Substitution between Clean and Dirty Energy with Directed Technical Change

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November 16, 2021

Abstract

Substitution between clean and dirty inputs and directed technical change lie at the center of leading economic analyses of environmental policy. Yet, empirical assessments of these two factors are scarce to date. This paper extends the empirical literature and jointly estimates the elasticity of substitution between clean and dirty energy and the direction of technical change. Using my estimates, I examine the historical increase in the relative share of clean energy in France, which suggests that changing factor prices were a relatively stronger driver than technical change in inducing energy transition.

Keywords: Directed technical change, energy transition, elasticity of substitution.
JEL Classification: Q40, Q55, O33.

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1 Introduction

The framework and insights of directed technical change have been widely applied in the leading economic analyses of optimal climate policy (Hémous and Olsen, 2021). For instance, a large number of studies have adopted the framework and investigated important outcomes such as induced innovation in green technologies for sustainable growth (e.g., Otto et al., 2007; Acemoglu et al., 2012; Fried, 2018), the relative efficacy of different policy instruments (e.g., Lemoine, 2017; Greaker et al., 2018; Hart, 2019), and the overall economic costs of climate change mitigation (e.g., Golosov et al., 2014; Baccianti, 2019).

As the primary driving force in the theory of directed technical change, the importance of the substitution elasticity is strongly emphasized in the literature. In the context of climate change, for example, Acemoglu et al. (2012) consider two inputs, clean and dirty, and demonstrate that if clean and dirty inputs are highly substitutable, a temporary carbon tax is sufficient to shift the direction of technical change towards clean technologies and avert an environmental disaster. On the other hand, the shift would occur much more slowly and require a permanent carbon tax, if the two inputs are less substitutable or complements. This illustrates that optimal climate policy may depend sensitively on the degree of the substitution elasticity and the direction and speed of technical change.

Yet, there exists a surprising lack of empirical knowledge in the substitutability between clean and dirty inputs and even less in the direction of technical change in the energy context.[1] A well-known study by Papageorgiou et al. (2017) estimates the substitution parameter from macro-level data, yet it abstracts away from direct assessments of the bias in technical change despite the theoretical interconnectedness of the two factors. In this paper, I extend the empirical literature and jointly estimate the elasticity of substitution between clean and dirty energy and the direction of technical change, thereby making a clear connection to the theoretical literature. Using the estimates, I then assess the relative strength of the two factors in inducing energy transition.

For the purpose, I use firm-level panel data from the French manufacturing sector with rich variation in energy use and expenditure by fuel across firms. Using the data, I first provide evidence for the presence of non-neutral efficiency differences across clean and dirty energy, which motivates investigating factor-specific technology in clean and dirty energy (therefore the direction or bias of technical change) rather than assuming neutral technology. This encourages the specification of a constant elasticity of substitution (CES) energy

[1] As a result, studies that involve numerical simulations or calibration in the related literatures therefore often choose values that are very different from one another. For instance, Otto et al. (2007) choose a value of 2 and Acemoglu et al. (2012) use 3 and 10 for the weak and strong substitutes scenario, respectively. On the other hand, Karydas and Zhang (2019) choose a conservative benchmark value of 0.7.

aggregate that combines clean and dirty energy with a separate technology parameter for each energy type, which allows flexibly investigating the direction of technical change.

Most existing studies estimating CES functions adopt one of the two approaches, namely, the estimation of the CES function itself or its first-order conditions (FOCs) from profit maximization. However, the estimation of the production function alone is generally only accomplished with restrictive assumptions on the nature of technical progress such as Hicks neutrality (Antras, 2004; León-Ledesma et al., 2010). Therefore, this approach is not suitable for the goal of this paper which is to estimate factor-specific technical progress as well as the elasticity of substitution. Similarly, the FOC approach does not allow flexibly estimating two separate technical parameters. The FOC with respect to one type of energy does not allow estimating the technical progress parameter of the other energy type.

To overcome these limitations, I employ the system of equations approach that combines the production function and FOCs, which offers clear advantages in the current setting. Most importantly, in contrast to the other two methods mentioned above, the system approach enables one to identify all parameters of interest: the elasticity of substitution as well as two separate technical progress parameters. Furthermore, the system exploits cross-equation restrictions that force the parameters to be the same across the two equations, which substantially improves the efficiency of estimation (Greene, 2000). Relatedly, Klump et al. (2007) and León-Ledesma et al. (2010) demonstrate that cross-equation restrictions imposed in the system approach lead to its superior performance compared to the single equation approaches (either the production function or FOCs), particularly in identifying the factor-specific technical progress parameters.

To address the endogeneity of firm-level energy prices and demands, I follow earlier studies and develop instruments based on national energy prices (Linn, 2008; Sato et al., 2019; Marin and Vona, 2019; Dussaux, 2020; Marin and Vona, 2021). To the best of my knowledge, this paper is the first to directly assess the bias in technical change in the energy context along with the elasticity of substitution and thus to empirically shed light on the workings of directed technical change at the firm level.

I find micro estimates of the long-run elasticity of substitution between clean and dirty energy sufficiently above one, a necessary condition that allows sustainable growth in many macroeconomic growth models, ranging between 2 and 5. More importantly, the estimated technical progress parameters provide clear evidence that technical change was biased toward dirty-energy-augmenting technology between 1995 and 2015. This observed dirty-energy-biased technical change is consistent with the framework of directed technical change. The theory suggests the path of innovation is influenced by two opposing forces: the *market size* effect that encourages innovation in technologies that use the cheaper and more abundant input and the *price* effect that spurs the development of technologies that favor the more expensive input. Which effect dominates the other is determined by the elasticity of substitution between the two inputs. When the inputs are gross substitutes, which is the case for clean and dirty energy as suggested by my estimates, it is predicted that the market size effect dominates the price effect (Acemoglu, 2002; Acemoglu et al., 2012). Given that dirty energy was considerably cheaper than clean energy throughout the sample period in France, the dirty-energy-biased technical change (or the market size effect dominating the price effect) observed in the data is in line with the prediction of the directed technical change framework.

However, I also find evidence that there was a shift in the direction of technical change. Despite the overall trend in technical change that favors dirty energy, examining variation over time shows that clean-energy-augmenting technology is growing faster than dirty-energy-augmenting technology in recent years. Several alternative estimation methods corroborate the shift. This observation can still be interpreted within the theory of directed technical change. First, the *relative* price competitiveness of dirty energy has been decreasing, although it was still cheaper than clean energy in absolute levels. For example, dirty energy was 3.5 times cheaper than clean energy in 1995, but less than 2 times cheaper in 2015. This decreasing price competitiveness of dirty fuels might have lowered the incentive to innovate dirty-energy-augmenting technology over time. Second, the literature has also emphasized the role of R&D subsidies in influencing the path of innovation. Indeed, government subsidies for clean energy were steadily growing in France, eventually surpassing the amount of subsidies for R&D in fossil fuels, the timing of which coincides with the shift in the direction of technical change observed in the data.

Finally, I use my estimates of the elasticity of substitution to decompose the historical increase in the relative share of clean energy in France into two driving forces, namely, the contribution of changing energy prices and of biased technical change. The exercise shows that the contribution of changing factor prices was relatively stronger thus far than that of technical change, accounting for two-thirds of the increase in the relative share of clean energy cumulatively. This suggests the importance of strong price signals through policy instruments such as a carbon tax in raising the share of clean energy in manufacturing (Fischer and Newell, 2008; Hart, 2019). It is, however, important to note that the contribution of technical change to energy transition is likely to grow in the future, given the observed shift in the path of innovation towards clean technologies in recent years.

These results provide a strong micro-empirical foundation for a large number of studies that investigate the possibilities of sustainable growth with directed technical change in the presence of climate change (e.g., Acemoglu et al., 2012; Hassler et al., 2021; Golosov et al., 2014; Bretschger et al., 2017; Van den Bijgaart, 2017; Fried, 2018; Greaker et al., 2018; Borissov et al., 2019; Hart, 2019). The estimated technical parameters validate the framework of directed technical change applied in this literature. The dirty-energy-biased technical change observed in the data especially in the early years of the sample is consistent with the theoretical prediction, given the historical movement of relative energy prices and the two inputs being substitutes.

I also connect with empirical studies on directed technical change (see Popp (2019) for a review of this literature) such as, most notably, Popp (2002) and Aghion et al. (2016). Both studies find that energy prices and past knowledge stocks strongly influence the path of innovation. The novelty of my paper is that I assess biased technical change *jointly* with the elasticity of substitution, a key parameter that determines how price signals affect the direction of innovation (Acemoglu, 2002, 2007). The joint assessments of the elasticity of substitution and technical change empirically corroborate the workings of directed technical change at the micro level.

Finally, this paper also relates to a growing number of studies that advance our understanding of the substitutability between clean and dirty inputs, addressing a well-known concern in the field of environmental economics regarding the lack of reliable estimates of this parameter (Pindyck, 1979; Fried, 2018; Karydas and Zhang, 2019). For instance, Papageorgiou et al. (2017) find estimates of the elasticity of substitution ranging between 1.7 and 2.9 from sector-level data. Meng (2021) recovers an estimate of the substitution parameter around 3 from a structural model of energy transition. I attempt to improve upon their analyses by directly using firm-level panel data on energy price and consumption and accounting for endogeneity, which yields micro estimates of the long-run elasticity of substitution ranging between 2 and 5. Through numerical exercises, Wiskich (2019) and Stöckl and Zerrahn (2020) explore the determinants of the substitution elasticity between clean and dirty inputs in electricity generation with a focus on the evolution of the substitutability over time.

