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DIRECTING TECHNICAL CHANGE FROM FOSSIL-FUEL TO RENEWABLE ENERGY INNOVATION: AN APPLICATION USING FIRM-LEVEL DATA

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Directing Technical Change from Fossil-Fuel to Renewable Energy Innovation: An Application Using Firm-Level Patent Data

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Abstract

This paper investigates the determinants of directed technical change at the firm level in the electricity generation sector. We use firm-level data on patents filed in renewable (REN) and fossil fuel (FF) technologies by 5,261 European firms over the period 1978-2006. We investigate how energy prices, market size and knowledge stocks affect firms' incentives to innovate in one technology relative to another and how these factors may thereby induce a shift from FF to REN technology in the electricity generation sector. We separately study small specialized firms, which innovate in only one type of technology during our sample period, and large mixed firms, which innovate in both technologies. We also separate the extensive margin innovation decision (i.e. whether to conduct innovation) from the intensive margin decision (i.e. how much to innovate). Overall, we find that all three factors - energy prices, market sizes and past knowledge stocks - matter to redirect innovation towards REN and away from FF technologies. Yet, we find that these factors have a larger impact on closing the technology gap through the entry (and exit) of small specialized firms, rather than through large mixed firms' innovation. An implication of our results is that firm dynamics are of direct policy interest to induce the replacement of FF by REN technologies in the electricity generation sector.

Keywords: Directed technical change; Renewable energy; Fossil fuel energy; Patents; Innovation; Firm dynamics

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1 Introduction

Today about 70% of world electricity is produced from highly carbon-intensive fossil fuels, namely coal, oil and gas. Some countries such as Australia, China, India and Poland even produce between 70% and 95% of their electricity through the combustion of coal only (IEA, 2010). This large reliance on fossil fuels explains why the sector of electricity generation is by far the largest producer of carbon emissions. Electricity production generates 41% of worldwide carbon emissions – twice the share of the transport sector – and emissions are expected to increase sharply in the future due to increasing electricity demand, notably from developing countries. In light of this, achieving substantial emission reductions will imply de-carbonizing the electricity generation sector and thus moving away from the dominance of fossil fuel technologies.

Renewable energy such as solar, wind, and renewable combustibles, can provide a clean alternative for electricity production. Yet despite rapid recent developments, renewable energy represents only 18% of world electricity. Accelerating technological innovation in renewable technologies can contribute to lower the costs of renewables so that they can compete on a level playing field with conventional fossil fuel energy sources (IEA, 2010). Specifically, directing technological innovation away from traditional fossil fuel technologies towards renewable ones might be particularly effective in this respect.

This paper investigates whether and how the factors affecting firm-level innovation may induce a shift from fossil-fuel to renewable innovation in the electricity generation sector. Most previous literature looked at the factors affecting innovation in clean technology – or clean electricity generation in particular (Hascic, Johnstone and Lanzi, 2009; Johnstone, Hascic and Popp, 2010) – but not whether these factors also effectively induce a shift away from dirty technologies. In addition, a large range of the empirical literature focuses on country-level analysis, ignoring firm-level determinants of innovation. Finally, the environmental economics literature has so far neglected aspects of firm dynamics in driving clean technology transitions, while existing literature in growth and innovation economics instead emphasizes the role played by heterogeneous innovating firms in driving the replacement of old technologies by new ones. This paper begins to bridge this gap by looking at how incentives for clean innovation affect not only firms' level of innovation (i.e. the intensive margin of innovation) but also firms' decision to undertake R&D in a given technology (i.e the extensive margin of innovation).

We use firm-level data on patents filed in renewable (REN) and fossil fuel (FF) technologies by 5,261 European firms over the period 1978-2006 and estimate the impacts of three main innovation drivers, namely: fuel prices, market size and the past knowledge stock (Acemoglu et al., 2012*a*). We conduct separate analyses for specialized firms, which innovate in only one type of technology over the 1978-2006 period, and mixed firms, which innovate in both technologies over the same period as our data show important differences between these two firm types. Compared to mixed firms, specialized firms are younger, smaller (in terms of turnover, assets, and employees) and innovate more incidentally. Our descriptive analysis shows that the distinction between these two types of firms is also important for understanding how REN technologies can replace FF ones. We find that in recent years the catch-up of REN with FF patents in the electricity generation sector is mainly induced by an increase in the set of specialized REN firms and a decrease in the number of specialized FF firms. Instead, innovation by mixed firms is still largely concentrated in FF technologies, with only a very moderate shift towards REN technologies.

