Do firm credit constraints impair climate policy?*

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Abstract

This paper shows how credit constraints at the firm level affect the conduct of climate policy. Using a large international panel of listed firms, this paper empirically demonstrates that firms with tighter credit constraints, measured by their distance-to-default, exhibit a smaller emission reduction after a carbon tax increase than their less constrained peers. We incorporate this channel into a quantitative E-DSGE model with *credit frictions* that depend on structural parameters and give rise to *endogenous credit constraints*. In the model, increasing the severity of credit frictions is associated with a tightening of credit constraints and an increase of the default probability. We show analytically that more severe credit frictions reduce the incentives to invest into emission abatement, since shareholders are less likely to receive the payoff from such an investment. In a calibrated of the model, we find that increasing the severity of credit frictions to such a degree that the default probability increases by 2 percentage points substantially impairs climate policy. In this case, carbon taxes have to be almost 8 dollars per tonne of carbon larger in order to remain consistent with net zero.

Keywords: Climate Policy, Carbon Taxes, Credit Constraints, Emission Reduction, Firm Heterogeneity, E-DSGE model

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. Since investment at the firm-level is typically debt-financed, this immediately raises the question whether firms' access to credit impairs climate policy. Up to this point, the literature on firm credit constraints and emissions has largely focused on the supply of bank credit.[1] While credit supply plays an important role in answering this question, the success of climate policy ultimately depends on emission reductions at the firm level. An assessment of the relevance of credit constraints for the efficacy of climate policy, therefore, needs to look further than credit supply. This paper aims to broaden our understanding of firm credit constraints for climate policy.

We document the relevance of firm credit constraints for climate policy in a large international sample of listed firms from 2011 to 2019. To do so, we obtain emissions data from ISS-ESG and measure credit constraints by the firm-specific distance-to-default, 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. We show that, in response to a carbon tax hike, 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. A one standard deviation increase of the distance-to-default implies an additional emission reduction by 1.1 percentage points in response to an increase in carbon taxes by 10$/ToC. These effects are particularly strong in the manufacturing sector and for firms with lower capital ratios.[2] Furthermore, we do not find significant anticipation effects of climate policy on emission reduction when interacting credit constraints with future carbon tax increases. We also verify that the effect is robust to including firm profitability, size or age as well as their interactions with carbon tax increases. This alleviates concerns that our empirical specification in fact picks up a differential emission response by younger and smaller firms.

We incorporate this empirical finding into a quantitative E-DSGE model with endogenous credit constraints firm investment, and emission abatement, along the lines of Giovanardi et al. (2023). The production technology of manufacturing firms is subject to uninsurable idiosyncratic productivity shocks and entails socially harmful carbon emissions as a by-product, which are subject to carbon taxes. Firms can either invest into their production technology or into emission abatement. The possibility of abatement allows firms to reduce their carbon tax bill without reducing their production.

Firms finance their investment either by issuing defaultable debt or equity. A firm defaults on its debt if production revenues net of carbon taxes fall short of repayment obligations (see Gomes et al. (2016) among others). Corporate default entails a resource loss, which is borne by creditors and fully reflected in borrowing conditions, i.e. the price of corporate debt. The yield

[1]Kacperczyk and Peydro (2022) study the effect of bank-level emission reduction targets on firm-specific outcomes, such as emission abatement. For empirical work on credit supply and climate performance at the firm level, see Accetturo et al. (2023). Goetz (2019) uses a shock to bank funding conditions to study credit supply to polluting versus non-polluting firms.

[2]We define the capital ratio as PPE over gross revenues. Such firms might be more constrained in their access to credit since they can pledge less physical assets as collateral.

spread above the risk-free rate that debt holders require increases in the default probability, which in turn depends on the representative firms' capital structure choice. Firm owners are assumed to be more impatient than households, which hold all corporate debt. The solution to the shareholder value maximization problem requires firms to 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 is depends on structural parameters of the economy.

The capital structure choice depends on the credit friction, which is governed by deep structural parameters of the economy, and gives rise to *endogenous credit constraints*. In the model, tight credit constraints are associated with a high default probability and a low distance-to-default, which provides a direct link to our empirical analysis. and has implications for real investment and abatement. Different from prior literature, for example Heutel (2012), abatement goods have to be purchased one period ahead. The first-order condition for abatement takes into account that firm-owners do not receive the payoff from abatement in the case of default. This reduces the benefits of acquiring abatement goods for any carbon tax rate and reduces their demand in equilibrium.

We quantitatively evaluate the macroeconomic relevance of endogenous credit constraints for the conduct of climate policy. The model is calibrated to standard values in the E-DSGE and financial cycle literature. For our main policy experiment, we vary the discount factor of firm owners, which affects default risk and the tightness of credit constraints in equilibrium. Specifically, we compare a low-risk economy with an annualized default rate of 1% to a high-risk economy with an annualized default rate of 3% and tighter credit constraints. A permanent carbon tax increase by 10$/ToC reduces emissions by 11.53% in the low-risk economy, while the emission reduction is only 11.13% in the high-risk economy. To put this result into perspective, we demonstrate that the full-abatement tax increases from 140$/ToC in the low-risk economy to 148$/ToC in the high-risk economy. Endogenously tight credit constraints place macroeconomically relevant restrictions on the conduct of climate policy in the transition to net zero.

In addition to impairing long term climate policy, severe credit frictions also make *any* carbon tax hike more disruptive in the short term. Default risk increases by more, in absolute terms, if the equilibrium default risk is high. This puts climate policy in an uncomfortable place: it has to implement a *larger* increase carbon taxes to achieve its emission reduction objective. Its impact on short term default risk is additionally amplified by the comparatively large equilibrium default risk. We show, however, that it is still not optimal to delay the transition from a utilitarian welfare perspective. The gains of emission reduction far outweigh the short term losses associated with elevated default risk for all reasonable parameterizations of our model.

Our analysis has also implications for the conduct of credit policies as a policy instrument that might be complementary to carbon taxes. Note that the climate externality is the only source of market failure in the model. There is no *inefficiency* associated with corporate default in our model since default risk is correctly priced by debt holders and the borrowing decision is optimal, taken the debt price schedule as given.[3] While climate policy is impaired in an economy with severe credit frictions, it would be a foregone conclusion to recommend credit easing policies as facilitator of more stringent climate policy. In this model, credit easing policies can be interpreted as an outward shift of debt price schedules and effectively *increase* the relative impatience of borrowers vis-a-vis debt owners. Credit constraints tighten endogenously and impair the efficacy of carbon taxes. In contrast to models with exogenously imposed credit constraints, debt subsidies such as targeted asset purchases can be *detrimental* to climate policy in our model. Instead, policies that reduce the riskiness of real investments or mitigate enforcement frictions associated with corporate borrowing endogenously reduce credit constraint and effectively support climate policy.

Related Literature There is a growing body of research studying the interactions between credit constraints and emission reductions, typically 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 et al. (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. At the firm level, Bartram et al. (2022) show that financially constrained firms respond to a tightening of climate policy in California by shifting their production to other states. Similarly, Berg et al. (2023) show that large public firms sell emission-intensive assets after the Paris agreement to other firms that are lower levels of public scrutiny. This channel further impairs the efficacy of climate policy.

A series of papers analyzes credit constraints, investment and endogenous climate policy in a joint framework, see for example Döttling and Rola-Janicka (2022), Heider and Inderst (2022) or Haas and Kempa (2023). By tying credit constraints to deep structural parameters of the economy, our model provides a general equilibrium perspective on the interactions between credit constraints and climate policy. Our analysis illustrates that some implications of this model class, particularly with respect to the desirability of green credit policies, do not necessarily carry over to a general equilibrium setting.

Lastly, we also contribute to the quantitative E-DSGE literature by explicitly introducing credit frictions into firms' abatement decision. This differs from Carattini et al. (2023), who

[3] Potential negative externalities of corporate default have been discussed in the corporate finance literature, see for example Benmelech and Bergman (2011) and the references therein.

discuss the macroeconomic effects of asset stranding or Kolb and Frankovic (2023), who study the role of emission disclosures at the firm level, or from Giovanardi and Kaldorf (2023), who add bank capital regulation to an E-DSGE model with corporate financing frictions. Iovino et al. (2023) provide a complementary analysis of asset-based borrowing constraints in a general equilibrium model with heterogeneous firms and corporate taxation.

This paper is structured as follows. In Section 2 we describe our dataset, while the main empirical results are presented in Section 3. Our augmented E-DSGE model is shown in Section 4, while its qualitative and quantitative properties are discussed in Section 5. Section 6 concludes.

2 Data

In this section, we describe our approach to measure climate policy, credit constraints and carbon emissions.

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., 2023 for a detailed description). Index values between 1 and 5 correspond to 10$/ToC intervals. An increase of the index by one point, thus, corresponds to an increase of *approximately* 10$/ToC.[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 the dataset and its construction, we refer to Kruse et al. (2023). In Appendix A.1 we show 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

[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.

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 over all firms is mostly positive, 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 different from firms classified as "unconstrained". Therefore, we measure credit constraints by the *distance-to-default (D2D)* 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. Figure A.4 in Appendix A.3 shows the evolution of the country-specific median 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 between 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*, i.e. the country of its headquarters as the matching entity. Implicitly, our baseline specification assumes that firms only respond to the climate policy in their primary location. Lastly, we exclude financial firms (SIC-codes between 60 to 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 $\times$ year observations.