The article proceeds as follows. Section 2 provides motivating evidence for investigating factor-specific technology. Section 3 derives estimating equations from a model of the firm's energy use and Section 4 presents estimation results. Section 5 reports robustness checks and Section 6 examines the observed increase in clean energy shares using the empirical estimates. Section 7 concludes.

2 Motivating evidence

2.1 Data

For the analysis here and what follows, I use data on the French manufacturing industry from two main sources. First, the Enquête sur les Consommations d'Énergie dans l'Industrie (EACEI) administered by the French National Institute of Statistics and Economic Studies (Insee) provides plant-level information on energy use and expenditures by fuel. It covers a representative sample of manufacturing plants with at least 20 employees. Second, Fichier de comptabilité unifié dans SUSE (FICUS), also collected by Insee, provides firm-level information on key characteristics such as industry, number of employees, date of creation and cessation, as well as detailed financial information including turnover, export, and operating costs.[2] To merge the two datasets, I aggregate the plant-level information from the EACEI to the firm-level. Given that the EACEI covers a sample of manufacturing plants, I 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 leads to an unbalanced panel of 12,864 manufacturing firms that covers the period of 1995 - 2015.

I aggregate energy consumption of different fuels to a clean and a dirty bundle for each firm. Following Papageorgiou et al. (2017), I add up electricity, steam and renewables into a clean aggregate and all other types (natural gas, petroleum products, etc) into a dirty aggregate.[3] The information on expenditure by fuel is similarly aggregated into a clean and a dirty energy expenditure. Energy purchase prices are deflated by the GDP deflator to reflect real prices. To construct the unit prices for clean and dirty energy, I divide the expenditure measures by corresponding consumption measures.

Table 1 provides key descriptive statistics. The growth of the relative share of clean energy ranges from -1.7% to 11.7% and positive in most industries (column (1)). This observation is consistent with the decreasing relative price of clean to dirty energy over time in all industries (column (2)). The measure of energy efficiency in column (7) shows that energy efficiency has been growing in most industries (except for Plastic, rubber and Pharmaceutical).

[2]The Unified Corporate Statistics System (SUSE) is an annual fiscal census of manufacturing, mining and utilities firms on which the FICUS is based. SUSE covers all firms that are required to make tax declarations to the French Ministry of the Economy and Finance. The FICUS was replaced by Fichier approché des résultats d'Esane (FARE) in 2008.

[3]Information on the use of renewable energy sources is included in the survey from 2005. Thus, up to 2004, only electricity and steam comprise the clean energy aggregate.

Table 1: Descriptive statistics

	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.

2.2 Factor-specific technology

Using the data described above, I provide motivating evidence for investigating factor-specific technology in clean and dirty energy (therefore the direction or bias of technical change) rather than assuming neutral technology. For the purpose, I follow Raval (2019) and explore whether overall energy efficiency of the firm, measured by revenue divided by the total amount of energy consumption, is correlated with the relative share of clean energy. This will reveal the presence of non-neutral efficiency differences across the two inputs. To explain, if differences in energy efficiency were neutral and therefore affect both types of energy proportionately, these differences would not be correlated with the factor ratio. On the other hand, a correlation between overall energy efficiency and the factor ratio would suggest non-neutral efficiency differences across clean and dirty energy.

As a starting point, I calculate the correlation coefficient between energy efficiency and the relative share of clean energy across all firms and find the coefficient of 0.094 significant at 1 percent level. I also check the role of age as a potentially important determinant of the relative share of clean energy and find that younger firms tend to have higher shares of clean energy (with a correlation coefficient of -0.017 significant at 1 percent level).

Next, I examine whether the correlation remains robust in regressions that include region and industry fixed effects by regressing the relative share of clean energy on overall energy efficiency and a set of fixed effects as well as the firm's age as a control. Table 2 reports these results. All regressions are weighted by the total energy consumption. Column (1) shows a strong positive association between the relative clean energy share and energy efficiency. I include age as a control in column (2) and find that it does not explain much variation in the share of clean energy any more. The correlation between energy efficiency and the relative input ratio remains statistically significant when region and industry specific factors are controlled for (column (3)). These results point to the strong presence of non-neutral, factor-specific technology across the two types of energy. Motivated by this evidence, I formulate a CES function of the energy aggregate that combines clean and dirty energy with a separate technical parameter for each energy type that allows the investigation of factor-specific technical progress.[4]

[4]Estimating two technical progress parameters rather than focusing on one of them is in contrast to recent studies in industrial organization that tend to focus on labor-augmenting technology rather than considering both labor- and capital-augmenting technology. Their focus is motivated by theoretical predictions that technical change would be biased toward labor in the long-run (e.g., Doraszelski and Jaumandreu, 2018; Raval, 2019). In the energy context, however, no strong theoretical predictions exist for either direction and the bias in technical progress might change over time (for which I do find evidence later). Thus, I estimate two technical parameters in order to separately and flexibly estimate the direction of technical change.

Table 2: Correlation between energy efficiency and the relative share of clean energy

	(1)	(2)	(3)
Energy efficiency	0.440***	0.424***	0.228***
	(0.092)	(0.094)	(0.062)
Age		-0.001**	-0.001**
		(0.000)	(0.000)
N	65,884	61,070	61,070
R^2	0.02	0.03	0.23
Industry FE			✓
Region FE			✓

Notes: The dependent variable is the relative share of clean energy. All regressions are weighted by the total energy consumption of the firm. Standard errors are clustered at the firm level.

3 Estimation strategy

3.1 Main specification

I focus on how different sources of energy are combined and/or substituted in response to price signals and how efficiency associated with each energy type evolves, while abstracting away from the use of other production factors such as labor and capital. Formulating a production function with non-energy inputs as well as energy inputs necessitates imposing assumptions on the representation of these factors. For instance, for parsimony and tractability, previous studies have assumed the same elasticity of substitution between all inputs (Doraszelski and Jaumandreu, 2018; Raval, 2019). However, existing empirical evidence suggests that the elasticity of substitution between labor and capital is significantly below one (e.g. Antras, 2004; Klump et al., 2007; Doraszelski and Jaumandreu, 2018; Raval, 2019), while that between clean and dirty energy is likely to be above one (Papageorgiou et al., 2017). This growing body of empirical evidence makes it unrealistic to assume the elasticity of substitution between labor, capital, clean and dirty energy (or the energy aggregate) to be the same.

Alternative approach is to simplify the specification by assuming a Cobb-Douglas relationship between some of the inputs, for instance, between the energy aggregate and non-energy inputs (Papageorgiou et al., 2017). Yet, Hassler et al. (2021) find that the elasticity of substitution between energy and non-energy inputs is not significantly different from zero (Hassler et al., 2021), which again makes it difficult to assume a Cobb-Douglas with its implied elasticity of substitution equal to one.[5] Thus, I abstract from other production factors and focus on the standard specification of energy aggregate that combines two types of energy:

$$E_{it} = \left[\gamma(A^C_{it}E^C_{it})^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A^D_{it}E^D_{it})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where E_{it} is the total energy consumption of firm i in year t, E^C_{it} and E^D_{it} are the consumption of clean and dirty energy, respectively.[6] The parameter σ represents the elasticity of substitution between the two types of energy. Following the literature in estimating production functions with factor-specific technical progress (David and Van de Klundert, 1965; Panik, 1976; Kalt, 1978; Antras, 2004; Klump et al., 2007; León-Ledesma et al., 2010), I assume the following functional form for technical progress:

$$A^C_{it} = A^C_0\, e^{\tau_C t}, \tag{2}$$

$$A^D_{it} = A^D_0\, e^{\tau_D t}$$

where τ_i represents economy-wide growth in productivity associated with factor i and t represents a time trend. Without loss of generality, the components of technical progress are scaled such that $A^C_0 = A^D_0 = 1$. The assumption of linear growth in technology might seem restrictive but is necessary in estimating factor-specific technology of more than one input.[7] This assumption is relaxed in Appendix B as a robustness check, which yields similar results. The distribution parameter γ reflects the intensity of clean energy use. Following earlier studies both theoretical (Acemoglu et al., 2012; Hémous, 2016; Fried, 2018) and empirical (Hassler et al., 2021; Papageorgiou et al., 2017), I suppress the distribution parameter in the subsequent estimation.

3.2 Estimation method

Two popular methods for estimating CES functions are the estimation of the CES function itself or the estimation of one of its first-order conditions (FOCs) from profit maximization (Klump et al., 2012). Regarding the first approach, León-Ledesma et al. (2010) argue that the

[5]Hassler et al. (2021) use US data for the period of 1949- 2008 for their analysis. Given that their sample period is much longer than what is available for my analysis here, it is unlikely that the same elasticity would be larger in my context.

[6]First-order conditions with respect to energy inputs from a larger production function would still be the same as those derived from equation (1). As a robustness check, I estimate the first-order conditions in Section 5.2 which produce very similar estimates as those from specifications that involve the energy production function. This mitigates the concern that the results are driven by the specification choice.

[7]Based on this approach, studies mentioned above separately estimate technical progress of labor and capital and provide evidence for labor-biased technical change.

estimation of the production function alone is generally only accomplished with restrictive assumptions on the nature of technical progress such as Hicks neutrality. For instance, Papageorgiou et al. (2017) adopt this approach by assuming neutral technical progress and focus on estimating the substitution parameter. However, this approach is not suitable for estimating the specification in (1) that allows for non-neutral technical change.