Our estimation results show that all three factors – fuel prices, market size and knowledge stocks – are effective in redirecting innovation away from FF and towards REN technologies. Yet, we find that the drivers of innovation have an economically stronger impact on reducing the REN-FF technology gap for specialized firms than for mixed firms. This is mainly due to the fact that these factors are particularly effective in driving specialized firms' decisions to enter innovation in REN technologies (and to exit innovation in FF technologies), thus leading to substitution between the different types of firms at the sector level. The impacts on mixed firms have much less economic significance, since for these firms price and market signals do not lead to a significant substitution of FF by REN innovation at the firm level. In addition, these firms appear to be locked into FF innovation, in which they have a long history of past innovation.

The rest of this paper is organized as follows. Section 2 provides some first descriptive trends of innovation activities by heterogenous firms in REN and FF electricity generation technologies. Section 3 discusses the related literature, motivating theory and hypotheses that we will test in our empirical section. Section 4 presents the data sources and empirical strategy. Section 5 gives the main results and robustness analysis. Section 6 concludes.

2 Trends in electricy generation innovation

Before investigating the determinants of innovation, we provide a first glance at the patenting behaviour of firms in electricity generation. We use patent data to measure innovations in renewable and fossil-fuel technologies.[1] Since the pioneering work of Popp (2002), patents have been widely used to study innovation in environmental technologies. We construct a dataset of firms that have filed patents in REN or FF technologies related to electricity generations. The data are extracted from the Orbis dataset from Bureau van Dijk, which contains information on patents derived from the European Patent Office's (EPO) PATSTAT dataset. A major advantage of using the Orbis dataset is that patent applicants' names have been harmonized and corrected for variations in spelling in order to be matched with business register data. In addition, the Orbis database also includes financial and operational business data for some of the firms that could be matched with our REN and FF patents over the 2003-2006 period. We will use some of this information to describe the types of firms included in our dataset in more detail.

We focus on firms that have been granted at least one renewable or fossil-fuel patent at the European Patent Office (EPO) and at 17 national patent offices of the EU-15 countries, Switzerland and Norway over the 1978-2006 period.[2] We count the number of granted patents per firm per year.[3] Hence, our patent sample adds up patents from both EPO and national offices.[4] Although there might be some concerns about comparing patents of heterogeneous

[1]The advantages and limitations of patents as a measure of innovation, have been discussed at length in the literature. A main caveat of working with patents is that not all inventions are patented, as for strategic reasons firms may prefer not to disclose some valuable information in a patent. Also, the value of patents is very heterogeneous: only few patents will lead to successful commercial applications, while many will in the end never be used. Yet, patents have a close (if not perfect) link to invention and are strongly correlated with other indicators of innovative activity such as R&D expenditures or new product introductions (Griliches, 1990). For our purpose the main advantage of using patent data is that these data are highly disaggregated and are available at the firm and technology level.

[2]We focus on these 17 European countries since, even though firms and inventors worldwide can apply for patents at the EPO, we expect that non-EU applicants are more likely to (first) file patents at their domestic or regional patent offices. Restricting the analysis to European firms should limit the possibility that we miss out on a substantial part of a firm's patent applications.

[3]We take the application year of (priority) patents as this is closer to the year of the inventive idea than the year in which the patent was granted. When one patent has several applicants, we weight the patent counts accordingly.

[4]We follow hereby the suggestion of an anonymous referee. In addition, in the robustness analysis we provide additional estimations after selecting for the subset of higher value patents that have been filed in at least two other patent offices (Lanzi, Verdolini and Hascic, 2011; Popp, Hascic and Mehdi, 2011). Selecting only EPO patents, which would allow for a more homogeneous and comparable set of patents, would reduce strongly the set of (REN) patents under study and would be affected by the fact that filing at EPO became increasingly popular only in the mid 1990s (Eaton, Kortum and Lerner, 2004).

value filed at different patent offices, our baseline sample is not likely to include the lowest quality patents since we select only granted patents that could be matched with the business register data in Orbis, thus excluding patents from individuals. In addition, since our focus is on firm dynamics, we would be particularly concerned about eliminating small innovating firms that may not have the financial capacity to file their patents at EPO or in several countries, as this may create a bias towards innovation by large firms who are more likely to patent in FF innovation as we will demonstrate below.[5]

Building on previous work by Lanzi, Verdolini and Hascic (2011) and Johnstone, Hascic and Popp (2010), we use International Patent Classification (IPC) codes to select patents in REN and FF energy generation. REN technology classes are aimed at creating and improving the generation of renewable energy. In particular, we consider innovations in seven different technological classes: wind, solar, hydro, marine, biomass, geothermal and waste. Regarding FF innovations, we consider the following technologies: production of fuel gases by carburetting air, steam engines plants, gas turbines plants, hot-gas or combustion-product positive displacement engine, steam generation, combustion apparatus, furnaces and improved compressed-ignition engines.[6]