3 Empirical Analysis

In this section, we present our 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 ToC) 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. $\Delta Tax_{c,t}$ measures the tax increase from *t-1* to *t* country-level, i.e. $\Delta Tax_{c,t} \equiv Tax_{c,t} - Tax_{c,t-1}$. The coefficient of interest β_1 on the interaction term $D2D_{j,t-1} \times \Delta Tax_{c,t}$ measures the role of credit constraints for the pass-through of climate policy. $X_{j,t-1}$ 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, 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.[5] 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 intensity. 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. Qualitatively, a one standard deviation increase of the distance-to-default, which is 5.5 in the full sample, is

[5] 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 × 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.

associated with an additional emission reduction by 1.1 percentage points. This effect is quite sizable compared to the median emission growth by country, as shown 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 faster 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 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.[6] The coefficient remains highly significant, and its size even slightly increases.

To further tease out the mechanism, we re-estimate our baseline specification in sub-samples of firms with a high and low capital intensities within their industries. Specifically, we classify firms has *highly capital intensive* if their ratio of property, plants, and equipment over total assets exceeds the industry-specific median. Columns (2) and (3) show that the effect is more pronounced for the low capital intensity sub-sample, while it is insignificant for more capital intensive firms. This is consistent with theories and recent empirical work on the distinction between cash-based and asset-based borrowing, see Lian and Ma (2020) and the references therein.[7] Informed by this observation, we will employ a notion of cash-flow based borrowing in our model.

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. 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 et al., 2023). Third, firms in the model presented in Section 4 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 (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

[6] 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.

[7] Notably, firms with a higher capital intensity strongly respond to carbon tax increase if they are *not* interacted with the distance-to-default, as the coefficient β_3 shows: those firms can be interpreted as less affected by credit constraints due to a relatively high collateral value of their physical assets. For a discussion on asset-based borrowing in the context of climate policy, we refer to Iovino et al. (2023).

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 intensity also yields slightly more pronounced effects within the manufacturing sector and especially when controlling for industry × year fixed effects.

Anticipation and Persistence To test whether firms anticipate changes to climate policy, we use changes in the tax policy from period t to $t+1$.

$$\Delta \log(Emi)_{j,t} = \beta_0 + \beta_1 \cdot \mathrm{D2D}_{j,t-1} + \beta_2 \cdot \Delta\mathrm{Tax}_{c,t+1} + \beta_3 \cdot \mathrm{D2D}_{j,t-1} \times \Delta\mathrm{Tax}_{c,t+1} + \beta_4 \cdot X_{j,t-1} + \delta_i \cdot \tau_t + \chi_c + \epsilon_{j,t} \; . \tag{2}$$

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 intensity: 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:

$$\Delta \log(Emi)_{j,t+1} = \beta_0 + \beta_1 \cdot \mathrm{D2D}_{j,t-1} + \beta_2 \cdot \Delta\mathrm{Tax}_{c,t} + \beta_3 \cdot \mathrm{D2D}_{j,t-1} \times \Delta\mathrm{Tax}_{c,t} + \beta_4 \cdot X_{j,t-1} + \delta_i \cdot \tau_t + \chi_c + \epsilon_{j,t} \; . \tag{3}$$

As column (4)-(6) in table 2 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 4.

4 Model

Time is discrete and denoted by $t = 1, 2, ...$ The model features a representative household, final good firms, capital good firms, abatement good firms, and intermediate good firms (manufacturers). Emissions enter the model at the stage of intermediate good firms, which can best be interpreted as manufacturers. Accumulated emissions inflict damage on final good producers, such that the competitive equilibrium is socially inefficient. Carbon taxes are levied on manufacturers, who can mitigate their tax burden either by reducing their production or by engaging in costly abatement.

Households The representative household has standard preferences over consumption and labor $u(c_t, n_t) = \log(c_t) - \frac{\omega_N}{1+\gamma_N} n_t^{1+\gamma_N}$. We denote by β their time-preference parameter that pins down the (steady state) real interest rate in equilibrium. The wage rate is denoted by w_t. Solving their maximization problem yields standard intra- and inter-temporal optimality

Table 2: **Anticipation and Persistence**

	Anticipation			Persistence		
VARIABLES	(1) $\Delta log(Emi)_{j,t}$	(2) $\Delta log(Emi)_{j,t}$	(3) $\Delta log(Emi)_{j,t}$	(4) $\Delta log(Emi)_{j,t+1}$	(5) $\Delta log(Emi)_{j,t+1}$	(6) $\Delta log(Emi)_{j,t+1}$
$D2D_{j,t-1} \times \Delta Tax_{c(j),t+1}$	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 (2) and column (4)-(6) for Equation (3) 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.

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 (sdf).

Final, Investment, and Abatement 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

$$y_t = (1 - \mathcal{D}_t) z_t^{\alpha} n_t^{1-\alpha} \ .$$

Here, $\mathcal{D}_t$ reflects damages from accumulated emissions that represent the climate externality in our model and will be described below. Let the price of the intermediate good be denoted by p_t^Z. Their profit maximization problem yields demand functions for labor and the intermediate good that are shown in detail in Appendix C.

Capital good firms transform $\big(1 + \frac{\psi_K}{2}(\frac{i_t}{i_{t-1}})\big)$ units of the final good into one unit of capital goods, which they sell at price p_t^K. The profit maximization problem

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

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

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

In a similar fashion, *abatement good firms* transform $\frac{\alpha_0}{1+\alpha_1} a_{t+1}^{\alpha_1}$ units of the final good into one unit of the abatement good, sold at price p_t^A. Solving the maximization problem yields an abatement good supply curve that positively depends on a_{t+1}:

$$p_t^A = \alpha_0 a_{t+1}^{\alpha_1} \ . \tag{4}$$

Manufacturing Firms While final, investment, and abatement 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 the empirical part.

Manufacturers are perfectly competitive and managed on behalf of impatient firm owners, who have a subjective discount factor $\widetilde{\beta} < \beta$ that is smaller than the household discount factor. They use a production technology that is linear in capital k_t and are subject to emission taxes τ_t. The production technology is 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 that it follows a log-normal distribution with standard deviation ς_M and mean $-\frac{\varsigma_M^2}{2}$, which ensures that the shock as a mean of one. The manufacturing good is sold at price p_t^Z. Emissions e_t are proportional to production, consistent with empirical evidence presented in Zhang (2023), but we allow for of costly abatement: firms have to acquire abatement goods a_{t+1} one period in advance. Total

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

emissions are therefore given by $e_t = (1 - a_t)z_t$ and the total emission tax payed in period t follows as $\tau_t(1 - a_t)z_t$.

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 implicitly defined through

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

All else equal, (5) implies that the default threshold increases in response to a tax hike. This makes repayment less likely, since a firm needs to draw a higher productivity level in order to be able to repay.

While this already suggests that carbon tax *shocks* increase firm default, the threshold productivity level $\overline{m}_{t+1}$ depends on firm decisions and will adjust endogenously in response to carbon taxes. To characterize these endogenous responses, we next specify the firm's shareholder value maximization problem. To maintain tractability, we follow Gomes et al. (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

$$div_t = \mathbb{1}\{m_t > \overline{m}_t\} \cdot \Big(p_t^Z z_t - \tau_t(1 - a_t)z_t - \chi l_t\Big) - p_t^K i_t - p_t^A a_{t+1} + q(\overline{m}_{t+1})\Big(l_{t+1} - (1 - \chi)l_t\Big) \; .$$

Each firm only receives its after-tax production revenues in the repayment case, but at the same time only repay their debt obligations if their productivity draw m_t exceeds $\overline{m}_t$. Due to the assumption of immediate restructuring, a firm can invest into capital and abatement as well as change its net debt position $l_{t+1} - (1-\chi)l_t$ irrespective of its productivity draw. As customary in the literature, we assume that the representative firm owner and the representative households perfectly share their income risk and define the firm owner sdf by $\widetilde{\Lambda}_{t,t+1} \equiv \widetilde{\beta}\frac{c_{t+1}^{-1}}{c_t^{-1}}$. 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:

$$\begin{aligned}
\max_{a_{t+1},k_{t+1},l_{t+1},\overline{m}_{t+1}} & -p_t^K k_{t+1} - p_t^A a_{t+1} + q(\overline{m}_{t+1})\Big(l_{t+1} - (1 - \chi)l_t\Big) + \\
& \mathbb{E}_t\Bigg[\widetilde{\Lambda}_{t,t+1} \cdot \Bigg\{\int_{\overline{m}_{t+1}}^{\infty} \big(p_{t+1}^Z - \tau_{t+1}(1 - a_{t+1})\big)m_{t+1}k_{t+1} - \chi \cdot l_{t+1} dF(m_{t+1}) \\
& \quad + p_{t+1}^K(1 - \delta_K)k_{t+1} + q(\overline{m}_{t+2})\Big(l_{t+2} - (1 - \chi)l_{t+1}\Big)\Bigg\}\Bigg] \; , \\
& \text{s.t.} \quad \overline{m}_{t+1} \equiv \frac{\chi l_{t+1}}{(p_{t+1}^Z - \tau_{t+1}(1 - a_{t+1}))k_{t+1}}
\end{aligned}$$