Regarding the FOC approach, the standard log-linear FOCs of profit maximization are written as:

$$\text{w.r.t. } E_C: \quad \log\left(\frac{E_{it}}{E^C_{it}}\right) = \sigma \log P^C_{it} + (1-\sigma)\,\tau_C\, t \tag{3}$$

$$\text{w.r.t. } E_D: \quad \log\left(\frac{E_{it}}{E^D_{it}}\right) = \sigma \log P^D_{it} + (1-\sigma)\,\tau_D\, t \tag{4}$$

$$\text{w.r.t. price ratio}: \quad \log\left(\frac{E^D_{it}}{E^C_{it}}\right) = \sigma \log\left(\frac{P^C_{it}}{P^D_{it}}\right) + (1-\sigma)\,(\tau_C-\tau_D)\, t. \tag{5}$$

The limitation of estimating one of these equations in the current setting is that it does not allow identifying two separate technical parameters. It is clear from equation (3) and (4) that only one technical parameter can be estimated. It is possible to have both technical parameters in the regression equation by combining the two FOCs with respect to each energy type as in equation (5). However, the specification allows one to recover only overall bias $(\tau_C - \tau_D)$ rather than identifying the technical parameters separately.

To overcome these limitations, I employ the alternative approach of combining the FOCs and production function and jointly estimating them as a system of equations:

$$\log\left(\frac{E^D_{it}}{E^C_{it}}\right) = \sigma \log\left(\frac{P^C_{it}}{P^D_{it}}\right) + (1-\sigma)\,(\tau_C-\tau_D)\, t \tag{6}$$

$$\log E_{it} = \frac{\sigma}{\sigma-1}\log\left[\left(e^{\tau_C t}\, E^C_{it}\right)^{\frac{\sigma-1}{\sigma}} + \left(e^{\tau_D t}\, E^D_{it}\right)^{\frac{\sigma-1}{\sigma}}\right] \tag{7}$$

Although less popular than the other two methods, the system approach offers clear advantages in the current setting.[8] Most importantly, in contrast to the other two methods explained above, the system approach allows identifying all parameters of interest: the elasticity of substitution as well as two technical progress parameters. Furthermore, the system exploits cross-equation restrictions that force the parameters to be the same across the two equations, which substantially improves the efficiency of estimation (Greene, 2000). Relat-

[8]The reason for the system approach being less popular has to do with most studies in the macroeconomics literature being interested in labor-augmenting technical change (along with Hicks-neutral technical progress), rather than both labor- and capital-augmenting technical change. To infer technical progress of one factor, much simpler single equation approaches suffice.

edly, Klump et al. (2007) and León-Ledesma et al. (2010) demonstrate that cross-equation restrictions imposed in the system approach lead to its superior performance compared to the single equation approaches (either the production function or FOCs), particularly in identifying the factor-specific technical progress parameters.[9]

I include the combined FOCs in the system (equation (6)) rather than two separate FOCs with respect to each energy type in order to reduce omitted variable bias affecting both types of energy proportionately such as overall (factor-neutral) unobserved productivity shocks or demand shocks experienced at the firm level. Such biases are expected to cancel out in the system and what remains is likely to be factor-specific omitted variable bias that affects the two types of energy disproportionately. In the next section, I discuss endogeneity concerns in more detail and propose instruments to improve identification.

I do not include firm fixed effects in the main specification for two reasons. First, it is known that exploiting time-variation in time-series data or panel data with fixed effects captures short-run substitution, while exploiting cross-sectional variation captures long-run substitution (Arnberg and Bjørner, 2007). Thus, not having fixed effects enables interpreting the estimates as long-run elasticities of substitution, which correspond closely to the interpretation of the parameter in the theoretical literature. Second, exploiting only time variation within firms will lead to discarding changes in fuel prices that induce firms to adjust fuel choices at the extensive margin (i.e., start or stop using a certain energy type) or to close down. Thus, not having firm fixed effects allows me to provide estimates that incorporate fuel choices at the extensive margin and more generally entry, exit and the reallocation of inputs across firms. This specification is again in line with the goal of the analysis which is to inform the economy-wide possibility of sustainable growth through input substitution and technical change. As a robustness check, I also provide within estimates that correspond to short-run elasticities of substitution in Appendix B. As expected, they tend to be smaller in magnitude than those without firm fixed effects (Table B3).

3.3 Addressing endogeneity

Potential endogeneity in firm-level energy demands and prices has been recognized in the literature. For example, demand and productivity shocks are likely to be correlated with both energy demands and prices through quantity discounts (i.e., lower unit price through purchasing a large amount of energy) and changes in the energy mix (the share of different types

[9]The two studies use a normalized CES function to estimate the elasticity of substitution between labor and capital and technical parameters from time-series data where variables are normalized relative to their sample averages (see León-Ledesma et al. (2010) for a detailed discussion of the normalization approach when using time-series data). However, there is no need for explicit normalization when using cross-sectional or panel data since such normalization is implicitly done by the constant term or fixed effects, respectively.

of energy used in a given firm). In discussing these sources of endogeneity, I distinguish between *factor-neutral* sources of endogeneity that affect both types of energy proportionately and *factor-specific* sources that affect the two types of energy disproportionately.

To mitigate factor-neutral shocks such as demand shocks or productivity shocks experienced at the firm level, I choose to include the combined FOCs in the system of equations (equation (6)) rather than two separate FOCs with respect to each energy type shown in equation (3) and (4). Such factor-neutral unobservables that affect both types of energy proportionately are expected to cancel out in equation (6) that relates the price *ratio* to the input *ratio*. They are also likely to be innocuous in equation (7), since the CES representation specifies how fuel choices are determined through the degree of substitutability between the two types of energy and the efficiency associated with each type. Unobserved factors that affect both types of energy proportionately are not likely to affect either channel.

Regarding factor-specific omitted variable bias that affects fuel choices disproportionately, Antras (2004) discusses potential factor-specific productivity shocks at the firm level and how they can be correlated with factor demands. That is, to the extent that firms take into account their factor-specific productivity when choosing inputs, it would affect input demands as well as input prices through resulting quantity discounts.[10]

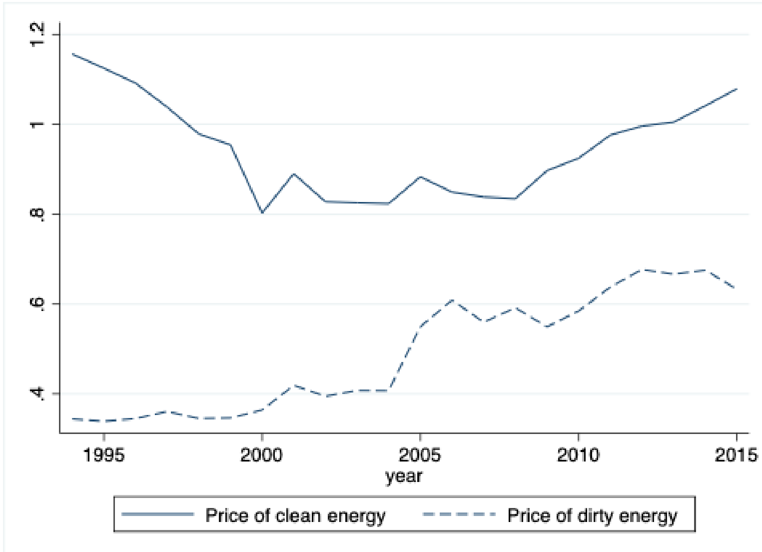
To account for such factor-specific omitted variable bias at the firm level, I follow the approach taken in earlier studies and develop instruments that rely on national energy prices by applying the growth rates of national energy prices to the pre-sample firm-level price (Linn, 2008; Sato et al., 2019; Dussaux, 2020; Marin and Vona, 2021). Specifically, the instrument for the firm-level price of clean energy $\tilde{P_{it}^C}$ is constructed as:

$$\tilde{P_{it}^C} = P_{it_0}^C \times \prod_{j=1}^{t} (1 + G_j^C) \tag{8}$$

where P_{it0}^C is firm i's unit price of clean energy observed in the pre-sample period ($t = t_0$) and G_t^C is the growth rate of the national average price of clean energy in year t. The firm-level variation in the instrument comes from the pre-sample price, which provides information on the relative intensity of clean energy consumption. For example, a firm's unit price of clean energy that is lower than the average national price is likely to imply that the firm uses a larger amount of clean energy than other firms and receives more sizeable quantity discounts. The firm-level variation makes the instrument sufficiently strong for the firm-level energy prices, avoiding a weak-instrument problem. The same logic applies in constructing

[10]For example, a firm experiencing a positive productivity shock associated with clean energy might increase its demand for clean energy, which may lower the unit price of clean energy through quantity discounts.

Figure 1: Average price of clean and dirty energy



Source: Enquête sur les Consommations d'Énergie dans l'Industrie (EACEI).

$\tilde{P_{it}^D}$. In Appendix B, I also try an alternative specification for the instruments that weight national prices of different fuels using the pre-sample firm-level fuel mix as weights ('shift-share' instruments), which yields similar results (Table B4, Figure B1).[11] Using $\tilde{P_{it}^C}$ and $\tilde{P_{it}^D}$ as instruments, I estimate the system of equations (6)-(7) by using the two-step generalized method moments (GMM) estimator of Hansen (1982).[12] Standard errors are clustered at the firm level.

The exclusion restriction is that factor-specific unobservables such as factor-specific efficiency shocks at the firm level are not correlated with the growth rates of the national energy prices. Given that the sample includes around 13,000 firms (see Appendix A for detailed descriptions of the data), it is unlikely that productivity shocks in a given firm are correlated with national energy prices. In addition, the validity of the instruments also assumes that the pre-sample price is not correlated with such idiosyncratic firm-level productivity shocks in subsequent years. The assumption of no serial correlation in idiosyncratic productivity

[11]The alternative specification is not chosen as the preferred specification because it does not provide as strong firm-level variation in the current setting where energy is already partitioned into the clean and dirty bundle with the two most popular fuels, electricity and natural gas, belonging to each one (compared to other studies where energy is considered as a whole). In particular, the share of electricity in the clean bundle is very high (98 percent on average) and does not vary substantially across firms. On the other hand, two firms that display the same share of electricity in their clean energy consumption might still be charged substantially different unit prices due to the differences in the *absolute* amount of electricity consumption and resulting differences in quantity discounts.

