Optimal Carbon Taxes and Misallocation across Heterogeneous Firms*

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Abstract

This paper studies the optimal carbon tax in an economy with heterogeneous emission intensity and factor misallocation across firms. My starting point is a simple theoretical insight: when firms with lower emission intensity exhibit higher marginal products of production factors, then a carbon tax that reallocates resources to cleaner firms also enhances allocative efficiency. Using firm-level data, I show that firms with lower emissions relative to their output indeed have higher marginal products of capital and labor. Based on the empirical evidence, I develop a quantitative firm dynamics model that incorporates carbon emissions, emission externalities, adjustment costs, and financial frictions. In a calibrated version of this model, the optimal carbon tax is three times higher than in a counterfactual economy in which there is no relation between emission intensity and marginal products. Furthermore, I find that a policy directly targeting adjustment costs and financial frictions can simultaneously reduce carbon emissions and boost output, ultimately surpassing a carbon tax in increasing overall welfare.

JEL Codes: E22, E44, G32, H23, O44, O47, Q58.

Keywords: Carbon Tax; Externalities; Firm Dynamics; Misallocation; Adjustment Costs; Financial Frictions; Sequence-Space Jacobian.

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1 Introduction

Greenhouse gas (GHG) emissions have emerged as a pressing global challenge, prompting the need for comprehensive carbon management policies. When the externality from carbon emissions is the only inefficiency in an economy, the Pigouvian principle applies: the optimal carbon tax rate is equal to the marginal damage of carbon emissions. However, a carbon externality does not exist in isolation when there are other frictions in the economy. Thus, it is crucial to understand how carbon policies interact with other inefficiencies in designing optimal carbon management policies.

This paper investigates the optimal carbon tax in an environment where firms are heterogeneous in emission intensity, coupled with the presence of production factor misallocation among these firms. When firms have different emission intensities, a carbon tax reallocates resources towards relatively cleaner firms. The extent to which this resource reallocation enhances allocative efficiency hinges on whether these cleaner firms yield higher marginal products of production factors in comparison to their more emission-intensive counterparts. If cleaner firms have higher marginal products in the absence of a carbon tax, reallocating resources to these cleaner firms increases aggregate productivity. Consequently, the introduction of a carbon tax would yield additional advantages for a social planner by mitigating the pre-existing factor misallocation.

The starting point of my analysis is a simple theoretical model, building on Hsieh and Klenow (2009), in which I formalize this intuition. I theoretically show that the correlation between emission intensity and marginal products, where the dispersion of marginal products arises from firm-level distortions, is a key statistic in determining the optimal carbon tax. When a positive correlation exists between emission intensity and marginal products, meaning that cleaner firms exhibit lower marginal products, implementing a carbon tax that directs resources towards these cleaner firms can lead to a further reduction in their marginal products. Consequently, this contributes to an increase in the dispersion of marginal products and exacerbates the existing misallocation. When the correlation between emission intensity and marginal products is negative, a carbon tax decreases the dispersion in marginal products and alleviates the prevailing misallocation. However, when the carbon tax is set excessively high, further escalating it can amplify misallocation. This is because a carbon tax inadvertently contributes to the dispersion in marginal products, even in the negative correlation case. Hence, the optimal carbon tax rate would be higher in situations where a negative correlation between emission intensity and marginal products exists, compared to cases with a positive correlation. This happens as a social planner capitalizes on the advantage of addressing the prevailing misallocation.

I then show that, in firm-level data, cleaner firms indeed tend to face higher distortions, reflected by higher marginal products. I use the merged Compustat-Worldscope data to estimate firm-level emission intensity and marginal products. I incorporate industry-year indicators to account for potential industry-specific effects. By doing so, I isolate the cross-sectional variation among firms within the same industry in the relation between emission intensity and marginal products. I find that cleaner firms have higher marginal revenue product of capital (MRPK), marginal revenue product of labor (MRPL), and revenue productivity (TFPR), with these variables serving as measures of distortions.[1] In addition, I find that firms with higher levels of productivity tend to exhibit lower emission intensities. This finding contributes to explaining the negative correlation between emission intensity and distortions. This is particularly noteworthy, considering that previous literature often reports a positive correlation between productivity and distortions (Blackwood et al. (2021)).

Based on my theoretical and empirical insights, I build a novel quantitative model of firm dynamics. I incorporate a standard firm dynamics framework, as outlined in Khan and Thomas (2013), and expand upon it by including environmental externalities as described by Golosov et al. (2014). This model features externalities stemming from carbon emissions, while also encompassing endogenized distortions such as information frictions, adjustment costs, and financial constraints. I calibrate the model to match salient firm dynamics and carbon-related moments, avoiding direct targeting of the correlation between emission intensity and marginal products. Nevertheless, the calibrated version of the model aptly replicates the correlation.

Using the calibrated model as a quantitative laboratory, I conduct three experiments. First, I compute the optimal carbon tax rate in a baseline economy, yielding a value of $7.3 per ton of GHGs emissions. The calculation of this optimal tax rate necessitates a simulation of the transition from a non-carbon-tax economy to a carbon-tax environment. As this is computationally demanding, the Sequence-Space Jacobian method is employed to compute the transition path, following the approach outlined by Auclert et al. (2021). Second, I explore the importance of the correlation between emission intensity and distortions by evaluating the optimal carbon tax in an environment where this correlation is zero. The analysis reveals that the optimal carbon tax diminishes to one-third of the baseline value, in alignment with the intuitive

[1] See Hsieh and Klenow (2009) and Hopenhayn (2014a) for an extensive discussion of variables that represent distortions.

argument presented in the simplified model. Third, I directly eliminate underlying distortions such as adjustment costs and financial frictions, which hamper the efficient allocation toward cleaner/productive firms. Even as total output rises, the elimination of distortions leads to a reduction in total carbon emissions. This result is driven by the substantial reallocation of resources toward cleaner firms, which are relatively under-producing in a distorted world. When contrasted with a carbon-tax scenario achieving equivalent carbon reduction, this exercise demonstrates that the removal of distortions results in a 9 percent higher welfare than that of the carbon-tax economy.

This paper delivers two broader policy implications that could challenge conventional wisdom. First, a carbon tax might be more desirable for developing countries as opposed to developed ones. Often, policymakers in developing countries question the necessity of bearing the cost of carbon emissions, attributing much of global warming to developed counterparts. However, due to higher distortions, productive firms in developing countries tend to be smaller (Bartelsman et al. (2013)). The findings of this paper suggest that a carbon tax might have a higher unintended benefit in alleviating existing misallocation within developing economies. Second, alternative policies geared towards directly mitigating the underlying distortions can be useful as a means of curbing carbon emissions. Sometimes, policymakers contend that price-based carbon policies, such as carbon taxes or cap-and-trade programs, face challenges in securing legislative approval.[2] As an alternative approach, the paper posits that policies directly targeting the underlying distortions could serve as effective tools in addressing climate change.

Contribution to the literature. This paper makes contributions to four areas of research. First, it contributes to the literature on second-best environmental policy in a distorted economy. Buchanan (1969) argues that the Pigouvian tax, which internalizes environmental damages, may be excessive in cases of insufficient competition, as concentrated industries are already producing below the socially optimal level. Goulder (1995) and Bovenberg (1999) study the optimal environmental tax when there are other distortionary taxes in play, such as capital and labor income taxes. In such cases, a government can recycle revenues from environmental taxes to mitigate the impact of these existing distortionary taxes. This is commonly referred to as the double-dividend hypothesis of environmental taxes, wherein such taxes not only

[2] See "Remarks by Heather Boushey on How President Biden's Invest in America Agenda has Laid the Foundation for Decades of Strong, Stable, and Sustained, Equitable Growth," May 31, 2023, Peterson Institute for International Economics.

reduce emissions (the first dividend) but also ameliorate inefficiencies arising from the distortionary tax system (the second dividend) simultaneously.[3] I contribute to this literature by showing that misallocation across heterogeneous firms can be an additional source of inefficiencies, potentially yielding another second dividend from environmental taxes.

Second, this paper advances the existing literature on climate change and environmental policies under firm heterogeneity. Lyubich et al. (2018) show substantial heterogeneity in emission intensity among manufacturing plants within the same industry, based on U.S. Census data. Berthold et al. (2023) investigate how a carbon pricing shock, identified using Känzig (2023)'s methodology, affects equity prices at the firm level. They find that relatively dirtier firms within a sector experience a larger decline in equity prices in response to an increase in carbon price. Caggese et al. (2023) quantify how climate change affects misallocation and aggregate productivity, by leveraging a general equilibrium structural model and grid-cell level temperature data. To my knowledge, Qi et al. (2021) is the closest in spirit to my paper. They extend a model based on Hsieh and Klenow (2009), demonstrating that correlated distortions lead to simultaneous reductions in output and increases in water pollution. However, my paper diverges from theirs in three key aspects. First, I focus on carbon emissions, while they focus on industrial water pollution.[4] Second, I incorporate externalities arising from carbon emissions, enabling a comprehensive normative analysis of carbon taxes. Lastly, in my quantitative model, I endogenize the wedges outlined in Hsieh and Klenow (2009) using investment uncertainty, adjustment costs, and financial frictions. This allows me to explore the precise role of specific distortions in influencing aggregate carbon emissions.

Third, this paper contributes to the literature on misallocation across heterogeneous firms. Numerous studies have investigated the sources of this dispersion in TFPR, examining whether these sources indeed indicate misallocation in terms of overall welfare. They also quantify the extent to which each source contributes to misallocation.[5] Beyond quantification, this literature has evolved to explore how

[3]Fried et al. (2018) argue that recycling revenue through lump-sum rebates could lead to higher welfare compared to when a government recycles revenue to reduce distortionary taxes when they consider the transitional dynamics of living agents. However, the conventional wisdom holds true when the analysis focuses on steady state welfare.

[4]This distinction is potentially important because abatement technology can vary for different environmental objects. For instance, addressing carbon emissions may necessitate the use of carbon capture and storage (CCS) technology, which might not be cost-effective (Martin (2011)), whereas industrial pollution can often be more readily mitigated through end-of-pipe treatment.

[5]Among many examples, see Asker et al. (2014) and David and Venkateswaran (2019) for adjustment

existing misallocation interacts with changing environments or policies.[6] For instance, Gopinath et al. (2017) examine the impact of a decrease in real interest rates following EU integration on aggregate productivity and misallocation in southern Europe. Similarly, Baqaee et al. (2023b) investigate how increases in market size impact welfare. They argue that expanding the market would decrease misallocation, a phenomenon they term the Darwinian effect. This effect reallocates resources to firms with higher markup, which were previously under-producing from a welfare perspective. Bau and Matray (2023) analyze the capital liberalization episode in India. Their study reveals that firms with higher MRPK experience faster growth compared to those with lower MRPK after the capital liberalization, indicating that this policy reduces misallocation. My contribution to this literature involves examining how carbon taxes impact misallocation in the presence of heterogeneity in emission intensity and pre-existing misallocation that interacts with the emission heterogeneity. I formally show that the connection between emission intensity and distortions plays a crucial role in determining the level of optimal carbon taxes in this context.[7]

Lastly, this paper is related to the existing literature on optimal policy in a heterogeneous agent framework. Nuño and Moll (2018) derive constrained efficient allocation by considering the cross-sectional distribution as a control variable. Similarly, Ottonello and Winberry (2023) characterize constrained efficient allocation in the presence of non-rivalry of ideas and financial frictions. González et al. (2022) focus on the optimal monetary policy when firms are heterogeneous, while Dávila and Schaab (2023) explore the optimal monetary policy in the presence of heterogeneous households. Both papers formulate a Ramsey planner's problem, with the latter solving it using the Sequence-Space Jacobian method. My paper also employs the Sequence-Space Jacobian method, leveraging it to derive a transition path multiple times in order to determine an optimal policy choice, in my setting that of a carbon tax.

Structure of the paper. Section 2 develops a simple model of heterogeneous firms to elucidate the main intuition. Section 3 empirically investigates a key statistic, derived

costs; Buera et al. (2011) and Midrigan and Xu (2014) for financial frictions; Dhingra and Morrow (2019) and Peters (2020) for markups; and David et al. (2016) for information frictions.

[6] Among others, see González et al. (2022) and Baqaee et al. (2023a) for monetary policy and misallocation; Andreasen et al. (2023) for macroprudential policy and misallocation.