Our analysis focuses on a sample of 31,377 patents filed by 5,261 European firms. The REN and FF patents represent 13% and 87% of the patents, respectively. As shown in Figure 1(a), the total number of FF patents granted to the firms in our sample is fairly stable around 900 patents per year during the 1980s. It then increases and stabilizes around 1,100 patents per year during the 1990s. Finally, it drops off rather rapidly since the early 2000s. The number of REN patents is substantially smaller. The trend shows a small peak in the early 1980s, a stable period during 1985-1995, an a subsequent acceleration. All together, this figure suggest that the aggregate technology gap between REN and FF patents has become smaller in recent

[5] Additionally, since many of the REN patents are very recent, correcting for the quality of patents using forward citations would give a positive bias to FF patents.

[6] In the remainder, we coin the REN technologies as follows: *wind*, *solar*, *hydro*, *biomass*. *geo*, and *waste*, respectively; and the FF technologies as: *coal*, *engines*, *turbines*, *hotgas*, *steam*, *burners*, *furnaces* and *ignition*, respectively. The definition of these general classes of fossil-fuel technologies is described in more detail in Lanzi, Verdolini and Hascic (2011). With the help of patent experts, the authors started the classification by identifying energy efficient fossil-fuel patent classes (e.g. improved steam engines, cogeneration) and by eliminating restrictions on the technology's orientation towards efficiency improvement. By selecting hierarchically superior IPC classes, they were able to identify IPC classes that in general refer to fossil combustion technologies. Subclasses containing irrelevant patents (e.g. motor vehicle-related inventions within the improved compressed-ignition engines category) and classes that are generic and applicable to energy generation using a wide range of fuels (not only fossil) are not included (e.g. heat exchange technologies).

years, due to an increase in REN innovation relative to FF one.

Looking at the types of firms, we find that our sample is composed of 1,307 (25%) and 3,674 (70%) firms which innovate only in REN or FF technologies over the whole sample period, respectively. By contrast, we observe that 280 firms (5%) innovate in both technologies over this 30-year period. In the remainder of the analysis, we coin these firms as specialized REN, specialized FF and mixed firms, respectively. Figure 1(b) counts the number of active (i.e. innovating) firms in each sample year, and breaks them down into specialized and mixed firms. The trend in the number of specialized REN firms strongly mirrors the trend in REN patent counts in Figure 1(a). A similar correspondence is observed between specialized FF firms and the trend in the number of FF patens since the early 2000s. The number of innovating mixed firms is relatively constant over time.

<< **INSERT FIGURE 1 ABOUT HERE** >>

Figure 2 further disaggregates the patent counts in Figure 1(a) by firm type. Figure 2(a) presents REN and FF patent counts for specialized firms. The overlap with Figure 1(a) is even more pronounced in this case. Figure 2(b) presents REN and FF patent counts for mixed firms. Two notable differences stand out relative to the total patent counts in Figure 2(a). First, the decrease in FF patent counts starts earlier, around 1995. Second, the increase in REN patents in the second half of the sample period is much less pronounced. In sum, in the specialized firm sample, the convergence between REN and FF patents is induced by an increase in REN patents and a simultaneous decrease in FF patents. In the mixed firm sample however, it is only induced by a decrease in FF patenting.

<< **INSERT FIGURE 2 ABOUT HERE** >>

Comparing patent and firm counts in Figures 1 and 2, these results suggest that specialized firms are relatively small in terms of their total patent counts. As a result, developments in their REN and FF patent counts are rather strongly driven by underlying firm dynamics, i.e. a change in the set of firms conducting innovation. Mixed firms on the other hand are much larger. In their case, firm dynamics are much less important drivers of innovation activity, as the number of innovating firms is rather constant. Instead, the changes in the rate of innovation at the firm level are much more important. Further inspection shows that specialized firms account for 70% and 65% of REN and FF patents, respectively. Mixed firms comprise approximately 5% of the total firm sample, yet they account for approximately 30% of REN patents, and 35% of FF patents. This suggests that mixed firms are indeed larger than specialized firms.

Table 1 explores this further using a subset of our sample of firms for which we have additional data on firms' characteristics.[7] From panels A, B, and C it is clear that mixed firms are substantially larger on average than specialized firms in terms of turnover, total assets, and number of employees. Panel D demonstrates that mixed firms are also older on average than specialized firms. Finally, panel E depicts the number of active innovation years per firm type, i.e. the number of years in which a firm was actually granted a (REN or FF) patent. As can be seen, mixed firms are substantially more active in terms of REN or FF innovation than specialized firms.[8] T-tests on the average differences reported in panels A-E of Table 1 confirm that the differences between mixed firms and specialized firms are statistically significant (all below the 1% significance level). Taken together, these results illustrate fundamental differences in the characteristics and innovation activities of specialized versus mixed firms.