[12]Another possible estimator is nonlinear Three Stage Least Square (3SLS), which is simpler than GMM. However, it is asymptotically efficient only under the assumption of homoskedasticity (Wooldridge, 2010).

shocks is relatively common in the literature (e.g., Olley and Pakes, 1996). Finally, the identification of the technical parameters requires that the national growth rates in energy prices are uncorrelated with the linear growth in factor-specific technologies specified in (2). Figure 1 shows that the evolution of energy prices at the national level is not necessarily linear: the price of clean energy decreases initially and remains stable before it starts to increase toward the end of the sample period, while the price of dirty energy also evolves with annual fluctuations.

4 Results

4.1 The elasticity of substitution between clean and dirty energy and technological bias

Table 3 reports the baseline results from estimating the system of equations (6)-(7) without instruments. I begin by estimating the system without any fixed effects in column (1). The estimate of the elasticity of substitution between clean and dirty energy is well above one around 2.2 and precisely estimated. The estimated technical progress parameters suggest -0.8% and 1.5% per year growth in the clean- and dirty-energy-augmenting efficiency, respectively.[13] The estimates indicate that technical change was clearly biased towards dirty energy over the period of 1995-2015.

With industry fixed effects in column (2), the estimate of the elasticity falls slightly and yet remains close to 2. In column (3) also with region fixed effects, the estimated elasticity of substitution and technical progress parameters remain qualitatively similar. In column (4), I re-estimate the specification in column (3) using the total energy consumption E_{it} as weights in order to put more emphasis on the behavior of heavy energy-using firms. The elasticity estimate appears to be slightly larger when more weight is given to large and heavy energy-using firms. Technical progress estimates are comparable to the results from the non-weighted specifications with -1.9% and 1.9% annual growth in efficiency associated with clean and dirty energy, respectively.

I further estimate the system by industry to examine how the parameters vary across industries based on the French classification of economic activities (NAF rev.2) and report the results in Appendix B. Table B1 presents estimates of the elasticity of substitution and technical parameters by industry. Elasticity estimates range between 1.6 and 3.2 and are

[13]A downward trend in efficiency is not infrequently found in factor-augmenting technology estimates. For instance, Antras (2004) and Doraszelski and Jaumandreu (2018) report negative estimates of capital-augmenting technology.

Table 3: Estimation of the elasticity of substitution and technical change in the energy aggregate

	(1)	(2)	(3)	(4)
$\hat{\sigma}$	2.193***	1.963***	1.915***	2.209***
	(0.040)	(0.037)	(0.077)	(0.083)
$\hat{\tau_C}$	-0.008***	-0.014***	-0.014***	-0.019***
	(0.000)	(0.001)	(0.001)	(0.001)
$\hat{\tau_D}$	0.015***	0.019***	0.019***	0.019***
	(0.000)	(0.000)	(0.000)	(0.001)
Industry FE		✓	✓	✓
Region FE			✓	✓
Weighted by E_{it}				✓
Observations	65,884	65,884	65,884	65,884

Notes: Estimates from estimating the system (6)-(7) are reported. Standard errors are clustered at the firm level.

precisely estimated for all industries. Technical parameters yield very similar results with positive $\hat{\tau_D}$ and negative $\hat{\tau_C}$ in most industries. The implied bias in technical change, $\hat{\tau_D} - \hat{\tau_C}$, ranges between 1.0% and 5.1%, indicating dirty-energy-biased technical change in all but one industry (Plasters, line , and cement).

Table 4 reports GMM estimates that address endogeneity concerns. Even formally accounting for endogeneity arising from factor-specific omitted variable bias, the results are similar to those obtained from the baseline specification. Over the period between 1995 and 2015, the estimated elasticity of substitution between clean and dirty energy ranges between 1.6 and 2.2 when unweighted (column (1)-(3)) and tends to be larger when weighted by the total energy consumption (3 in column (4)), again strongly suggesting that the two inputs are substitutes. The estimated technical progress parameters provide a similar pattern observed from the baseline specifications: -2.3% and 2.2% per year growth in the clean- and dirty-energy-augmenting efficiency, respectively (column (4)), implying that the direction of technical change was clearly biased towards dirty fuels.

The general picture arising from these results largely confirms the prediction from the theory of directed technical change. The theory argues that there are two opposing forces influencing the path of innovation. First, the *market size* effect encourages innovation in technologies that use the cheaper input and second, the *price* effect spurs the development

Table 4: Estimation of the elasticity of substitution and technical change in the energy aggregate: GMM estimates

	(1)	(2)	(3)	(4)
$\hat{\sigma}$	1.623***	2.176***	2.222***	3.000***
	(0.091)	(0.082)	(0.078)	(0.101)
$\hat{\tau_C}$	-0.024***	-0.026***	-0.026***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.001)
$\hat{\tau_D}$	0.024***	0.023***	0.023***	0.022***
	(0.001)	(0.000)	(0.000)	(0.001)
Industry FE		✓	✓	✓
Region FE			✓	✓
Weighted by E_{it}				✓
Observations	65,884	65,884	65,884	65,884

Notes: Estimates from estimating the system (6)-(7) using instruments are reported. Instruments are constructed according to equation (8). Standard errors are clustered at the firm level.

of technologies that favor the more expensive input. Which effect dominates the other is determined by the elasticity of substitution between the two inputs. When the inputs are gross substitutes, which is the case for clean and dirty energy as suggested by the estimates above, the market size effect is predicted to dominate the price effect (Acemoglu, 2002; Acemoglu et al., 2012).[14] Looking at relevant prices in France, Figure 1 shows that the price of dirty energy was considerably lower than that of clean energy throughout the sample period. Thus, the dirty-energy-biased technical change (or the market size effect dominating the price effect) observed in the data is consistent with the relative price movement, given the estimated elasticity of substitution between clean and dirty energy sufficiently above one.

[14] When the two inputs can be easily substituted, it is intuitive that the cheaper input would be favored and innovation efforts will be directed to improving its efficient use. In contrast, when the two inputs are complements, it is likely that innovation will go in the direction of improving the efficiency of the more expensive but necessary (since both inputs are needed in this case) input.

4.2 Government interventions and the evolution of technology

4.2.1 Empirical documentation

Figure 1 shows a shift in the trend in energy prices, clean energy in particular, around the early 2000s. The shift coincides with a number of government interventions in the energy sector implemented in France. First, the government introduced a tax scheme applying to all final consumers of electricity in 2002 with a purpose of using the tax revenue to support renewable energy and co-generation (Contribution au Service Public de l'Electricité). Further, as part of the government's initiative to liberalize energy markets, the electricity and gas markets in France have been opened to competition for all non-residential users since 2004 and all final consumers have been able to choose between regulated tariffs and market-based prices with the supplier of their choice since then. The transition to competitive markets, however, led to higher electricity prices due to limited competition.[15] Although not specific to the French context, the EU Emissions Trading Scheme that started operating in 2005 might have also influenced energy prices though changes in fossil fuel consumption or cost pass-through by electricity producers (Alexeeva-Talebi, 2011; Fabra and Reguant, 2014).[16]

I try to investigate whether and to what extent such large-scale reforms in the energy sector affected the elasticity of substitution between clean and dirty energy and the direction of technical change. For the purpose, I divide the sample into the pre- (1995 - 2003) and post-intervention period (2004 - 2015) and re-estimate the system of equations (6)-(7) separately on these two sub-periods. Table 5 reports the GMM estimates from this exercise. Column (1) reproduces the estimation results from the baseline specification on the entire sample period with industry and region fixed effects (column (4) in Table 4) for reference. Results from the pre- and post-intervention period are reported in column (2) and (3), respectively. The elasticity estimates remain sufficiently above one in both periods as in the main specification. In contrast, technical progress parameters change substantially. To begin, dirty-energy-biased technical change observed over the entire sample period appears to be largely driven by the trend in the pre-intervention period. The estimates have the same signs and tend to be larger in magnitude, while the signs of the technical progress estimates flip in the post-intervention period. The estimated technical parameter associated with clean energy is

[15] Limited competition is due to the dominant role of the incumbent utility, for instance, Électricité de France (EDF) in the electricity market. EDF controls a large nuclear fleet with production costs lower than wholesale electricity prices.

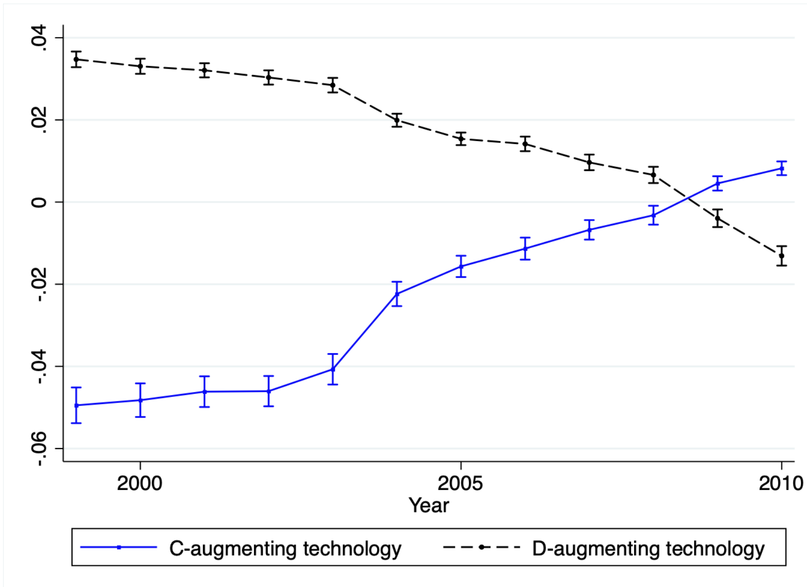
[16] Marin and Vona (2021) explore in an econometric analysis the role of these energy policies in driving firm-level energy prices in France and find that the tax scheme applying to all final consumers of electricity (Contribution au Service Public de l'Electricité) had an impact of the largest magnitude, although the other two policies also had a significant impact on energy prices.