[7] Restuccia and Rogerson (2008) demonstrate that the correlated distortion is much more critical in decreasing aggregate productivity. Hopenhayn (2014b) suggests that the conventional wisdom, which holds that an increase in the correlation between fundamentals and distortions decreases allocative efficiency, is not necessarily correct. My paper shows that the correlated distortion remains critical in investigating how changes in policies interact with existing misallocation.

from the simple model, using firm-level data. Section 4 outlines a quantitative firm dynamics model that incorporates externalities from carbon emissions, as well as heterogeneity in emission intensity and distortions. Section 5 demonstrates how the quantitative model is calibrated to data. Section 6 calculates the optimal carbon taxes in the quantitative model and conducts counterfactual analyses. Section 7 presents the conclusion.

2 Main intuition from a simple theoretical model

This section formalizes the main insights of this paper in a simple theoretical model. I demonstrate that the correlation between emission intensity and market distortions is a key metric for examining the impact of a carbon tax on allocative efficiency. This model provides a natural guideline for the empirical analysis presented in Section 3. It will be generalized in Section 4.

2.1 Model environment

My starting point is a model with heterogeneous firms in which externalities from carbon emissions exist, building upon Hsieh and Klenow (2009). In addition to differing in their productivity and output distortions, I assume that firms have different emissions per output. Firms produce homogeneous goods with a single factor and operate in a perfectly competitive market. The production function is given by a decreasing returns to scale function of firm productivity z and factor f.[8] In addition, total carbon emissions E are damaging to firms, and this carbon damage is modeled as aggregate productivity loss, following Golosov et al. (2014). Notably, firms do not account for the impact of their production choices on this overall carbon damage, thus leading to externalities arising from carbon emissions. The production function for firm i is

$$y_i = exp(-\gamma E) z_i f_i^{\alpha}, \quad \alpha < 1, \tag{1}$$

where γ is the parameter that governs the degree of carbon damage.

[8] In Hsieh and Klenow (2009), firms operate under the assumption of a production technology with constant returns to scale and a market structure characterized by monopolistic competition. Provided the profit function exhibits concavity, there will be a nondegenerate distribution of firms, and the fundamental logic of a simple model in this paper will remain unchanged.

I denote distortions that increase the marginal products of factor as τ. Following the *indirect* approach in the misallocation literature, distortions are represented as reduced-form output taxes that hinder the equalization of marginal products, as discussed by Restuccia and Rogerson (2017). The firm-level distortions aim to account for various frictions and distortions that could potentially generate dispersion in marginal products. In Section 4, I am going to employ a *direct* approach where I can generate dispersion in marginal products from structural frictions and distortions, such as uncertainties in investment, adjustment costs, and financial frictions.

Firms have different emission intensities $m_i = \frac{e_i}{y_i}$, where e_i are firm-level carbon emissions. I assume that firms take emission intensities as given, so carbon emissions e_i are generated as a by-product of their production. Firms could have different emission intensities at least for two reasons, as outlined by Shapiro and Walker (2018). First, firms may adopt different levels of abatement technologies. Second, differences in productivity can lead to varying emissions per unit of output, as long as carbon emissions are tied to input factors. In this simple model, I do not delve into the specific underlying causes for these differences in emission intensities. Instead, I focus on examining the implications of such heterogeneity. Additionally, firms are subject to a uniform per-emission carbon tax, denoted as τ_c.

A representative household and the government play passive roles. The household owns firms, supplies factors, and consumes. I assume that the total factor supply, $\bar{F}$, remains constant, and the household's utility solely depends on their consumption. This assumption is deliberately chosen to focus exclusively on the role of factor reallocation in determining the optimal carbon taxes. The government collects carbon taxes and output taxes (distortions) and then redistributes a lump-sum rebate to the household. As a result, carbon taxes and distortions do not directly affect the resource constraint:

$$C = Y, \tag{2}$$

where C is the consumption of the representative household and Y is the aggregate output.

2.2 Social welfare

The social planner aims to increasae the consumption of the representative household by adjusting the carbon tax τ_c. Consumption of the representative household is linked to the production choices of firms. To show this, I define aggregate productivity TFP and represent it using aggregation:

$$TFP \equiv \frac{Y}{\bar{F}^{\alpha}} = exp(-\gamma E) \times \frac{\int z_i^{\frac{1}{1-\alpha}} (f_i/y_i)^{\frac{\alpha}{1-\alpha}} di}{[\int z_i^{\frac{1}{1-\alpha}} (f_i/y_i)^{\frac{1}{1-\alpha}} di]^{\alpha}}. \tag{3}$$

Since $C = Y = TFP \times \bar{F}^{\alpha}$ holds, and the factor supply is fixed, analyzing how the aggregate productivity TFP is affected by carbon taxes is enough to convey the welfare consequences of these taxes.

2.3 Firm problem

Given the model environment, firm i's optimization problem is

$$\max_{f_i}(1-\tau_i)y_i - pf_i - \tau_c e_i = (\underbrace{1-\tau_i-\tau_c m_i}_{\equiv \xi_i})y_i - pf_i \tag{4}$$

$$s.t.$$

$$y_i = exp(-\gamma E) z_i f_i^{\alpha},$$

where p is the factor price and ξ_i are the net distortions after carbon taxes. The first-order condition illustrates how marginal products (MP_i) have a one-to-one mapping to the after-carbon taxes distortions ξ_i:

$$MP_i \equiv \frac{\partial y_i}{\partial f_i} = \alpha exp(-\gamma E) z_i f_i^{\alpha-1} = \alpha \frac{y_i}{f_i} = \frac{p}{1-\tau_i-\tau_c m_i} = \frac{p}{\xi_i}. \tag{5}$$

By combining (3) and (5), aggregate productivity is represented as follows:

$$TFP = \underbrace{exp(-\gamma E)}_{\text{carbon damages}} \times \underbrace{\frac{\int z_i^{\frac{1}{1-\alpha}} \xi_i^{\frac{\alpha}{1-\alpha}} di}{[\int z_i^{\frac{1}{1-\alpha}} \xi_i^{\frac{1}{1-\alpha}} di]^{\alpha}}}_{\text{allocative efficiency}}. \tag{6}$$

Aggregate productivity TFP is higher when there are fewer carbon emissions and a higher degree of allocative efficiency. Assuming a joint log-normal distribution of (z_i, ξ_i), I express the factor misallocation term as a direct function of the dispersion in marginal products:

$$log(TFP) = -\gamma E + log\left(\int z_i^{\frac{1}{1-\alpha}} di\right)^{1-\alpha} - \frac{\alpha}{2(1-\alpha)}\sigma^2_{logMP_i},$$

where $\sigma^2_{logMP_i}$ is the dispersion in (log) marginal products.

2.4 Misallocation and the optimal carbon tax

When the carbon tax τ_c is zero, a firm with higher distortions τ_i experiences higher marginal products. In this case, the dispersion in marginal products only depends on the dispersion in distortions. However, when the government imposes a positive carbon tax, a firm with higher distortions does not necessarily have higher marginal products. If a firm with higher τ_i also has a lower m_i, it could result in lower marginal products because its 'effective' costs of carbon emissions $\tau_c m_i$ are lower. Consequently, depending on the relationship between distortions and emission intensity, carbon taxes could either increase or decrease the dispersion in marginal products.

Proposition 1 *Suppose $E(m_i) = 0$. (i) If the correlation between emission intensities and distortions is positive, i.e., $\rho = \rho(m_i, \tau_i) > 0$, a carbon tax increases the dispersion in marginal products. (ii) If $\rho < 0$, a modest increase in carbon tax decreases the dispersion in marginal products, however, a sufficiently high carbon tax increases the dispersion in marginal products, i.e.,*

$$\frac{d\sigma^2_{logMP_i}}{d\tau_c} = \begin{cases} \geq 0, \textit{if } \rho \geq 0 \textit{ or } (\rho < 0, \tau_c \geq \frac{\rho\sigma_{\tau_i}}{\sigma_{m_i}}) \\ < 0, \textit{if } (\rho < 0, \tau_c < \frac{\rho\sigma_{\tau_i}}{\sigma_{m_i}}). \end{cases}$$

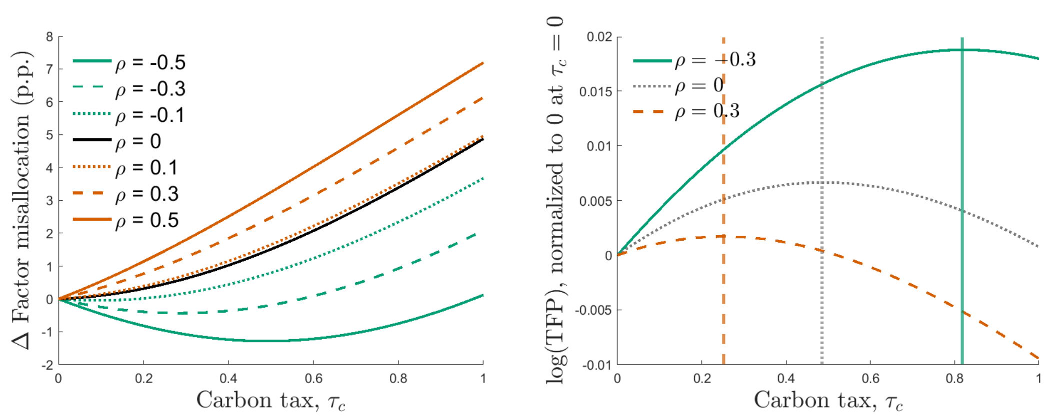
Proof. See Appendix A.1. ■

Proposition 1 shows the importance of the correlation between emission intensities and distortions in understanding how carbon taxes impact allocative efficiency. When there is a positive correlation, meaning cleaner firms have lower marginal products, implementing a carbon tax that directs resources towards these cleaner firms can lead to a further reduction in their marginal products. Consequently, this exacerbates the existing misallocation by increasing the dispersion of marginal products. A similar intuition applies when the correlation between emission intensity and marginal products is negative, particularly at a modest level of carbon tax. In this case, a carbon tax decreases the dispersion in marginal products and alleviates the existing misallocation. However, when the carbon tax is set excessively high, further increases in the carbon tax can make misallocation worse. This is because carbon taxes, combined with heterogeneous emission intensities, work as a source of the dispersion in marginal products.

2.5 Numerical illustration

Figure 1 shows how the reallocation of factors due to carbon taxes interacts with existing misallocation. The left panel demonstrates the impact of carbon taxes on allocative efficiency for different levels of correlation. When the correlation is positive, any level of carbon taxes exacerbates misallocation. However, in cases of a negative correlation, a modest increase in carbon taxes mitigates misallocation, while further increases deepen it. The right panel describes how carbon taxes affect aggregate productivity, the welfare measure in this model. As a result of the allocative efficiency improvements stemming from carbon taxes, the optimal level of carbon taxes is higher when the correlation between emission intensities and distortions is negative.[9]

Figure 1: Factor misallocation and the optimal carbon taxes



(a) Misallocation

(b) Optimal carbon taxes

Notes. I simulate 10,000 firms with different levels of productivity, distortions, and emission intensity, but with varying degrees of correlation between emission intensity and distortions, denoted as ρ. For each level of the ρ and carbon taxes, I calculate the degree of misallocation as $(1 - \text{allocative efficiency})$, and $log(TFP)$ using Equation (6). I plot the degree of misallocation and $log(TFP)$ relative to the value when the carbon tax is zero for each value of ρ. In Panel (b), the vertical lines represent carbon taxes that maximize $log(TFP)$. Parameter values: $\alpha = 0.8$, $\gamma = 0.005$, $\mu_{logz} = 0$, $\sigma_{logz} = 0.2$, $\mu_\tau = 0$, $\sigma_\tau = 0.2$, $\mu_m = 0$, $\sigma_m = 0.2$, and $\bar{F} = 10$.

[9] In Appendix A.2, I demonstrate the impact of carbon taxes on the degree of misallocation and TFP when $E(m_i) > 0$. While carbon taxes may lead to an increase in misallocation in scenarios where the correlation between emission intensity and distortions is negative, this increase is less severe compared to cases with a positive correlation. Consequently, the optimal level of carbon tax remains higher for negative correlation cases.

It is important to note that there is a welfare gain from imposing carbon taxes, even when the correlation is positive and misallocation worsens. This is because firms do not internalize carbon damages in their production decisions. Carbon taxes make them internalize these carbon damages.

3 Empirical evidence on emissions and distortions

This section examines the relationship between emission intensities and distortions, leveraging firm-level data. The empirical analysis reveals that firms with lower emissions per output tend to exhibit higher marginal products, resulting in a negative correlation between emission intensities and distortions.

