Firm Heterogeneity, Industry Dynamics and Climate Policy

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Abstract

We develop a dynamic general equilibrium model to quantify the interaction between climate policy, industry dynamics, and the elasticity of substitution between clean and dirty energy in the economy. The model incorporates empirical observations that firms differ substantially in their potential for energy substitution and that the economy is growing more capable of substituting clean for dirty energy over time as environmental regulation becomes more stringent. Our model highlights the effect of dynamic industry response on increasing the average elasticity of substitution in the economy due to the exit of least flexible firms in response to climate policy. The higher average elasticity of substitution increases the effectiveness of the policy at reducing emissions, resulting in a 35 percent decrease in the size of the carbon tax required to achieve carbon neutrality.

Keywords: industry dynamics, elasticity of substitution, climate policy.
JEL Classification: Q40, Q55, Q54, O33.

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1 Introduction

The transition from fossil fuels to renewable energy takes a central role in the policy visions to halt the progress of global warming (IPCC, 2018). As a crucial factor that governs the transition process, the degree of substitutability between clean and dirty energy has been shown to strongly influence the predictions for sustainable growth and optimal designs of climate policy.[1] However, microfoundations behind the elasticity of substitution between different types of energy are hitherto lacking in the literature. For instance, is there heterogeneity across firms and sectors in their potential to substitute clean for dirty energy? Is our economy becoming more capable of energy substitution over time? If so, what are the drivers behind the evolution?

In this paper, we tackle these questions by developing a dynamic general equilibrium model that allows us to quantify the interaction between climate policy, industry dynamics, and the elasticity of substitution in the economy. Our model builds on the large macroeconomic literature of directed technical change and the environment (e.g., Acemoglu et al., 2012), but extends these models by incorporating firm heterogeneity in the elasticity of substitution between clean and dirty energy in their production process and endogenous exit and entry. These margins are critical for our investigation of optimal climate policy and how it interacts with the economy-wide capability of achieving energy transition.

Our economy comprises two main economic segments: industrial production and energy services. In the industrial segment, incumbent firms produce differentiated products by combining clean and dirty energy and incurring a fixed cost of operation in terms of low-skilled labor. Forward-looking potential entrants make optimal entry decisions based on their expected lifetime profits relative to the fixed cost of entry. Firms are heterogeneous with respect to their elasticity of substitution between clean and dirty energy, which affects their potential to cope with climate policy. Due to the presence of the fixed cost, firms may exit if their operating costs increase and profits drop below a certain threshold, which we characterize. The energy segment of our model consists of the clean and dirty sector and provides energy inputs to the

[1] The elasticity of substitution between clean and dirty energy critically determines important outcomes such as induced innovation in green technologies (Otto et al., 2007; Acemoglu et al., 2012; Fried, 2018), the relative efficacy of different policy instruments (Lemoine, 2017; Greaker et al., 2018; Hart, 2019), and the overall economic costs of climate change mitigation (Golosov et al., 2014). For an in-depth discussion on the role of this parameter in the literature, see Section 2 in Jo and Miftakhova (2022).

heterogeneous firms in the industrial segment. As in Acemoglu et al. (2012) and Fried (2018), among others, it is also the source of innovation-induced growth of the economy.

The interplay of firm heterogeneity, industry dynamics and climate policy leads to an endogenous change in the equilibrium distribution of the elasticity of substitution across firms and therefore in the economy-wide potential for energy substitution. Climate policy, or the consequent increase in the relative price of fossil-based energy, induces least flexible firms to exit the market, while simultaneously allowing the entry of firms that are relatively more capable of substituting clean for dirty energy and therefore have lower operating costs and sufficiently high expected profits to cover the sunk entry costs. This dynamic industry response increases the average elasticity of substitution among active firms, creating larger demand shifts to clean energy in the industry, as well as stronger innovation response in the energy sector.

The key features of our model are empirically motivated using microdata from the French manufacturing sector for 1995-2015 that provide information on energy consumption and expenditure by energy source and detailed firm characteristics. We first provide empirical evidence on firm heterogeneity in their energy substitution capabilities. Although the presence of heterogeneity along this dimension has been recognized in the policy arena as well as by practitioners (Environment Agency, 2008), we are not aware of existing empirical evidence establishing this pattern.[2] Hence, we estimate the elasticity of substitution between clean (electricity, steam, and renewables) and dirty energy (all others) by quantile regression that allows us to examine heterogeneity across firms in different quantiles of the distribution of the input ratio (dirty to clean). We find that the estimated elasticity of substitution varies significantly across firms: cleaner (dirtier) firms tend to be more (less) capable of substituting clean for dirty energy.

Second, we empirically document that the average elasticity of substitution has been increasing over time. In particular, it is noteworthy that the change has been concurrent with climate policy becoming more stringent over the same time period in France. This correlation provides strong motivating evidence for our model that explores the interaction between climate policy and the economy-wide potential for energy substitution.

For the quantitative analysis, we calibrate the parameters of our model by method

[2]For example, Environment Agency (2008) documents the presence of heterogeneity in the potential for energy substitution across cement and lime producers, despite the industry generally thought of as having very little potential for energy transition.

of moments to match key moments implied by the model with their empirical counterparts in micro and macro data. It is important for our model to capture the relationships between energy prices, industry dynamics, and production and innovation in the energy sector. Thus, we target moments in the data that capture these features to discipline our parameters. For instance, a crucial empirical moment for our model to match is the average elasticity of substitution between clean and dirty fuels among manufacturing firms that we estimate from our microdata. The model performs well and matches the targeted and non-targeted moments closely, suggesting that the model's fit is reasonably strong.

We use our calibrated model to quantify the interaction between firm heterogeneity, industry dynamics and the average elasticity of substitution in the economy. We compute a set of counterfactual stationary equilibria to understand the role of dynamic industry response to climate policy. We compare two equilibria that achieve the same policy goal of carbon neutrality but one where the channel of industry dynamics is at play (the endogenous model) and the other where this channel is shut off (the exogenous model). Three main findings emerge. First, failing to take into account the dynamic industry response can lead to an overestimation of the optimal tax that achieves carbon neutrality by 35 percent. The exit of least flexible firms in the endogenous model increases the average elasticity of substitution among active firms by 5 percent in the new equilibrium. This enables larger demand shifts to clean energy in the industry, lowering the required size of the tax to achieve the same emissions reduction target in the endogenous model.

Second, the dynamic industry response via the endogenous elasticity of substitution leads to a structural change in the economy: as inflexible firms exit the market, essential resources (labor) reallocate to the clean energy sector, as demand for clean energy is now higher. The mass of active firms falls by 3.4 percent in the endogenous model and the market size of the clean relative to dirty energy sector increases twice as much compared to the exogenous model, absorbing the freed labor from the industry. Finally, innovation response is also stronger in the endogenous model: the relative technology in the clean sector grows by 23 percentage points more when the channel of industry dynamics is at work. The difference is again primarily driven by the stronger demand response in the industry brought about by the higher average elasticity of substitution, which creates stronger incentives to innovate in the clean sector.

Third, we investigate the implications of different policy instruments, namely, a carbon tax and a research subsidy to clean innovation, in the presence of endogenous industry dynamics. Consistent with prior findings in the literature (e.g., Fischer and Newell, 2008), a research subsidy tends to be more costly in terms of gross welfare than a carbon tax as a single policy in our model. However, we find that dynamic industry responses lower the welfare cost of the subsidy as the indirect price incentives generated by improving clean technologies (as opposed to direct price incentives provided by the tax) tend to induce larger demand shifts due to the increasing average elasticity of substitution in the endogenous model. Further, our model shows that it is possible to achieve carbon neutrality at lower welfare costs when a carbon tax is combined with a research subsidy for clean technologies as emphasized in Acemoglu et al. (2012).

Our paper is most closely related to the literature on directed technical change and climate in general equilibrium.[3] Our theoretical framework extends the literature in noteworthy dimensions. Most importantly, our model allows energy-consuming firms to be heterogeneous in their capability to substitute clean for dirty fuels, in contrast to most models featuring a single elasticity of substitution parameter (constant and exogenous through the CES aggregate production function) applying to the whole economy. Furthermore, endogenous exit and entry in response to climate policy induced by firm heterogeneity in our model is able to reproduce the empirical observation that the economy as a whole becomes more capable of substituting clean for dirty energy over time as climate policy becomes more stringent, which is a feature not captured by previous models. Particularly related to our paper are Baccianti and Smulders (2021) where the aggregate elasticity of substitution between clean and dirty inputs changes endogenously through the interaction between sectoral heterogeneity in pollution intensities and demand for polluting inputs, and Jo and Miftakhova (2022) where the elasticity of substitution is endogenized as a function of the relative use of clean energy in the economy. Yet, neither paper explicitly models industry dynamics through endogenous entry and exit of firms, which is the central focus of our analysis. Finally, our paper is related to the growing group of papers that emphasize the structure and dynamics of the industries in the context of environmental regulation (Ryan, 2012; Fowlie et al., 2016; Miller et al., 2017; Leslie, 2018), but is distinguished by our framework that marries the issue of industry dynamics to directed technical change and by our focus on how dynamic industry response affects the economy-wide elasticity of substitution

[3] See, for example, Acemoglu et al. (2012); Bretschger and Smulders (2012); Golosov et al. (2014); Fried (2018); Greaker et al. (2018); Borissov et al. (2019); Hart (2019); Hassler et al. (2021); Baccianti and Smulders (2021); Jo and Miftakhova (2022).

which is a critical determinant of the cost of environmental policy.

The rest of the paper is organized as follows. Section 2 provides stylized empirical facts that motivate our model. Section 3 presents the model. Section 4 describes our data and quantitative analysis. Section 5 presents results from our quantitative analysis. The last section concludes.

2 Stylized facts

This section documents two stylized facts that motivate the key features of our model, namely, firm heterogeneity in the capability to substitute clean for dirty energy and a positive correlation between the economy-wide potential for energy substitution and the stringency of climate policy. We use microdata from the French manufacturing sector for 1995 - 2015. The data come from two main sources: the *Enquête sur les Consommations d'Énergie dans l'Industrie* (EACEI) that provides information on energy consumption and expenditure by fuel and *Fichier approché des résultats d'Esane* (FARE) that contains information on detailed firm characteristics. We aggregate the consumption of different fuels to a clean and a dirty bundle for each firm in order to investigate the elasticity of substitution between the two types of energy. Following prior studies (Papageorgiou et al., 2017; Jo, 2020), we add up electricity, steam and renewables into the clean bundle and all other types (natural gas, petroleum products, etc.) into the dirty bundle. The unit costs for clean and dirty energy are obtained by dividing the expenditure measures (that are similarly aggregated to the clean and dirty bundle) by the corresponding consumption measures. Detailed descriptions of the data are relegated to Section 4.1.

2.1 Firm heterogeneity in the elasticity of substitution

To document heterogeneity in the elasticity of substitution between different types of energy across firms, we estimate the following equation with industry θ_s, region μ_r, year fixed effects δ_t by quantile regression:

$$\ln\left(\frac{b_{jt}}{g_{jt}}\right) = \sigma \ln\left(\frac{p_{gjt}}{p_{bjt}}\right) + \theta_s + \mu_r + \delta_t + \epsilon_{jt} \tag{1}$$

where g_{jt}, b_{jt} are clean and dirty energy consumption of firm j in year t and p_{gjt} and p_{bjt}

reflect the unit cost of clean and dirty energy, respectively.[4] The quantile estimation allows us to examine heterogeneity in firms' capabilities of energy substitution across different quantiles of the conditional distribution of the relative input ratio, $\ln(b_{jt}/g_{jt})$.