Table 5: Estimation of the elasticity of substitution and technical change in the energy aggregate: Pre- & post-2004

	(1)	(2)	(3)
		GMM	
	All	pre-2004	post-2004
σ	3.000***	3.286***	5.034***
	(0.101)	(0.100)	(0.214)
τ_c	-0.023***	-0.057***	0.001
	(0.001)	(0.003)	(0.001)
τ_d	0.022***	0.039***	-0.002**
	(0.001)	(0.001)	(0.001)
Industry FE	✓	✓	✓
Region FE	✓	✓	✓
Weighted by E_{it}	✓	✓	✓
Observations	65,884	31,637	34,247

Notes: Results from estimating the system (6)-(7) with instruments. Instruments are constructed according to equation (8). Samples used are indicated in each column. Standard errors are clustered at the firm level.

Figure 2: Annual growth of clean- and dirty-augmenting technologies: on a 10-year rolling window



Notes: GMM estimates of technology parameters with confidence intervals from estimating the system (6)-(7) on a 10-year rolling window. Year is the median year in each 10-year window.

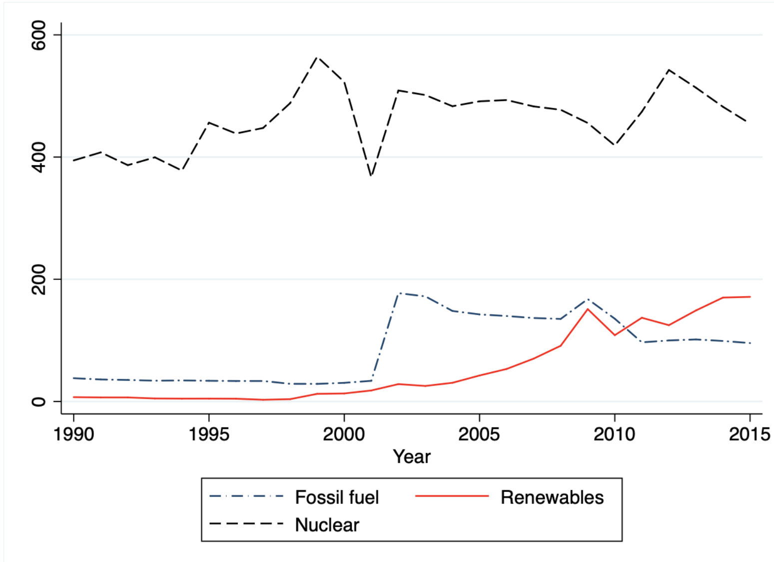
now positive, although imprecise, in the post-intervention period, while that associated with dirty energy turns negative. These estimates point to a shift in the direction of technical change that favors clean energy in recent years. I further examine the shift in the direction of technical change in different industries and find that despite a large degree of heterogeneity across sectors, technical change appears to be biased towards clean energy in the post-intervention period for 15 out of 19 industries (Table B2).

To check the possibility that the division of the sample period (before and after 2004) is arbitrary and the results depend on it, I estimate the system on a 10-year rolling window using the specification in column (4) of Table 4. The results from this exercise are graphically reported in Figure 2. It is readily observable that the growth rates of two technologies exhibit markedly different patterns. Clean-energy-augmenting technology grows at a faster rate as the rolling window moves to the right and includes more recent years, eventually surpassing the growth rates of dirty-energy-augmenting technology, while the growth of dirty-energy-augmenting technology appears to attenuate slowly over time.

4.2.2 Theoretical explanations

The directed technical change framework offers theoretical explanations for the observed shift in the direction of technical change. One explanation is that the *relative* price compet-

Figure 3: Government R&D expenditure by energy source



Source: International Energy Agency (IEA).

itiveness of dirty energy has been decreasing, although it was still cheaper than clean energy in absolute levels. For example, dirty energy was 3.5 times cheaper than clean energy in 1995, but less than 2 times cheaper in 2015. This decreasing relative price competitiveness of dirty fuels might have had a negative influence on the incentives to innovate dirty-energy-augmenting technology over time.

The literature has also emphasized the role of R&D subsidies for clean energy in inducing clean-energy-biased technical change (Acemoglu et al., 2012; Greaker et al., 2018; Fried, 2018). Figure 3 shows the government expenditure on R&D support for fossil fuels, renewables and nuclear in France since 1990. The data come from the International Energy Agency (IEA). While subsidies for R&D related to nuclear remained highest with no clear pattern, subsidies for R&D in fossil fuels have been falling since 2002. At the same time, government support for renewables grew continuously from the late 1990s, eventually exceeding support for fossil fuels around 2010.[17] The steady increase in the R&D subsidies for clean energy is consistent with the observed technical progress biased towards clean energy from mid-2000

[17]This observation can be seen in the context of the comprehensive environmental programme launched in 2007, *Grenelle de l'Environnement*, which puts forward a series of policies and measures including specific plans for strengthening R&D on clean energy technologies in order to achieve France's long-term greenhouse gas emissions reduction target (75 percent reduction by 2050) (IEA, 2009). For example, the government has provided subsidies through a € 57 billion investment program "Investments for the Future" for the integration of renewable energy into industrial plants since 2010. The program includes full subsidies granted to research institutes, subsidies and grants to companies and direct capital investment for the development of renewable energy. Similarly, the government has initiated a series of calls for tenders since 2004 in order to stimulate investments in large-scale renewable energy plants (IEA, 2004, 2009).

in the data.

5 Robustness checks

5.1 Kmenta approximation

In this section, I test the sensitivity of the estimates to alternative estimation methods other than the system of equations approach by trying two other popular methods used in the literature, namely, the estimation of a linearized production function and of the FOCs. First, I try the Kmenta approximation, which is a first-order Taylor expansion of the CES function around $\sigma = 1$. The approximation leads to:

$$\log\left(\frac{E_{it}}{E_{it}^D}\right) = \gamma \log\left(\frac{E_{it}^C}{E_{it}^D}\right) + \underbrace{\frac{(\sigma-1)\gamma(1-\gamma)}{2\sigma}}_{a}\left[\log\left(\frac{E_{it}^C}{E_{it}^D}\right)\right]^2 + \underbrace{[\gamma\tau_C + (1-\gamma)\tau_D]}_{b}\, t + \underbrace{\frac{(\sigma-1)\gamma(1-\gamma)}{2\sigma}[\tau_C - \tau_D]^2}_{c}\, t^2 \quad (9)$$

again assuming $A_{it}^C = A_0^C\, e^{\tau_C t}, A_{it}^D = A_0^D\, e^{\tau_D t}$ and $A_0^C = A_0^C = 1.$[18] Using $\hat{\gamma}$, σ is identified from the composite a. One drawback of this specification is that it is difficult to identify τ_C and τ_D without prior information on which technology parameter is larger. Thus, as in León-Ledesma et al. (2010), I use this specification to check for the robustness of the σ estimates only. Results are reported in Table 6. Column (1) shows the estimate of the substitution parameter around 2.9, which is comparable to those from the system of equations approach. I include industry and region fixed effects in column (2). When weighted by the total energy consumption, the estimate falls but remains qualitatively similar to the previous ones.

5.2 First-order conditions

Second, I estimate the combined FOCs in equation (5), which I reproduce below, to estimate the elasticity of substitution and the overall bias in technical change captured by $\tau_C - \tau_D$ using the instruments developed in Section 3.3:

$$\log\left(\frac{E_{it}^D}{E_{it}^C}\right) = a_2 + \sigma \log\left(\frac{P_{it}^C}{P_{it}^D}\right) + (1-\sigma)\,(\tau_C - \tau_D)\, t + \epsilon_{it} \quad (10)$$

[18]In approximation, the term that multiplies input ratio by the time trend, $\frac{(\sigma-1)\gamma(1-\gamma)}{2\sigma} log \frac{E_{it}^C}{E_{it}^D} t$, is dropped as in León-Ledesma et al. (2010) without any significant loss of precision.

Table 6: Kmenta approximation of the energy technology function

	(1)	(2)	(3)
	Dependent var: E/E_D		
E_C/E_D	0.497***	0.497***	0.490***
	(0.001)	(0.001)	(0.002)
$(E_C/E_D)^2$	0.081***	0.081***	0.070***
	(0.001)	(0.002)	(0.003)
t	-0.000**	-0.000	0.000
	(0.000)	(0.000)	(0.001)
t^2	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Industry FE		✓	✓
Region FE		✓	✓
Weighted			✓
Observations	65,884	65,884	65,884
R^2	0.99	0.99	0.99
σ	2.851	2.819	2.263

Notes: Results from estimating equation (9). Standard errors are clustered at the firm level.

Table 7: Estimation of the elasticity of substitution and technical change in the energy aggregate: First-order conditions

	(1)	(2)	(3)
		IV	
	All	pre-2004	post-2004
Log price ratio	2.794***	3.032***	4.752***
	(0.166)	(0.166)	(0.327)
t	0.084***	0.214***	-0.028***
	(0.007)	(0.016)	(0.007)
Age	0.000	0.001	0.002
	(0.001)	(0.001)	(0.001)
Industry FE	✓	✓	✓
Region FE	✓	✓	✓
weight by E_{it}	✓	✓	✓
Observations	61,070	27,942	33,128

Notes: Results from estimating equation (10) with instruments. Standard errors are clustered at the firm level.