<< INSERT TABLE 1 ABOUT HERE >>

A potential concern regarding our definition of specialized and mixed firms is that some of our specialized firms will develop into mixed firms in the post-sample period. That is, mixed firms might typically start innovating in one area (REN or FF) before venturing into the other. If this initial "period of specialization" is relatively long, we could mistakingly classify young firms (i.e. that innovate for the first time towards the end of our sample) as specialized. In order to investigate this, we identified the first year of both REN and FF innovation in our sample of mixed firms, and considered the delay between these first years of innovation. The first year of FF (REN) innovation for the average mixed firm in our sample is 1989 (1991).[9] That is, the first REN innovation in mixed firms occurs (on average) two years after the first FF innovation. The median difference is just one year, and the distribution of differences exhibits a high peak

[7]The final column in Table 1 presents the number of firms on which the statistics are based. Financial data were only available for a subset of firms on the 2003-2006 period.

[8]Since mixed firms by definition patent in both REN and FF technologies, this is not surprising. However, notice that the median mixed firm patents almost three times as much as the median specialized REN and FF firms combined.

[9]Note that these first innovation years occur relatively late in the sample (more than 10 years after the start of the sample period in 1978). We take this to indicate that we are not (on average) picking up continued FF or REN innovation that already started before the sample period.

at this median value. Although this obviously does not rule out that some of our specialized firms might still become mixed firms in the post-sample period, these results demonstrate that on average, initial REN and FF innovations in mixed firms tend to be clustered together in time rather tightly. As such, we are not overly worried that our classification of specialized and mixed firms is driven by the sample period.[10]

Finally, we inspect the prevalence of different REN and FF technologies in the two different firm types. According to Table 2 – and as indicated above – specialized firms are responsible for 70% of REN innovation and mixed firms for 30%. In terms of importance, solar and wind technologies are the two most important categories in both firm types, although wind is comparatively more important in specialized firms than in mixed firms. Overall, the distribution of innovation is slightly less skewed in specialized firms than in mixed firms.

<< **INSERT TABLE 2 ABOUT HERE** >>

Table 3 demonstrates a similar split of innovation in FF technologies between firm types: 65% for specialized firms and 35% for mixed firms. Compared to REN innovation, the distribution of innovation shares across the different technologies is somewhat less skewed in both firm types. Furnaces and burners are the most important technologies in both firm types, but the difference in their relative importance is small. Engines and turbines are also relatively important.

<< **INSERT TABLE 3 ABOUT HERE** >>

In summary, we observe that FF patents make up the lion's share of our total energy patent counts, and their numbers have consistently outranked those of REN patents. Only from the mid 1990s onwards do we observe a convergence between REN and FF patents, i.e. a closing of the technology gap, that is induced by a simultaneous increase of the former and a decrease of the latter. However, even though both specialized and mixed firms have driven

[10] Another concern regarding our distinction between specialized and mixed firms is that the former might be subsidiaries of a larger (multinational) corporate network, and as such are eventually part of a mixed firm after all. Using the ownership relations provided in Orbis, we examined this possibility. A drawback of this analysis is that we only have non-missing information on the identities of (global) ultimate owners (defined as firms that own at least 25% of a focal company's stock and are diffused firms themselves) for 8.1% of the firms in our sample. For this small subset, we found that only 3.1% of specialized REN firms are part of a larger corporate network that also incorporates specialized FF subsidiaries. For specialized FF firms this percentage is 3.6%. Based on these findings at least, our distinction between specialized and mixed firms seems warranted. We thank one of the anonymous referees for drawing our attention to this point.

the reduction in FF patents, only specialized firms are responsible for the increase in REN innovation. The descriptive results further suggests that this latter development is mainly driven by firm dynamics, i.e. more (specialized) firms becoming active in REN innovation. Finally, we have demonstrated that mixed firms are fundamentally different from specialized firms – in terms of turnover, total assets, number of employees and age – and that they are more frequent and persistent innovators.