The endogeneity of firm-level energy prices stemming from omitted variable bias is recognized in the literature.[5] Thus, we follow earlier studies (e.g., Linn, 2008; Sato et al., 2019; Jo, 2020; Marin and Vona, 2021) and apply instruments based on national energy prices. The instrument for the price of clean energy $\tilde{p}_{gjt}$ is constructed as follows:

$$\tilde{p}_{gjt} = p_{gj0} \times \prod_{s=1}^{t} (1 + \gamma_s^g) \tag{2}$$

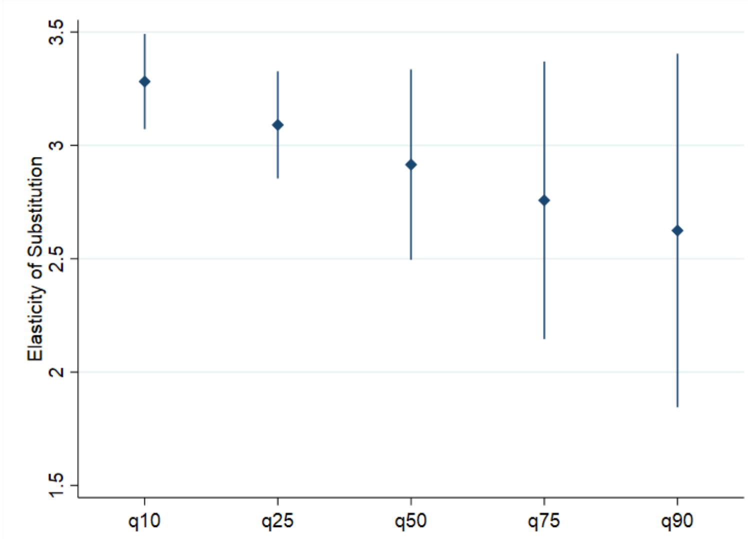
where γ_t^g is the growth rate in the national average price of clean energy between $t-1$ and t. Intuitively, the instrument applies the growth rates of the clean energy price at the national level to the firm-specific pre-sample price of clean energy, thus isolating variation caused only by changes in national energy prices that are unlikely to be correlated with firm-level unobservables. The instrument for the price of dirty energy is similarly constructed. We use these two instruments to instrument for the log price ratio in equation (1).

Figure 1 graphically reports IV estimates of the elasticity of substitution between clean and dirty energy across five different quantiles associated with the distribution of the relative dirty energy consumption (our dependent variable). The graph shows that the elasticity of substitution varies significantly across firms with different levels of the relative dirty energy consumption even within the same sector (note that all regressions include sector fixed effects). Firms in the 10th percentile (cleaner firms) are associated with an elasticity of substitution over 3, while those in the 90th percentile (dirtier firms) display a lower elasticity of substitution around 2.6. The estimates are

[4]It is known that exploiting time-variation in time-series data or panel data with fixed effects captures short-term substitution, while exploiting cross-sectional variation captures long-term substitution (Arnberg and Bjørner, 2007). Therefore, we do not include firm fixed effects to be able to interpret the estimates as a long-run elasticity of substitution, which is closer to the theoretical interpretation of the parameter. Further, exploiting only within firm variation discards changes in prices that induce entry, exit and the reallocation of inputs across firms, which is a key feature of our theoretical model in the next section.

[5]For instance, there might be productivity shocks at the firm level that may affect energy demand and the unit price of energy. That is, to the extent that firms take into account their factor-specific productivity when choosing inputs, a positive productivity shock in the use of green energy, for instance, would affect the relative input ratio by changing the demand for green energy, which in turn may affect the price ratio through changes in quantity discounts (i.e., lower unit price due to higher demand for green energy).

Figure 1: Heterogeneity in the Elasticity of Substitution across Firms



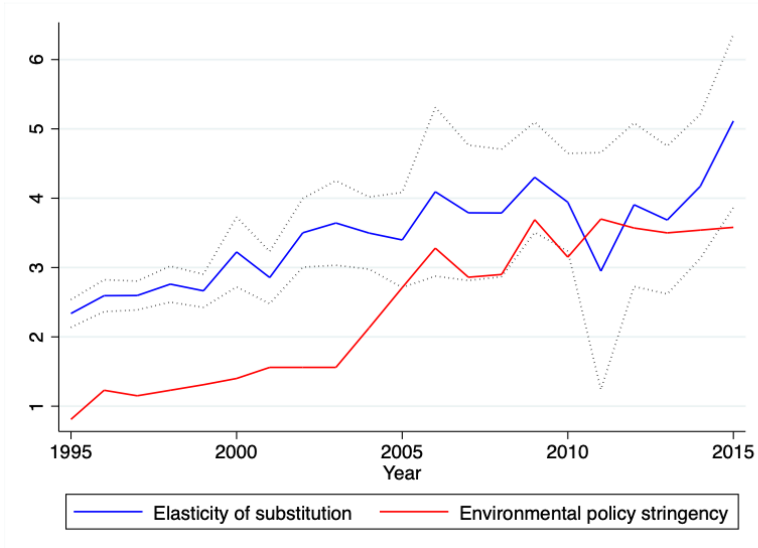
Note: Estimates of the elasticity of substitution between clean and dirty energy from quantile regressions. Lower quantiles refer to firms with lower relative shares of dirty energy (cleaner firms) and higher quantiles refer to firms with higher relative shares of dirty energy (dirtier firms).

statistically different at 1 percent level. Across the whole distribution, we observe a stable negative association between the relative dirty energy consumption and the capability of energy substitution. OLS estimates reported in Table A1 show similar patterns. The results provide evidence for a substantial degree of heterogeneity across firms in their potential to substitute clean for dirty energy. We conjecture that the heterogeneity in the elasticity of substitution across firms may lead to heterogeneity in their ability to cope with climate policy that raises the relative price of dirty energy.

2.2 Substitution capability and the stringency of climate policy

Next, we examine how the economy-wide elasticity of substitution has evolved over time and importantly, how it relates to the stringency of climate policy. For the purpose, we now estimate equation (1) separately for each year between 1995 and 2015 in order to obtain the elasticity of substitution at each point in time. The instruments and the set of fixed effects same as in the previous section (without year fixed effects) are used in all regressions. The IV estimates and the 95 percent confidence intervals are graphically reported in Figure 2. We observe a clear upward trend in the average elasticity of

Figure 2: Evolution of the Average Elasticity of Substitution and the Stringency of Environmental Policy



Note: Cross-sectional IV estimates of the elasticity of substitution for each year with 95 percent confidence intervals. EPS index from OECD.

substitution among manufacturing firms: the estimated elasticity of substitution more than doubles over the 20-year period, increasing from just above 2 in 1995 to over 5 in 2015.

We now explore if there exists any correlation between the observed increase in the elasticity of substitution over time and the stringency of environmental policy. To measure policy stringency in the environmental domain, we use the Environmental Policy Stringency (EPS) index from the OECD for the same time period. Figure 2 shows that environmental policy was becoming more stringent over the examined 20-year period in France. It is noteworthy that this movement in the index was concurrent with firms on average growing more capable of substituting clean for dirty energy over time, pointing to a positive correlation between the two measures. We now turn to our modeling framework.

3 Model

In this section, we introduce our theoretical framework and characterize the stationary balanced growth equilibrium.

3.1 Final good and industrial output

3.1.1 Final good technology

The final good Y is produced competitively using the output of a continuum of intermediate firms in a Dixit and Stiglitz (1977) form with an elasticity of substitution $\epsilon > 1$:

$$Y = \left[\int_{j \in J} y_j^{\frac{\epsilon-1}{\epsilon}} dj \right]^{\frac{\epsilon}{\epsilon-1}}. \tag{3}$$

The demand for each differentiated intermediate good y_j and the price index for good Y are given by profit maximization as:

$$y_j = A p_j^{-\epsilon}, \qquad A \equiv Y P^{\epsilon} \qquad \text{and} \qquad P = \left[\int_{j \in J} p_j^{1-\epsilon} dj \right]^{\frac{1}{1-\epsilon}}. \tag{4}$$

where p_j is the price of intermediate good y_j. We choose the final good as the numeraire and set its price to unity, i.e., $P = 1$ and $A = Y$.

3.1.2 Intermediate good production

Production of intermediate goods by firms requires a fixed cost of operation f_p in terms of unskilled labor. Once the fixed cost is covered, each intermediate firm j produces their output by combining clean/green (g_j) and dirty/brown (b_j) inputs according to the CES production function:

$$y_j = \varphi_j \left(a_j g_j^{\frac{\sigma_j - 1}{\sigma_j}} + (1 - a_j) b_j^{\frac{\sigma_j - 1}{\sigma_j}} \right)^{\frac{\sigma_j}{\sigma_j - 1}}$$

where $\varphi_j > 0$ denotes a productivity parameter, $a_j \in (0, 1)$ a distribution parameter and $\sigma_j > 0$ the firm-specific elasticity of substitution between clean and dirty inputs.

In order to distinguish firms by their elasticities of substitution, the CES production function has to be normalized to a benchmark point. This is because the productivity parameter φ_j and the distribution parameter a_j are intrinsically linked to the elasticity of substitution (see, for example, Klump and de La Grandville (2000), León-Ledesma et al. (2010), and Klump et al. (2012) for relevant theoretical discussions), which makes it difficult to differentiate firms only by the substitution elasticity while holding other parameters constant.[6] Thus, with benchmark values of input demands, output and input prices denoted as $\{g_0, b_0, y_0, p_{g0}, p_{b0}\}$, the normalized production function reads:

$$y_j = y_0 \left[\kappa_0 \left(\frac{g_j}{g_0} \right)^{\frac{\sigma_j - 1}{\sigma_j}} + (1 - \kappa_0) \left(\frac{b_j}{b_0} \right)^{\frac{\sigma_j - 1}{\sigma_j}} \right]^{\frac{\sigma_j}{\sigma_j - 1}},$$

where $\kappa_0 = p_{g0} g_0 / (p_{g0} g_0 + p_{b0} b_0)$ is the expenditure share of the clean input at the point of normalization. Since firms differ only with respect to their elasticity of substitution once normalized, we drop j and index firms from now on by σ; for instance, we refer to y_j as $y(\sigma)$.

With p_g and p_b representing the input prices and τ a tax on the dirty input, the variable cost of production $c_\sigma(p_g, p_b)$ reads:

$$c(\sigma) = c_0 \left[\kappa_0 \left(\frac{p_g}{p_{g0}} \right)^{1-\sigma} + (1 - \kappa_0) \left(\frac{p_b + \tau}{p_{b0}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{5}$$

with $c_0 \equiv (p_{g0} g_0 + p_{b0} b_0)/y_0$ represents the benchmark variable cost. By Shephard's lemma, the demand for each input can be written as:

$$\begin{aligned} g(\sigma) &= y(\sigma) \left(\kappa_0 \frac{c(\sigma)}{p_g} \right)^{\sigma} \left(\frac{g_0}{y_0} \right)^{1-\sigma}, \\ b(\sigma) &= y(\sigma) \left((1 - \kappa_0) \frac{c(\sigma)}{p_b + \tau} \right)^{\sigma} \left(\frac{b_0}{y_0} \right)^{1-\sigma}. \end{aligned} \tag{6}$$

The following lemma establishes that a firm with a higher elasticity of substitution is able to produce at a lower cost compared to another firm producing the same amount of output with a lower elasticity of substitution.