When maximizing shareholder value, firms take the debt pricing condition (6) as given. We derive that pricing condition under the assumption that debt is priced using the household sdf. To characterize the debt pricing condition, it is helpful to introduce two definitions related to firm default. The expected profitability of a defaulting firm is denoted by $G(\overline{m}_{t+1}) \equiv \int_0^{\overline{m}_{t+1}} m dF(m)$ and the default probability by $F(\overline{m}_{t+1}) \equiv \int_0^{\overline{m}_{t+1}} dF(m)$. Using these definitions, the capital structure choice $\overline{m}_{t+1}$ is linked to the debt price via the debt payoff through the following recursion:

$$q(\overline{m}_{t+1}) = \mathbb{E}_t \left[\Lambda_{t,t+1} \left\{ \chi \left(1 - F(\overline{m}_{t+1}) + \frac{G(\overline{m}_{t+1})}{\overline{m}_{t+1}} - F(\overline{m}_{t+1})\varphi \right) + (1-\chi) q(\overline{m}_{t+2}) \right\} \right] . \tag{6}$$

The first term reflects the 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 second term is the rollover share $(1-\chi)$ of outstanding debt, valued at next period's market price $q(\overline{m}_{t+2})$. Solving the firm maximization problem, we obtain the following first-order conditions

$$p_t^A - \mu_t \tau_{t+1} \frac{\overline{m}_{t+1}}{p_{t+1}^Z - \tau_{t+1}(1-a_{t+1})} = \mathbb{E}_t \left[\widetilde{\Lambda}_{t,t+1} \left\{ \big(1 - G(\overline{m}_{t+1})\big) \tau_{t+1} k_{t+1} \right\} \right] , \tag{7}$$

$$p_t^K - \mu_t \frac{\overline{m}_{t+1}}{k_{t+1}} = \mathbb{E}_t \left[\widetilde{\Lambda}_{t,t+1} \left\{ (1-\delta_k) p_{t+1}^K + \big(1 - G(\overline{m}_{t+1})\big) \Big(p_{t+1}^Z - (1-a_{t+1})\tau_{t+1} \Big) \right\} \right] , \tag{8}$$

$$q(\overline{m}_{t+1}) - \mu_t \frac{\overline{m}_{t+1}}{l_{t+1}} = \mathbb{E}_t \left[\widetilde{\Lambda}_{t,t+1} \left\{ \chi(1 - F(\overline{m}_{t+1})) + (1-\chi) q(\overline{m}_{t+2}) \right\} \right] , \tag{9}$$

$$-\mu_t - q'(\overline{m}_{t+1}) \Big(l_{t+1} - (1-\chi) l_t \Big) = \mathbb{E}_t \left[\widetilde{\Lambda}_{t,t+1} \left\{ \Big(l_{t+2} - (1-\chi) l_{t+1} \Big) q'(\overline{m}_{t+2}) \frac{\partial \overline{m}_{t+2}}{\partial \overline{m}_{t+1}} \right\} \right] , \tag{10}$$

Here, μ_t denotes the multiplier on the default threshold. Equation (7) 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 (8) equates the cost of purchasing one unit of capital (p_t^K) to 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. In contrast, increasing debt issuance 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 (9) shows, the debt choice also takes into account how an additional unit of debt affects the default threshold. Lastly, (5) 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 the capital structure $\overline{m}_{t+2}(\overline{m}_{t+1})$. We will derive analytical results on the interactions between credit frictions and firms' abatement effort in Section 5.1.

Emissions and Resource Constraint Following Heutel (2012), emissions accumulate according to

$$\mathcal{E}_t = e_t + \delta_E \mathcal{E}_{t-1} , \tag{11}$$

with $\delta_E < 1$. The damage associated with emissions depends on the stock of carbon,

$$\mathcal{D}_t = 1 - \exp(-\gamma_E \mathcal{E}_t) ,$$

where the parameter γ_E determines the relative GDP loss associated with cumulated emissions. Carbon taxes τ_t are taken as given by all agents in the model, which is closed by assuming that carbon tax revenues are rebated to households in lump sum fashion.

5 Analyzing the Model

This section proceeds in two steps. We first derive key model implications regarding credit frictions and emissions in a slightly simplified version of our model. We then show that these implications carry over to the more general setting, which we also use to quantify the macroeconomic relevance of credit frictions in the context of emission abatement.

5.1 Illustrating the Mechanism

For simplicity, consider the case of one-period debt ($\chi = 1$) and full capital depreciation ($\delta_K = 1$). Plugging $\chi = 1$ into (10) reveals that the multiplier on the default threshold reduces to $\lambda_t = -q(\overline{m}_{t+1})l_{t+1}$. To simplify the algebra, we also assume that all output is lost in the case of default and there is no additional resource loss for banks ($\varphi = 0$). In this case, the debt price is given by

$$q(\overline{m}_{t+1}) = \mathbb{E}_t \left[\Lambda_{t,t+1}\Big(1 - F(\overline{m}_{t+1})\Big)\right] \tag{12}$$

The first-order condition for abatement simplifies to

$$p_t^A + q'(\overline{m}_{t+1})\overline{m}_{t+1}^2\tau_{t+1}k_{t+1} = \mathbb{E}_t\left[\widetilde{\Lambda}_{t+1}\Big\{\big(1 - G(\overline{m}_{t+1})\big)\tau_{t+1}k_{t+1}\Big\}\right] . \tag{13}$$

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

$$p_t^K + q'(\overline{m}_{t+1})\overline{m}_{t+1}^2\widetilde{p}_{t+1}^Z = \mathbb{E}_t\left[\widetilde{\Lambda}_{t+1}\Big\{(1 - G(\overline{m}_{t+1}))\widetilde{p}_{t+1}\Big\}\right] . \tag{14}$$

The demand condition for debt issuance equates the revenues from raising a marginal unit of debt (LHS) with the discounted expected repayment obligation (RHS):

$$q(\overline{m}_{t+1}) + q'(\overline{m}_{t+1})\overline{m}_{t+1} = \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}(1 - F(\overline{m}_{t+1}))\right] . \tag{15}$$

We can use the simplified debt price (12) to express the first-order condition for debt issuance in terms of the relative impatience of firm owners and households:

$$\mathbb{E}_t\left[\left(\Lambda_{t,t+1}-\widetilde{\Lambda}_{t,t+1}\right)\left(1-F(\overline{m}_{t+1})\right)\right]=\mathbb{E}_t\left[f'(\overline{m}_{t+1})\overline{m}_{t+1}\right]$$

By the assumption of perfect risk-sharing, the household and firm owner sdf only differ in their subjective discount factors ($\beta-\widetilde{\beta}>0$). Similar to Giovanardi et al. (2023), eq. (15) pins down the equilibrium capital structure choice by equating the relative impatience of firm owners to marginal default risk associated with a marginal increase of the default threshold. Here, marginal default risk is measured by the hazard rate, which 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 $\frac{\partial(h(m)m)}{\partial m}>0$, an increase in the relative impatience of firm owners increases the capital structure choice. The severity of credit frictions as measured by $\beta-\widetilde{\beta}$ is, thus, positively related to firm default risk $F(\overline{m}_{t+1})$ and negatively related to the debt price $q(\overline{m}_{t+1})$.

To relate credit frictions to the abatement effort, we can rewrite the first-order condition for abatement (13) as

$$p_t^A=\mathbb{E}_t\left[\widetilde{\Lambda}_{t+1}\left\{\underbrace{\left((1-G(\overline{m}_{t+1}))-f(\overline{m}_{t+1})\overline{m}_{t+1}^2\right)}_{=\Xi_{t+1}(\text{impairment term})}\tau_{t+1}k_{t+1}\right\}\right].$$

Demand for the abatement good increases in the expected carbon tax and in next period's capital k_{t+1}. Credit frictions drive a impairment term Ξ_{t+1} into this optimality condition. Absent credit frictions, the impairment term is irrelevant for the abatement choice ($\Xi_{t+1}=1$). However, the impairment term is smaller than one, because the capital structure choice implies a strictly positive $\overline{m}_{t+1}$ by our distributional assumption on the revenue shock. This directly reduces demand for the abatement good and impairs the pass-through of carbon taxes to emissions. The impairment is particularly strong if Ξ_{t+1} is small.

The extent to which credit frictions reduce abatement demand can therefore be related to the derivative of Ξ_{t+1} with respect to the capital structure choice $\overline{m}_{t+1}$, which is given by