3.1 Description of data

I construct a firm-level panel dataset by merging three sources: firms' financial information from Compustat North America Fundamentals and carbon emissions data from Thomson Reuters Worldscope and Bloomberg. Compustat offers detailed accounting information for publicly traded companies, allowing me to compute the marginal products of firms. Worldscope and Bloomberg provide data on greenhouse gas emissions at the firm-level, measured in metric tons of CO_2 equivalent.[10] I use scope 1 carbon emissions, emissions from sources that a firm controls directly, as a measure of carbon emissions. I do not consider scope 2 and scope 3 carbon emissions to prevent any potential double-counting. My empirical analysis covers firms from 2002 to 2018, specifically focusing on non-financial companies incorporated in the U.S.

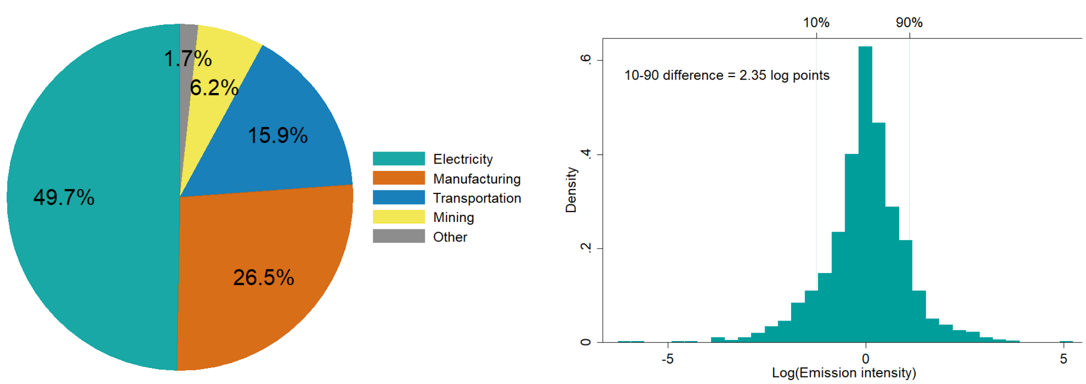
In the merged sample, the total carbon emissions for the year 2018 amount to approximately 2.1 gigatonnes of CO_2 equivalent, representing about 62.5% of the total emissions from the electric power and industrial sectors in the U.S. (EPA (2022)). Figure 2a provides a breakdown of carbon emissions by industry within the merged sample. It reveals that non-electricity generating sectors, such as manufacturing, transportation, and mining, contribute to roughly half of the total emissions. This industry distribution emphasizes the equal significance of reducing direct carbon emissions in these non electricity generating sectors, alongside efforts in the electricity generation sector. It is important to note that these carbon emissions are scope 1 emissions. This means that

[10]I primarily rely on Worldscope for carbon emissions data as it covers a larger number of firms. In cases where a firm lacks carbon emissions data in Worldscope, I turn to Bloomberg for this information.

even if the electricity generation sectors were to fully transition to green energy sources, the emissions from these non-electricity generating sectors would remain unchanged. Furthermore, this industry composition is not unique to my merged sample; I observed a similar distribution of carbon emissions across industries in the U.S. EPA GHGRP dataset, which gathers plant-level carbon emissions data. This comparison is detailed in Appendix C.

Figure 2b presents the within-industry distribution of emission intensity. An important observation is that the dispersion in emission intensity within industries is large, echoing the findings of Lyubich et al. (2018) for manufacturing plants in the U.S. A firm in the 90th percentile of the distribution of emission intensity has a 2.35 higher log point of emission intensity than firms in the 10th percentile, implying that firms in the 90th percentile emit around 10 times more per unit of sales than firms in the 10th percentile. Moreover, the standard deviation of the logarithm of emission intensity in the raw sample is 2.65. When I compute the same statistics for residuals generated from a regression that controls for 4-digit industry-year dummies, the value is 1.01. This means that within-industry variations in emission intensity account for almost 40% of the variations in emission intensity.

Figure 2: Distribution of carbon emissions across and within industry in Year 2018



(a) Carbon emissions across industry **(b)** Emission intensity within industry

Notes. Panel (a) illustrates the distribution of carbon emissions across various industries. For Panel (b), I regress the firm-level logarithm of emission intensity on 4-digit industry-year dummies, which account for any variation in emission intensity across industries, and then take the residuals. Subsequently, I create a histogram of the residuals.

3.2 Measurement and empirical specifications

The key variables in this empirical analysis are emission intensities and distortions. Emission intensities are measured as the ratio between carbon emissions to output, with the latter deflated using industry-specific output deflators from the EU KLEMS dataset. This is expressed as $m_i = \frac{e_i}{y_i}$, where m_i represents emission intensities, e_i are carbon emissions, y_i denotes real output, and i stands for a firm. The output is computed as real sales adjusted by the change in inventories.

To measure distortions, I adopt the standard approach commonly employed in the misallocation literature. I employ three metrics: the marginal revenue product of capital, the marginal revenue product of labor, and revenue productivity. The MRPK is defined as the ratio of revenue to capital, $MRPK_i = y_i/k_i$.[11] Similarly, the MRPL is calculated as revenue per work, $MRPL_i = y_i/n_i$. TFPR is the geometric mean of MRPK and MRPL, where the weights determined by industry-specific cost shares (α_j), given by $TFPR_i = MRPK_i^{\alpha_j} MRPL_i^{1-\alpha_j}$. These cost shares are derived from industry-specific revenue elasticities, which are estimated using the control function approach pioneered by Olley and Pakes (1996). Furthermore, I gauge a firm's fundamentals, which encompass firm-specific demand and productivity. I will use the terms "fundamentals" and "productivity" interchangeably throughout this paper. These fundamentals are derived as the residuals from the production function estimation employed to calculate the industry-specific revenue elasticities.[12] Productivity will be employed in an auxiliary empirical specification, which I will elaborate on below.

I present two empirical specifications. First, I examine the relationship between emission intensities and the distortion measures, concentrating specifically on the relationship within industries. This is achieved by incorporating 4-digit industry-year dummies as control variables. One rationale for focusing on within-industry relationships is the challenge in empirically discerning whether dispersions in marginal products across industries truly signify distortions. Firms in different industries are more likely to have fundamentally different production technologies, meaning that dispersion in marginal products could also capture differences in production technologies, not just distortions. Additionally, I take the logarithm of all variables

[11] In fact, the marginal revenue product of capital is *proportional* to the revenue-capital ratio, as demonstrated by Hsieh and Klenow (2009). However, in my analysis, I use the revenue-capital ratio y_i/k_i as a proxy for $MRPK_i$. This choice is justified as I control for industry dummies to investigate the within-industry relationship between emission intensities and distortions in my empirical specifications. Thus, using y_i/k_i as a measure for $MRPK_i$ is innocuous.

[12] Blackwood et al. (2021) provide an in-depth discussion regarding the distinction between TFPR and productivity. Although both measures pertain to revenue productivity, they rely on different elasticities. TFPR is calculated using cost shares, whereas productivity is based on revenue elasticities. It is emphasized that TFPR captures distortions, while revenue productivity, estimated with revenue elasticities, reflects a firm's productivity.

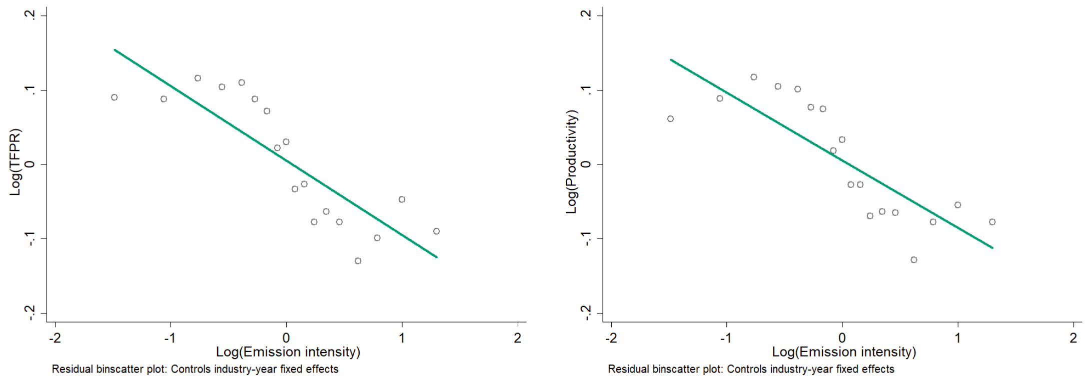
to address unit-related concerns.

In the second empirical specification, I examine the relationship between productivity levels and emission intensities. This analysis aims to shed light on the connection between emission intensities and distortions. Drawing on Census manufacturing data, Blackwood et al. (2021) demonstrate a positive correlation of approximately of 0.7 between productivity and TFPR. This suggests that firms with higher productivity tend to experience greater distortions. If a firm with higher productivity also exhibits lower emission intensity, in conjunction with the findings of Blackwood et al. (2021), it could potentially support a negative correlation between emission intensities and distortions. To explore this relationship, I incorporate industry-year dummies, or two-way fixed effects, accounting for firm and year fixed effects. Additionally, I control for size and age. Size is measured as the logarithm of total assets, while age is calculated as the number of years since a firm's incorporation, utilizing information sourced from Jay Ritter's website. Similarly, I take the logarithm of both productivity and emission intensities.

3.3 Empirical findings

Figure 3 provides binscatter plots as a preliminary view of the cross-sectional relationship between emission intensities, TFPR, and productivity. The left panel illustrates the connection between emission intensities and TFPR, while the right panel displays the relationship between emission intensities and productivity. To derive these plots, I first regress the logarithms of emission intensities, TFPR, and productivity on industry-year dummies, and then extract the residuals. These residuals are used to create bins based on the level of the logarithm of emission intensities. I then calculate the average of the residuals for each variable and plot them. Therefore, these binscatter plots specifically represent relationships within industries across firms.

Figure 3: Binscatter plots for TFPR and productivity with emission intensity



(a) TFPR **(b)** Productivity

Notes. I regress the logarithms of emission intensities, TFPR, and productivity on industry-year dummies and then extract the residuals. The industries are categorized at the SIC 4-digit level. Subsequently, I divide the residuals into 20 bins based on the level of log(emission intensities). For each bin, I calculate the average values of log(emission intensities), log(TFPR), and log(productivity). These average values are then plotted along with the corresponding fitted linear lines.

Both panels, on the left and the right, indicate a negative relationship between emission intensities and both TFPR and productivity. In simpler terms, companies with lower emissions tend to face higher distortions and have higher productivity. Next, I will present the formal empirical results from the regression analysis. Initially, I will illustrate the empirical relationship between emission intensities and distortions, followed by the relationship between productivity and emission intensities.

Fact 1. Firms with lower emission intensities tend to face higher distortions.

Table 3 presents the empirical findings regarding the relationship between emission intensities and distortions. I control for 4-digit industry-year dummies to ensure that the results are primarily estimated by cross-sectional variation among firms within the same industries. Columns 1, 2, and 3 display the regression results when distortions are measured as MRPK, MRPL, and TFPR, respectively. Regardless of how distortions are measured, firms with lower emissions intensities tend to encounter higher levels of distortions. To put it in perspective, based on the TFPR result, a firm with emission intensities lower by 1 standard deviation experiences a 22% increase in TFPR.[13]

[13] If a firm exhibits a higher TFPR compared to other firms, primarily due to a higher markup, there might be a spurious correlation between emission intensity (defined using sales) and TFPR. Table B.1 presents regression results of emission intensity against distortion measures when emission intensity is defined by the costs of goods sold (COGS). The main results hold for this alternative definition of emission intensity as well.

Table 1: Emission intensities and measures of distortions across firms

	(1) log(MRPK)	(2) log(MRPL)	(3) log(TFPR)
log(emissions/sales)	-0.152***	-0.075***	-0.094***
	(0.023)	(0.022)	(0.019)
Adj. R^2	0.827	0.734	0.650
Ind x Year FE	✓	✓	✓
N	2,848	2,820	2,820

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table provides the results of empirical analysis, where I conduct regressions of distortions measures (MRPK, MRPL, and TFPR) on emission intensities. This analysis incorporates controls for 4 digit industry-year dummies and focuses on firms within non-financial sectors. Standard errors, which are presented in parentheses, are clustered at both the firm and year levels.