Lemma 1. *All else equal, the variable cost of production $c(\sigma)$ is decreasing in σ.*

Proof. See Appendix A2. □

[6] In macroeconomics literature, this is particularly important when examining the effects of variation in the elasticity of substitution on economic growth over time or across countries (Klump et al., 2012). As the substitution elasticity varies, the 'dimensional constants' (the productivity and distribution parameters) also vary in the CES function, making it hard to isolate the impact of varying elasticities of substitution. de La Grandville (1989) and Klump and de La Grandville (2000) among others have emphasized the importance of normalizing CES functions as a way to deal with this dimensional problem when analyzing the theoretical consequences of variation in the elasticity of substitution.

The Dixit-Stiglitz structure in (3) supports monopolistic competition in the supply of each differentiated variety $y(\sigma)$. Profit maximization of intermediate firms implies that each firm charges a price that includes a constant markup over its variable cost $c(\sigma)$:

$$p(\sigma) = \frac{\epsilon}{\epsilon - 1} c(\sigma). \tag{7}$$

Firm revenue is then given by $p(\sigma)y(\sigma) = Yp(\sigma)^{1-\epsilon}$ (see (4)) and firm profit is written as:

$$\pi(\sigma) = (Y/\epsilon)p(\sigma)^{1-\epsilon} - w_{li} f_p, \tag{8}$$

where w_{li} represents the wage rate of (unskilled) labor in the industrial segment. Note that since the cost of production is declining in the elasticity of substitution according to the lemma above, a higher σ is associated with cheaper production, a lower market price, and higher revenues and profits (because demand is elastic with $\epsilon > 1$), holding all else constant.

3.1.3 Firm entry and exit

Our setup of firms' exit and entry closely follows Melitz (2003). There is a large pool of ex-ante identical potential entrants. Entry into the market entails an initial investment $f_e > 0$ in terms of unskilled labor, which is thereafter sunk. Once the entry cost is paid, firms then draw their substitution elasticity parameter σ from a common distribution $\phi(\sigma)$ with a positive support $(0, \infty)$; we denote with $\Phi(\sigma)$ its cumulative distribution.[7] An entrant with a bad draw of σ may exit immediately and never produce. If a firm remains in the market and produces, it faces an idiosyncratic shock that forces it to exit the market at a constant rate δ. As in Melitz (2003), the specification of a common distribution $\phi(\sigma)$ and the exit rate δ exogenously determine the shape of the equilibrium distribution of the substitution elasticity and the ex ante survival probabilities. However, the simple model is nevertheless able to endogenously determine the range of substitution elasticities for surviving firms and therefore the average economy-wide capability for energy transition, which are critical margins for our investigation on how climate policy interacts with the average elasticity of substitution in the economy.

With r representing the discount rate, a firm's value at the time of entry $v(\sigma)$ is

[7] We view this set up of firms drawing their level of elasticity of substitution as firms facing uncertainty about their potential for input substitution once production begins. For example, there may be uncertainty about the best-practice technologies at the time of firm establishment or about the conditions of energy supply contracts due to poor management.

equal to the discounted expected lifetime profits:

$$v_t(\sigma) = \max\left\{0, \sum_{s=0}^{\infty}\left(\prod_{u=0}^{s-1}\frac{1}{1+r_{t+s-u}}\right)(1-\delta)^s\pi_{t+s}(\sigma)\right\}.$$

With growth stemming from technological innovation in the energy segment of our economy (will be introduced in the next section) profits in (8) grow with the aggregate economy-wide technology Q (see Appendix A3), which in turn grows at a constant rate of g in a stationary equilibrium. Thus, we normalize profits by Q such that $\tilde{\pi}(\sigma) \equiv \pi(\sigma)/Q$ is constant. The equilibrium stationary value of a firm then reads as:

$$\tilde{v}(\sigma) = \max\left\{0, \sum_{s=0}^{\infty}\left(\frac{(1-\delta)(1+g)}{1+r}\right)^s\tilde{\pi}(\sigma)\right\} = \max\left\{0, \frac{1}{\omega}\tilde{\pi}(\sigma)\right\} \tag{9}$$

where $\omega \equiv \frac{r-g+\delta(1+g)}{1+r}$ is an augmented discount factor that incorporates the probability of exogenous destruction and growth.

Since firms face fixed costs of operation and profits increase in σ, an entering firm with a bad draw of σ may be forced to exit the industry immediately and never produce, thus earning zero profits. This decision defines a cutoff level elasticity of substitution σ^* that solves $\tilde{\pi}(\sigma^*) = 0$, the zero cutoff profit condition, below which firms exit and do not produce. The distribution of active firms conditional upon successful entry is then endogenously determined by σ^* as:

$$\psi(\sigma) = \begin{cases} \frac{\phi(\sigma)}{1-\Phi(\sigma^*)} & \text{if } \sigma \geq \sigma^* \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

with $1 - \Phi(\sigma^*)$ being the ex-ante probability of successful entry. Subsequently, the average elasticity of substitution of active firms as a function of the threshold σ^* is given by:

$$\bar{\sigma}(\sigma^*) = \int_{\sigma^*}^{\infty}\sigma\psi(\sigma)d\sigma. \tag{11}$$

The last two equations reveal how the shape of the equilibrium distribution of elasticities is tied to the exogenous ex-ante distribution $\phi(\sigma)$ while allowing the range of elasticities $\psi(\sigma)$ and hence the average elasticity of substitution levels in the economy $\bar{\sigma}(\sigma^*)$ to be endogenously determined.

All active firms (other than the cutoff firm that makes a zero profit) earn positive profits, which implies that the average profit $\bar{\pi}$ must be positive. Free entry suggests that the expectation of future profits conditional on successful entry must be equal to zero in order to prevent unbounded entry. From (9), we derive the free entry condition:

$$\frac{1-\Phi(\sigma^*)}{\omega}\bar{\pi} = w_{li} f_e \tag{12}$$

where the average profit reads $\bar{\pi} = \int_{\sigma^*}^{\infty} \pi(\sigma)\psi(\sigma)d\sigma$.

3.1.4 Industry aggregates

The zero cutoff profit condition and the free entry condition jointly determine the cutoff elasticity level σ^*:

$$J(\sigma^*) = \omega f_e/f_p, \qquad J(\sigma^*) \equiv \int_{\sigma^*}^{\infty} \Big[\Big(\frac{c(\sigma)}{c(\sigma^*)}\Big)^{1-\epsilon} - 1\Big]\phi(\sigma)d\sigma. \tag{13}$$

Although there is no closed form solution for σ^*, it can be computed numerically given the exogenous distribution $\phi(\sigma)$ and input prices.[8] The following proposition characterizes how the cutoff elasticity of substitution relates to the size of the tax on dirty inputs.

Proposition 1. *All else equal, the cutoff level of elasticity of substitution σ^* is non-decreasing in the tax on the dirty input τ.*

Proof. See Appendix A2. □

A higher tax on the dirty input increases the cost of production $c(\sigma)$, which lowers the profits in (8). According to lemma 1, firms with lower levels of σ that cannot easily switch to the relatively cheaper clean input will experience a larger increase in their operating costs and a larger decrease in profits. For some of these firms (close to the cutoff level of elasticity of substitution), the fall in profits can be substantial enough to make them unable to meet the fixed cost of operation and to exit the market, pushing up the survival cutoff level of the elasticity of substitution.

Once σ^* is determined, we can characterize all aggregate variables such as aggregate revenue and profit as well as the mass of active firms in the industry (see Appendix

[8] We note that while σ is non-negative by definition, $J(\sigma^*)$ is technically defined on $(-\infty, \infty)$, which implies that σ^* may also be negative. Restricting the parametric space such that $J(0) > \omega f_e/f_p$ holds, ensures that σ^* is non-negative.

A3 for details). With M denoting the mass of active firms, the aggregate demand for the clean and dirty inputs, respectively, reads:

$$
\begin{aligned}
G &= \int_{\sigma^*}^{\infty} g(\sigma) M \psi(\sigma) d\sigma = M\bar{g}, \\
B &= \int_{\sigma^*}^{\infty} b(\sigma) M \psi(\sigma) d\sigma = M\bar{b},
\end{aligned}
\tag{14}
$$

where $g(\sigma)$ and $b(\sigma)$ are defined in (6); $\bar{g}$ and $\bar{b}$ denote averages.

In addition, let M_e denote the mass of potential entrants. In a stationary equilibrium, the additional value from the mass of successful entrants must exactly replace the changing value of incumbents according to the augmented discount factor ω that accounts for the probability of exogenous exit as well as growth:

$$
\left(1 - \Phi(\sigma^*)\right) M_e = \omega M. \tag{15}
$$

The aggregate labor employed in the industry L_i is distributed between the labor used by the entrants L_e (both successful and unsuccefful) and the labor employed by incumbents L_p, which leads to: $L_i = L_p + L_e = M f_p + M_e f_e$. From (12) and (15), we note that the aggregate industry profit Π_I exactly covers the aggregate entry cost incurred by entrants: $\Pi_I = w_{li} L_e$.

3.2 Energy sector

We now turn to the energy sector that supplies the two energy inputs used by intermediate goods producers in the industrial segment described above.

3.2.1 Energy inputs

Clean and dirty energy inputs are produced competitively and are available to every industrial firm of the economy. The production function for each of the two inputs combines (unskilled) labor and a unit mass of machines in a constant returns to scale fashion:

$$
\begin{aligned}
G &= L_g^{1-\alpha_g} \int_0^1 x_{gi}^{\alpha_g} q_{gi}^{1-\alpha_g} di, \\
B &= L_b^{1-\alpha_b} \int_0^1 x_{bi}^{\alpha_b} q_{bi}^{1-\alpha_b} di.
\end{aligned}
\tag{16}
$$

Variable q_{ki}, with $k \in \{g, b\}$, denotes the technology embodied in machine x_{ki} and

$\alpha_k \in (0,1)$ is the factor share of machines in sector k. A representative producer of input k maximizes profits by choosing labor L_k and machines x_{ki}, while taking prices (the wage rate and the price of machines) and the level of machine-embodied technology as given. Note that labor is mobile between the industrial sector and the energy sector, which is an important margin for our quantitative analysis we present in the next section. Labor market clearing requires that $L_g + L_b \leq L - L_i$, where L is the fixed exogenous supply of unskilled workers in the economy and L_i is the aggregate labor employed in the industrial sector. The profit maximization problem of a representative input producer is described in detail in Appendix A3.