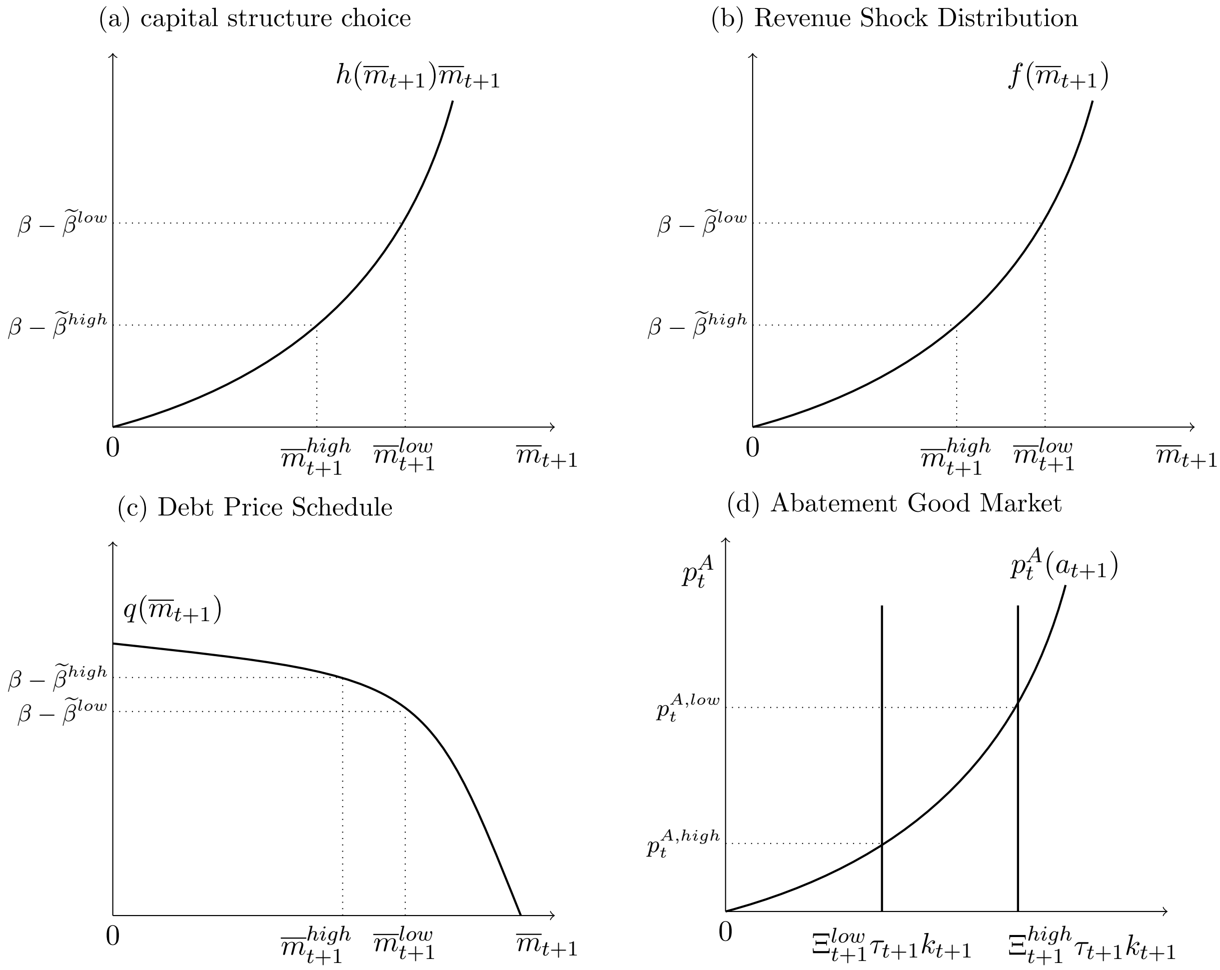
$$\frac{\partial\Xi_{t+1}}{\partial\overline{m}_{t+1}}=-2\overline{m}_{t+1}^2f(\overline{m}_{t+1})-f(\overline{m}_{t+1})\overline{m}_{t+1}-f'(\overline{m}_{t+1})\overline{m}_{t+1}^2<0\,. \tag{16}$$

The Ξ_{t+1} is decreasing in $\overline{m}_{t+1}$, since the capital structure choice is associated with the upward-sloping part of the revenue shock pdf ($f'(\overline{m}_{t+1})>0$).[9] Equation (16) demonstrates that a tightening of credit frictions (a decrease in $\widetilde{\beta}$) reduces the optimal abatement effort at the firm level. Intuitively, this is related to two distinct channels. First, firms receive the payoff from purchasing one unit of the abatement good in fewer states *next period*. Second, the debt price is smaller for every choice of k_{t+1} and a_{t+1} due to the adjustment term on the LHS of (13) and (14), respectively. Choosing a higher abatement share or a higher capital stock has a comparatively

[9] A capital structure choice on the downward sloping part of the revenue shock pdf is not optimal. Decreasing $\overline{m}_{t+1}$ would increase the revenues that can be raised by borrowing today and increase expected dividends tomorrow.

smaller effect on the funds that can be raised on the corporate debt market *this period*. This further reduces demand for either investment good.

Figure 1: Credit Frictions, capital structure choice, and Abatement Demand



We provide an illustration of the key mechanism in Figure 1, where we consider two economies that differ in the time preference rate of firm owners. With patient firm owners ($\widetilde{\beta}^{high} < \beta$), the optimal default threshold and the associated default frequency is lower than in the case of 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 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 1 shows how the severity of credit frictions affects abatement in equilibrium. While the supply of abatement goods merely depends on its price p_t^A, the payoff from purchasing one unit of abatement goods is *smaller* in the economy with β^{low}, such that the market clears at a lower p_t^A.

Before turning to the quantitative analysis, we briefly relate the key implications of our model to the empirical analysis in Section 3. The effect of increasing the relative impatience on the debt price is closely related to our empirical approach to 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 1 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 and not from exogenous restrictions placed on the availability of funds.

It should also be stressed that our model strikes a convenient middle-ground between clear analytical implications and numerical tractability: In the limit, the debt price schedule is *vertical*, such that a firm can not raise additional funds if its capital structure choice exceeds a certain threshold. In this situation, firm actions are subject to a hard debt constraint. While debt price schedules are never exactly vertical in practice, it has turned out to be analytically helpful to assume hard credit constraints in many models (see for example Haas and Kempa (2023) and the references therein). However, those constraints might only bind occasionally in general equilibrium, which reduces numerical tractability. Our model of endogenous default implies a finite sensitivity of the debt price schedule with respect to capital structure choices and, thereby, circumvents such numerical complications. We now turn to the quantitative analysis of our model.

5.2 Quantitative Analysis

In this section, we show how we parameterize the full model presented in Section 4 and then study its quantitative properties.

Calibration Parameters governing household preferences and the technology of manufacturing firms are set to standard values. The time discount factor $\beta = 0.995$ implies an annual risk-free rate of 2%. A relative risk aversion parameter of $\gamma_C = 2$ is also used in similar models, see for example Heutel (2012) or Giovanardi and Kaldorf (2023). 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 $n_t = 0.33$ in the deterministic steady state.

The next group of parameters affects technology and the closely related climate block of our model. We set the capital depreciation rate to $\delta_K = 0.025$ and the investment adjustment cost parameter to $\psi_K = 10$, which are typical values in medium scale DSGE models. The abatement cost function is parameterized according to Heutel (2012): we set $\theta_1 = 0.056$ and $\theta_2 = 1.6$. Similarly, the emission decay parameter is fixed at $\delta_E = 0.997$, while the pollution damage parameter $\gamma_E = 3e-05$ implies that a GDP loss of 10%, which is a standard value used in E-DSGE models (see also Giovanardi et al., 2023). Under this parameter, full abatement maximizes utilitarian welfare, both in the low- and high-risk economy. We map the carbon tax in the model into a price in dollars per tonne of carbon using world GDP ($y^{world} = 105$ trillion USD in 2022, at PPP, see IMF, 2022) and world emissions ($e^{world} = 33$ gigatonnes in 2022). Absent carbon taxes, the model implies a GDP of $y^{model} = 0.957363$ and emissions of $e^{model} = 8.47054$. The carbon price associated with a given tax is thus given $p_t^C = \frac{y^{\text{world}}/y^{\text{model}}}{e^{\text{world}}/e^{\text{model}}}\tau_t$ \$/ToC. Under our abatement cost function, full abatement is reached for a carbon price of 140\$/ToC.

Table 3: Baseline Calibration

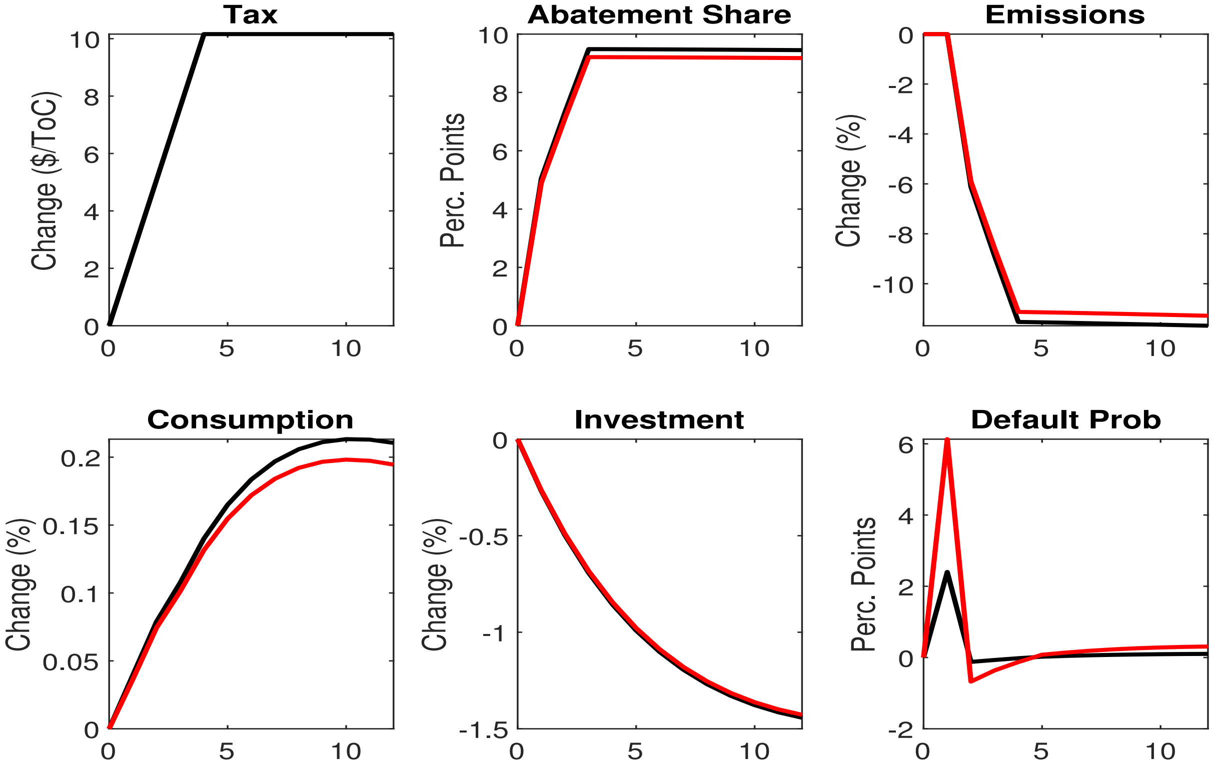
Parameter	Value	Source/Target
Households		
Household discount factor β	0.995	Standard
Labor disutility curvature γ_N	1	Standard
Labor disutility weight ω_N	8	Labor supply $n^{SS} = 1$
Technology		
Inv. adj. parameter ψ_K	10	Standard
Capital depreciation rate δ_K	0.025	Standard
Abatement cost parameter α_1	0.056	Heutel (2012)
Abatement cost parameter α_2	1.6	Heutel (2012)
Emission decay δ_E	0.997	Heutel (2012)
Damage parameter γ_E	3e-05	10% Damage-to-GDP ratio
Financial Markets		
Entrepreneur discount factor $\widetilde{\beta}$	0.9941	**Target: Default rate 1% p.a. (low-risk)**
Entrepreneur discount factor $\widetilde{\beta}$	0.99225	**Target: Default rate 3% p.a. (high-risk)**
St. dev. firm productivity ς_m	0.31	**Target: Book Leverage Ratio 25%**
Debt maturity parameter χ	0.05	5-year average maturity
Restructuring costs φ	0.6	**Target: Recovery rate 30%**
Shocks		
Persistence TFP ρ_A	0.95	Standard
TFP shock st. dev. σ_A	0.005	Standard