In column (1) of Table 7, I find an IV estimate of the elasticity of substitution between clean and dirty energy of 2.794, which is within the range of estimates from the system of equations approach reported above. Reassuringly, the coefficient on the time trend is positive (0.084), implying that the overall bias in technical change $(\hat{\tau_C} - \hat{\tau_D})$ is negative over the whole sample period (i.e., dirty-energy biased technical change) given the estimate of the the elasticity of substitution greater than one. When splitting the sample into pre- and post-2004, the implication regarding the change in the direction of technical change is remarkably similar to the findings from the the system of equations approach. In the pre-2004 period, the bias is towards dirty-energy, while technical change appears slightly clean-energy-biased in the post-2004 period (a positive and a negative coefficient on the time trend in column (2) and (3), respectively). The similar estimates from alternative approaches reported in this section add confidence that the main estimates from the system of equations approach are not driven by the choice of the estimation method.

Figure 4: Relative share and price of clean energy over time

Notes: Input ratio refers to the relative share of clean energy and price ratio refers to the relative price of clean energy.

6 The increase in the relative share of clean energy

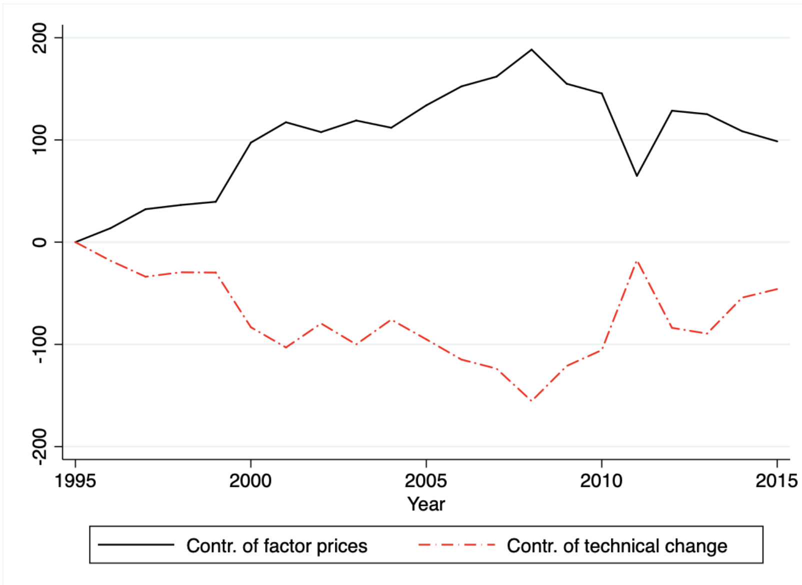
Figure 4 shows the relative share (E_C/E_D) and price (P_C/P_D) of clean energy between 1995 and 2015 in the French manufacturing sector. The relative price of clean energy over time is depicted in the dashed line. The measure declines sharply from 3.8 in 1995 to the lowest point of 1.5 in 2008 and rises afterwards. On the other hand, the relative share of clean energy has been steadily increasing from 1.1 in 1995 and 1.8 in 2015.[19] The growth appears to have slightly slowed down in the second half of the period, but not significantly so. In this section, I examine the historical increase in the relative share of clean energy in France through a simple decomposition exercise that separates the increase into the effect of changing relative prices and that of technical change.

It is suitable to look into the changes in each component over time to assess their contributions to the increase in the relative share of clean energy. Thus, following Oberfield and Raval (2021), the percentage change in input ratio is decomposed as follows:

$$\mathrm{d}\ln\frac{E_C}{E_D} = \underbrace{\frac{\partial\ln\frac{E_C}{E_D}}{\partial\ln\frac{P_C}{P_D}}\,\mathrm{d}\ln\frac{P_C}{P_D}}_{\text{contr. from factor prices}} + \underbrace{\left(\mathrm{d}\ln\frac{E_C}{E_D} - \frac{\partial\ln\frac{E_C}{E_D}}{\partial\ln\frac{P_C}{P_D}}\,\mathrm{d}\ln\frac{P_C}{P_D}\right)}_{\text{contr. from technical change}} \tag{11}$$

[19]Note that the measure seems large (above one) since clean energy also includes electricity as explained in Section 2.1.

Figure 5: Cumulative contribution of factor prices and of biased technical change to the increase in the relative share of clean energy



Notes: All changes are in percentage points.

where the first term measures the contribution of factor price changes. The residual (the second term) is labelled as the contribution of technical change.[20] To compute the contribution of changing factor prices, I use my estimate of the elasticity of substitution from Section 4.2.[21]

Figure 5 displays the cumulative contribution of each component to the increase in the relative share of clean energy. Changes in relative energy prices have contributed to an increase of almost 100 percentage points from 1995 and 2015. Consistent with the evolution of price movements shown in Figure 4, the declining relative price of clean energy caused its relative share to increase gradually, peaking in 2008. From then on, the increase in the relative price of clean energy attenuates this increase. Moving as a mirror image of the contribution of factor prices, technical change has cumulatively contributed to a decline of 45 percentage points in the share of clean energy, which is in line with the observed dirty-energy-biased technical change between 1995 and 2015 (Table 3, 4).

It is noteworthy that the contribution of changing factor prices was relatively stronger, at least thus far, compared to that of technical change, accounting for two thirds of the increase in the relative share of clean energy cumulatively. This points to the importance of strong

[20]With this expression, Oberfield and Raval (2021) note that any change in the economy other than changes in factor prices that would alter relative factor demand is considered biased technical change. These include, for instance, changes in preferences, markups, demographics, technology, or trade barriers.

[21]Specifically, I use the estimate of 2.22 in column (3) of Table 4.

price signals through policy instruments such as a carbon tax in raising the share of clean energy in manufacturing (Fischer and Newell, 2008; Hart, 2019). However, I also note that the contribution of technical change to energy transition may grow in the future, as hinted by the growth of clean-energy-augmenting technology in more recent years (Figure 2). For instance, Markard (2018) argues that energy transition occurs through multiple phases and the impact of technological advances tends to emerge in later phases. In earlier phases, new technologies are immature and cannot compete with established technologies, while in later phases, technologies mature substantially and diffuse much faster than before.

7 Conclusion

The elasticity of substitution between clean and dirty energy and the direction of technical change, either dirty-energy-biased or clean-energy-biased, are central parameters in discussing one of the most challenging questions facing the world today, climate change. However, there is limited consensus on the magnitude of this substitution elasticity and much less on the nature of technical change due to a dearth of empirical estimates for these key parameters. In this paper, I made an attempt to fill this gap by estimating the elasticity of substitution between clean and dirty energy inputs jointly with the direction of technical change in the energy aggregate.

I find micro estimates of the elasticity of substitution between clean and dirty energy inputs greater than one, around 3. Moreover, largely dirty-energy-biased technical change observed in the data is consistent the framework of directed technical change widely applied in the large sustainable growth literature, given the historical movement of relative energy prices and the estimated elasticity of substitution above one. However, my analysis also provides clear evidence of a shift in the path of innovation towards clean-energy-augmenting technologies in recent years. A simple decomposition exercise shows that changes in relative energy prices were a stronger driver behind the historical increase in the relative share of clean energy than technical change. This points to the importance of strong price signals in raising the share of clean energy in manufacturing, although the contribution of technical change to energy transition may grow in the future.

Although the findings presented in this paper provide a strong empirical foundation for a large number of papers that investigate the possibilities of sustainable growth with directed technical change, there is ample room for improvement and future research. For instance, expanding the method to include public and private R&D to investigate their causal impacts on the switch in the direction of technical change would provide further insight. Moreover, although the elasticity of substitution parameter is considered time-invariant in most of the literature, the kind of technical progress that allows substitution between factors easier, in other words, 'sigma-augmenting' technical change can be also very relevant, particularly in the context of climate change (Stöckl, 2020). It has been noted in the macroeconomic literature that an increase in the elasticity of substitution between labor and capital has strong effects on growth, although the mechanisms are not well understood (Klump et al., 2012). I believe the knowledge of how such sigma-augmenting technical change may occur and operate will broaden the scope of our understanding of sustainable growth.

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Appendix A

Data

The sample consists of 12,864 firms observed at least twice between 1994 and 2015. The first observation of each firm is dropped in constructing the instruments (explained in detail in Section 4.2) and thus the final sample runs from 1995. Since the FICUS/FARE is a census and the EACEI is a survey, the sample size is influenced by the EACEI, which is representative of manufacturing plants with more than 20 employees. In merging the two datasets, I 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. In what follows I define the variables used in the main analysis.

- Total energy consumption (E): Total Amount of energy consumed in the calendar year in TOE.
- Clean energy consumption (E_C): Amount of electricity, steam and renewables consumed in the calendar year in TOE.
- Dirty energy consumption (E_D): Amount of natural gas, other types of gas, coal, lignite, coke, propane, butane, heavy fuel oil, heating oil and other petroleum products consumed in the calendar year in TOE.
- Unit price of clean energy (P_C): Expenditure on clean energy purchase (electricity, steam and renewables) in the calendar year deflated by GDP deflator and divided by clean energy consumption (E_C). Thus, using self-generated electricity or steam (not purchased) lowers the firm's unit price of energy.
- Unit price of dirty energy (P_D): Expenditure on dirty energy purchase in the calendar year deflated by GDP deflator and divided by dirty energy consumption (E_D).
- Weights: EACEI sample weights are used in the baseline regressions and EACEI sample weights multiplied by the total energy consumption are used in the regressions weighted by energy consumption (E).