3.2.2 Machines

There exists a unit mass of machine producers in each energy sector. The machine producers sell their machines to the energy input producers in their specific sectors. A machine x_{ki} costs one unit of the final good to produce. The market for machines is monopolistically competitive, such that the machine producers earn positive profits. In addition, each sector-specific machine producer hires scientists at the market wage for scientists w_{sk}, with $k \in \{g, b\}$ to innovate on the embodied technology of their machines. The evolution of technology for machine producer i in sector k is:

$$q_{kit} = q_{kt-1}\left(1 + \gamma s_{kit}^{\eta}\left(\frac{Q_{t-1}}{q_{kt-1}}\right)^{\theta}\right), \qquad k \in \{g, b\}. \tag{17}$$

Note that time subscript t is introduced to make the state dependence in the evolution of technology explicit: technology in sector k builds on the existing level of technology q_{kt-1}. s_{kit} denotes the number of scientists hired by machine producer i in sector k in period t. Parameter η captures the degree of diminishing returns to scientific research and γ addresses efficiency in innovation. We allow cross-sector spillovers in innovation by the parameter $\theta \in [0,1]$, following Fried (2018). This is to incorporate the empirical observation that innovation has been taking place in both sectors, rather than only in one sector.[9] Thus, the specification captures the intuition that if sector k is relatively backward, then there are many ideas from the other sector that have not yet been applied in sector k. This "low-hanging fruit" increases the productivity of research in sector k.

[9] In France, for example, all energy sources (fossil fuels, nuclear, and renewables) show active R&D activities measured by non-zero expenditure since the 2000s (IEA, 2019).

Variable q_k denotes the aggregate (average) technology level in sector k:

$$q_{kt} = \int_0^1 q_{kit} di. \tag{18}$$

The aggregate economy-wide technology Q_t is defined as the average of the technologies in the two sectors. On a balanced growth path, Q grows at a constant rate of which we denote with g.

Each machine producer chooses the quantity of machines, the machine price, and the number of scientists to maximize her profits. She takes the existing levels of technology as given. Scientist market clearing requires that $S_{gt} + S_{bt} \leq S$ where S is the fixed exogenous supply of scientists in the economy and S_{kt} is the number of scientists in sector k in period t. Appendix A3 discusses the profit maximization problem of machine producers in detail.

3.3 Household

The representative household is inhabited by L workers, S scientists, a unit mass of intermediate goods producers and a unit mass of machine producers in each energy input sector. The relative supplies of workers and scientists are fixed. Additionally, we assume that both workers and scientists are mobile across sectors so that they can switch sectors without incurring adjustment costs (again, low-skilled labor is mobile across economic segments, i.e., the industry and the energy sector, as well as between the two energy sectors). The representative household's budget constraint is given by:

$$C = w_{li}L_i + w_{lg}L_g + w_{lb}L_b + w_{sg}S_g + w_{sb}S_b + \Pi_g + \Pi_b + T \tag{19}$$

where Π_g and Π_b are aggregate profits earned by machine producers in the clean and dirty energy sector, respectively.[10] T denotes non-distorting lump-sum transfers, which in equilibrium are $T = \tau B$, where τ, again, is the carbon tax on the dirty energy consumption.

The aggregate resource constraint implies the final good can be consumed or used for production of machines:

[10]Note that profits earned by active intermediate goods producers in the industrial segment of the economy exactly cover the aggregate entry costs incurred by entrants, and therefore do not enter the household's budget constraint as income.

$$Y = C + \int_0^1 (x_{gi} + x_{bi}) di. \tag{20}$$

3.4 Equilibrium

A *stationary decentralized equilibrium* consists of prices for intermediate goods ($p(\sigma)$), prices for energy inputs (p_g, p_b), prices for machines (p_g^x, p_b^x), wages for low-skilled workers and scientists ($w_{li}, w_{lg}, w_{lb}, w_{sg}, w_{sb}$), the cutoff level of elasticity of substitution (σ^*), a mass of active firms (M), a mass of potential entrants (M_e), allocation of low-skilled workers (L_i, L_g, L_b), allocation of scientists (S_g, S_b), energy inputs choices ($g(\sigma), b(\sigma)$), and machines (x_{gi}, x_{bi}) such that (i) $g(\sigma), b(\sigma)$ and $p(\sigma)$ maximize the intermediate goods producers' profits; (ii) x_{gi}, x_{bi} and L_g, L_b maximize the energy input producers' profits; (iii) p_g^x, p_b^x, S_g, S_b, x_{gi}, x_{bi} maximize the machine producers' profits; (iv) L_i, L_g, L_b and S_g, S_b maximize the representative household's utility; (v) σ^* is given by (13); (vi) M and M_e satisfy (15); (vii) $p(\sigma)$ clear the intermediate goods market; $(viii)$ p_g, p_b clear the energy input markets; (ix) p_g^x, p_g^x clear the machine markets; and (x) w_{li}, w_{lg}, w_{lb} and w_{sg}, w_{sb} clear labor markets for low-skilled workers and scientists, respectively.

Although the equilibrium is relatively complex, all equilibrium objects can be written in closed form, given the cutoff level of elasticity of substitution and energy input prices, which we compute numerically. We use this computation in the method of moments procedure outlined in the next section.

4 Quantitative analysis

To quantify the interplay between firm heterogeneity, industry dynamics and climate policy, we calibrate our model using micro- and macro economic data between 1995 and 2015 for France. Following the literature, we directly calibrate a group of parameters from the data series. Next, we jointly calibrate the remaining parameters to match moments implied by our model to their empirical counterparts. We describe our data sources and estimation procedures in the next sections.

4.1 Data

We use the same microdata from the French manufacturing sector as in Section 2. It comes from two main sources. The first dataset is the EACEI collected by the French National Institute of Statistics and Economic Studies (Insee) that provides plant-level information on energy use and expenditures by fuel. It covers a representative sample of manufacturing plants with at least 20 employees. The second dataset is the FARE, also collected by Insee. Being a census, the FARE contains information on key firm-level characteristics such as industry, employees, date of creation and cessation, and financial information for the universe of businesses operating in France.[11]

To merge the two datasets, we aggregate the plant-level information from the EACEI to the firm-level. Since the EACEI covers only a sample of manufacturing plants (although representative in all covered sectors), we only keep firm-year pairs for which all plants of a firm were surveyed in the EACEI to ensure that the aggregation of energy use and expenditure is comprehensive at the firm level. The final dataset covers around 13,000 firms in 19 manufacturing industries for the period between 1995 and 2015.

We aggregate the consumption of different sources of energy to a clean and a dirty bundle for each firm, with the clean bundle including electricity, steam and renewables and the dirty bundle consisting of all other fuels (natural gas, petroleum products, etc.). The firm-specific unit cost of each type of energy is constructed by dividing the expenditure measures (that are similarly aggregated to a clean and dirty bundle) by the corresponding consumption measures. The variation in the unit costs of energy across firms is largely driven by quantity discounts in the French context (Marin and Vona, 2021). Table A2 provides key descriptive statistics by industry. We use the microdata to obtain key moments such as the average elasticity of substitution between clean and dirty energy and entrants' share of employment.

We define the industrial segment of our model (the final and intermediate goods production) as manufacturing. The energy sector is split into clean and dirty. The clean sector corresponds to renewables and electricity, a large proportion of which (over 75 percent) is generated by nuclear energy in France (Eurostat, 2021). The dirty sector corresponds to mining and quarrying in the data that comprises mining of coal and lignite, extraction of crude petroleum and natural gas, mining of metal ores, other mining and quarrying, and mining support service activities. The data sources of

[11] FARE replaced Fichier de comptabilité unifié dans SUSE (FICUS) in 2008.

various moments at the sector level are summarized in Table A3.

4.2 External calibration

We take one period to be five years. The discount rate is set to 1.5 percent and we take the elasticity of substitution between different intermediate products to be $\epsilon = 2.9$. The labor share in the dirty energy sector $1-\alpha_b$ is set to 0.26, which corresponds to the average labor cost share in total operating costs in mining and quarrying (Eurostat, 2022b). We normalize the workforce to unity. During our sample period (1995 - 2015), on average 0.8 percent of workers were engaged in research activities in France (OECD, 2021b). Thus, we set the number of scientists to 0.008.

The parameter θ determines the strength of the cross-sector spillover in innovation. All else equal, weaker spillover (small θ) will strengthen the effect of directed technical change with all innovation occurring in one sector. On the other hand, stronger spillover (large θ) will lead to a stable interior balanced growth path where innovation occurs in both clean and dirty energy sector. Given that green technologies are relatively more advanced in the context of France due to the prominence of nuclear energy in France's energy system, a small θ will rapidly lead to a corner solution where innovation only occurs in the clean sector. Thus, we choose a conservative benchmark value of 0.65 for the parameter. We check the robustness of our results to alternative values of this parameter in the sensitivity analysis. Following Fried (2018), the level of diminishing returns to innovation parameter η is set to 0.78. The impact of this parameter on our results is also explored in the sensitivity analysis. Table 1 collates the values of the parameters discussed so far.

Table 1: External Parameter Values

Parameter	Description	Value
r	Discount rate	0.015
ϵ	Elasticity of substitution between goods	2.9
α_b	Machine share in dirty energy	0.74
θ	Cross-sector spillover	0.65
η	Diminishing returns	0.78
L	Number of workers	1
S	Number of scientists	0.008

The exogenous distribution $\phi(\sigma)$ from which firms draw their elasticities of subsitution is assumed to follow the gamma distribution defined on a positive support $(0, \infty)$ with shape parameter a and scale parameter b. The resulting mean and the variance of the distribution is ab and ab^2, respectively. To parameterize the distribution, we first note that the average elasticity of substitution we observe from the data — the point estimate — is estimated from the sample of surviving firms. However, the underlying exogenous distribution should also capture firms that exit or cannot enter the market due to their low elasticities of substitution. To operationalize the idea, we note from Figure 1 that dirtier firms tend to display lower levels of input substitution capability. Based on this observation, we make the assumption that the dependent variable $\ln(b_{jt}/g_{jt})$ in equation (1) is truncated from above: firms that are very dirty and thus likely to have a low elasticity of substitution are not observed in the data. This assumption allows us to formulate the problem at hand as a sample selection problem (also known as incidental truncation). Then, the popular Heckman's two-step procedure can be applied to recover the average elasticity of substitution of the underlying distribution.

The estimation method applied to our microdata yields 2.84 for the average substitution elasticity of the underlying distribution, which is as expected smaller than the point estimate that does not correct for the positive selection bias or relates to surviving firms only, 2.98. Appendix A4 explains the estimation in detail. In the baseline, we set $a = 2.84$ and $b = 1$ so that the resulting average of the distribution is equal to 2.84. We try other combinations of a and b that keep the average of the distribution constant but differ in the associated variance of the distribution in the sensitivity analysis.[12]

Finally, for parameters that normalize the CES production function across intermediate goods producers, we assume $g_0 = b_0 = y_0 = 1$ without loss of generality. p_{g0} and p_{b0} are set to 0.67 and 0.33, respectively, according to the average unit prices of clean and dirty energy among French manufacturing firms based on the EACEI data.[13]

[12] An alternative approach to calibrate $\phi(\sigma)$ would to use the distribution implied by the point estimate (2.84) and its standard error. However, the estimate is very precisely estimated with a small standard error (0.13) (Table A5), while the quantile estimates in Figure 1 and their associated standard errors suggest that there exists more substantial heterogeneity than implied by the standard error of the point estimate. Thus, we fit a gamma distribution on a positive support (since σ is defined on $(0, \infty)$) such that its mean matches the point estimate and try different standard deviations of the distribution in the sensitivity analysis. As will be shown in the next sections, this parameterization fits the data well on the targeted and non-targeted moments.