The last set of parameters are related to entrepreneurs and, thus, to credit frictions. We set $\chi = 0.05$ to obtain an average debt maturity of five years. A standard deviation of the idiosyncratic productivity shock $\varsigma_M = 0.31$ implies a leverage ratio of 25% in deterministic steady state. Here, leverage is defined as debt over assets, both expressed as book values. Setting the restructuring cost parameter to $\varphi = 0.6$ Finally, the entrepreneur discount factor is set to $\widetilde{\beta} = 0.9941$ to match a default rate of 1% p.a. in the baseline economy and to $\widetilde{\beta} = 0.99225$ to match a default rate of 3% p.a. in the economy with tight credit constraints. In the high risk economy, the long term leverage ratio *increases* to around 28%. This underscores the importance of looking beyond leverage ratios, which are endogenous firm choices, as measures of financial constraints.

Carbon Tax Shocks and Credit Constraints Using our calibrated model, we study the effects of an *unanticipated* permanent increase to carbon taxes. Consistent with our empirical analysis, we start with a linear carbon tax increase from an initial level of 10\$/ToC by 10\$/ToC that takes four quarters to complete (see the upper left panel of Figure 2). Taxes stay constant after the increase, such that we can solve the model by perfect foresight.[10]

[10] 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.

Figure 2: Effects of a Carbon Tax Shocks



Notes: This figure displays the effects of an unanticipated and permanent carbon tax increase over time. Each model period corresponds to one quarter. We solve the model under perfect foresight, assuming that all uncertainty about the carbon tax path is revealed immediately.

The upper row of Figure 2 shows that an increase in carbon taxes has a positive effect on the abated share of emissions, such that emissions decline. Comparing the baseline (black lines) to the economy with high default risk (red lines), we observe that larger credit frictions imply a smaller increase of the abatement share. This translates into an emission reduction of 11.53% after one year for the baseline and an emission reduction of 11.13% for the economy with severe credit frictions. The implied damage reduction is also smaller, such that consumption increases by less than in the baseline economy.

Furthermore, the same carbon tax increase is more disruptive in the economy with severe credit frictions. On impact, annualized default rates increase to almost 6%, as shown in the bottom right panel of Figure 2.[11] This is consistent with empirical evidence by Berthold et al. (2023), who show that financing conditions worsen after positive shocks to carbon prices. This might alter the policymaker's willingness to implement large carbon taxes. We explore this channel at the end of this section.

Long Term Policy Analysis We use the model to study the impact of credit constraints on the carbon tax that is necessary to reach full abatement. Table 4 shows that full abatement

[11] Analytically, the cross-derivative of the default threshold (5) with respect to τ_t and $\overline{m}_t$ is always positive: $\frac{\partial^2 \overline{m}_t}{\partial \tau_t \partial \overline{m}_t} = \frac{1-a_t}{p_t^Z-(1-\tau_t)a_t}$.

($a_t = 1$) is reached under a 140.07$/ToC tax in the low-risk economy. Tightening credit frictions, such that they imply a default rate of 3%, necessitates a 147.77$/ToC tax to achieve full abatement. The difference of 7.70$/ToC illustrates that credit frictions at the firm level have a macroeconomically relevant on the conduct of climate policy even in the long tern. Notably, firm default rates are independent of carbon taxes in the long term. This can best be seen from the capital structure choice (10), which does not depend on τ_t above and beyond the effect τ_t has on $\overline{m}_t$.

Table 4: Effects of Long Term Carbon Taxes

	Low-Risk	High-Risk	Δ
Effects of 10$/ToC tax			
Abated Emissions	17.5%	17.0%	0.5%
Δ Emissions	-16.26%	-15.87%	0.49%
GDP Increase	1.94%	1.77%	0.17%
Full Abatement			
Necessary Tax ($/ToC)	140.07	147.77	7.70
Transition			
Welfare, Business-as-Usual	-159.4549	-159.4926	
Welfare, Transition	-156.4221	-156.8017	
Welfare Gain (CE)	1.53%	1.35%	

Notes: The transition paths are based on a linearly increasing carbon tax from 10$/ToC to the tax consistent with full abatement in the respective economy. Utilitarian welfare is defined through the following recursion: $V_t = u(c_t, n_t) + \beta\mathbb{E}_t[V_{t+1}]$. We always evaluate V_t in the first period of the transition, when all uncertainty about the future tax path is resolved. We convert welfare differences into consumption equivalents using $c^{CE,policy} = 100(\exp\{(1-\beta)(V^{policy} - V^{b.a.u.})\} - 1)$ due to the assumption of log-utility.

Transition Dynamics While such a long term comparison provides a good illustration of the role of credit frictions for climate policy, transition dynamics have to be taken into account as well in a welfare comparison of different policies. Recall that our parameterization of the damage and abatement functions implies that full abatement maximizes welfare in the long term. We can use our model with endogenous default risk to test whether the pronounced adverse effects of carbon taxes on corporate default rates in the economy with severe credit frictions might render a delayed transition optimal from a utilitarian welfare perspective.

We show that this is not the case. Even when taking the large increase of corporate default rates into account, it is not optimal to slow down the transition. We operationalize this by imposing a linear tax path from current taxes of 10$/ToC to full abatement taxes in both economies. The speed of the transition is then governed by the number of periods until the terminal tax rates is reached. For any reasonable severity of credit frictions, welfare monotonically declines if the transition is delayed, i.e. the later full abatement is reached. The reason behind this is the comparatively small welfare loss of temporarily high corporate default risk relative to the welfare gains of reducing emission damages.

Lastly, we demonstrate that the welfare gain of full abatement is considerably smaller in the economy with severe credit frictions when accounting for transition dynamics. We refer to the scenario with a permanent carbon tax of 10$/ToC as "business-as-usual". For simplicity, we assume that full abatement is reached after 30 years. Welfare increases by 1.53% in consumption equivalents when comparing the "business-as-usual" scenario to the linear tax increase to full abatement, see the lower panel of Table 4. In the economy with severe credit frictions, welfare is generally lower due to the higher prevalence of firm default. The welfare gain from reaching full abatement in 30 years amounts to 1.35% in consumption equivalents and falls well short of the welfare gain in the baseline economy. Taken together, the indirect welfare effects of severe credit frictions operating through their impairment of climate policy are larger in our model than their direct effects through resource losses of corporate default.

6 Conclusion

In this paper, we demonstrate that firm credit constraints directly impair the efficacy of climate policies as measured by emission growth at the firm level. Combining a cross-country dataset of emissions and credit constraints of publicly traded firms between 2012 and 2019 with a measure of carbon taxes, we show that firms with tight credit constraints, measured by their distance-to-default, experience a smaller emission reduction than unconstrained firms. These effects are particularly strong in the manufacturing sector and for firms with a low capital intensity within their industry. Such firms experience an emission reduction which is around 3 percentage points smaller after a carbon tax increase of 10$/ToC, compared to their unconstrained peers. This points towards financial barriers to the adoption of clean technologies.

Incorporating this channel into an E-DSGE model with endogenous credit constraints, we show that carbon taxes are less effective in an economy with more severe credit frictions, but otherwise identical structural parameters. The equilibrium emission reduction to a 10$/ToC tax falls around half a percentage point short in the economy with more severe credit frictions, as measured by the average corporate default rate. The tax associated with full abatement is almost 8$/ToC larger when the default rate increases from one to three percent, such that achieving net zero requires a more stringent climate policy. This has also implications for the transition to net zero: implementing any carbon tax inflicts higher financial stress on the economy with tighter credit frictions, since default rates are more sensitive to carbon taxes. The need for a higher carbon tax further amplifies this channel, such that the short term adverse consequences of the net zero transition are considerably larger in economies with more severe credit frictions.