Table 2, provides the within-industry relationship between emission intensities and distortions separately for different sectors. Specifically, my focus is on the mining, manufacturing, transportation, and electricity-generating sectors, as they collectively account for approximately 99% of the total carbon emissions and are the top four sectors in this regard. I use TFPR as a measure for distortions, although MRPK and MRPL yield similar findings. I maintain control for 4-digit SIC industry-year dummies, recognizing that these top four sectors encompass a broader scope than a typical 4-digit SIC industry classification. The estimates reveal that firms with lower emission intensities in the mining, manufacturing, and transportation sectors tend to face higher distortions. However, this pattern does not hold for firms within the electricity-generating sectors. Drawing on insights from the simplified theoretical model, one could conjecture that resource reallocation by imposing carbon taxes might alleviate existing misallocation in the mining, manufacturing, and transportation sectors. Nevertheless, its impact may be less significant for the electricity-generating sectors.

Table 2: Emission intensities and the measures of distortions by industries

log(TFPR)	Mining	Manufacturing	Transportation	Electricity
log(emissions/sales)	-0.156**	-0.110***	-0.364***	-0.014
	(0.070)	(0.026)	(0.058)	(0.028)
Adj. R^2	0.456	0.562	0.751	0.069
Ind x Year FE	✓	✓	✓	✓
N	221	1,490	254	335

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table provides the results of empirical analysis, where I conduct regressions of a distortions measure (TFPR) on emission intensities. This analysis incorporates controls for 4-digit SIC industry-year dummies and conducts separate analyses for firms within the mining, manufacturing, transportation, and electricity-generating sectors. Standard errors, which are presented in parentheses, are clustered at both the firm and year levels.

Fact 2. Firms with higher productivity tend to have lower emission intensities.

Table 3 displays the findings about the connection between firms' productivity and emission intensities. I explore this relationship employing various fixed effects and additional controls. For instance, column (1) and (4) control industry-year dummies, while I introduce firm-fixed effects in other specifications. Moreover, in columns (4) to (6), I include controls for size and age. Across all specifications, there is a consistent finding: firms with higher productivity tend to exhibit lower emission intensities.[14] These regression results align with the observations made in the binscatter plot. Notably, the size and age do not seem to play a substantial role in explaining emission intensities.[15]

Table 3: Emission intensities and productivity

log(emissions/sales)	(1)	(2)	(3)	(4)	(5)	(6)
log(productivity)	-0.750***	-0.643***	-0.638***	-0.880***	-0.624***	-0.653***
	(0.155)	(0.089)	(0.107)	(0.171)	(0.095)	(0.114)
Size				0.137**	-0.076	0.053
				(0.051)	(0.071)	(0.108)
Age				0.001	0.000	0.000
				(0.002)	(.)	(.)
Adj. R^2	0.825	0.978	0.981	0.827	0.979	0.981
Year FE		✓			✓	
Ind x Year FE	✓		✓	✓		✓
Firm FE		✓	✓		✓	✓
N	2,820	3,791	2,673	2,820	3,791	2,673

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table provides the results of empirical analysis, where I conduct regressions of emission intensities on firms' productivity. Column (1) and (4) control industry-year dummies. In Column (2) and (5), I conduct two-way fixed effects regressions, accounting for both firm and year effects. Column (3) and (6) involve firm-fixed effects regressions, with additional control for industry-year dummies. Column (4) to (6) also include controls for firm size, measured by log(total assets), and firm age. Standard errors, which are presented in parentheses, are clustered at both the firm and year levels.

In Table 4, I also investigate the relationship between productivity and emission intensities for different sectors. Echoing the findings in Table 3, firms with higher productivity tend to have lower emission intensities across all sectors, while this relationship is not statistically significant for firms in electricity-generating sectors. This

[14] Shapiro and Walker (2018) show a negative correlation between non-carbon pollutions, such as NO_x, per real sales and total factor productivity at the firm level. However, their analysis does not control industry dummies.

[15] Table B.3 displays the regression results of emission intensity against productivity, using the COGS-based definition of emission intensity. These findings align with those presented in Table 3.

could be the case if the variation in emission intensity within electricity-generating sectors is more influenced by the choice of fuel—such as coal, oil, natural gas, nuclear, and renewable energy sources—used by power plants, rather than the efficiency of electricity production. In contrast, firms in the mining, manufacturing, and transportation sectors may face greater challenges in using nuclear and renewable energy to operate their boilers, furnaces, ovens, and blast furnaces, so production efficiency might be more important in determining emission intensity for them.

Table 4: Emission intensities and productivity by industries

log(emissions/sales)	Mining	Manufacturing	Transportation	Electricity
log(productivity)	-0.791***	-1.221***	-1.349***	-0.474
	(0.247)	(0.249)	(0.181)	(0.835)
Size	0.028	0.165***	0.099	-0.096
	(0.090)	(0.054)	(0.065)	(0.290)
Age	0.001	0.001	0.007**	-0.009
	(0.003)	(0.003)	(0.003)	(0.021)
Adj. R^2	0.405	0.647	0.960	-0.037
Ind x Year FE	✓	✓	✓	✓
N	221	1,490	254	335

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table provides the results of empirical analysis, where I conduct regressions of emission intensities on firms' productivity. This analysis incorporates controls for 4-digit SIC industry-year dummies and conducts separate analyses for firms within the mining, manufacturing, transportation, and electricity-generating sectors. I also include controls for firm size, measured by log(total assets), and firm age. Standard errors, which are presented in parentheses, are clustered at both the firm and year levels.

4 A quantitative model with externalities and distortions

This section introduces a quantitative firm dynamics model, which generalizes the simple model discussed in Section 2. I endogenize frictions and distortions that impede the equalization of marginal products using investment uncertainty, adjustment costs, and financial frictions. Moreover, I incorporate endogenous capital accumulation. There are three types of economic agents: firms (comprising both incumbents and entrants), a representative household, and a government.

4.1 Firms

4.1.1 Incumbent firms

Incumbent firms operate within a perfectly competitive market. These firms differ in terms of productivity (z), capital (k), and debt (b). Productivity follows an exogenous process, evolving with a probability distribution $P(z'|z)$, while capital and debt are determined endogenously. Firms produce homogeneous goods using capital and labor (n), employing a production technology characterized by decreasing returns to scale. They incur fixed operating costs denoted as c_f. I include the concept of carbon damage, akin to the approach taken by Golosov et al. (2014), which is represented as the reduction in aggregate productivity due to carbon stock in the atmosphere. Incumbent firms consider this carbon damage as a given, thus there are externalities stemming from carbon emissions. The production technology is described by the following function:

$$y = exp(-\gamma_d S) z k^{\alpha} n^{\nu}, \quad \alpha + \nu < 1, \tag{7}$$

where S represents the aggregate carbon stock, and γ_d denotes the carbon damage parameter.

Firms generate emissions as a by-product of production, following the models of Copeland and Taylor (1994) and Shapiro and Walker (2018). Building on the empirical findings in Section 3, I assume that emissions (e) per unit of composite inputs decrease as productivity increases:

$$\frac{e}{k^{\alpha} n^{\nu}} = z^{-\eta}, \quad \eta > 0, \tag{8}$$

where η is a parameter that determines the sensitivity of emission intensity to productivity. Equation (8) indicates that emissions per unit of output decline with increasing productivity, i.e., $\frac{e}{y} \propto z^{-(1+\eta)}$. While I adopt the 'emissions as a by-product of production' approach, this can be justified with a production function where non-energy inputs (capital and labor) and energy are perfect complements:

$$y = exp(-\gamma_d S) z \min\{k^{\alpha} n^{\nu}, z^{\eta} e\}, \tag{9}$$

where e represents energy, and using one unit of energy results in one unit of emission. Hassler et al. (2012) find that energy and non-energy inputs have near-zero substitutability in the short-run.[16] For each unit of emissions, firms face a carbon tax τ_c.

Firms in this model own and adjust their capital stock through investment. When making investments, firms know the expected future productivity but lack information about the actual realization of productivity given their present state. They also encounter capital adjustment costs, denoted as $\Phi(k, k')$, which encompass both convex and non-convex components. Lastly, firms face financial frictions, modeled as borrowing constraints (both asset-based and earnings-based) and restrictions on equity issuance, defined by the conditions:

$$b' \leq \max(\theta_k k, \theta_\pi \pi), \tag{10}$$

$$d \geq 0, \tag{11}$$

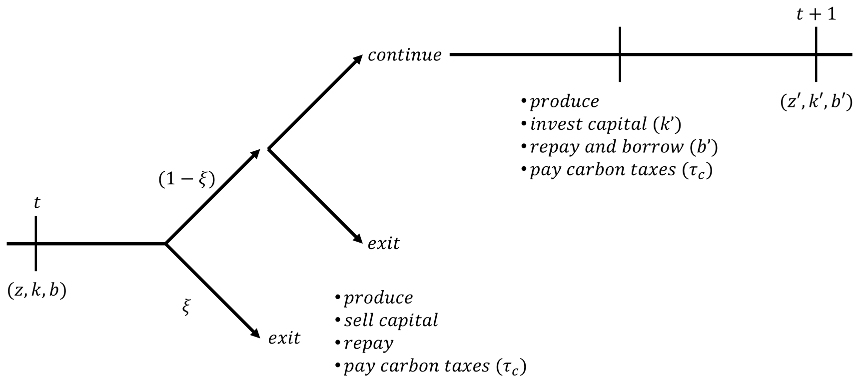
where π represents profits after carbon taxes, θ_k and θ_π dictate the tightness of asset-based and earnings-based borrowing constraints, respectively. The term d denotes dividends.

Investment uncertainty, adjustment costs, and borrowing constraints all contribute to the dispersion in marginal products of capital, as shown by Gopinath et al. (2017). In Section 5.2, I will explain how these frictions and distortions create a positive correlation between productivity and TFPR, which in turn explains the negative correlation between emission intensity and TFPR, in combination with Equation (8).

Figure 4 provides a visual representation of the decision timeline for incumbent firms. At the start of each period, firms begin with idiosyncratic states (z, k, b) and confront aggregate variables including carbon stock, interest rates (r), and wages (w), which they treat as given. I denote these aggregate variables as $G = \{S, r, w\}$. They are also subject to exogenous exit shocks, which occur with a probability represented by ξ. After surviving these exit shocks, they make an optimal decision regarding whether to continue their operations or opt for an exit. Firms that choose to exit, whether due to exogenous shocks or endogenous decisions, engage in activities such as production, payment of carbon taxes, sale of undepreciated capital, and repayment of existing debt before leaving the market. In contrast, firms that weather the exit shocks and choose to continue operations engage in production, pay carbon taxes, make capital investments, repay existing debt, and borrow to finance these investments.

[16]They also find evidence of substitution between energy and non-energy inputs over the medium term. This is interpreted as an indication of directed technological change at the aggregate level.

Figure 4: Timing for incumbent firms



Given these assumptions about incumbent firms, their beginning-of-the-period value function $V(z, k, b; G)$ is determined as follows:

$$V(z, k, b; G) = \xi V_x(z, k, b; G) + (1 - \xi)\max(V_x(z, k, b; G), V_c(z, k, b; G)), \tag{12}$$

where $V_x(z, k, b; G)$ and $V_c(z, k, b; G)$ represent value functions for exiting and continuing firms, respectively. For exiting firms, the value function is

$$V_x(z, k, b; G) = \max_n \{\pi + (1 - \delta)k - \Phi(k, 0) - b\}, \tag{13}$$

where $\pi = y - wn - c_f - \tau_c e$. When $V_x(z, k, b; G) > V_c(z, k, b; G)$ holds, incumbent firms optimally choose to exit.

The continuing firms choose labor, next period's capital and debt to maximize the discounted sum of dividends:

$$V_c(z, k, b; G) = \max_{n,k',b'} \left\{ d + \frac{1}{1+r} E_{z'|z} V(z', k', b'; G') \right\} \tag{14}$$

$$\textit{subject to}$$

$$d = \pi - (k' - (1 - \delta)k) - \Phi(k, k') - b + \frac{1}{1+r} b' \geq 0$$

$$b' \leq \max(\theta_k k, \theta_\pi \pi).$$

4.1.2 Entrants

I adopt the approach of Clementi and Palazzo (2016) to model the problems faced by potential entrants. In every period, there is a constant mass M of potential entrants, each receiving a signal $q \sim Q(q)$ regarding their initial productivity. The initial productivity draws z' follow the same conditional probability distribution for the evolution of incumbents' productivity, denoted by $P(z'|q)$. If they decide to enter, they start their operations next period with initial capital k_0 and no debt. The value of a potential entrant with signal q, $V_e(q;G)$, is described as follows:

$$V_e(q;G) = -k_0 + \frac{1}{1+r} E_{z'|q} V(z', k_0, 0; G'). \tag{15}$$

Potential entrants choose to enter if $V_e(q) \geq 0$ holds. Here, since I assume $P(\cdot|q)$ is decreasing in q, $V_e(q;G)$ is strictly increasing in q. Thus, there exists a unique $\hat{q}$ such that $V_e(\hat{q};G) = 0$.