[13] We rescale the actual average prices (0.929 euro per TOE for clean and 0.473 euro per TOE for fossil energy) so that they add up to one. Given $g_0 = b_0 = y_0 = 1$, this ensures internal consistency

These values lead to the distribution parameter κ_0 and the variable unit cost c_0 of 0.67 and 1, respectively, according to their definitions.

4.3 Method of moments

The remaining parameters $\{\alpha_g, \delta, f_e, f_p, \gamma\}$ are jointly calibrated using the quantitative implications of our model. For the first four parameters, we use method of moments that chooses the parameter vector so as to minimize the distance between several key moments implied by our model and the corresponding moments in the data. The approach iteratively searches across sets of parameter values for α_g, δ, f_e and f_p until the model's moments are as close as possible to the empirical moments. Additionally, we target the annualized growth rate of GDP per capita of 2 percent on the balanced growth path, which pins down the innovation efficiency parameter γ.

It is important for our model to capture the relationships between energy prices, industry dynamics, and production and innovation in the energy sector. We use four moments in the data — the average elasticity of substitution between clean and dirty energy in the manufacturing industry, the size of manufacturing relative to the energy sector in terms of employment, the market size of the clean relative to dirty energy sector (again in terms of employment), and R&D expenditure in green technologies as a share of total research expenditure in the energy sector — to discipline our parameters. In particular, a crucial moment from our model to match its empirical counterpart is the average elasticity of substitution between clean and dirty energy among active manufacturing firms, $\bar{\sigma}$. Using the microdata on French manufacturing firms, we estimate equation (1) across all firms to obtain the target empirical moment of 2.98. The same instruments as in Section 2.1 are used to address endogeneity concerns and the estimation controls for industry, region, year fixed effects.

The empirical moment that captures the relative size of the manufacturing sector in the economy is 0.887, calculated as the share of labor employed in manufacturing in the sum of labor employed in manufacturing and the energy sector (ILOSTAT, 2022). The market size of the clean relative to dirty energy sector is measured by the relative employment in those sectors (Acemoglu et al., 2012) and equal to 5.92 according to the Structural Business Survey 1996-2008. The share of R&D expenditures in clean energy sources (renewables and nuclear) in total research expenditures in the energy sector is 0.87 (IEA, 2020). As mentioned above, the relatively large share of green R&D is due

of the normalization parameters: $y_0 = \frac{p_{g0}}{\kappa_0} g_0$ and $p_{b0} = \frac{(1-\kappa_0)y_0}{b_0}$ (León-Ledesma et al., 2010).

to the prominence of nuclear energy (and a large amount of R&D resources devoted to it), which generates around 75 percent of electricity in France.

Table 2: Internal Parameter Values

Parameter	Description	Value
α_g	Machine share in clean energy	0.941
f_e	Fixed cost of entry	0.538
f_p	Fixed cost of operation	0.020
δ	Exogenous rate of destruction	0.085
γ	Scientist efficiency	7.642

Table 2 summarizes our parameter estimates. The calibrated α_g is 0.94, which is consistent with green energy technologies such as nuclear and solar, being highly capital intensive. The model predicts a sizable fixed-cost advantage for operating firms: their fixed cost of operation is around 4 percent of the entrants' fixed cost. The exogenous rate of destruction is calibrated to approximately 1.7 percent per year (8.5 percent over a five-year period). The scientist efficiency parameter $\gamma = 7.64$ matches the targeted 2 percent long-run annual growth rate.

Table 3 reports the values of the moments used for calibration, which match the data very closely. While all parameters are calibrated jointly by the targeted moments, the average elasticity of substitution and the size of the industry pin down primarily the internal parameters associated with the industry, f_e, f_p, and δ. For instance, a higher rate of exogenous destruction δ requires the probability of successful entry to be also higher, which lowers the cutoff level of elasticity of substitution and consequently its average.[14] The market size of the clean relative to dirty energy sector and the research expenditure moment pin down the labor share in clean energy parameter $1 - \alpha_g$. All else equal, a higher market size of clean relative to dirty energy is associated with a higher labor share in clean energy. It also raises the share of R&D in clean technologies by raising the profitability in innovation in that sector.

[14]This is because in a stationary equilibrium, the additional value from successful entrants must exactly replace the change in the value of incumbents due to the exogenous destruction and growth (see (15)).

Table 3: Targeted Moments of Model and Data

Moments	Model	Data
Average elasticity of substitution	2.977	2.977
Industry size	0.887	0.887
Market size of clean relative to dirty	5.293	5.293
Share of R&D in green	0.871	0.871

4.4 Goodness of fit

We evaluate the performance of our model by looking at several non-targeted moments, namely, firm entry and the labor cost share in the industry as well as the clean-to-dirty capital ratio in the energy sector. Firm entry is measured through employment shares using the microdata from FARE, restricting the sample to manufacturing industries covered in EACEI. The data on labor cost shares in manufacturing come from Eurostat (2022b). The amount of capital in the clean relative to dirty energy sector is measured by the ratio of gross investment in tangible goods in electric power generation, transmission and distribution to the same measure in mining and quarrying (Eurostat, 2022b).

Table 4: Non-targeted Moments of Model and Data

Moments	Model	Data
Entrant share	0.059	0.063
Labor cost share in industry	0.187	0.161
Capital in clean relative to dirty	37.8	26.4

Table 4 shows that the values of these non-targeted moments are comparable across the model and the data, suggesting that the model's fit is reasonably strong. The share of entrants and the labor cost share in manufacturing are very similar across the model and the data. The relative amount of capital in the clean energy sector implied by our model is higher than the corresponding empirical moment. It is mostly driven by the machine share parameter in the clean sector α_g calibrated to a very high number (0.94 in Table 2) to fit the French context where the clean sector is much larger in terms of its market share as well as innovation activities compared to the dirty sector.

Additionally, we calculate the standard errors of the calibrated parameters by bootstrap. Doing so requires computing the standard errors of the data moments. The standard error of the first moment in Table 3 is available from the regression (Table A5). For the last three moments, we compute their standard errors from the annual data series (when the moments themselves are the averages of the series). Then, we resample the empirical moments 500 times with each iteration being its original moment plus a random error drawn from a normal distribution with mean zero and standard deviation equal to the standard errors computed from the data. Finally, we calibrate the model parameters by targeting these randomly generated empirical moments and derive their standard errors from their distribution across these 500 calibrations. The standard errors reported in Table A6 imply a reasonable degree of precision for all the parameter estimates.

5 Results

5.1 Carbon tax and industry dynamics

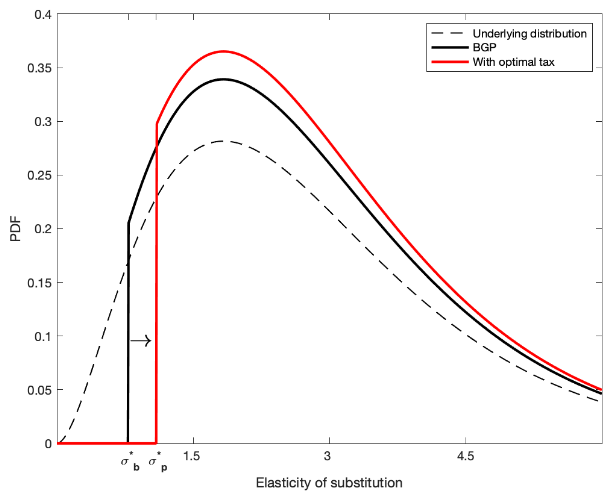
We compute a set of counterfactual stationary equilibria to understand and quantify the effects of dynamic industry response to climate policy. First, we consider two economies that begin on the same baseline balanced growth path, but in one model, which we refer to as the endogenous model, the cutoff level of elasticity of substitution changes in response to climate policy, thus affecting firms' entry and exit decisions and the average energy substitution capability among active firms as described in our theoretical model. In the other model, which we refer to as the exogenous model, this channel is shut off. Thus, the cutoff as well as the average elasticity of substitution is fixed at the baseline level.

Our goal is to compare the size of the carbon tax that achieves carbon neutrality in the new long-run equilibrium across these two economies, in line with France's long-term climate policy of reaching net zero emissions.[15] It translates to a 76.5 percent reduction in emissions from the baseline growth path, which we take to be 2015 in our model.[16]

[15]Conforming to the European Green Deal in the European Union approved in 2020, France aims to achieve carbon neutrality by 2050 which we consider sufficiently long-run, corresponding to our new long-run equilibria.

[16]Achieving carbon neutrality entails a reduction in emissions at least by 80 percent compared to 1990 level in addition to large investments in carbon sinks and the utilization of carbon capture and

Figure 3: The Impact of the Optimal Carbon Tax on the Distribution of the Substitution Elasticity among Active Firms



We find that the carbon tax required to achieve the policy goal is 214 and 138 euros per tCO_2 (in 2015 euros) in the exogenous and endogenous model, respectively.[17] The optimal tax in the endogenous model is 35 percent lower compared to the one in the exogenous model. The difference is driven by the change in the equilibrium distribution of elasticity of substitution induced by industry dynamics. In the endogenous model, firms with limited substitution capability that cannot easily switch to the relatively cheaper clean energy experience an increase in operating costs, hence a decrease in profits. Some of these firms (close to the cutoff elasticity of substitution) are forced to exit the market when they can no longer cover the fixed cost of operation. Figure 3 graphically shows the impact of the carbon tax on the equilibrium distribution of the substitution parameters across active firms in the endogenous model. When the tax is implemented, the cutoff level of elasticity of substitution σ^* is pushed to the right and firms with the level of substitution capability between σ_b^* and σ_p^* are forced to exit the market in the new equilibrium. Consequently, the average elasticity of substitution among active firms is higher in the long run as a result of the climate policy.

The higher elasticity of substitution in the industry where demand for energy inputs are determined increases the effectiveness of the carbon tax by shifting the demand for

storage (Eurostat, 2022a). Since France has already reduced their emissions by 15 percent by 2015, achieving the target mitigation rate of 80 percent requires a further 76.5 percent reduction in emissions from the 2015 level.

[17] For reference, the effective carbon price in 2021 was 93 euros per tCO_2 in France (OECD, 2021a).

clean energy by a larger margin in response to the same size of the tax. This in turn lowers the required tax to achieve the same emissions reduction target in the endogenous model, compared to the exogenous model. In addition, the larger shifts in demand lead to stronger incentives to innovate in the clean sector where the demand is now higher. Over time, more innovation in the clean sector reduces the relative price of clean energy, which induces further shifts in demand towards clean energy among industrial firms.

The higher effectiveness of the carbon tax in the endogenous model can also be demonstrated by applying the optimal tax from the endogenous model (138 euros per tCO_2) to the exogenous model. We find that the same tax leads to a 10 percentage points lower reduction in emissions when the channel of endogenous industry dynamics is shut off (66 percent reduction compared to the 76 percent reduction in the endogenous model). This exercise illustrates that failing to account for dynamic industry response to climate policy and the subsequent change in the economy-wide capability of energy substitution can lead to a substantial overestimation of the optimal carbon tax.