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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 raw 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**

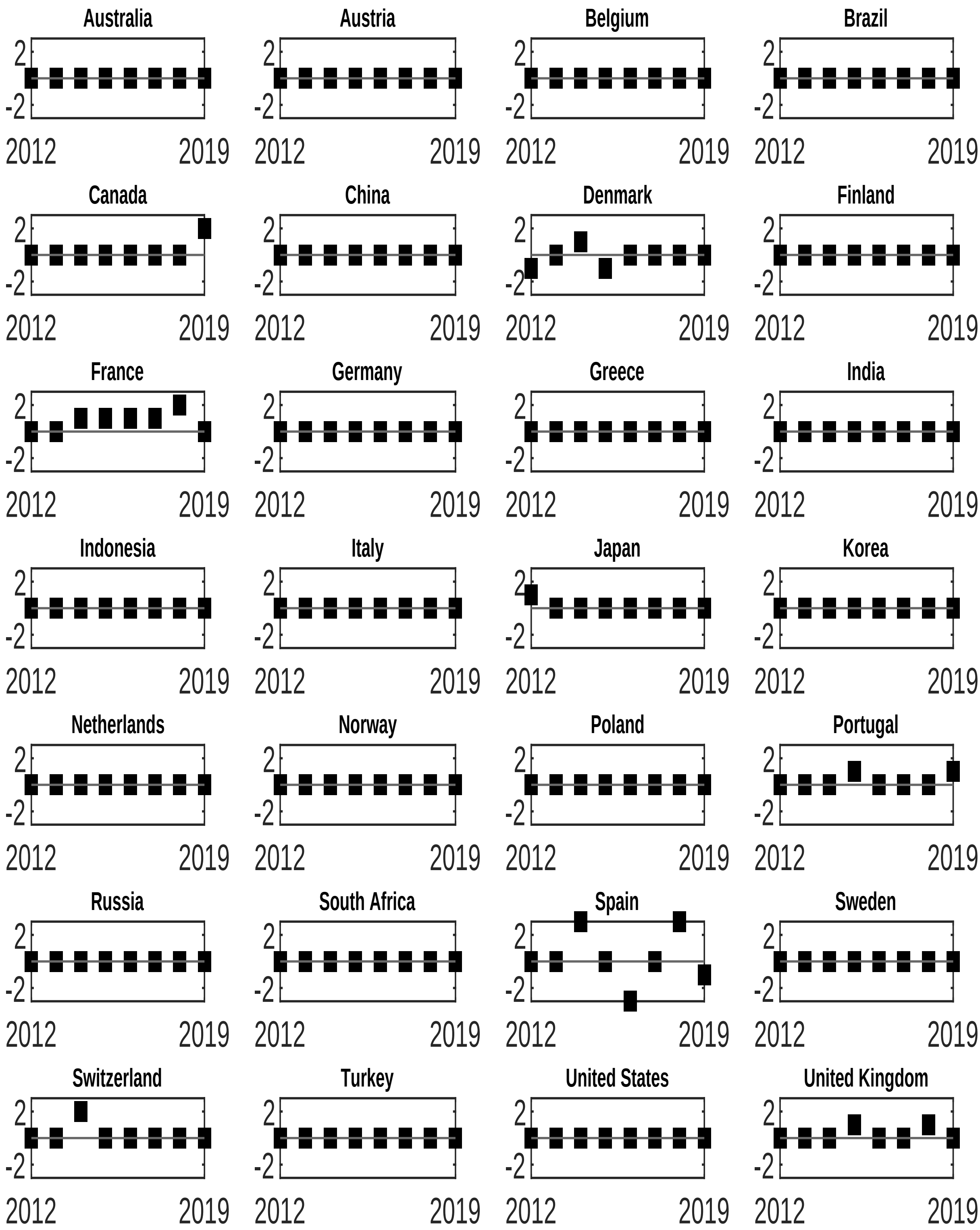
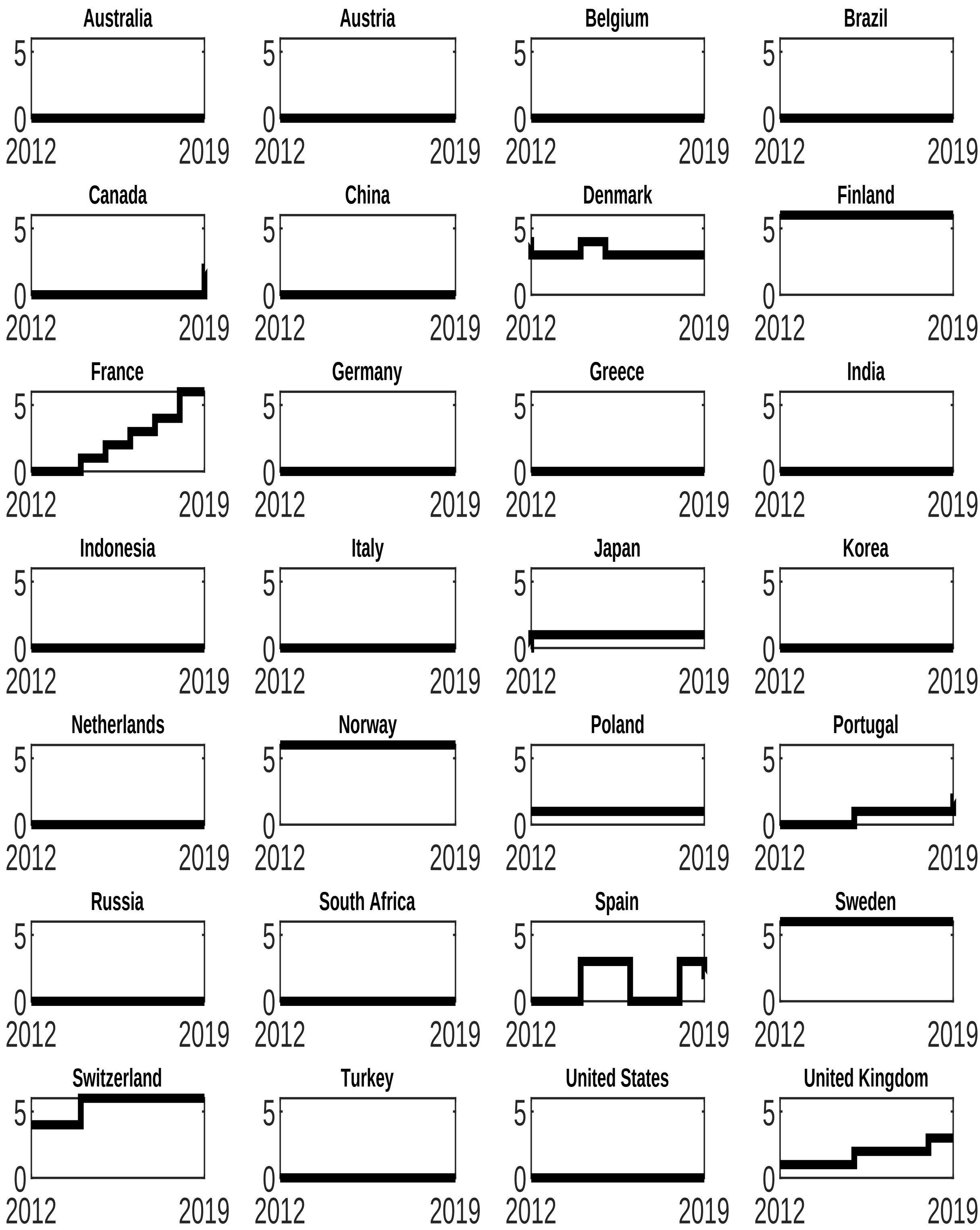