4.2 Representative household and government

The representative household's problem is standard. They make decisions on consumption (C), purchase bonds (B'), and hold shares in firms ($\{S_i'\}$) in order to maximize their lifetime utility. Additionally, they receive lump-sum transfers (T) from the government. The household supplies labor inelastically, with the labor supply denoted as $\bar{N}$. The recursive representation of their problem is described as follows:

$$V_H(B, \{S_i\}; G) = \max_{C, B', \{S_i\}} \{u(C) + \beta V_H(B', \{S_i'\}; G')\} \tag{16}$$

subject to

$$C + \frac{1}{1+r} B' + \int p_i S_i' di = w\bar{N} + \int (p_i + d_i) S_i di + B + T,$$

where p_i represents the stock price of firm i. The standard Euler equation illustrates the relationship between the interest rate and the marginal rate of substitutions across periods:

$$\frac{1}{1+r} = \frac{\beta u'(C')}{u'(C)}. \tag{17}$$

The government's role is also standard. They simply collect carbon taxes and provide lump-sum transfers to households to ensure balanced budgets:

$$T = \tau_c \int e_i di. \tag{18}$$

4.3 Evolution of carbon stock

Similar to Golosov et al. (2014), the law of the change in atmospheric carbon stock is determined by past carbon emissions and follows a linear relationship:

$$S' = (1-\delta_c)S + \varphi E, \quad E = \int e_i di, \tag{19}$$

where the carbon stock decays at a geometric rate δ_c and a fraction of $(1-\varphi)$ of carbon emissions leaves the atmosphere immediately. This depreciation structure reflects the natural process by which the biosphere, land, and surface ocean absorb carbon stock.[17]

4.4 Evolution of the distribution of firms

The evolution of the distribution of firms, denoted as Γ, can be described as follows:

$$\begin{aligned}\Gamma(z', k', b') = (1-\xi) \int_{(z,k,b)} & \mathbb{1}_{[k'=k^*(z,k,b), b'=b^*(z,k,b), \text{no exit}]} dP(z'|z) d\Gamma(z,k,b) \\ & + M \int_{q \geq \hat{q}} \mathbb{1}_{[k'=k_0, b'=0]} dP(z'|q) dQ(q),\end{aligned} \tag{20}$$

where $k^*(z,k,b)$ and $b^*(z,k,b)$ represent the optimal capital and debt choices for a firm with idiosyncratic state (z,k,b). A stationary distribution, denoted as Γ^*, is a fixed point of (20).

4.5 Equilibrium

I define the equilibrium for this economy; both in steady state, and along a perfect foresight transition path. A perfect foresight transition path is necessary to compute the optimal carbon taxes.

Steady state equilibrium A steady state equilibrium consists of (i) a policy vector $\phi(z,k,b) = \{n, k', b'\}$, value functions $V(z,k,b)$, $V_x(z,k,b)$, and $V_c(z,k,b)$, (ii) a stationary distribution $\Gamma^*(z,k,b)$ and the entry cut-off $\hat{q}$, (iii) household consumption C^*, bond

[17] In Golosov et al. (2014)'s model, a more general carbon depreciation structure is assumed: $S_t = \bar{S} + \sum_{s=0}^{t+T}(1-d_s)E_{t-s}$, where $\bar{S}$ is the pre-industrial carbon stock and $(1-d_s) = \varphi_P + (1-\varphi_P)\varphi(1-\delta_c)^s$. φ_P represents the proportion of carbon emissions that remain in the atmosphere permanently. I assume $\varphi_P = 0$ in order to compute a steady state. Without this assumption, the carbon stock would grow uncontrollably, leading to a convergence of aggregate productivity (net of carbon damages) towards zero, making a steady state ill-defined. See Nakov and Thomas (2023) for a similar discussion.

purchase B'^{*}, stocks $\{S_i^*\}$, and (iv) a wage w^*, an interest rate r^*, and carbon concentration S^*, such that:

1. For given S^*, r^*, and w^*, $\phi(z,k,b)$, $V(z,k,b)$, $V_x(z,k,b)$, and $V_c(z,k,b)$ solve the firm problem (12), (13), and (14).

2. The entry cut-off $\hat{q}$ satisfies, $V_e(\hat{q}) = 0$.

3. The equilibrium steady state carbon stock should be consistent with the carbon cycle: $\delta_c S^* = \int_{(z,k,b)} e(z,k,b) d\Gamma^*(z,k,b)$.

4. Household Euler equation: $r^* = \frac{1}{\beta} - 1$.

5. Market clearing conditions for labor, bonds, stocks, and goods market hold.

Perfect foresight transition path I consider a perfect foresight transition path from an economy with a zero carbon tax to one with positive carbon taxes. The equilibrium along this transition path is defined analogously to the steady state equilibrium.

5 Mapping the model to data

In this section, I calibrate the quantitative model and assessing whether the calibrated model accurately reproduces key non-targeted data moments. Prior to delving into the calibration process, I elucidate the assumptions pertaining to the time frame, exogenous processes, adjustment costs, and household preferences. First, I assume that one period corresponds to a year. Second, the exogenous productivity process follows a standard AR(1) process:

$$log(z') = \rho_z log(z) + \epsilon_z, \quad \epsilon_z \sim N(0, \sigma_\epsilon^2). \tag{21}$$

The entrant's signal q is drawn from the ergodic distribution of the productivity process. With regards to capital adjustment costs, I accommodate both convex and non-convex forms:

$$\Phi(k,k') = F\mathbb{1}_{k'-(1-\delta)k\neq 0} + \frac{\gamma}{2}\left(\frac{k'-(1-\delta)k}{k}\right)^2 k, \tag{22}$$

where F represents the fixed cost of capital adjustment costs, and γ denotes the parameter governing the convex adjustment costs. Finally, I assume a linear utility function for household preferences, $u(C) = C$, which ensures that interest rates remain constant both in steady state equilibrium and along a perfect foresight transition path.

5.1 Calibration

The baseline calibration matches investment behavior and carbon emissions at both the micro level and the aggregate evolution of carbon stock. The parameterization proceeds in two steps. Initially, I set a subset of parameters exogenously. Subsequently, I determine the remaining parameters to correspond with specific data moments. However, I will clarify these steps in three distinct categories: standard parameters, carbon parameters, and firm dynamics parameters. Parameters listed on rows shaded in green are calibrated internally.

Table 5 outlines the standard parameters utilized in this model. First, I set the household discount factor, β, at 0.96 to yield an annual interest rate of 4%, which is a standard value in firm dynamics literature. It is important to note that in climate economics literature, lower interest rates are commonly used. For instance, Stern (2007) employs 0.1%, while Nordhaus (2008) uses 1.5% interest rates per year for discounting future values. This implies that future utility holds relatively higher importance in welfare computations. Consequently, with lower interest rates, the socially optimal carbon taxes tend to be higher, as a planner places less emphasis on current economic costs and places greater weight on the future benefits of emissions reduction through carbon taxes. The returns to scale $\alpha + \nu$ are set at 0.85, in line with Kaymak and Schott (2019). The labor coefficient in production, ν, is set at 0.56, which is equivalent to 0.85 multiplied by 2/3, consequently implying a capital coefficient (α) of 0.29. Additionally, the annual depreciation rate (δ) is set at 10%.

Table 5: Standard parameters

Parameter	Description	Value
β	Discount factor	0.96
α	Capital coefficient	0.29
ν	Labor coefficient	0.56
δ	Depreciation rate	0.10

In Table 6, I present the parameter values associated with carbon emissions. First, I assume that carbon emissions do not immediately dissipate from the atmosphere, $\varphi = 1$, based on my assumption that a period in the model corresponds to a year.

Second, based on IPCC (2007), approximately half of a CO2 pulse is removed from the atmosphere after a span of 30 years. To reflect this, I set the carbon depreciation parameter (δ_c) at 0.02. Moving forward, according to Lyubich et al. (2018), the within-industry standard deviation of the logarithm of emission intensity is 2.47 times greater than that of the logarithm of productivity. Derived from Equation (8), this relationship can be expressed as:

$$\sigma_{log(\frac{e}{y})} = (1+\eta)\sigma_{log(z)}. \tag{23}$$

Therefore, I set the elasticity (η) of emission intensity with respect to productivity at 1.47. Lastly, I internally calibrate the carbon damage parameter (γ_d) to match the established carbon damage-to-GDP ratio from climate economics literature. The DICE-2023 model by Barrage and Nordhaus (2023) employs the following relationship to depict the connection between temperature changes since 1765 and carbon damages per GDP (Ω):

$$\Omega = 0.003467 \times (\Delta T)^2. \tag{24}$$

As of 2020, the temperature has risen by $1.25°C$ since 1765. According to Equation (24), this corresponds to a carbon damage per GDP of approximately 0.5%. To internally match this, I set the carbon damage parameter γ_d at 7.45×10^{-5}.

Table 6: Carbon parameters

Parameter	Description	Value
$1-\varphi$	Immediate carbon depreciation	0
δ_c	Geometric carbon depreciation	0.02
η	Emission elasticity	1.47
γ_d	Carbon damage	7.45×10^{-5}

Notes. Parameters listed on rows shaded in green are calibrated internally.

Table 7 provides parameter values related to the firm dynamics block. To begin, the persistence of the idiosyncratic productivity process is set at $\rho_z = 0.66$, and the standard deviation of productivity shocks is $\sigma_\epsilon = 0.12$, following Khan and Thomas (2013). Second, parameters related to financial frictions are drawn directly from studies focusing on micro-level data. Kermani and Ma (2020) show that the average liquidation recovery rate of PPE falls between 0.25 and 0.35, depending on whether industry-level or firm-level statistics are considered. As the liquidation recovery rate significantly impacts the tightness of asset-based constraints (as indicated by Lian and Ma (2021)), I set θ_k at 0.30, which stands as the median value between 0.25 and 0.35. Similarly, Drechsel (2023) examines loan-level contract data, revealing an average debt-to-EBITDA ratio of 4.6. Consequently, I establish θ_π as 4.6. Lastly, the mass of entrants is calibrated to normalize the equilibrium wage in steady state at 1.

The remaining parameters $(c_f, F, \gamma, \xi, k_0)$ are jointly calibrated to match salient moments related to firm dynamics and investment heterogeneity. First, the proportion of firms subject to earnings-based constraints is employed to determine the fixed operating cost parameter, c_f. As the operating cost increases, earnings decrease, subsequently leading to a decrease in the going-concern value of the firm. Consequently, firms are less likely to face earnings-based constraints. In the U.S., Lian and Ma (2021) report that 80% of firms face earnings-based borrowing constraints. Second, I use both the inaction rate (which represents the proportion of firms with an absolute investment rate lower than 1%) and the average investment rate to determine the adjustment costs parameters (F, γ). I obtain the values of the inaction rate (8%) and the average investment rate (12%) from Cooper and Haltiwanger (2006). Third, the exit rate of establishments is used to identify the exogenous exit rate, ξ. I calculate the average exit rate for establishments as 9.8% for the period spanning from 2002 to 2018, using the Business Dynamics Statistics (BDS). Lastly, the relative number of employees of entrants compared to the average establishments is employed to determine the size of entrants' capital, k_0. I compute this relative size using data from the BDS, and on average, the size of entrants is found to be 31.4% of the average establishments.

Table 7: Firm dynamics parameters

Parameter	Description	Value
ρ_z	Persistence of TFP	0.66
σ_ϵ	SD of innovations to TFP	0.12
θ_k	Borrowing limit (asset)	0.30
θ_π	Borrowing limit (earnings)	4.60
M	Mass of entrants	0.70
c_f	Fixed operating cost	0.07
F	Fixed adjustment cost	2.95×10^{-5}
γ	Convex adjustment cost	0.23
ξ	Exit shocks	0.02
k_0	Entrants' capital	0.15

Notes. Parameters listed on rows shaded in green are calibrated internally.

Table 8 shows that the calibrated model reasonably matches the targeted moments. Specifically, it closely matches the proportion of firms facing earnings-based constraints, the inaction rate, the exit rate, the relative size of entrants, and the carbon damage to GDP. However, it slightly over-predicts the average investment rate.