Next, to compare welfare in the two economies, we compute consumption-equivalent changes in welfare by considering the fraction of baseline consumption that will ensure the same level of consumption in the new equilibria as in the baseline. The gross welfare costs of climate policy are 7 percentage points lower when dynamic industry response is taken into account.[18]

Table 5 provides more details on the mechanisms behind the effect of endogenous industry dynamics. Panel A reports the equilibrium objects related to the industrial part of the economy. As explained before, the cutoff level of elasticity of substitution σ^* increases from 0.79 in the baseline to 1.1 in the endogenous model (39 percent increase), pushing up the average elasticity of substitution among active firms $\bar{\sigma}$ by approximately 5 percent. The implication of this can be seen in the mass of active firms M in the manufacturing industry. While there is a slight increase in the number of active firms in the exogenous model, there are 3.4 percent fewer firms in the new equilibrium of the endogenous model due to the exit of least flexible firms.[19]

[18] In our quantitative analysis, we generally observe a reduction in welfare with policy interventions. This is largely because our model does not incorporate the impact of lower emissions and a higher environmental quality on welfare. Other studies that integrate the environmental quality in the economy with climate policy often find that reductions in welfare are lower or potentially positive when the positive impact of the improved environmental quality on welfare is taken into account (e.g., Bretschger, 2021).

[19] The change in the number of active firms in the exogenous model results from the changing average price that intermediate goods producers charge, which goes up in response to the carbon tax. The

Table 5: The Impact of the Optimal Carbon Tax

		Percentage difference from baseline	
	Baseline model	Endogenous model	Exogenous model
Panel A. Industry			
σ^*	0.79	39.1	0.0
$\bar{\sigma}$	2.98	4.8	0.0
M	16.05	-3.4	1.0
Panel B. Energy sector			
L_g/L_f	5.29	188.3	173.0
q_g/q_f	10.05	260.3	237.2
S_g/S	0.87	9.2	8.9
Emissions	-	-76.5	-76.5
Carbon tax	-	138.1	213.9
Welfare cost	-	13.0	20.1

Notes: The baseline model is the balanced growth path with no carbon tax. The percentage differences compare equilibrium objects in the endogenous and exogenous model that achieve the same emissions reduction target.

The equilibrium objects relevant for the energy sector in Panel B show that the production and innovation response is generally stronger in the endogenous model compared to the exogenous model. For example, the relative market size (measured in labor) of clean energy (L_g/L_f) increases by 15 percentage points more in the endogenous model than in the exogenous model. The driver behind the difference is partly the low-skilled labor (previously employed to cover the fixed cost of operation) released from the manufacturing industry with the exit of firms with limited capability to substitute clean for dirty energy, which is now going into the clean energy sector where the demand is higher. This finding is in line with empirical evidence on the reallocation of labor (Walker, 2011) or creation of green jobs in response to environmental regulation (Vona et al., 2018; Popp et al., 2020).

Furthermore, the economy in the endogenous model features the relative technology in the clean sector (q_g/q_f) and the share of scientists working in clean technologies

increase in the average price of intermediate goods is associated with an increase in the mass of active firms due to the normalization of the final good's price. See (A.4) in Appendix A3.

(S_g/S) that are 23 and 0.3 percentage points higher in the new growth path, respectively, compared to the economy in the exogenous model. This stronger innovation response in the endogenous model is induced by larger demand shifts toward clean energy in the industry facilitated by the higher average elasticity of substitution in the new stationary equilibrium.

5.2 Sensitivity analysis

We examine the robustness of our results to four parameters $\{a, b, \theta, \eta\}$ that are neither internally calibrated by method of moments nor directly come from the data series. To begin, the parameters a and b form the underlying exogenous distribution $\phi(\sigma)$ and are set to 2.84 and 1, respectively, in the baseline calibration so that the mean of the distribution (computed as ab in the gamma distribution) matches the empirical target of 2.84. Alternatively, we try two other combinations of a and b that preserve the same mean as in the baseline but are associated with the standard deviation (SD) that is larger and smaller than the baseline level.[20] Economically, a larger SD in the distribution $\phi(\sigma)$ indicates a larger degree of firm heterogeneity, while a smaller SD implies a weaker degree of heterogeneity in the energy substitution capability across firms. Further, we try values of θ and η that are 15 percent smaller and larger than their baseline values. A smaller (larger) θ implies weaker (stronger) cross-sector spillovers in innovation, while a smaller (larger) η implies lower (higher) efficiency in innovation. For each set of alternative parameterization (6 in total, two sets of a and b, two values for θ and η each), we recalibrate the model to match model moments with their empirical targets as close as possible.

Table A7 reports results from the sensitivity analysis. We note that our main results are relatively sensitive to the parameterization of the exogenous distribution $\phi(\sigma)$. The difference between the required tax in the endogenous and exogenous model is smaller when firm heterogeneity is more pronounced, the difference being 26 percent compared to 35 percent in the baseline. This results from the larger required carbon tax to achieve the same goal of carbon neutrality in the endogenous model (larger by 13 percent compared to 138 euros per tCO_2 in the baseline). Intuitively, the cutoff level of elasticity of substitution has to increase by a larger magnitude when firms

[20]Specifically, the two sets are $a = 2.84/2, b = 1*2$ and $a = 2.84*2, b = 1/2$. The standard deviation (SD) of the first and second alternative set are 2.38 and 1.19, respectively, each larger and smaller than the SD of 1.68 in the baseline model. See Figure A1 for illustration.

are more spread out across the distribution in order to reduce emissions by the same amount, which is accomplished by a larger carbon tax. The larger carbon tax in the endogenous model reduces the difference in the optimal tax between the two economies. Weaker firm heterogeneity has the opposite impact: the difference in the required tax between the endogenous and exogenous model is now slightly larger (37.5 percent). When firms are more similar to one another with respect to their energy substitution capability, a slight increase in the cutoff elasticity of substitution is enough to induce a sizeable exit of inflexible firms. The average elasticity of substitution among surviving firms is therefore more responsive to the same amount of the carbon tax, increasing its effectiveness on reducing emissions in the endogenous model compared to the exogenous model.

The results are not sensitive to the values of the other two parameters. Generally speaking, weaker (stronger) cross-sector spillovers and higher (lower) innovation efficiency strengthen (weaken) the innovation response in the energy sector in response to climate policy. However, the difference in the required tax between the endogenous and exogenous model is very similar to the baseline.

5.3 Subsidy to clean research and industry dynamics

In this section, we compare the implications of different policy instruments, namely, a carbon tax and a subsidy to clean innovation, in the presence of endogenous industry dynamics. To do so, we compute the size of a research subsidy required to achieve the same policy goal as before in the new long-run equilibrium and compare the implications of key equilibrium objects associated with the two policy instruments.

We find that optimal research subsidy that achieves carbon neutrality in the new long-run equilibrium is very large, 73 percent. As a result, the gross welfare cost is higher (or welfare is lower) by 0.7 percentage points in the economy with the subsidy compared to the economy with the carbon tax.

Research subsidies as a single policy being more costly than a carbon tax is consistent with findings in prior studies (e.g., Fischer and Newell, 2008). Given that all policy instruments operate through price incentives that shift demand toward clean energy, this is primarily due to subsidies providing only indirect price incentives by advancing clean technologies which lower the price of the clean input over time, rather than directly affecting final energy prices as in the case of a carbon tax. Another factor contributing to the difference in our context is cross-sector spillovers in innovation.

Table 6: Comparison of Tax and Subsidy

	Baseline	Percentage difference from baseline: Tax	Subsidy
Panel A. Industry			
σ^*	0.79	39.1	39.1
$\bar{\sigma}$	2.98	4.8	4.8
M	16.05	-3.4	-3.6
Panel B. Energy sector			
L_g/L_f	5.29	188.3	111.8
q_g/q_f	10.05	260.3	1,087.3
S_g/S	0.87	9.2	12.7
Emissions	-	-76.5	-76.5
Welfare cost		13.0	13.7

Notes: The baseline is the balanced growth path with no policy intervention. The percentage differences compare equilibrium objects in the economy with the carbon tax and those in the economy with the subsidy to clean innovation. The level of each policy is computed to achieve the same emissions reduction target.

This makes the effect of directed technical change weaker as research directed to clean technologies also benefits dirty technologies through spillovers, dampening the price effect induced by the increasing productivity in the clean relative to dirty sector.

Table 6 reports equilibrium objects associated with the two different policy instruments that achieve the same emissions reduction target in the long run. The baseline and tax outcomes are identical to the values in Table 5, but reproduced for convenience. Panel A shows that the two policies lead to changes of similar magnitudes in the equilibrium objects relevant for the industry. The average elasticity of substitution goes up by 4.8 percent in response to the tax and the research subsidy. The difference is more pronounced in Panel B with equilibrium objects relevant for the energy sector. We find that, without direct price incentives, clean technologies in the economy with the research subsidy have to expand by four times as much in order to achieve the same policy target, compared to the economy with the carbon tax. This drives up the amount of the subsidy required to meet the target, making it more costly than the carbon tax in terms of associated gross welfare costs.

Yet, we note that endogenous industry dynamics still plays a role. Turning back to the exogenous model, the difference in the welfare costs between a carbon tax and a research subsidy is more than twice as large (1.6 percentage points as opposed to 0.7 percentage points in the endogenous model) when the channel of industry dynamics is shut off (Table A8). Intuitively, indirect price incentives generated by subsidies to clean innovation lead to larger demand shifts toward clean energy in the endogenous model where the average elasticity of substitution goes up in response to climate policy. It makes the the research subsidy less ineffective in the endogenous model, resulting in a smaller difference in the welfare costs (although it is still more costly than the tax) compared to the difference in the exogenous model.

5.4 Optimal combination of different policy tools

Prior studies have shown that a combination of policies generally outperforms single policies (Goulder and Parry, 2008). Thus, in this section we use our model to characterize an optimal combination of a carbon tax and a research subsidy that achieves the policy goal with the minimum welfare costs. To do so, we compute the size of the subsidy required to achieve carbon neutrality in the new equilibrium for different levels of the carbon tax ranging between the current carbon tax in France (93 euros per tCO_2) and the required tax to achieve the policy goal in our model as a single policy (138 euros per tCO_2) and compare associated welfare costs.

Panel A of Table 7 shows that the combination of policies that achieves the policy target with the minimum welfare costs involves a carbon tax of 114 euros per ton of CO_2 and a 23 percent subsidy for research in clean technologies. Compared to the single policy scenarios, the tax and the subsidy are lower by 18 and 68 percent, respectively. Relative to the tax-only scenario, we find that the combined policies improve welfare slightly by 0.07 percent in our model, which is consistent with the finding in Acemoglu et al. (2012) that welfare costs can be lowered by combining a carbon tax with a research subsidy rather than relying solely on a carbon tax.

Relative to the subsidy-only scenario, welfare improves by 0.9 percent with the combined policies. The larger welfare gain compared to moving from the tax-only scenario to the combined policies (0.07 percent) is explained by equilibrium objects in Table A9 which shows that the combination of policies achieves the emissions reduction target without expanding clean technologies as much as the subsidy-only case requires, growing 3.6 times larger in the new equilibrium as opposed to 10 times larger in the subsidy-only equilibrium (Table 6).

Table 7: Welfare Comparison between Single and Combination of Policies

	Single policy		Combination policy
	Tax	Subsidy	
Panel A. Endogenous model			
Tax	138.1	-	113.8
Subsidy	-	0.726	0.23
Welfare cost	13.0	13.7	12.9
Panel B. Exogenous model			
Tax	213.9	-	190.7
Subsidy	-	0.853	0.23
Welfare cost	20.1	21.7	20.0

Notes: The table compares policy outcomes in models that use either a carbon tax or a research subsidy as a single policy and in a model that applies a combination of the two policies. Welfare costs show percentage reductions in consumption relative to baseline welfare on the baseline balanced growth path without any policy intervention.