3 Literature review and conceptual framework

3.1 Background literature

The goal of this study is to understand whether and how the factors affecting firm-level innovation may induce a shift from fossil-fuel to renewable innovation in the sector of electricity generation. There is an extensive literature in environmental economics studying the factors affecting clean innovation. The starting point of this literature is the induced innovation hypothesis of Hicks (1932), stating that inventions are triggered by changes in the relative prices of production factors. In line with Hicks' original idea, Popp (2002) finds strong evidence for a positive effect of energy prices on patents in 11 clean energy-related technologies over the 1970-1994 period. He also finds evidence that the quality of knowledge available to inventors matters for successful patent applications. Environmental policy can also foster technological change in environmental and energy-related technologies, as taxes or subsidies can affect the profits of firms engaged in innovation. Johnstone, Hascic and Popp (2010) provide an analysis of how energy prices and various policy instruments affect innovation in different renewable energy technologies. They find that price-based policies, such as feed-in tariffs, can effectively increase innovative activities in the more costly renewable technologies, such as solar power.

Recent theoretical work on directed technical change aims to investigate the factors that can induce a relative shift towards clean technologies and away from dirty ones at the aggregate level (Acemoglu et al., 2012*a*; Smulders and Nooij, 2003; Di Maria and van der Werf, 2008). Acemoglu et al. (2012*a*) emphasize the role of three factors affecting the direction of technological change at the sector level: first, the price effect, encouraging innovation in the sector with higher prices;[11] second, the market size effect, encouraging innovation in the sector for which there is

[11] In this case, high fossil fuel prices will tend to encourage energy-saving innovation in the dirty sector.

a bigger market (i.e. demand); third, the direct productivity effect, which pushes innovation towards technologies with a higher productivity or existing stock of knowledge. This latter force results from the ability to "build on the shoulders of giants": future innovations are building on the existing stock of knowledge or technology, thereby generating path-dependencies in knowledge creation. A main result from Acemoglu et al. (2012*a*) is that when the clean and dirty inputs are strong substitutes, the market size and initial productivity advantage of dirty inputs will direct innovation towards the dirty sector, leading to an environmental disaster. In that case, government intervention is necessary and temporary taxes or subsidies can redirect innovation towards the clean sector. Building on Acemoglu et al. (2012*a*)'s framework, Aghion et al. (2012) study how carbon taxes and firms' past knowledge stocks induce firms in the automobile sector to invest more in clean (e.g. electric and hybrid) than in dirty (e.g. internal combustion engine) technologies. They find that firms tend to innovate relatively more in clean technologies when they face higher tax-inclusive fuel prices. They also find evidence for path-dependency in innovation from both aggregate knowledge spillovers and from the firm's own innovation history. Popp and Newell (2012) examine the trade-offs between clean and dirty innovation at the firm level by looking at the patent portfolio of large publicly traded firm. They find that these firms adapt their research portfolio as a response to market incentives: as opportunities for alternative energy research become more profitable, firms will increase innovation in alternative energy patents and reduce other types of innovation, suggesting some form of within-firm substitution. They do not find evidence that such crowding out occurs because firms are financially constrained.

In parallel to these developments in environmental economics, the economic growth and innovation literature has witnessed in recent years a renewed interest for Schumpeter's notion of creative destruction – the process by which new innovations replace older ones (Aghion, Akcigit and Howitt, 2013). This literature provides useful insights to understand how technological transitions can take place via innovation from heterogeneous firms, namely new entrants and incumbent firms (Klette and Kortum, 2004; Acemoglu and Cao, 2010).[12] The empirical literature in this line of research documents some key stylized facts about innovating firms: (1) the distribution of R&D intensity among firms is highly skewed: a large number of firms perform

However, if there is a high degree of substitution between the clean and dirty inputs, high fossil fuel prices will also encourage innovation in the clean sector.

[12]See Acemoglu et al. (2012*b*) for a first application to clean technology transition.

low R&D, while a small number of firms has high R&D intensity; (2) large established firms innovate a lot but tend to focus on improving existing technologies (Cohen and Klepper, 1992; Akcigit and Kerr, 2010); (3) small firms and new entrants are often believed to be the source of more major and radical innovations than large firms (Akcigit, 2011; Kamien and Schwartz, 1975);[13] (4) there are high sunk and fixed costs to start R&D, such as the setup of an R&D lab, the purchase of equipment, and the configuration of the necessary infrastructure (Stiglitz, 1987; Hall and van Reenen, 2000; Arque-Castells and Mohnen, 2012).[14] Moreover, these costs may vary across firms (Stiglitz, 1987; Hall and van Reenen, 2000; Manez et al., 2009). For example, Manez et al. (2009) finds that large firms in high-tech sectors incur higher sunk costs in the decision to invest in R&D than small firms in low-tech sectors.

Malerba and Orsenigo (1999) use patent data to illustrate some of those key differences among innovating firms. Looking at patenting firms in a wide number of technologies and countries over 13 years, they find that for all technological fields a large fraction of new innovators is composed by occasional innovators that exit the innovating scene very fast. Only a few of them are able to grow and to become persistent innovators. They also find that the only firms that are able to diversify their patenting activities and enter new research areas are large patenting firms that have already invested a lot in research activities. These so-called "lateral entrants" (i.e. firms that start innovating in new research field in which they have no experience so far) are also on average older than other firms. These findings are consistent with our observation in Section 2 that mixed firms are on average larger, older, and more innovative than specialized firms.