Table 8: Target moments: model vs. data

Moment	Description	Data	Model
$\mathbb{E}[\mathbb{1}_{EBC}]$	Share of EBC firms	0.80	0.84
$\mathbb{E}[\mathbb{1}_{\lvert i/k\rvert<0.01}]$	Inaction rate	0.08	0.08
$\mathbb{E}[i/k]$	The average investment rate	0.12	0.17
$\mathbb{E}[\mathbb{1}_{Exit}]$	Exit rate	0.10	0.09
$n_0/\bar{n}$	The relative size of entrants	0.31	0.30
$1-exp(-\gamma_d S)$	Carbon damage to GDP	5.0×10^{-3}	5.0×10^{-3}

5.2 Non-targeted moments

As outlined in Section 2, the key statistic in determining the optimal carbon taxes is the correlation between emission intensities and distortions. I investigated this moment empirically using firm-level data, as detailed in Section 3. However, I do not directly target the empirical findings for consistency of my calibration. My other targeted moments stem from Census microdata, which feature a distinct distribution of firms compared to Compustat data.[18]

Given my assumption of a direct negative relationship between productivity and emission intensity, which is supported by the empirical results in Table 3, it's crucial to examine the connection between productivity and distortions. This relationship is pivotal in explaining the negative correlation between emission intensity and distortions. Following Hopenhayn (2014a), TFPR, representing distortions in a model with perfectly competitive firms, is calculated as:

$$\begin{aligned} log(TFPR) &= log(y) - \frac{\alpha}{\alpha+\nu}log(k) - \frac{\nu}{\alpha+\nu}log(n) \\ &= \frac{\alpha}{\alpha+\nu}log(y/k) + \frac{\nu}{\alpha+\nu}log(y/l), \end{aligned} \tag{25}$$

where y/k and y/l represent the marginal products of capital (MRK) and labor (MPL) under a homogeneous production function. As MPL is always equalized in the absence of carbon taxes, any dispersion in TFPR solely stems from dispersion in MPK.

[18] Ottonello and Winberry (2020) follow a similar approach.

Various factors in my quantitative model, including investment uncertainty, adjustment costs, and financial frictions, contribute to a positive correlation between productivity and MPK (or TFPR). First, due to investment uncertainty, firms commit to capital investment without knowing the precise productivity level for the next period. Consequently, even initially identical firms that invest the same amount of capital may yield different outcomes post-investment. In the subsequent period, a firm experiencing a high realization of productivity produces output using a lower level of capital than it would have utilized if it had prior knowledge of its productivity. This implies that a firm with a high realization of productivity possesses a relatively higher marginal product of capital.

Secondly, adjustment costs and borrowing constraints can also lead productive firms to have higher MPK. For instance, if we compare firms with the same amount of capital and debt but different levels of productivity (as is the case with new entrants), those with higher productivity typically exhibit a greater demand for investment. However, due to the presence of adjustment costs and financial frictions, these highly productive firms may face limitations in their growth, leading them to have a higher MPK compared to firms with lower productivity. Nevertheless, in a steady state, productive firms tend to hold larger amounts of capital and earn higher profits. These productive firms may encounter less restrictive borrowing limits. Thus, determining which of these forces dominates is a quantitative question.

To gain a clearer understanding of which forces exert a stronger influence, I undertake a simulation of the steady state economy of the calibrated quantitative model. Following this, I conduct two regression analyses. First, I regress log(TFPR) on log(z). Second, I regress log(TFPR) on the lag of log(z), denoted as log(z_{-1}). The second specification provides insight into how adjustment costs and financial frictions, while controlling for investment uncertainty, contribute to the relationship between productivity and TFPR by considering ex-ante productivity.

Table 9 indicates that, although controlling for investment uncertainty leads to a reduction in the regression coefficient and R^2, a notable and statistically significant positive relationship between productivity and TFPR persists. This relationship is attributed to the influence of adjustment costs and financial frictions.

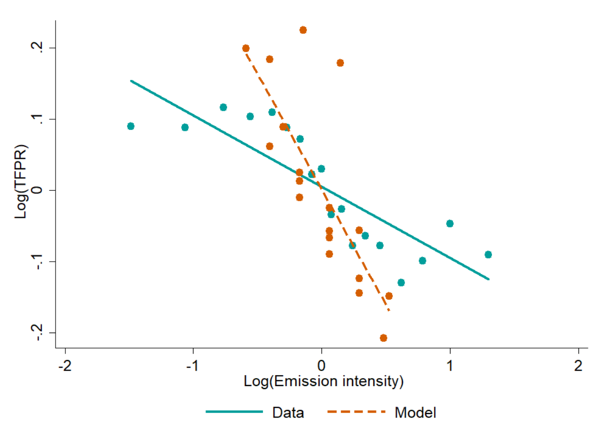
Table 9: Relationship between distortions and ex-ante and ex-post productivity

	(1)	(2)
	log(TFPR)	log(TFPR)
$\log(z)$	0.717***	
	(0.001)	
$\log(z_{-1})$		0.422***
		(0.001)
R^2	0.752	0.270
N	258,425	258,425

Notes. I conduct a simulation of the economy utilizing policy functions within the steady state of the calibrated model. In this simulation, I consider a pool of 3000 potential entrants. I generate a dataset covering a span of 150 years, but discard the initial 134 years in order to align with the sample period duration outlined in Section 3. To calculate TFPR, I employ Equation (25).

Figure 5 shows a binscatter plot illustrating the connection between emission intensities and TFPR, comparing data to the model. The green dots and line represent the relationship between emission intensity (matching Figure 3a) and TFPR derived from the firm-level data. Meanwhile, the red dots and line show the relationship generated by my quantitative model. This figure demonstrates that my model reproduces the negative correlation between emission intensity and TFPR.

Figure 5: Relationship between emission intensity and TFPR: model vs. data



Notes. The binscatter plot generated from data, which is described with green dots and fitted line is the same with Figure 3a. The orange dots and fitted line represent the model counterpart.

Table 10 provides the actual values for key non-targeted moments. For instance, in Compustat, the regression coefficient of log(TFPR) to log(emission intensity) was approximately -0.10 (as shown in Column (3) of Table 1). However, in my model, this regression implies a value of -0.31 for the same relationship. Furthermore, my model also aligns well with the correlation between log(productivity) and log(TFPR), which is calculated using Census microdata by Blackwood et al. (2021). In the Census data, this correlation ranges between 0.71 and 0.74, depending on the method used for estimating the production function. In my model, this correlation is 0.60.

Table 10: Key non-targeted moments: model vs. data

Moment	Data	Model
$\beta_{log(TFPR)\|log(\text{emission intensity})}$	-0.10	-0.31
$\rho(log(z), log(TFPR))$	$0.71 \sim 0.74$	0.60

Notes. $\beta_{log(TFPR)|log(\text{emission intensity})}$ represents the regression coefficient obtained when regressing log(TFPR) against log(emission intensity). $\rho(log(z), log(TFPR))$ is the correlation between log(productivity) and log(TFPR). The value for $\beta_{log(TFPR)|log(\text{emission intensity})}$ in the data is sourced from column (3) in Table 1. On the other hand, the values for $\rho(log(z), log(TFPR))$ are sourced from the study by Blackwood et al. (2021).

The difference between the coefficients obtained from the model and those from the regression of log(TFPR) to log(emission intensity) in the Compustat data warrants examination. Several potential explanations for this discrepancy can be considered. First, it might be important to acknowledge the possibility of classic measurement errors in emission intensity. GHG emissions reported by firms to data vendors like Worldscope and Bloomberg are estimations, and variations in estimation methods among firms can introduce errors.

Second, when calibrating my parameters related to firm dynamics, I rely on empirical moments from Census microdata rather than moments from the Compustat-Worldscope data used in the empirical analysis. If there are disparities in the regression coefficient between Compustat and Census data, the utilization of different datasets could be a contributing factor. While I cannot directly compute the regression coefficient for the Census sample, there is additional information that sheds light on this hypothesis. For instance, the ratio between the standard deviation of log(emission intensity) and that of log(productivity) – which I used to calibrate the parameter η – is informative. In the Census sample, this ratio is 2.47, whereas in my Compustat-Worldscope sample, it is 3.17. This suggests that emission intensity is more dispersed in the Compustat-Worldscope sample, which could account for the lower regression coefficient in the Compustat data.

Lastly, there could be a more structural issue within my quantitative model. I assume a one-to-one mapping between productivity and emission intensity, an assumption grounded in empirical findings in Section 3. However, there may exist alternative mechanisms that contribute to the dispersion in emission intensity. For instance, Lanteri and Rampini (2023) propose a theoretical model suggesting that financially constrained firms are more likely to employ capital with higher emissions due to the relatively higher cost of cleaner capital. This implies a positive correlation between emission intensity and distortions in production. If I incorporate this channel into the model, I anticipate that the regression coefficient of log(TFPR) to log(emission intensity) would be less negative.

6 Optimal carbon taxes and counterfactual analyses

In this section, I compute optimal carbon taxes and conduct three counterfactual analyses using the calibrated quantitative firm dynamics model from Sections 4 and 5.

6.1 The optimal carbon tax

I compute the optimal carbon tax with the following steps. First, for each carbon tax level, I compute the steady state equilibrium. Second, I generate a perfect foresight transition path of consumption from the baseline economy, where carbon taxes are zero, to an economy with a positive carbon tax. I employ the Sequence-Space Jacobian method, developed by Auclert et al. (2021), which allows for fast and accurate computation of this transition path. Third, I calculate the lifetime utility of the representative household over this transition path. Consequently, I am able to generate a curve representing social welfare for each carbon tax level, enabling me to identify the carbon tax level that maximizes welfare.

Two aspects of my procedure warrant clarification. First, I compute the simple optimal carbon tax level, rather than computing an optimal path of Ramsey policy or constrained efficient allocation.[19] Second, it is crucial to be aware that identifying a carbon tax that maximizes steady state consumption might be misleading.[20] Researchers often use steady state consumption as a measure of welfare for policy evaluation due to the computational challenges of computing transition paths in a

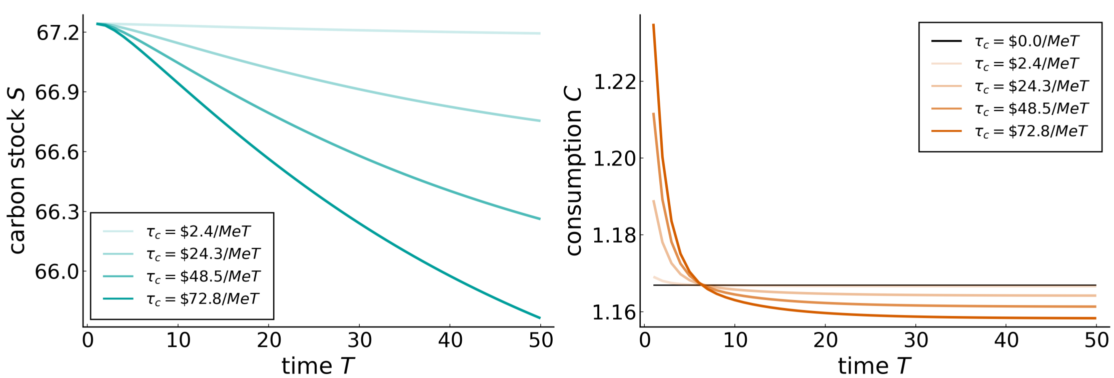
[19] The full path of Ramsey carbon tax would be difficult to characterize as the government should find the optimal path of carbon taxes when a state of the economy is characterized by a distribution of firms, which is an infinite-dimensional object. However, a recent development from the literature on optimal policy in a heterogeneous agent model could make this work doable. Among others, see Nuño and Moll (2018), González et al. (2022), and Ottonello and Winberry (2023). I leave applying their methodology to characterize the optimal path of carbon taxes for future work.

[20] In a neoclassical growth model, it is important to distinguish between the Golden Rule capital level, which maximizes steady state consumption, and the level of steady state capital chosen by an agent who maximizes lifetime utility in an efficient economy (referred to as the Golden Rule versus the modified Golden Rule). Mukoyama (2013) discusses this point in the context of unemployment insurance policy.

heterogeneous firm model. However, I have addressed this computational challenge by employing the Sequence-Space Jacobian method. Figure C.1 illustrates that using steady-state consumption as a welfare measure results in a zero optimal carbon tax. However, this outcome is not reasonable in a model that incorporates externalities stemming from carbon emissions.