In Panel B, we find that the combined policies outperform single policies even when the channel of industry dynamics is shut off. With the tax and the subsidy lower by 11 and 73 percent compared to the respective single-policy scenarios, welfare improves by 0.07 percent compared to the tax-only scenario, which is similar to the observation from the endogenous model. Compared to the subsidy-only scenario, however, the welfare gain from applying the combination of policies is much larger in the exogenous model than in our endogenous model (2 percent increase compared 0.9 percent increase in the endogenous model). This is again because the subsidy is more ineffective in the exogenous model that does not take into account dynamic industry response than it is in the endogenous model, as discussed in the previous section. Hence, reducing the amount of the subsidy leads to larger welfare gains in the exogenous model where the subsidy tends to be more ineffective.

6 Conclusion

In this paper we build a microfounded model of directed technical change with heterogeneous firms. The rich features of the model including heterogeneity across firms in their capabilities to substitute clean for dirty energy and endogenous exit and entry allow us to fully explore the interaction between climate policy, industry dynamics and the average elasticity of substitution. These features of our model are also empirically motivated from microdata. For our quantitative analysis, we calibrate the parameters of our model from micro and macro data through method of moments. Our model fits the key targeted moments well and also performs well on nontargeted moments.

We use the model to examine and quantify the effects of endogenous industry dynamics on the effectiveness and operation of different policy instruments. We find that accounting for dynamic industry response to climate policy is crucial in the analyses of optimal climate policy: failing to take into account industry dynamics can lead to an overestimation of the optimal carbon tax by 35 percent. Our model also reveals that climate policy can free up resources (labor) from the least flexible firms that exit the market as a consequence of climate policy, which is then reallocated to the clean energy sector. Further, we find that a subsidy to clean innovation, which is generally more costly than a carbon tax, is also more cost effective when industry dynamics is taken into account.

Several follow-up research questions are left for future research. First, our analysis can be made richer by allowing the firms to invest in improving their capability to substitute clean for dirty energy over time. Currently, there is no mechanism for investment within industrial firms, which leads to their immediate exit when they can no longer cover the fixed cost of operation. Moreover, exploring the determinants of the elasticity of substitution at the firm level would also be informative. In our model, firms randomly draw their level of elasticity of substitution from an exogenous distribution, as in Melitz (2003) where firms randomly draw their productivity levels. However, some knowledge in the determinants of firms' capability of energy substitution at the firm level will be useful in providing firms with the right incentives that could lead to an optimal level of substitution capability.

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Appendix

A1 Descriptive statistics and more empirical results

Table A1: Quantile regression: Elasticity of substitution between clean and dirty energy

Quantiles	0.1	0.25	0.5	0.75	0.9
$\hat{\sigma}$	1.841***	1.950***	1.870***	1.651***	1.369***
	(0.024)	(0.017)	(0.014)	(0.014)	(0.015)
Observations	65,884	65,884	65,884	65,884	65,884

Notes: OLS estimates from quantile regression of equation (1). Each column reports estimates for the quantile specified in the first row of the table. All regressions include sector, region, year fixed effects. Standard errors are clustered at the firm level.

Table A2: Descriptive statistics: EACEI and FARE

	Rates of Growth						
	E_C/E_D	P_C/P_D	E_C/E	E_D/E	P_C	P_D	Rev/E
Industry	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Steel	-0.017	-0.035	0.013	-0.008	-0.000	0.032	0.083
Metals	-0.017	-0.028	0.011	-0.010	0.000	0.030	0.021
Minerals	-0.037	-0.028	-0.007	0.004	0.010	0.040	0.076
Plaster, lime, cement	0.072	-0.038	0.050	-0.033	0.009	0.050	0.079
Ceramic	0.041	-0.030	0.016	-0.010	0.004	0.035	0.043
Glass	0.051	-0.031	0.018	-0.020	-0.000	0.032	0.041
Fertilizer	0.017	-0.041	0.009	-0.005	-0.003	0.038	0.061
Other chemicals	0.114	-0.028	0.031	-0.021	0.009	0.040	0.040
Plastic, rubber	-0.117	-0.034	0.007	-0.009	-0.001	0.034	-0.019
Pharmaceutical	0.013	-0.028	0.011	-0.010	0.002	0.032	-0.013
Steel processing	0.024	-0.026	0.010	-0.010	-0.001	0.027	0.032
Machinery	0.039	-0.029	0.012	-0.012	-0.004	0.029	0.017
Electronics	0.035	-0.028	0.005	-0.006	0.001	0.032	0.009
Transport equipment	0.044	-0.027	0.009	-0.009	-0.003	0.026	0.027
Shipbuilding	0.060	-0.035	0.012	-0.014	-0.010	0.029	0.034
Textile	0.017	-0.030	0.009	-0.007	0.001	0.040	0.031
Paper	0.045	-0.030	0.011	-0.010	-0.001	0.030	0.006
Rubber products	-0.100	-0.030	0.003	-0.004	0.000	0.031	0.024
Plastic products	0.067	-0.027	0.002	-0.004	0.002	0.030	0.032

Notes: Calculated for 1995-2015. Rev/E in column (7) denotes energy intensity measured by revenue per unit energy consumption (in kTOE).

Table A3: Data Sources for Macro Moments

Description	Source
Labor cost share	Eurostat
Scientists per 1000 workers	OECD
Employment in manufactoring and energy	ISOSTAT
Employment in clean and dirty sector	Structural Business Survey
Fuel specific R&D expenditure	IEA
Investment in clean and dirty sector	Eurostat

Notes: Labor cost share and investment in the clean and dirty sector are available for 2009-2015. Employment in manufacturing and energy is available for 2010-2020. Employment in clean and dirty sector is available for 1996-2008. Scientists per 1000 workers and fuel specific R&D expenditure is available for 1995-2015.

A2 Proofs

Proof of Lemma 1: The proof follows de La Grandville and Solow in de La Grandville (2017, p.111). One can show that

$$\text{sign}\left\{\frac{\partial \log c(\sigma)}{\partial \sigma}\right\} =$$
$$\text{sign}\left\{H\left(\kappa_0\left(\frac{p_g}{p_{g0}}\right)^{1-\sigma} + (1-\kappa_0)\left(\frac{p_b+\tau}{p_{b0}}\right)^{1-\sigma}\right) - \kappa_0 H\left(\left(\frac{p_g}{p_{g0}}\right)^{1-\sigma}\right) - (1-\kappa_0)H\left(\left(\frac{p_b+\tau}{p_{b0}}\right)^{1-\sigma}\right)\right\}$$

with $H(z) \equiv z \log z$ being a convex function. The negative sign of $\frac{\partial \log c(\sigma)}{\partial \sigma}$ follows from the definition of convexity. □

Proof of Proposition 1: First note that $J(.)$ is monotonically decreasing with $\frac{dJ(\sigma^*)}{d\sigma^*} < 0$ and $\lim_{\sigma^* \to \infty} \frac{dJ(\sigma^*)}{d\sigma^*} = 0$, given $\epsilon > 1$ and lemma 1. Moreover, $\frac{dJ(\sigma^*)}{d\tau} > 0$ for $\epsilon > 1$ since $\frac{dc(\sigma)}{d\tau} < \frac{dc(\sigma^*)}{d\tau}$ for $\sigma > \sigma^*$ according to lemma 1. Then, $\frac{d\sigma^*}{d\tau} \geq 0$ follows from (13) and the monotonicity of $J(.)$. □

A3 Characterization of the equilibrium

Industry aggregates Once σ^* is determined by (13), we can characterize the distribution of all firm performance measures such as sales, revenue and profit. Let M denote the mass of active firms in the industrial segment of the economy. The aggregate revenue, profit and market value are, respectively:

$$R_I = Y = \left(\int_{\sigma^*}^{\infty} y(\sigma)^{\frac{\epsilon-1}{\epsilon}} M\psi(\sigma)d\sigma \right)^{\frac{\epsilon}{\epsilon-1}} = M^{\frac{\epsilon}{\epsilon-1}} \bar{y}, \tag{A.1}$$

$$\Pi_I = \int_{\sigma^*}^{\infty} \pi(\sigma) M\psi(\sigma)d\sigma = M\bar{\pi}, \tag{A.2}$$

$$V_I = M\bar{v}, \tag{A.3}$$

with average profit $\bar{\pi}$ and firm market value $\bar{v}$ defined before. In equation (A.1), $\bar{y} \equiv \left(\int_{\sigma^*}^{\infty} y(\sigma)^{\frac{\epsilon-1}{\epsilon}} \psi(\sigma)d\sigma \right)^{\frac{\epsilon}{\epsilon-1}}$ is the average firm output and $M^{\frac{\epsilon}{\epsilon-1}}$ measures gains from specialisation in the use of intermediates, a common feature in the endogenous growth literature (Romer, 1990; Grossman and Helpman, 1991). The aggregate price index P (set to unity) is given by:

$$P \equiv 1 = \left(\int_{\sigma^*}^{\infty} p(\sigma)^{1-\epsilon} M\psi(\sigma)d\sigma \right)^{\frac{1}{1-\epsilon}} = M^{\frac{1}{1-\epsilon}} \bar{p} \implies \bar{p} = M^{\frac{1}{\epsilon-1}}, \tag{A.4}$$

where $\bar{p} = \left(\int_{\sigma^*}^{\infty} p(\sigma)^{1-\epsilon} \psi(\sigma)d\sigma \right)^{\frac{1}{1-\epsilon}}$. In turn, with (4), (A.4), the aggregate variable cost of production is:

$$K = \int_{\sigma^*}^{\infty} c(\sigma) y(\sigma) M\psi(\sigma)d\sigma = \frac{\epsilon - 1}{\epsilon} Y. \tag{A.5}$$

The industry's balance equates profits with revenues minus variable and overhead costs:

$$\Pi_I = Y - K - w_{li} L_p. \tag{A.6}$$

Also from (12) and (15), we derive $\Pi_I = w_{li} L_e$. This implies that the aggregate profits from active firms in (A.6) exactly cover the aggregate entry costs incurred by entrants. Combining the two expressions, we derive the total total unskilled labor employed in the industrial segment of the economy:

$$L_I = \frac{Y/\epsilon}{w_{li}}. \tag{A.7}$$

From (8), (A.6), (A.7), and (12), the mass of active industrial firms is written as:

$$M = \frac{L_I}{\frac{\omega}{1-\Phi(\sigma^*)} f_e + f_p}. \tag{A.8}$$

Input producers' optimization problem The energy input producer chooses labor and machines to maximize profits taking prices as given:

$$\max_{L_{ki}, x_{ki}} p_k L_{ki}^{1-\alpha_k} \int_0^1 x_{ki}^{\alpha_k} q_{ki}^{1-\alpha_k} di - w_{lk} L_{ki} - \int_0^1 p_{ki}^x x_{ki} di. \tag{A.9}$$

where p_k is the market price of energy input k and p_{ki}^x is the price of machine i in sector $k \in \{g, b\}$. The demand for machines is then:

$$x_{ki} = \left(\alpha_k \frac{p_k}{p_k^x}\right)^{\frac{1}{1-\alpha_k}} L_k q_{ki} \tag{A.10}$$

where $1/(1-\alpha_k)$ captures the price elasticity of demand for machines. This implies that the equilibrium production level of each energy input is written as:

$$\begin{aligned} G &= \left(\alpha_g \frac{p_g}{p_g^x}\right)^{\frac{\alpha_g}{1-\alpha_g}} L_g q_g, \\ B &= \left(\alpha_b \frac{p_b}{p_b^x}\right)^{\frac{\alpha_b}{1-\alpha_b}} L_b q_b. \end{aligned} \tag{A.11}$$

Finally, the inverse demand function for low-skilled labor reads:

$$w_{lk} = (1-\alpha_k)\left(\frac{\alpha_k}{p_k^x}\right)^{\frac{\alpha_k}{1-\alpha_k}} (p_k)^{\frac{1}{1-\alpha_k}} q_k, \qquad k \in \{g, b\}, \tag{A.12}$$

The two expressions above, (A.11) and (A.12), suggest that on the balanced growth path (BGP), G and B as well as the wage rate w_{lk} will grow with the aggregate technology Q (since q_g and q_b, and subsequently Q, grow at the same constant rate g on BGP). Note also the wage for low-skilled labor w_{lk} is the same as the wage in the industrial sector of the economy in equilibrium.