Figure A.2: **Carbon Taxes over Time**



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**

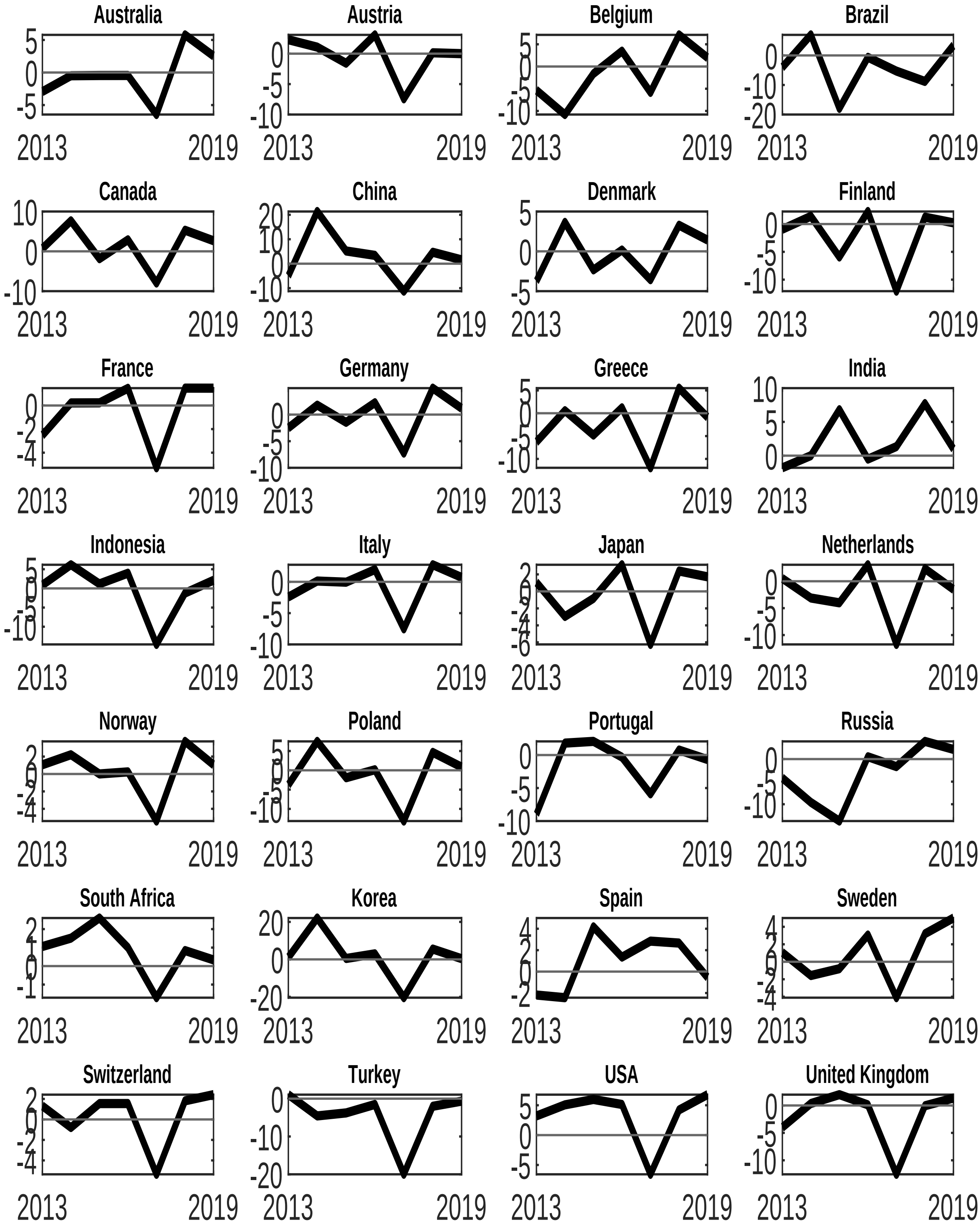


Table A.1: **Emission Growth: Summary statistics by country and sector**

	N	Mean	SD	Min	P25	P50	P75	Max
Panel A: Summary Statistics of Emission Growth across Countries								
Australia	2154	0.00	1.15	-3.13	-0.43	0.00	0.44	3.11
Austria	241	-0.01	0.76	-3.13	-0.25	0.00	0.23	2.71
Belgium	380	0.02	1.00	-3.13	-0.28	0.01	0.37	3.11
Brazil	778	0.03	1.21	-3.13	-0.44	-0.02	0.45	3.11
Canada	1590	0.00	0.93	-3.13	-0.31	0.00	0.32	3.11
China	14080	0.00	0.94	-3.13	-0.40	0.00	0.40	3.11
Czech Republic	31	-0.03	1.23	-3.13	-0.32	-0.03	0.21	3.11
Denmark	378	-0.02	0.88	-3.13	-0.38	-0.03	0.32	3.11
Finland	637	-0.01	0.88	-3.13	-0.31	-0.02	0.26	3.11
France	1797	-0.01	0.91	-3.13	-0.28	0.00	0.25	3.11
Germany	1827	0.00	0.83	-3.13	-0.28	0.00	0.27	3.11
Greece	517	-0.04	0.94	-3.13	-0.37	-0.01	0.32	3.11
Hungary	41	0.01	1.09	-3.13	-0.54	-0.03	0.41	3.11
India	4642	0.02	1.03	-3.13	-0.34	0.01	0.38	3.11
Indonesia	1771	-0.01	0.99	-3.13	-0.36	-0.01	0.32	3.11
Ireland	157	0.02	1.00	-3.13	-0.28	0.01	0.30	3.11
Italy	723	-0.03	0.90	-3.13	-0.27	-0.01	0.23	3.11
Japan	16545	0.00	0.77	-3.13	-0.22	0.00	0.22	3.11
Netherlands	448	0.00	0.91	-3.13	-0.27	0.00	0.32	3.11
Norway	636	-0.01	1.13	-3.13	-0.43	-0.01	0.37	3.11
Poland	1318	0.00	0.92	-3.13	-0.33	0.00	0.30	3.11
Portugal	172	0.02	0.93	-3.13	-0.30	0.00	0.27	3.11
Russia	529	-0.01	1.04	-3.13	-0.32	0.01	0.42	3.11
Slovakia	11	-0.06	0.43	-0.86	-0.15	-0.05	0.07	0.61
Slovenia	70	0.03	0.74	-1.77	-0.25	-0.01	0.17	2.70
South Africa	735	0.01	0.80	-3.13	-0.18	0.01	0.19	3.11
South Korea	6359	0.00	0.92	-3.13	-0.37	0.00	0.37	3.11
Spain	534	0.03	0.94	-3.13	-0.32	0.02	0.34	3.11
Sweden	1433	0.00	1.12	-3.13	-0.45	-0.01	0.40	3.11
Switzerland	825	-0.01	0.95	-3.13	-0.25	0.00	0.25	3.11
Turkey	1031	0.01	1.00	-3.13	-0.36	0.01	0.35	3.11
USA	12535	0.00	0.86	-3.13	-0.31	0.00	0.31	3.11
United kingdom	3479	0.01	0.93	-3.13	-0.30	0.00	0.30	3.11
Panel B: Summary Statistics of Emission Growth across Sectors								
Agriculture, forestry, fishing	534	0.00	1.05	-3.13	-0.35	-0.01	0.35	3.11
Mining	3258	-0.01	1.14	-3.13	-0.43	0.01	0.44	3.11
Construction	2569	0.00	0.91	-3.13	-0.29	0.01	0.30	3.11
Manufacturing	41641	0.00	0.87	-3.13	-0.31	0.00	0.31	3.11
Transportation & public utilities	6810	-0.01	0.96	-3.13	-0.28	0.00	0.26	3.11
Wholesale trade	3577	0.00	1.18	-3.13	-0.35	0.00	0.38	3.11
Retail trade	4504	0.01	0.81	-3.13	-0.27	0.00	0.27	3.11
Services	11836	-0.01	0.89	-3.13	-0.36	0.00	0.34	3.11
Full sample	74729	0.00	0.91	-3.13	-0.31	0.00	0.31	3.11

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. Panels 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**