Figure 6 provides an illustration of the economy's carbon stock and consumption change along a transition path for various levels of carbon taxes. As anticipated, higher carbon taxes lead to a more significant reduction in the carbon stock. Regarding consumption, the imposition of carbon taxes initially triggers increases due to smaller capital investment, eventually converging towards a lower steady state compared to that with zero carbon tax. Since I assume perfect complementarity between emissions and a composite input of capital and labor, carbon taxes that penalize carbon emissions also lead to a reduction in steady state capital. Consequently, steady state consumption decreases. This figure underscores why it can be misleading to rely solely on steady state consumption as a measure of welfare.

Figure 6: Carbon stock and consumption over a perfect foresight transition path

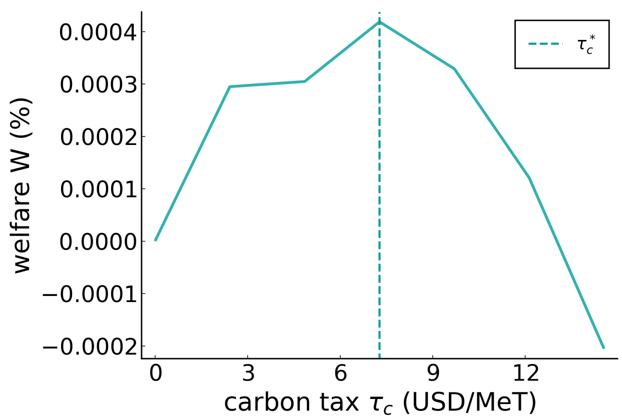


(a) Carbon stock **(b)** Consumption

Notes. Panel (a) depicts the evolution of carbon stock, while panel (b) illustrates consumption along a perfect foresight transition path for different levels of carbon taxes. Darker shades of green and red indicate higher carbon tax levels. In both panels, the x-axis represents the transition time.

Figure 7 presents the social welfare, quantified as the lifetime utility of the representative household along a perfect foresight transition path, for different levels of carbon taxes. The carbon tax that maximizes social welfare is \$7.3 per metric ton of CO2. This optimal carbon tax appears to be relatively lower compared to estimates from other studies like Stern (2007), Nordhaus (2008), and Golosov et al. (2014), although direct comparisons have challenges. One potential reason for this disparity could be the different assumptions regarding the discount rate. I assume a 4% interest rate, whereas these other papers operate with interest rates between 0.1% and 1.5%. In models where the social planner places greater emphasis on the future, as is the case in those studies, it is more likely for higher carbon taxes to be imposed. Additionally, alongside the relatively lower optimal carbon taxes, the gain in welfare is also somewhat modest.[21] This could stem from the perfect complementarity assumed between emissions and capital/labor. Within this framework, reducing emissions requires firms to directly curtail their production, incurring significant costs. Golosov et al. (2014) assume a Cobb-Douglas production function involving capital, labor, and energy, implying that energy can be substituted by capital and labor, potentially leading to relatively lower economic costs.

Figure 7: Welfare curve over carbon taxes



Notes. The x-axis represents the different levels of carbon taxes. The y-axis measures the difference in welfare, which is the lifetime utility of the representative household over a transition path, compared to the case with zero carbon tax. This difference is expressed in units of consumption equivalent welfare.

6.2 Counterfactual analysis

I conduct three counterfactual analyses to gain a deeper understanding of the quantitative model and to study alternative policies that can effectively address the challenge of climate change.

Counterfactual 1: Zero correlation between emission intensity and distortions

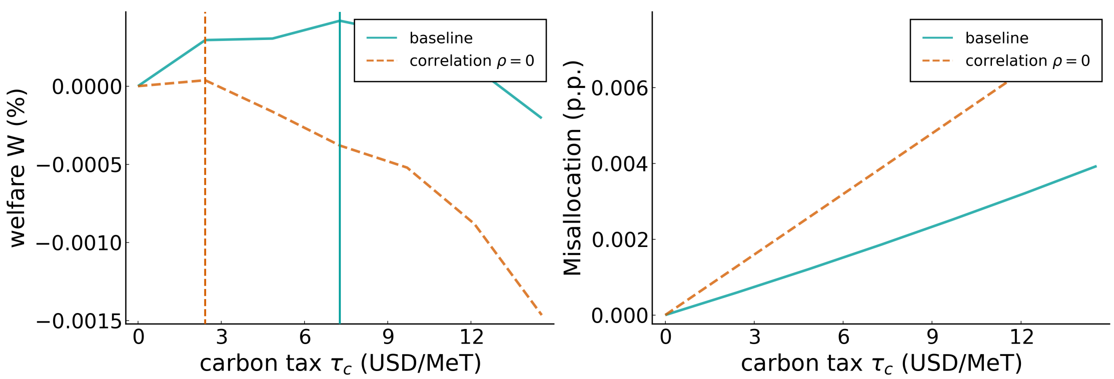
In this first counterfactual, I make the correlation between emission intensity and distortions zero by setting $(1 + \eta) = 0$. What I expect from this counterfactual analysis

[21] As a sanity check, I tripled carbon damage parameter to see if I observe a higher optimal carbon tax. Figure C.2 shows that higher carbon damage leads to a higher optimal tax.

is that the optimal carbon tax rate should be lower as there is no reallocation towards firms with higher marginal products.

Figure 8 illustrates the optimal carbon tax rate and the change in misallocation in response to carbon taxes for both the baseline calibration and the case where the correlation is zero. When the correlation between emission intensity and distortions is set to zero, the optimal carbon tax rate is \$2.4 per metric ton of CO_2, which is one-third of the optimal carbon tax rate under the baseline calibration, where the correlation is negative. Examining how steady-state misallocation reacts to carbon taxes, we observe that, compared to the baseline economy, misallocation worsens when the correlation is zero. This finding aligns with the theoretical insights from the simple model in Section 2 and A.2.

Figure 8: Welfare and misallocation when the correlation between emissions and distortions is zero



(a) Welfare **(b)** Misallocation

Notes. The x-axis represents the different levels of carbon taxes. In panel (a), the y-axis measures the difference in welfare, which is the lifetime utility of the representative household over a transition path, compared to the case with zero carbon tax. This difference is expressed in units of consumption equivalent welfare. In panel (b), the y-axis represents the difference in the extent of factor misallocation relative to the case with zero carbon tax. The solid lines correspond to the baseline case, while the dashed lines pertain to the case with zero correlation between emission intensity and distortions.

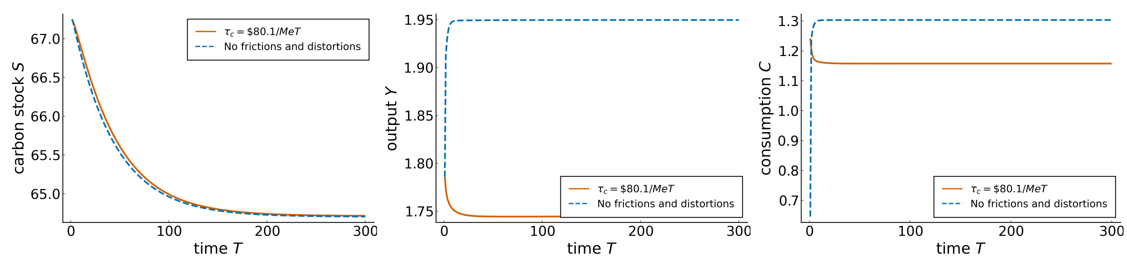
Counterfactual 2: Remove both adjustment costs and financial frictions

In the second counterfactual, I completely eliminate the non-environmental distortions, including adjustment costs and financial frictions, which contribute to the dispersion in marginal products. Specifically, I set adjustment cost parameters F and γ to zero, and the borrowing constraints parameters θ_k and θ_π to infinite. This analysis addresses a scenario where policymakers may consider alternative policies to carbon taxes or cap-and-trade, often due to political considerations. By directly mitigating the underlying distortions that divert production factors from relatively cleaner firms, resources could be redirected back to these cleaner firms, resulting in an overall reduction in aggregate carbon emissions.

Figure 9 illustrates the effects of removing adjustment costs and financial frictions on carbon emissions, output, and consumption. First, there is indeed a reduction in carbon emissions. To achieve the same level of emission reduction, I would need to implement a carbon tax of \$80.1 per metric ton of CO_2, which is over 10 times the optimal carbon tax.

I analyze the transition paths for output and consumption in two scenarios: first, from the baseline economy to one without frictions and distortions, and second, to an economy with a \$80.1 per metric ton of CO_2 carbon tax. As anticipated, the elimination of frictions and distortions leads to an increase in output, while the imposition of a relatively high carbon tax hampers output. In terms of consumption, despite an initial dip, the higher consumption in a frictionless economy is sustained for a much longer period. Comparing the welfare levels across these two consumption transition paths, I find a 9.05% increase in welfare, measured in terms of consumption equivalence, in the frictionless economy compared to the one with the \$80.1 per metric ton of CO_2 carbon tax.

Figure 9: Eliminate both adjustment costs and financial friction



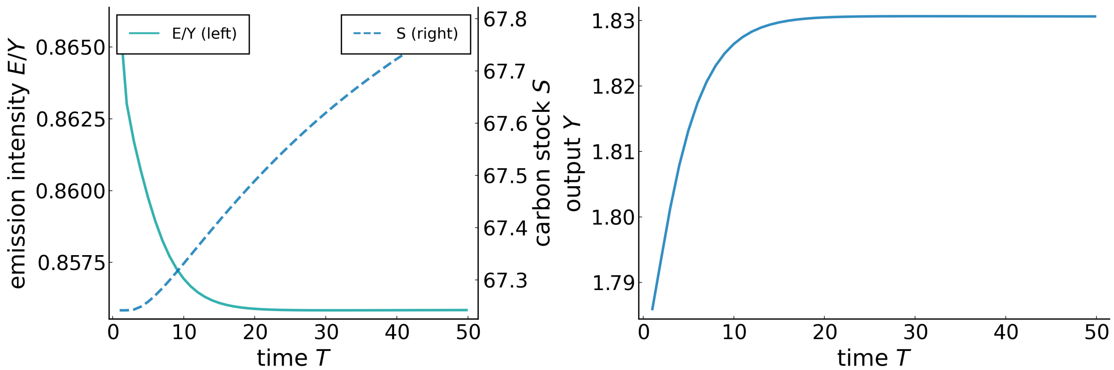
(a) Carbon stock **(b)** Output **(c)** Consumption

Notes. The x-axis denotes the transition time. The blue dashed lines illustrate the transition paths towards a frictionless economy, while the orange solid lines represent transition paths when I impose a \$80.1 per metric ton of CO_2 carbon tax, achieving an equivalent reduction in carbon emissions as the transition towards a frictionless economy.

Counterfactual 3: Remove only financial frictions

Adjustment costs are akin to technological constraints, so allowing a planner to remove them is a stark assumption. In this counterfactual, I solely eliminate financial frictions by setting θ_k and θ_π as infinite. Figure 10 illustrates that although aggregate emissions increase due to higher overall output, the aggregate emission intensity—defined as the ratio of aggregate emissions to aggregate output—decreases. This suggests that removing financial frictions reallocates resources towards cleaner firms. However, this reallocation is not potent enough to outweigh the increase in total output.

Figure 10: Remove only financial frictions



(a) Emission intensity and carbon stock

(b) Output

Notes. The x-axis denotes the transition time. In panel (a), the blue dashed line illustrates the transition paths of carbon stock, while the green solid line represents the transition paths of aggregate emission intensity, which is defined as the ratio of aggregate carbon emissions to aggregate output. The left y-axis and the right y-axis are for aggregate emission intensity and carbon stock, respectively.

7 Conclusion

This paper investigates the optimal carbon taxes in an environment where there is enormous within-industry heterogeneity in emission intensity and distortions. This exploration unfolds through theoretical, empirical, and quantitative lenses. From the simple theoretical model, I highlight the pivotal role played by the correlation between emission intensity and distortions. Specifically, carbon taxes that redirect resources towards cleaner firms have the potential to enhance allocative efficiency, particularly for those cleaner firms previously burdened by higher distortions. Utilizing firm-level data, I demonstrate that this correlation tends to be negative, indicating that carbon taxes are more inclined to reduce existing misallocation. Subsequently, through the development of a quantitative model integrating firm dynamics, carbon externalities, and firm-level frictions and distortions, I calculate the optimal carbon taxes. I conduct three counterfactual analyses. These exercises reveal that in cases where cleaner firms have been subject to greater distortion, policies directly targeting underlying distortions can serve as effective tools in combating climate change by reallocating resources towards cleaner firms.