3.2 Conceptual framework

Building on these two strands of literature, we can formulate expectations on how heterogeneous firms respond to incentives for innovation, and how firm dynamics may induce a replacement of FF by REN innovation in the electricity generation sector. We assume that firms employ scientists in corporate research laboratories and can innovate either in REN, FF or both technologies using technology-specific (REN or FF) inputs. Firms' profits from innovation activities

[13] Akcigit (2011) shows for instance that due to diminishing returns to innovation small firms have more incentives to increase their productivity and to choose higher quality innovation than large firms.

[14] Conducting R&D implies creating research labs, purchasing machinery and hiring and training a specialized workforce. As Stiglitz (1987) notes: "Most expenditures on R&D are, by nature, sunk costs. The resources spent on a scientist to do research cannot be recovered. Once this time is spent, it is spent." (p. 889)

in a given technology have two components: (1) variable innovation profits - which following the set up of Acemoglu et al. (2012*a*) are a function of input prices, input market size, and firm's past accumulated knowledge stock in the given technology;[15] (2) technology-specific fixed and sunk costs - where fixed costs, such as the salaries of R&D personnel, have to be incurred in every period, while sunk costs, such as the purchase of necessary equipment and machines for setting up a research lab, are incurred only once before the firm starts innovating in the given technology. As a result, sunk costs have to be incurred twice for mixed firms, but only once for specialized firms. This is consistent with empirical studies finding that only large firms are on average capable of incurring the large sunk costs needed to diversify their research portfolio and to sustain several research lines.

In every period, all firms face two types of innovation decisions (cf. Arque-Castells and Mohnen, 2012): (1) they first decide whether they enter the innovation market to undertake R&D in a given technology (or both) (i.e. the extensive margin of innovation); firms will only enter the innovation market in a given period if their expected innovation profits are nonnegative, i.e. if their variable innovation profits cover their sunk and fixed innovation costs; (2) conditional on entry, firms decide how much innovation they will conduct in the given technology (i.e. the intensive margin of innovation); the level of variable innovation profits in the given technology (or both) will determine the firm's rate of innovation.

We first formulate hypotheses regarding innovation decisions of specialized firms. Upon first entry, each firm compares REN and FF innovation profits to decide which innovation market to enter. If the firm's expected profits of entering REN technology are large enough to cover the firm's initial REN sunk and fixed costs and larger than the expected profits of entering FF innovation, then the firm will start innovating in REN technologies. Moreover, after this initial choice, specialized firms can always choose to diversify into the other technology and become mixed firms, if their expected innovation profits are large enough to incur the additional sunk costs of entering a new research line. In this set up, we expect the drivers of both REN and FF innovation profits to affect specialized firms' extensive margin innovation decision in every period. More specifically, we expect an increase in REN (FF) market size and a firm's REN past knowledge stock to increase the likelihood of undertaking R&D into REN (FF) innovation

[15] For now, we consider path-dependency in innovation at the firm level. In the empirical analysis we also consider path-dependency at the sector level, allowing for aggregate knowledge spillovers. In addition, we only consider the prices of FF inputs. As explained in Section 4, price data for REN inputs are not readily available.

by specialized firms, while an increase in FF (REN) market size will reduce it.[16] Regarding the impact of FF prices, the literature generally assumes that REN and FF technologies are good substitutes in electricity production (Lanzi and Sue-Wing, 2010; Baker and Shittu, 2006). Accordingly, the price effect described by Acemoglu et al. (2012*a*) implies that rising FF prices are expected to be associated with a relatively higher likelihood of entry for REN specialized firms and a lower likelihood of entry for FF specialized firms, leading to some substitution between the two types of firms.

Next, conditional on a positive entry decision, specialized firms make a decision regarding how much to innovate (i.e. the intensive margin decision). Since specialized firms have either chosen to enter the REN or FF innovation market (but not both), the intensive margin decision will only depend on the factors affecting the innovation profits of the given technology. Specifically, REN market size and knowledge stocks are expected to increase the level of innovation in specialized REN firms. By contrast, FF prices and market size are expected to have no impact on the level of innovation by REN firms, since FF inputs do not enter the innovation profit function of REN firms. A similar reasoning holds for the factors affecting the rate of innovation by specialized FF firms.