Machine producers' optimization problem The machine producers produce machines to sell to the energy input producers. As mentioned in the main text, each machine costs one unit of the final good to produce. Each machin producer chooses price, quantity of machines, and the number of scientists to maximize profits. The optimization problem is given by:

$$\max_{p^x_{ki}, x_{ki}, s_{ki}} p^x_{ki} x_{ki} - x_{ki} - w_s s_{ki} \tag{A.13}$$

which is subject to the evolution of technology (17) and the demand for machines (A.10). The optimization of the machine producer in the clean energy sector yields:

$$w_{sg} = \eta\gamma\alpha_g(1-\alpha_g) s_{git}^{\eta-1} \left(\frac{Q_{t-1}}{q_{gt-1}}\right)^{\theta} \left(\frac{q_{gt}}{q_{git}}\right)^{\alpha_g} \frac{q_{gt-1}}{q_{gt}} p_g G, \tag{A.14}$$

$$x_{gi} = \left(\alpha_g^2 p_g\right)^{\frac{1}{1-\alpha_g}} L_g q_{gi}, \tag{A.15}$$

where for (A.14) we employed (A.11). The optimization problem of the machine producer in the dirty sector is similar. With the usual assumption of symmetry across firms, each firm in sector $k \in \{g, b\}$ has the same level of technology $q_{ki} = q_k$ (such that in (A.14) $q_k/q_{ki} = 1$), sales $x_{ki} = X_k$, profits $\pi_{ki} = \Pi_k$, and scientific labor $s_{ki} = S_k$.

Equation (A.14) sets the marginal cost of scientific labor equal to its marginal benefit in innovation. Note that in equilibrium, $w_{sg} = w_{sb}$ holds, implying a no-arbitrage condition for active research in both sectors. Equation (A.15) combined with the inverse demand function for machines gives $p^x_k = 1/\alpha_k$.

A4 Calibration of the exogenous distribution $\phi(\sigma)$

In our model, firms draw their substitution elasticity parameter σ from a common distribution $\phi(\sigma)$ with a positive support $(0, \infty)$. We assume $\phi(\sigma)$ follows the gamma distribution which is also defined on a positive support $(0, \infty)$ and has two parameters: shape parameter a and scale parameter b. Since firms with a bad draw of σ immediately exit the market without producing, they are not observed in the data. Thus, the average elasticity of substitution estimated from the sample of active firms by using (1) is likely to be larger than the average substitution elasticity of the underlying distribution, or in other words, the observed sample of firms contains positive sample selection bias.

Formulating the problem at hand as a sample selection problem (also known as incidental truncation), we apply the popular Heckman's two-step procedure to correct

Table A4: Probit estimation: Exit and survival probability

	(1) Exit	(2) Exit	(3) Survival
$\log \frac{p_{git}}{p_{bit}}$	0.108***	0.002	-0.002
	(0.024)	(0.033)	(0.033)
Age	-0.003***	-0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Energy intensity	0.026***	0.015	-0.015
	(0.008)	(0.009)	(0.009)
Industry FE		✓	✓
Region FE		✓	✓
Year FE		✓	✓
Observations	55,228	55,228	55,228

Notes: Probit estimation results. The dependent variables are written below the column number.

for the selection bias and recover the average elasticity of the underlying distribution. The first step is to estimate the selection equation by Probit. Although we do not observe potential entrants that fail to enter the market due to their bad draws of σ, it is possible to identify firms that exit in the next period in our data. In light of our model, we view these firms as exiting due to their low elasticities of substitution. We first explore whether this view is reasonable. Table A4 reports the Probit estimates of the exit probability predicted by the log price ratio, the main explanatory variable in (1), as well as other variables that may affect exit probabilities but do not enter (1). Variables have expected signs. In column (1), we find that a higher unit price of clean energy relative to dirty energy is associated with a higher probability of exit. This is consistent with our model that dirtier firms that generally pay a higher unit price of clean energy due to lower quantity discounts are more likely to exit the market. Age is negatively correlated with exit probability, implying that younger firms are more likely to exit than older, established firms. Finally, energy intensity measured by energy consumption per employee is positively correlated with exit probability.

Since firms observed in the data are surviving firms, we use the estimation in column (3) where the dependent variable is transformed as survival (1- exit) in order to construct the Inverse Mill's Ratio (IMR) term that corrects for the selection bias.

Table A5: The average elasticity of substitution between clean and dirty energy

	(1) $\ln(b_{jt}/g_{jt})$	(2) $\ln(b_{jt}/g_{jt})$
$\log \frac{p_{git}}{p_{bit}}$	2.977***	2.835***
	(0.137)	(0.130)
IMR		-1.753
		(1.082)
Industry FE	✓	✓
Region FE	✓	✓
Year FE	✓	✓
Observations	65,884	53,765

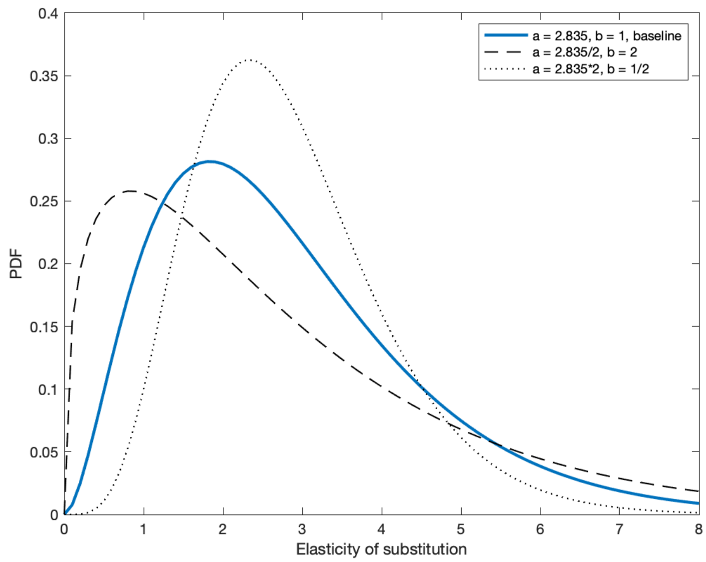
Notes: IV estimates using instruments developed in Section 2. Standard errors are clustered at the firm level.

Then, we estimate equation (1) using the same instruments developed in Section 2 with the IMR term as an additional control. Importantly, we treat firms that would exit in the next period as having exited in the current period already and hence treat their information on energy consumption and prices as missing (or truncated), estimating the second step only on the set of firms that continue to survive in the market.[21] The average elasticity of substitution with and without correcting for the selection bias are presented in Table A5. As expected, the estimate in column (2) with the IMR term is smaller than the estimate in column (1) that does not account for the positive selection.

In the baseline calibration, we set a to 2.84 and b to 1 so that the resulting average of the exogenous distribution is equal to the estimate in column (2). We try other combinations of a and b that keep the average of the distribution constant but differ in the associated variance of the distribution in the sensitivity analysis: for example, $a = 2.84/2$ and $b = 2$ and $a = 2.84 * 2$ and $b = 1/2$. Figure A1 plots these distributions.

[21] An typical example of the Heckman's two step procedure in labor economics is to estimate Probit in the first step to predict the probability of labor market participation on a sample of individuals and estimate the effect of some explanatory variables of interest (e.g., education, experience) on income in the second step on the sample of those who do participate in the market and whose income is observed in the data. See Greene (2008) for details.

Figure A1: Exogenous distributions of $\phi(\sigma)$



Note: Gamma distributions with different shape (a) and scale (b) parameters that have the same average but different standard deviations.

A5 Additional results from quantitative analysis

Table A6: Mean and Bootstrap Standard Errors of the Internal Parameters

Parameter	Description	Mean (SE)
α_g	Machine share in clean energy	0.940
		(0.02)
f_e	Fixed cost of entry	0.517
		(0.25)
f_p	Fixed cost of operation	0.021
		(0.02)
δ	Exogenous rate of destruction	0.105
		(0.04)
γ	Scientist efficiency	7.941
		(0.136)

Table A7: Optimal Carbon Tax in 6 Sensitivity Analyses

	Optimal tax		
Variation	Endogenous model	Exogenous model	Difference in percentage
Stronger firm heterogeneity	155.8	210.5	-26.0
Weaker firm heterogeneity	100.0	160.0	-37.5
Larger θ	153.9	229.9	-33.1
Smaller θ	118.7	194.3	-38.9
Larger η	121.5	197.1	-38.3
Smaller η	156.3	232.4	-32.7
Baseline	138.1	213.8	-35.4

Table A8: Comparison of Tax and Subsidy in the Exogenous Model

		Percentage difference from baseline	
	Baseline	Tax	Subsidy
Panel A. Industry			
σ^*	0.79	0	0
$\bar{\sigma}$	2.98	0	0
M	16.05	0.9	0.6
Panel B. Energy sector			
L_g/L_f	5.29	173.0	72.0
q_g/q_f	10.05	237.2	1,858.9
S_g/S	0.87	8.9	13.4
Emissions	-	-76.5	-76.5
Policy	-	213.9	0.85
Welfare cost		20.1	21.7

Notes: The exercises are run in the exogenous model. The baseline is the balanced growth path with no policy intervention. The percentage differences compare equilibrium objects in the economy with the carbon tax and those in the economy with subsidies to clean innovation. The level of each policy is computed to achieve the same emissions reduction target.

Table A9: The Effect of Combined Policy Instruments

	Baseline model	Percentage difference from baseline: Endogenous model	Percentage difference from baseline: Exogenous model
Panel A. Industry			
σ^*	0.79	39.1	0.0
$\bar{\sigma}$	2.98	4.8	0.0
M	16.05	-3.5	1.0
Panel B. Energy sector			
L_g/L_f	5.29	171.4	157.0
q_g/q_f	10.05	359.1	330.0
S_g/S	0.87	10.2	10.0
Emissions	-	-76.5	-76.5
Welfare cost		12.9	20.0

Notes: The baseline is the balanced growth path with no policy intervention. The percentage differences compare equilibrium objects in the economy in the endogenous and exogenous models that apply a combination of policies associated with the minimum welfare costs.