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APPENDIX TO

Optimal Carbon Taxes and Misallocation across Heterogeneous Firms

by Seho Kim

A Additional details for the simple theoretical model

A.1 Proof for Proposition 1

Proof. Equation (5) implies that $logMP_i \propto -log\xi_i$, thus $\sigma^2_{logMP_i} = \sigma^2_{log\xi_i}$ hold. When log ξ_i is close to $\mathbb{E}[\xi_i]$, $log\xi_i \approx log\mathbb{E}[\xi_i] + \frac{1}{\mathbb{E}[\xi_i]}(\xi_i - \mathbb{E}[\xi_i])$. Thus,

$$\begin{aligned}\sigma^2_{logMP_i} = \sigma^2_{log\xi_i} = Var(log\xi_i) &\approx Var(log\mathbb{E}[\xi_i] + \frac{1}{\mathbb{E}[\xi_i]}(\xi_i - \mathbb{E}[\xi_i])) \\ &= \frac{1}{\mathbb{E}[\xi_i]^2}Var(\xi_i),\end{aligned}$$

holds.

When $\mathbb{E}[m_i] = 0$,

$$\frac{1}{\mathbb{E}[\xi_i]^2}Var(\xi_i) = \frac{1}{(1-\mathbb{E}[\tau_i])^2}(\sigma^2_{\tau_i} + \tau_c^2\sigma^2_{m_i} + 2\tau_c Cov(\tau_i, m_i)).$$

This implies that,

$$\frac{\partial\sigma^2_{logMP_i}}{\partial\tau_c} = \frac{1}{(1-\mathbb{E}[\tau_i])^2}(2\tau_c\sigma^2_{m_i} + 2\rho\sigma_{\tau_i}\sigma_{m_i}),$$

where $\rho = \rho(\tau_i, m_i)$ is the correlation between emission intensity and distortions.

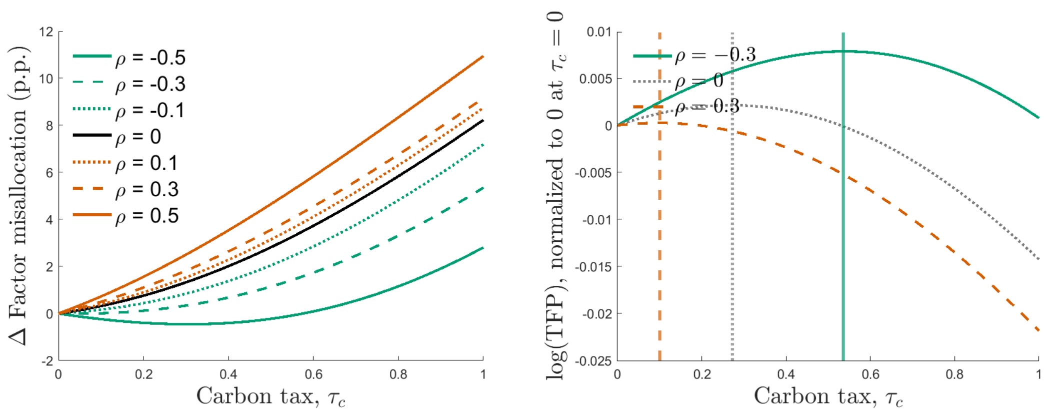
Thus,

$$\frac{d\sigma^2_{logMP_i}}{d\tau_c} = \begin{cases} \geq 0, \text{if } \rho \geq 0 \text{ or } (\rho < 0, \tau_c \geq \frac{\rho\sigma_{\tau_i}}{\sigma_{m_i}}) \\ < 0, \text{if } (\rho < 0, \tau_c < \frac{\rho\sigma_{\tau_i}}{\sigma_{m_i}}). \end{cases}$$

■

A.2 Numerical illustration for $E(m) > 0$

Figure A.1: Factor misallocation and the optimal carbon taxes when $E(m) > 0$



(a) Misallocation

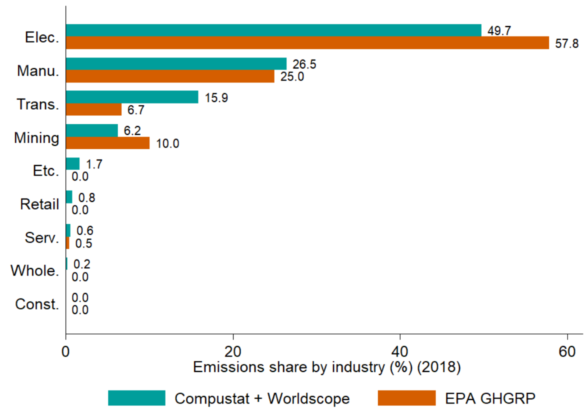
(b) Optimal carbon taxes

Notes. I simulate 10,000 firms with different levels of productivity, distortions, and emission intensity, but with varying degrees of correlation between emission intensity and distortions, denoted as ρ. For each level of the ρ and carbon taxes, I calculate the degree of misallocation as $(1 -$ allocative efficiency$)$, and $log(TFP)$ using Equation (6). I plot the degree of misallocation and $log(TFP)$ relative to the value when the carbon tax is zero for each value of ρ. In Panel (b), the vertical lines represent carbon taxes that maximize $log(TFP)$. Parameter values: $\alpha = 0.8$, $\gamma = 0.005$, $\mu_{logz} = 0$, $\sigma_{logz} = 0.2$, $\mu_\tau = 0$, $\sigma_\tau = 0.2$, $\mu_m = 0.2$, $\sigma_m = 0.2$, and $\bar{F} = 10$.

B Additional details on the empirical analysis

B.1 Compustat-Worldscope vs. EPA GHGRP

Figure B.1: Share of carbon emissions by industry in Year 2018: Compustat-Worldscope vs. EPA GHGRP



Notes. The EPA Greenhouse Gas Reporting Program (GHGRP) mandates the submission of greenhouse gas (GHG) data and pertinent details from significant GHG emission sources, fuel and industrial gas providers, and CO_2 injection sites across the United States. This reporting obligation applies to around 8,000 facilities annually. Generally, facilities are mandated to submit yearly reports if GHG emissions from covered sources surpass 25,000 metric tons CO_2e per year.

B.2 Additional regression results

Table B.1: Emission intensity (by COGS) and the measures of distortions

	(1)	(2)	(3)
	log(MRPK)	log(MRPL)	log(TFPR)
log(emissions/cogs)	-0.161***	-0.037	-0.070***
	(0.022)	(0.022)	(0.019)
Adj. R^2	0.827	0.734	0.650
Ind x Year FE	✓	✓	✓
N	2,847	2,819	2,819

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table provides the results of empirical analysis, where I conduct regressions of a distortions measure (TFPR) on emission intensities measured by the cost of goods sold (COGS). This analysis incorporates controls for 4-digit SIC industry-year dummies. Standard errors, which are presented in parentheses, are clustered at both the firm and year levels.

Table B.2: Emission intensities (by COGS) and the measures of distortions by industries

log(TFPR)	Mining	Manufacturing	Transportation	Electricity
log(emissions/cogs)	-0.150*	-0.086***	-0.382***	-0.020
	(0.076)	(0.028)	(0.054)	(0.028)
Adj. R^2	0.476	0.537	0.778	0.074
Ind x Year FE	✓	✓	✓	✓
N	221	1,490	254	335

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table provides the results of empirical analysis, where I conduct regressions of a distortions measure (TFPR) on emission intensities measured by the cost of goods sold (COGS). This analysis incorporates controls for 4-digit SIC industry-year dummies and conducts separate analyses for firms within the mining, manufacturing, transportation, and electricity-generating sectors. Standard errors, which are presented in parentheses, are clustered at both the firm and year levels.

Table B.3: Emission intensity (by COGS) and productivity

log(emissions/cogs)	(1)	(2)	(3)	(4)	(5)	(6)
log(TFPQ)	-0.581***	-0.518***	-0.585***	-0.746***	-0.509***	-0.629***
	(0.170)	(0.123)	(0.150)	(0.186)	(0.129)	(0.151)
Size				0.174***	-0.035	0.151
				(0.052)	(0.080)	(0.115)
Age				-0.001	0.000	0.000
				(0.003)	(.)	(.)
Adj. R^2	0.787	0.973	0.973	0.792	0.973	0.973
Year FE		✓			✓	
Ind x Year FE	✓		✓	✓		✓
Firm FE		✓	✓		✓	✓
N	2,819	3,789	2,671	2,819	3,789	2,671

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table provides the results of empirical analysis, where I conduct regressions of emission intensities measured by the cost of goods sold (COGS) on firms' productivity. This analysis incorporates controls for 4-digit SIC industry-year dummies. I also include controls for firm size, measured by log(total assets), and firm age. Standard errors, which are presented in parentheses, are clustered at both the firm and year levels.

Table B.4: Emission intensities (by COGS) and productivity by industries

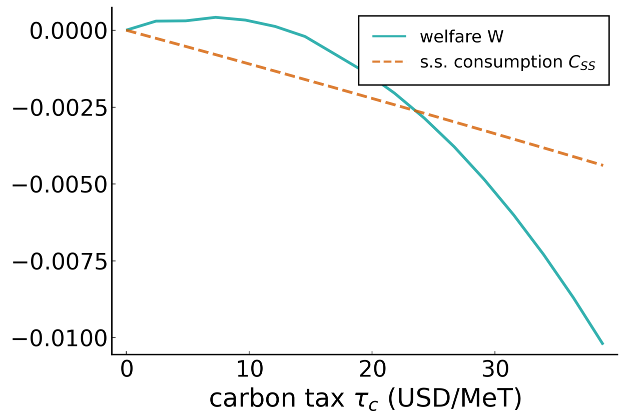
log(emissions/sales)	Mining	Manufacturing	Transportation	Electricity
log(productivity)	-1.053***	-0.944***	-1.446***	-0.340
	(0.338)	(0.278)	(0.158)	(0.378)
Size	0.043	0.194***	0.139*	-0.045
	(0.099)	(0.058)	(0.065)	(0.195)
Age	0.000	0.001	0.005*	0.000
	(0.003)	(0.003)	(0.003)	(.)
Adj. R^2	0.397	0.578	0.961	0.933
Ind x Year FE	✓	✓	✓	✓
N	221	1490	254	330

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table provides the results of empirical analysis, where I conduct regressions of emission intensities measured by the cost of goods sold (COGS) on firms' productivity. This analysis incorporates controls for 4-digit SIC industry-year dummies and conducts separate analyses for firms within the mining, manufacturing, transportation, and electricity-generating sectors. I also include controls for firm size, measured by log(total assets), and firm age. Standard errors, which are presented in parentheses, are clustered at both the firm and year levels.

C Additional details on the quantitative analysis

C.1 Welfare over transition path vs. steady state consumption

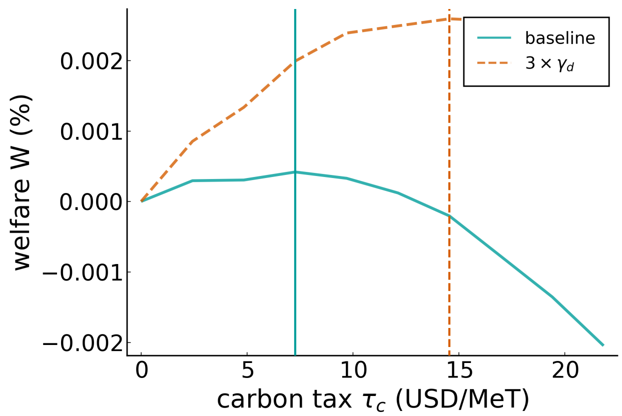
Figure C.1: Welfare over carbon taxes vs. steady state consumption



Notes. The x-axis represents the different levels of carbon taxes. The solid line represents the difference in welfare, which is the lifetime utility of the representative household over a transition path, compared to the case with zero carbon tax. This difference is expressed in units of consumption equivalent welfare. The dashed line represents steady state consumption relative to the case with zero carbon tax.

C.2 A higher carbon damage

Figure C.2: Welfare over carbon taxes: baseline vs. $3 \times \gamma_d$



Notes. The x-axis represents the different levels of carbon taxes. The y-axis measures the difference in welfare, which is the lifetime utility of the representative household over a transition path, compared to the case with zero carbon tax. This difference is expressed in units of consumption equivalent welfare. The solid lines correspond to the baseline case, while the dashed lines pertain to the case with a higher carbon damage parameter.