We now turn to our hypotheses regarding mixed firms' innovation decisions. Mixed firms are either former specialized firms that have found it profitable at some point to diversify, or firms that entered both the REN and FF innovation markets simultaneously upon first entry.[17] Once they have incurred both sunk costs and have the necessary equipment for both REN and FF innovation, they can still (in every period) decide to enter R&D in either one or both technologies, depending on which technology is expected to yield the largest innovation profits covering the per-period fixed costs. Hence, in their extensive margin decision, similar to specialized firms they will compare REN innovation profits with FF innovation profits. We expect similar effects of the drivers of innovation as under specialized firms, with the difference that since mixed firms have built knowledge stocks in both technologies, mixed firms' FF knowlegde stock will also affect the likelihood and level of REN innovation within the firm (and similarly for REN knowledge stocks).

Once mixed firms have decided to enter innovation, their level of innovation (i.e the intensive

[16] By definition REN (FF) specialized firms do not have any past knowledge stock in FF (REN) technologies.

[17] In Section 2 we find that in our sample the typical mixed firm starts out as a specialized FF firm, but very quickly (on average after two years) diversifies into REN innovation.

margin) will be driven by input prices, market size and knowledge stocks in a similar fashion as for specialized firms. Unlike specialized firms, however, mixed firms may decide to enter *both* innovation markets. As a consequence, also in the intensive margin decision, mixed firms are likely to compare net REN and FF innovation profits in order to determine how many resources to invest in each technology. Therefore, again the determinants of both REN and FF innovation profits are likely to enter both intensive margin innovation decisions. More specifically, we expect that REN (FF) market size increase the level of REN (FF) innovation in mixed firms. In line with the path-dependency hypothesis, we also expect that REN (FF) knowledge stocks increase (decrease) the rate of REN innovation by mixed firms, and reduce (increase) the rate of FF innovation. Regarding the impact of FF prices, assuming that FF and REN innovation are substitutes in the firm's technology portfolio (as suggested by the findings of Popp and Newell (2012) of within-firm substitution between alternative energy and other technologies), we expect an increase in FF prices to be associated with a decrease in FF innovation and an increase in REN innovation.[18] Table 4 summarizes our expectations regarding the drivers of specialized and mixed firms' innovation decisions.

<< **INSERT TABLE 4 ABOUT HERE** >>

Ultimately, we are interested in determining whether corporate innovation can be directed away from FF techhnologies and towards REN technologies. As can be seen in Table 4, in most cases prices, market size, and knowledge stocks in both technologies steer innovation in opposite directions. The question we aim to answer is to what extent developments in these different variables have been responsible for closing the aggregate FF-REN technology gap as observed in Figure 1(a). To guide our empirical evaluation, we write the change in innovation (i.e. the number of granted patents P) in firm i that is active in technology j (s.t. $j \in REN, FF$):

$$\Delta P_{ijt} = \mathbb{I}(.)P_{ijt} - \mathbb{I}(.)P_{ij,t-1} \tag{1}$$

where $\mathbb{I}$ is the indicator function that takes value 1 if the firm enters innovation market j, and

[18] In the end, however, whether these two technologies are substitutes or complements in the firm's knowledge production function is an empirical question. Other research in the innovation literature shows that when firms diversify their technology portfolio, they tend to invest in technologies that share a common or complementary knowledge with their past innovation, suggesting that firms tend to develop complementarities between different lines of research (Breschi, Lissoni and Malerba, 2003). In that case, the drivers of innovation in one technology may also positively affect innovation in the other technology.

0 otherwise.[19] Since we are interested in the impact of our model variables on the aggregate technology gap, we have to consider the gap between FF (d) and REN (c) patents, aggregated over all firms in the economy:

$$\begin{aligned}\sum_i \Delta P_{idt} - \sum_i \Delta P_{ict} &= \sum_i \left(\mathbb{I}(.)P_{idt} - \mathbb{I}(.)P_{id,t-1}\right) - \sum_i \left(\mathbb{I}(.)P_{ict} - \mathbb{I}(.)P_{ic,t-1}\right) \\ &= \left(N_{dt}\overline{P}_{idt} - N_{d,t-1}\overline{P}_{id,t-1}\right) - \left(N_{ct}\overline{P}_{ict} - N_{c,t-1}\overline{P}_{ic,t-1}\right)\end{aligned} \tag{2}$$

where N_{jt} are the number of active (i.e. innovating) firms in sector $j \in c, d$ in period t, and $\overline{P}$ are average firm-level patents. Directed technical change away from FF and towards REN innovation implies a reduction in this gap. This could happen either through the extensive margin (i.e. fewer firms engage in FF innovation and/or more firms engage in REN innovation), the intensive margin (i.e. average firm-level FF innovation decreases and/or average firm-level REN innovation increases), or both.

