and write the maximization problem as

$$\begin{aligned}\max_{a_{t+1}^{rf}, k_{t+1}^{rf}} \; & -p_t^K k_{t+1}^{rf} - \frac{\alpha_0}{1+\alpha_1}\left(a_{t+1}^{rf}\right)^{1+\alpha_1} \\ & +\mathbb{E}_t\left[\Lambda_{t,t+1}\left\{\left(p_{t+1}^Z - \tau_{t+1}(1-a_{t+1}^{rf})\right)k_{t+1}^{rf} + p_{t+1}^K(1-\delta_K)k_{t+1}^{rf}\right\}\right],\end{aligned}$$

with the first-order conditions

$$p_t^K + \frac{\alpha_0}{1+\alpha_1}\left(a_{t+1}^{rf}\right)^{1+\alpha_1} = \mathbb{E}_t\left[\Lambda_{t,t+1}\Big((1-\delta_K)p_{t+1}^K + p_t^Z - (1-a_{t+1}^{rf})\tau_{t+1}\Big)\right], \tag{C.20}$$

$$\alpha_0\left(a_{t+1}^{rf}\right)^{\alpha_1} = \mathbb{E}_t\left[\Lambda_{t,t+1}\tau_{t+1}k_{t+1}^{rf}\right]. \tag{C.21}$$

From the first-order condition for abatement (C.21), we immediately observe that a higher carbon tax τ_{t+1} induces firms to choose a higher abatement share a_{t+1}^{rf}.

D Additional Quantitative Results

Both the stance of climate policy and structural parameters governing its effects are subject to some uncertainty. Therefore, we show that our results are robust to varying the parameters of the abatement cost function, α_0 and α_1, the response of climate change damages to emissions Ψ_E, and the speed of the carbon tax path.