For the descriptive analysis, the following additional variables are used:

- Energy efficiency: Total sales of goods and services in million euro divided by total energy consumption in the calendar year in TOE.

- Age: Years in existence calculated by the year in which the firm is surveyed subtracted by the year in which the firm started operation.

Table A1 reports the number of observations by year.

Table A1: Number of observations (firms) by year

Year	Observations
1995	4,076
1996	4,359
1997	4,587
1998	4,608
1999	4,644
2000	1,913
2001	3,561
2002	1,909
2003	1,980
2004	2,236
2005	2,089
2006	3,326
2007	3,818
2008	3,326
2009	3,277
2010	3,459
2011	3,646
2012	2,609
2013	1,964
2014	1,964
2015	2,533
Total	65,884

Appendix B

B1 Additional results

Table B1: Estimation of the system of equations by industry

Industry	Observations	$\hat{\sigma}$	(SE)	$\hat{\tau_C}$	(SE)	$\hat{\tau_D}$	(SE)
Steel	203	1.890***	(0.261)	-0.019**	(0.008)	0.011***	(0.003)
Metals	874	3.171***	(0.421)	-0.007**	(0.003)	0.010***	(0.001)
Minerals	332	2.515***	(0.361)	-0.020***	(0.006)	0.011***	(0.003)
Plaster, lime, cement	167	2.311***	(0.231)	-0.004*	(0.002)	-0.008***	(0.002)
Ceramic	5,476	2.349***	(0.081)	-0.017***	(0.001)	0.012***	(0.000)
Glass	1,665	2.685***	(0.213)	-0.007***	(0.001)	0.011***	(0.001)
Fertilizer	328	1.896***	(0.215)	-0.030***	(0.010)	0.021***	(0.004)
Other chemicals	287	3.199***	(0.385)	-0.008**	(0.004)	0.009***	(0.001)
Plastic, rubber	731	2.736***	(0.240)	0.001	(0.002)	0.010***	(0.001)
Pharmaceutical	3,226	1.852***	(0.126)	-0.011***	(0.003)	0.013***	(0.001)
Steel processing	14,230	2.055***	(0.053)	-0.007***	(0.000)	0.014***	(0.000)
Machinery	8,513	1.782***	(0.088)	-0.012***	(0.002)	0.015***	(0.001)
Electronics	5,266	1.866***	(0.097)	-0.012***	(0.002)	0.020***	(0.001)
Transport equipment	3,327	1.980***	(0.099)	-0.009***	(0.002)	0.013***	(0.001)
Shipbuilding	1,289	1.923***	(0.172)	-0.006*	(0.003)	0.014***	(0.002)
Textile	8,386	2.253***	(0.067)	-0.018***	(0.002)	0.017***	(0.000)
Paper	4,470	2.140***	(0.085)	-0.006***	(0.002)	0.015***	(0.000)
Rubber products	889	1.597***	(0.348)	-0.017**	(0.007)	0.028***	(0.005)
Plastic products	6,225	2.173***	(0.062)	0.002**	(0.000)	0.012***	(0.000)

Notes: Estimates from estimating the system (6)-(7) by sector are reported. Standard errors are clustered at the firm level.

Table B2: Estimation of the system of equations by industry post-2004

Industry	Observations	$\hat{\sigma}$	(SE)	$\hat{\tau_C}$	(SE)	$\hat{\tau_D}$	(SE)
Steel	130	1.560***	(0.313)	0.004	(0.009)	0.001	(0.012)
Metals	477	3.633***	(0.492)	-0.000	(0.001)	-0.001	(0.002)
Minerals	229	2.898***	(0.663)	-0.004	(0.005)	0.006	(0.004)
Plaster, lime, cement	63	1.647***	(0.322)	0.014***	(0.004)	-0.012***	(0.004)
Ceramic	3,214	2.067***	(0.197)	0.012***	(0.003)	-0.007**	(0.003)
Glass	998	4.004***	(0.428)	0.001	(0.001)	-0.001	(0.001)
Fertilizer	153	1.860***	(0.477)	0.002	(0.004)	-0.010**	(0.005)
Other chemicals	175	5.623***	(1.094)	0.001	(0.001)	-0.001	(0.002)
Plastic, rubber	465	4.792***	(0.515)	0.003**	(0.001)	-0.002	(0.001)
Pharmaceutical	1,861	1.958***	(0.144)	0.001	(0.003)	-0.002	(0.004)
Steel processing	8,253	2.550***	(0.181)	0.002***	(0.000)	-0.001	(0.001)
Machinery	3,700	2.196***	(0.148)	0.009***	(0.000)	-0.018***	(0.001)
Electronics	2,525	2.655***	(0.272)	0.000	(0.001)	0.000	(0.002)
Transport equipment	1,603	2.800***	(0.201)	-0.001	(0.001)	0.002**	(0.001)
Shipbuilding	698	2.516***	(0.367)	0.005**	(0.002)	-0.009**	(0.003)
Textile	2,955	3.485***	(0.428)	0.000	(0.001)	-0.003***	(0.001)
Paper	2,601	3.653***	(0.208)	0.001*	(0.000)	-0.001***	(0.000)
Rubber products	369	1.538***	(0.559)	0.033	(0.027)	-0.017	(0.035)
Plastic products	3,778	4.026***	(0.216)	0.002***	(0.000)	-0.006***	(0.000)

Notes: GMM estimates from estimating the system (6)-(7) by industry in post-2004 period. Standard errors are clustered at the firm level.

B2 Sensitivity of the system of equations approach

B2.1 Firm fixed effects

In the main analysis, firm fixed effects are not included so that the estimates can be interpreted as long-run elasticities of substitution, which correspond closely to the theoretical literature. In this section, I examine within-estimates of the elasticity of substitution and technical parameters.

Table B3 reports the within estimates. When exploiting variation within firms only in column (1), the estimate of the elasticity of substitution between clean and dirty energy falls in magnitude, compared to the estimates in Table 3. This is not surprising since the within estimates correspond to short-run elasticities of substitution (Arnberg and Bjørner, 2007). Further, these do not incorporate changes in fuel prices that induce firms to adjust fuel choices at the extensive margin (or close down) that are likely to be larger in magnitude than changes in fuel prices that lead to adjustments in fuel choices only at the intensive margin. However, the estimate remains above one, thus qualitatively comparable to the estimates that exploit cross-sectional variation.

Technical parameters similarly indicate dirty-energy-biased technical change over the entire time period: -2 % and 2% per year growth in the clean- and dirty-energy-augmenting technology, respectively. Column (2) presents estimates weighted by energy consumption. Examining the shift in the direction of technical change, column (3) and (4) report estimates from the pre- and post-2004 period, respectively. Technical change appears biased toward dirty energy up to 2004 (column (3)). Again qualitatively similar to the earlier results, the technical parameter associated with clean energy turns positive in the post-2004 period, indicating 0.8% per year growth (column (4)). At the same time, the dirty-augmenting technical change parameter turns negative and is less precisely estimated.

B2.2 Alternative instruments

The preferred instruments used so far apply the growth rates of energy prices at the national level to the pre-sample firm-level price. Other studies have implemented a similar specification that weights national fuel prices using the pre-sample fuel share at the firm level (Linn, 2008; Sato et al., 2019; Marin and Vona, 2019). As a robustness check, I try this alternative specification to check the sensitivity of the system of equations approach. The alternative instrument for the price of clean energy $\hat{P}_{it}^{C}$ is constructed as:

Table B3: Estimation of the system of equations: within estimates

	(1)	(2)	(3) pre-2004	(4) post-2004
$\hat{\sigma}$	1.314***	1.402***	1.503***	1.379***
	(0.026)	(0.061)	(0.101)	(0.067)
$\hat{\tau_C}$	-0.014***	-0.020***	-0.043***	0.008**
	(0.003)	(0.003)	(0.005)	(0.004)
$\hat{\tau_D}$	0.020***	0.019***	0.023***	-0.005
	(0.002)	(0.003)	(0.004)	(0.005)
Firm FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Weighted by E_{it}		✓	✓	✓
Observations	65,884	65,884	65,884	65,884

Notes: Estimates from the within specification of the system of equations (6)-(7). Standard errors are clustered at the firm level.

$$\hat{P^C_{it}} = \sum_{j=1}^{3} \phi^j_{it_0} \, P^j_t \tag{12}$$

where P^j_t is the national price of fuel j and $\phi^j_{it_0}$ is the share of fuel j in the clean energy bundle (that includes electricity, steam, and renewables) in the pre-sample period ($t = t_0$). The alternative instrument for the price of dirty energy $\hat{P^D_{it}}$ is similarly constructed with the pre-sample share of each dirty fuel (10 in total) calculated within the dirty energy bundle.

Although the specification is slightly different, exclusion restrictions are similar to the main instruments. First, the national energy prices should not be correlated with factor-specific firm-level omitted variable bias such as firm-specific productivity shocks. Second, the pre-sample share $\phi^j_{it_0}$ in $t = t_0$ should not be correlated with idiosyncratic productivity shocks in subsequent periods.