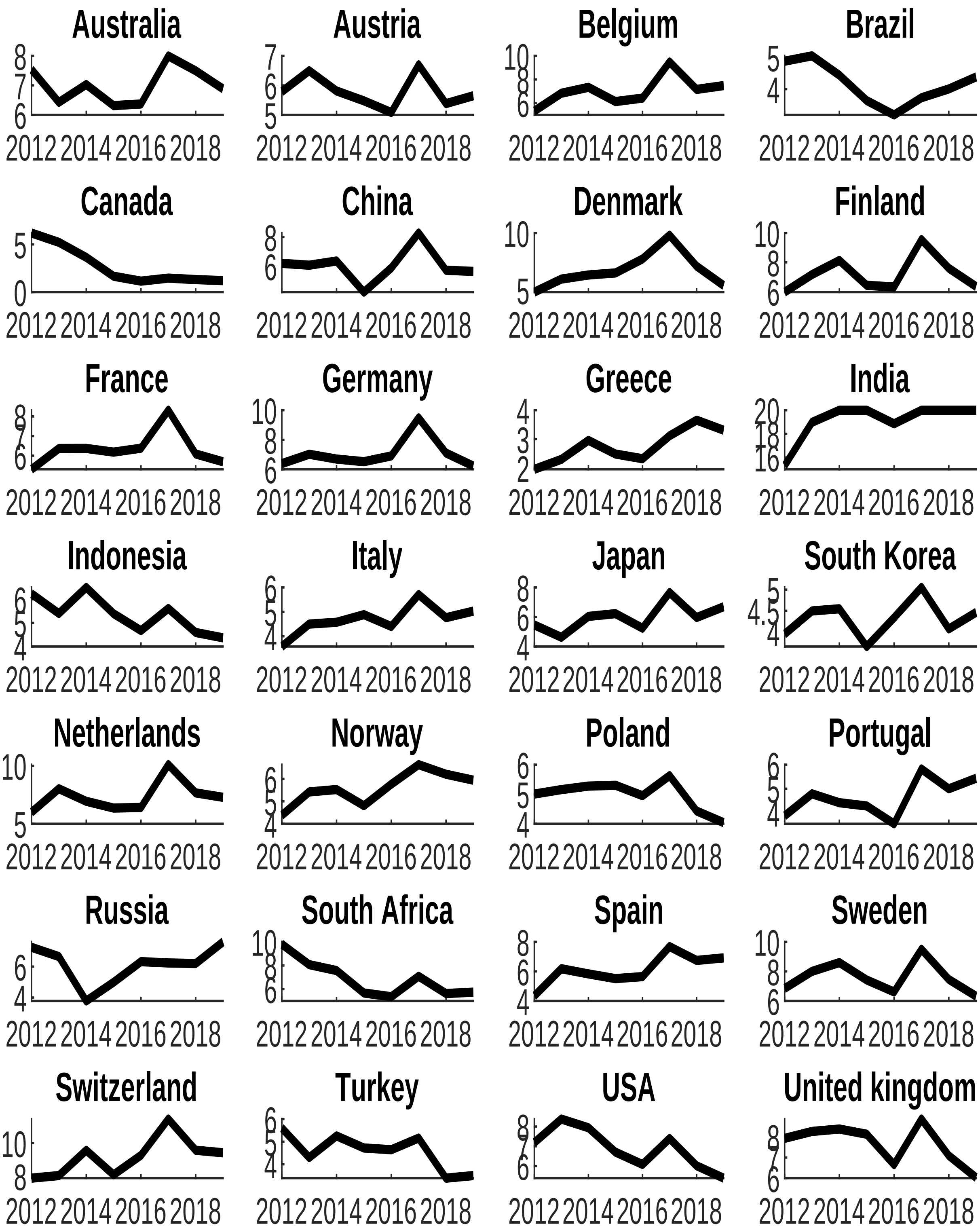


Table A.2: **Distance-to-Default: Summary statistics by country and sector**

	N	Mean	SD	Min	P25	P50	P75	Max
Panel A: Summary Statistics of D2D across Countries								
Australia	1584	8.53	5.83	0.66	4.32	6.89	11.01	20.00
Austria	268	7.29	4.42	1.01	4.57	5.93	8.20	20.00
Belgium	363	8.24	4.77	0.66	4.89	7.08	10.21	20.00
Brazil	747	5.24	4.13	0.66	2.58	4.12	6.76	20.00
Canada	1291	14.32	8.04	8.63	8.63	14.32	20.00	20.00
China	14420	7.95	5.61	0.66	4.01	5.85	9.77	20.00
Czech Republic	39	11.31	5.55	1.67	6.70	10.14	14.02	20.00
Denmark	348	8.09	5.74	0.66	4.04	6.08	10.57	20.00
Finland	446	7.99	4.32	0.66	4.98	7.08	9.94	20.00
France	1742	7.53	4.45	0.66	4.60	6.34	9.07	20.00
Germany	1547	8.49	5.53	0.66	4.65	6.66	10.23	20.00
Greece	433	4.50	5.16	0.66	1.36	2.66	4.98	20.00
Hungary	29	9.06	4.22	3.81	5.96	7.77	11.23	20.00
India	190	15.15	6.48	0.73	10.19	20.00	20.00	20.00
Indonesia	1724	8.75	6.93	0.66	3.19	5.47	15.74	20.00
Ireland	120	8.77	5.09	0.66	5.30	8.17	10.70	20.00
Italy	646	5.74	3.45	0.66	3.48	4.82	7.15	20.00
Japan	14309	7.54	4.95	0.66	4.05	6.03	9.37	20.00
Netherlands	319	8.11	4.94	0.66	4.43	7.26	10.43	20.00
Norway	608	6.94	5.42	0.66	3.41	5.43	8.33	20.00
Poland	1064	6.21	4.60	0.66	3.29	4.92	7.46	20.00
Portugal	134	5.16	3.93	0.66	1.87	4.60	7.01	18.73
Russia	425	8.15	6.12	0.66	3.49	6.01	11.45	20.00
Slovakia	24	7.29	7.56	0.66	2.17	3.64	13.33	20.00
Slovenia	78	8.79	6.28	0.66	3.52	7.70	12.45	20.00
South Africa	688	8.29	5.12	0.66	4.57	7.05	10.99	20.00
South Korea	5364	6.04	4.95	0.66	3.01	4.32	6.77	20.00
Spain	474	7.50	5.16	0.66	3.99	5.92	9.68	20.00
Sweden	848	9.20	5.80	0.66	4.86	7.48	11.60	20.00
Switzerland	798	10.11	5.38	0.66	6.06	8.97	13.43	20.00
Turkey	1170	6.23	4.97	0.66	3.10	4.46	7.27	20.00
USA	8779	10.42	6.50	1.47	5.18	8.40	20.00	20.00
United Kingdom	2551	9.58	5.77	0.66	5.21	7.80	12.95	20.00
Panel B: Summary Statistics of D2D across Sectors								
Agriculture, forestry, fishing	454	8.11	5.40	0.76	4.26	6.14	10.20	20.00
Mining	1525	8.33	6.47	0.66	3.50	5.72	11.55	20.00
Construction	1793	6.70	4.87	0.66	3.33	5.26	8.58	20.00
Manufacturing	28538	7.84	5.48	0.66	3.93	5.94	9.88	20.00
Transportation & public utilities	4046	6.85	4.80	0.66	3.72	5.44	8.15	20.00
Wholesale trade	2492	7.56	5.35	0.66	3.88	5.70	9.36	20.00
Retail trade	2671	8.23	5.44	0.66	4.36	6.45	10.42	20.00
Services	5859	8.94	6.05	0.66	4.31	6.89	12.15	20.00
Full Sample	47,378	7.86	5.50	0.66	3.95	6.01	9.90	20.00

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

B Additional Empirical Results

B.1 Exogeneity of Carbon Policy Shocks

An important 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:

$$\text{Prob}(\text{Tax}_{c,t} \neq \text{Tax}_{c,t-1}) = \beta_0 + \beta_1 \cdot \text{D2D}_{c,t-1} + \beta_2 \cdot X_{c,t-1} + \epsilon_{c,t} \; . \tag{17}$$

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.[12] We do not add country fixed effects, since we would loose observations in all countries without carbon tax changes. The standard error is 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 (17) 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.

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 policy 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 a concern, we are estimating

$$\begin{aligned}\Delta \log(Emi)_{j,t} = \beta_0 &+ \beta_1 \cdot \text{D2D}_{j,t-1} + \beta_2 \cdot \Delta\text{Tax}_{c,t} + \beta_3 \cdot \text{D2D}_{j,t-1} \times \Delta\text{Tax}_{c,t} \\ &+ \beta_4 \cdot X_{j,t-1} + \beta_5 \cdot X_{j,t-1} \times \Delta\text{Tax}_{c,t} + \chi_c + \tau_t + \epsilon_{j,t} \; .\end{aligned} \tag{18}$$

[12] 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 (17). 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.

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.

C Model Appendix

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

$$w_t = \omega_N n_t^{\gamma_N} c_t \ , \tag{C.1}$$

$$1 = \mathbb{E}_t \left[\Lambda_{t,t+1}(1 + r_t) \right] \ , \tag{C.2}$$

Final good producers:

$$y_t = (1 - \mathcal{D}_t) z_t^{\alpha} n_t^{1-\alpha} \ , \tag{C.3}$$

$$(1 - \alpha) y_t = p_t^Z z_t \ , \tag{C.4}$$

$$\alpha y_t = w_t n_t \ , \tag{C.5}$$

Investment and abatement good supply:

$$p_t^K = 1 + \frac{\psi_K}{2}\Big(\frac{i_t}{i_{t-1}} - 1\Big)^2 + \psi_K\Big(\frac{i_t}{i_{t-1}} - 1\Big)\frac{i_t}{i_{t-1}} - \mathbb{E}_t\left[\Lambda_{t,t+1}\psi_K\Big(\frac{i_{t+1}}{i_t} - 1\Big)\Big(\frac{i_{t+1}}{i_t}\Big)^2\right] \ , \tag{C.6}$$

$$p_t^A = \alpha_0 a_{t+1}^{\alpha_1} \ , \tag{C.7}$$

Intermediate good firms:

$$p_t^A - \mu_t \tau_{t+1} \frac{\overline{m}_{t+1}}{p_{t+1}^Z - \tau_{t+1}(1 - a_{t+1})} = \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}\Big\{\big(1 - G(\overline{m}_{t+1})\big)\tau_{t+1}k_{t+1}\Big\}\right] \ , \tag{C.8}$$

$$p_t^K - \mu_t \frac{\overline{m}_{t+1}}{k_{t+1}} = \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}\Big\{(1 - \delta_k)p_{t+1}^K + \big(1 - G(\overline{m}_{t+1})\big)\Big(p_{t+1}^Z - (1 - a_{t+1})\tau_{t+1}\Big)\Big\}\right] \ , \tag{C.9}$$

$$q(\overline{m}_{t+1}) - \mu_t \frac{\overline{m}_{t+1}}{l_{t+1}} = \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}\Big\{\chi(1 - F(\overline{m}_{t+1})) + (1 - \chi)q(\overline{m}_{t+2})\Big\}\right] \ , \tag{C.10}$$

$$-\mu_t - q'(\overline{m}_{t+1})\Big(l_{t+1} - (1 - \chi)l_t\Big) = \mathbb{E}_t\left[\widetilde{\Lambda}_{t,t+1}\Big\{\Big(l_{t+2} - (1 - \chi)l_{t+1}\Big)q'(\overline{m}_{t+2})\frac{\partial \overline{m}_{t+2}}{\partial \overline{m}_{t+1}}\Big\}\right] \ , \tag{C.11}$$

$$\overline{m}_{t+1} = \frac{\chi l_{t+1}}{(p_{t+1}^Z - \tau_{t+1}(1 - a_{t+1}))k_{t+1}} \ , \tag{C.12}$$

$$q(\overline{m}_{t+1}) = \mathbb{E}_t\left[\Lambda_{t,t+1}\Big\{\chi\Big(1 - F(\overline{m}_{t+1}^{\tau}) + \frac{G(\overline{m}_{t+1})}{\overline{m}_{t+1}} - F(\overline{m}_{t+1})\varphi\Big) + (1 - \chi)q(\overline{m}_{t+2})\Big\}\right] \ , \tag{C.13}$$

$$i_t = k_{t+1} - (1 - \delta_K)k_t \ , \tag{C.14}$$

Emission accumulation and damages:

$$\mathcal{E}_t = e_t + \delta_E \mathcal{E}_{t-1} \ , \tag{C.15}$$

$$\mathcal{D}_t = 1 - \exp(-\gamma_E \mathcal{E}_t) \ , \tag{C.16}$$

Final good market clearing:

$$y_t = c_t + \frac{\alpha_0}{1+\alpha_1} a_t^{\alpha_1} + i_t \left(1 + \frac{\psi_K}{2}\big(\frac{i_t}{i_{t-1}} - 1\big)^2\right) + \chi \varphi l_t F(\overline{m}_t)\ . \tag{C.17}$$