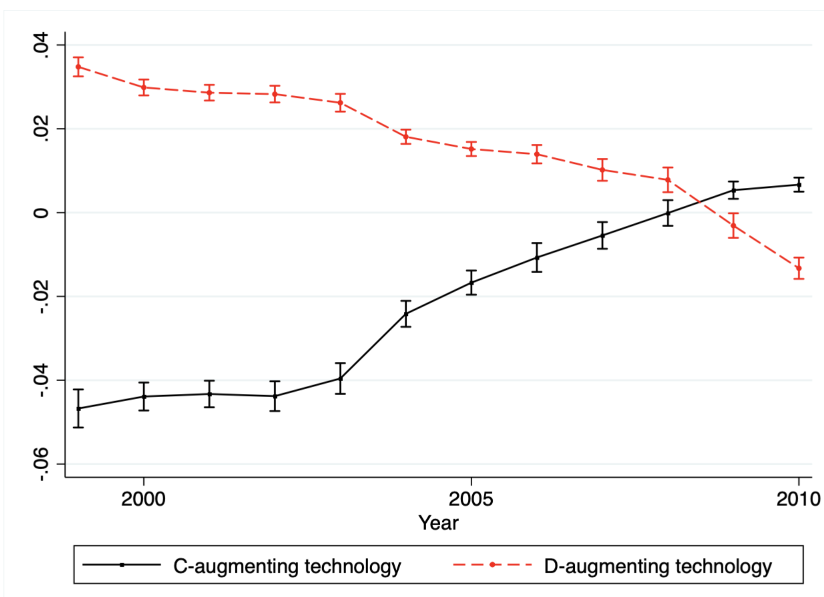
Table B4 reports GMM estimates from using the alternative instruments. The estimates of the substitution parameter tend to be smaller in magnitude than those in earlier specifications (except in column (4)), but remain above one. Technology parameters across all columns suggest largely dirty-energy-biased technical change. For instance, the clean- and dirty-energy-augmenting technology has experienced -2.1% and 2.3% per year growth, respectively (column (4)). To check the evolution of energy-specific efficiency growth over

Table B4: Estimation of the elasticity of substitution and technical change in the energy aggregate: GMM estimates using alternative instruments

	(1)	(2)	(3)	(4)
$\hat{\sigma}$	1.380***	1.206***	1.285***	2.422***
	(0.223)	(0.071)	(0.063)	(0.122)
$\hat{\tau_C}$	-0.022***	-0.045***	-0.040***	-0.021***
	(0.005)	(0.009)	(0.005)	(0.001)
$\hat{\tau_D}$	0.020***	0.042***	0.037***	0.023***
	(0.004)	(0.008)	(0.004)	(0.001)
Industry FE		✓	✓	✓
Region FE			✓	✓
Weighted by E_{it}				✓
Observations	65,884	65,884	65,884	65,884

Notes: Results from estimating the system (6)-(7). Standard errors are clustered at the firm level.

Figure B1: Annual growth of clean- and dirty-augmenting technologies: on a 10-year rolling window using alternative instruments



Notes: GMM estimates of technology parameters with confidence intervals from estimating the system (6)-(7) on a 10-year rolling window. Year is the median year in each 10-year window.

time, I estimate the system using the alternative instruments on a 10-year rolling window. The results are reported graphically in Figure B1. As before, one observes sharply different trends in the clean- and dirty-energy augmenting technology. The growth rates of clean-energy-augmenting technology gradually increase over time as the window moves into the post-2004 period, while those of dirty-energy-augmenting technology fall gradually.

B2.3 Alternative specification for technical progress

So far, I adopted the assumption of linear constant technical progress, following the relevant empirical literature. As a robustness check, I relax this assumption and allow technical progress to flexibly nest linear, log-linear and hyperbolic growth based on the Box-Cox transformation (Klump et al., 2007; León-Ledesma et al., 2010). This leads to the general expression, $A_i(t) = e^{g_i(t)}$ where $g_i(t) = \frac{\tau_i}{\lambda_i}\left[t^{\lambda_i} - 1\right], i = C, D$ and $t > 0$. The curvature parameter λ_i determines the shape of the technical progress function. $\lambda_i = 1$ implies the linear constant growth assumed so far; $\lambda_i = 0$ a log-linear specification; and $\lambda_i < 0$ a hyperbolic specification for technical growth. For instance, $\lambda_C = 1$ with $\tau_C > 0$ and $\lambda_D = 0$ with $\tau_D > 0$ corresponds to a scenario where the growth in clean-energy-augmenting technical progress is constant, while that in dirty-energy-augmenting technical progress continuously decelerates and asymptotically converges to zero.

Table B5 reports the estimates from this exercise. It is noteworthy that σ estimates remain comparable to those from the main specification despite the strong nonlinearities added by the new terms. The estimated technology parameters suggest largely dirty-energy-biased technical change over the sample period across different specifications, corroborating the findings from the main specification. But, they are much larger in magnitude than those produced by the previous specifications and likely to be beyond what is economically reasonable: -13 % and 17% per year growth in the clean- and dirty-energy-augmenting technology, respectively (column (3)). The estimates of the curvature parameters are less stable across different specifications. With industry and region fixed effects in column (3), both curvature parameters are imprecisely estimated with positive coefficients. Once weighted by total energy consumption in column (4), the estimates turn negative, making it difficult to draw firm conclusions about the patterns of growth in efficiency. León-Ledesma et al. (2010) also find that bias in estimates from this specification tends to be higher compared to the linear specification for technical progress especially when the elasticity of substitution is greater than one. GMM estimates that account for potential endogeneity are also qualitatively similar (Table B6), again pointing to a largely dirty-energy-biased technical change. Table B7 reports estimates from a 10-year rolling window to see how the rates of

Table B5: Estimation of the elasticity of substitution and technical change in the energy aggregate: Alternative specification for technical progress

	(1)	(2)	(3)	(4)
$\hat{\sigma}$	2.453***	2.106***	2.088***	2.457***
	(0.046)	(0.042)	(0.042)	(0.103)
$\hat{\tau_C}$	-0.082***	-0.134***	-0.137***	-0.156***
	(0.007)	(0.008)	(0.008)	(0.014)
$\hat{\lambda_C}$	-0.208*	0.034	0.044	-0.179*
	(0.107)	(0.093)	(0.092)	(0.108)
$\hat{\tau_D}$	0.110***	0.169***	0.172***	0.154***
	(0.006)	(0.007)	(0.007)	(0.011)
$\hat{\lambda_D}$	-0.027	0.061	0.066	-0.304***
	(0.080)	(0.071)	(0.070)	(0.102)
Industry FE		✓	✓	✓
Region FE			✓	✓
Weighted by E_{it}				✓
Observations	65,884	65,884	65,884	65,884

Notes: Estimates from the specification with Box-Cox transformation for technical progress. Standard errors are clustered at the firm level.

technical growth associated with each energy type evolve over time with the alternative specification for technical progress. Again, estimates of the elasticity remain above one across different sample periods. As observed in the previous specifications, the rolling-window estimates point to a shift in the path of innovation toward clean technologies. The growth of clean-energy-augmenting technology appears to surpass that of dirty-energy-augmenting technology in the last two windows that sit squarely in the post 2004 period, and yet again in economically unreasonable magnitude.

Table B6: GMM estimation of the system of equations with an alternative specification for technical progress

	(1)	(2)	(3)	(4)
$\hat{\sigma}$	2.950***	3.111***	3.834***	4.384***
	(0.154)	(0.134)	(0.132)	(0.148)
$\hat{\tau_C}$	-0.158***	-0.155***	-0.094***	-0.085***
	(0.024)	(0.020)	(0.020)	(0.025)
$\hat{\lambda_C}$	-0.856***	-0.869***	-1.549***	-1.465***
	(0.275)	(0.232)	(0.271)	(0.371)
$\hat{\tau_D}$	0.157***	0.165***	0.115***	0.119***
	(0.018)	(0.015)	(0.017)	(0.020)
$\hat{\lambda_D}$	-1.064***	-0.944***	-1.547***	-1.267***
	(0.215)	(0.176)	(0.216)	(0.248)
Industry FE		✓	✓	✓
Region FE			✓	✓
Weighted by E_{it}				✓
Observations	65,884	65,884	65,884	65,884

Notes: GMM estimates from the specification with Box-Cox transformation for technical progress. Standard errors are clustered at the firm level.

Table B7: Estimation of the system of equations on a 10-year rolling window with an alternative specification for technical progress

	(1)	(2)	(3)	(4)	(5)	(6)
Median year	1999	2000	2001	2002	2003	2004
$\hat{\sigma}$	2.645***	2.549***	2.482***	2.434***	2.393***	2.387***
	(0.035)	(0.050)	(0.048)	(0.061)	(0.061)	(0.063)
$\hat{\tau_C}$	-0.181***	-0.219***	-0.233***	-0.206***	-0.208***	-0.122***
	(0.013)	(0.019)	(0.017)	(0.014)	(0.010)	(0.018)
$\hat{\tau_D}$	0.140***	0.230***	0.261***	0.244***	0.261***	0.199***
	(0.013)	(0.019)	(0.013)	(0.011)	(0.009)	(0.016)
Obs	41,822	38,820	37,189	35,975	34,054	32,330

	(7)	(8)	(9)	(10)	(11)	(12)
Median year	2005	2006	2007	2008	2009	2010
$\hat{\sigma}$	2.372***	2.349***	2.311***	2.372***	2.404***	2.511***
	(0.060)	(0.060)	(0.059)	(0.061)	(0.060)	(0.063)
$\hat{\tau_C}$	-0.124***	-0.226***	-0.457***	-0.032	0.000***	0.001
	(0.021)	(0.044)	(0.164)	(0.041)	(0.000)	(0.001)
$\hat{\tau_D}$	0.205***	0.381***	0.763***	0.731***	-0.000***	-26.022***
	(0.019)	(0.045)	(0.139)	(0.270)	(0.000)	(2.517)
Obs	34,302	33,865	34,480	34,347	33,836	34,183

Notes: Estimates from the specification with Box-Cox transformation for technical progress. Standard errors are clustered at the firm level.