4 Data & methodology

4.1 Data

As described above, our dependent variable in the empirical model is patent counts to proxy innovation in REN and FF technologies. To empirically estimate the model, we further need data on prices, market size, and knowledge stocks.

Energy prices The Energy Prices and Taxes database of the IEA contains data on country-level prices of the different fossil-fuel energy sources oil, gas and coal.[20] These prices correspond to the prices paid at the power plant for electricity generation, i.e. prices paid by electricity facilities for a certain type of fuel, and include taxes. In the analysis we use a production-weighted average price of oil, gas and coal prices per country. Ideally, we would like to have data on input prices for both REN and FF innovations. Data for input prices for REN technologies are, however, not easily available so that we only consider FF prices.

In order to make fossil-fuel prices firm-specific, we take into account the fact that firms

[19] Hence, the value of the indicator function is based on the evaluation (and comparison) of innovation profits net of fixed (and potentially also sunk) costs discussed above.

[20] Missing prices were imputed using the IEA relevant price indices for oil, gas and coal.

might be exposed to both domestic and foreign prices to different degrees as in Aghion et al. (2012). As an illustration, we have to capture the extent to which a Dutch firm is influenced by German prices. Arguably, this impact will be bigger, the more important the German market is for the Dutch firm's innovations. To capture this, we use information on patents' families as provided in Orbis through the link with PATSTAT to identify the set of countries in which the original patent has been filed.[21] To this end, we use data provided in Orbis that indicates, for each of the patents in our sample, if and in which countries it has been validated. For each firm i we then compute a weight w_{ic} which captures the share of country c in the firm's overall patent validation portfolio. In addition, we weight the different countries' prices with their FF market size in order to make sure that small countries do not have a disproportionate impact on computed prices.

Taken together, this implies that the fossil-fuel price faced by firm i at time t is computed as:

$$\begin{aligned} p_{it} &= \sum_c w_{ic} \times p_{ct} \\ \text{s.t. } p_{ct} &= \sum_{f=\text{oil,coal,gas}} \frac{M_{fc}}{M_{FFc}} \times p_{fct} \end{aligned} \tag{3}$$

where p_{ct} is the sum of (log) fossil-fuel prices p_{fct} (oil, coal and gas) in country c at time t, weighted by the respective average market shares of each fossil fuel type in that country. This price is then multiplied by the weight $w_{ic} = \frac{P_{it} \times M_{FFic}}{\sum P_{it} M_{FFic}}$, where P_{ic} is the total number of patents validated by firm i in designation country c and M_{FFc} is the country's FF average market size.[22]

Figure 3 shows the average firm-level developments of prices for the weighted average price used in the analysis as well as for the different individual fuel prices (oil, coal, and gas).

<< INSERT FIGURE 3 ABOUT HERE >>

[21] For EPO patents we additionally extract information on validation countries from the INPADOC database. Since our focus is on European firms that we assume will be primarily affected by drivers in Europe, we only consider patents filings in European countries. We find indeed that the large majority of our patents (87%) have been filed only in European countries (while about 13% have subsequently been filed in Japan or US).

[22] All our weights are fixed, i.e. we compute total patent counts P_{ic} and average market sizes M_{FFc} over the whole sample period. If changes in FF prices affect the country mix of the patent portfolio or the size of the FF market, not fixing the weights might feed back into the prices, causing potential endogeneity.

Market size To proxy market size, we use data on electricity output from renewable and fossil-fuel energy sources. These data are derived from the Energy Statistics database from the IEA and are expressed as the total number of GWh generated by power plants. Regarding FF energy, we have separate data on electricity output by three different types of fuel sources, namely coal, gas, and oil. Renewable electricity output breaks down into solar, wind, hydro, marine, geothermal, biomass and waste. In our robustness analysis, we also use data on installed capacity in the various energy sources extracted from the Electricity Information database from the IEA.[23] Market size variables are also likely to capture demand-pull policies (e.g., guaranteed tariffs, investment and production tax credits) aiming to increase the market demand for renewables.

As with prices in (3), we construct fixed firm-specific designation country weights w_{ik} to compute firm-level FF and REN market sizes. However, we now also introduce fixed firm-specific technology weights w_{is} to account for the fact that e.g. a firm innovating mainly in solar power will be mostly concerned with the market size for solar energy. Hence we compute:

$$M_{it} = \sum_c \sum_s w_{isc} M_{sct} \tag{4}$$

with $w_{isc} = \frac{P_{isc}}{\sum_s \sum_c P_{isc}}$, where P_{isc} is the number of patents of firm i in technology s in country c and M_{sct} is the (log) market size of technology s in country c.

To compute FF technology weights w_{isc} we use a correspondence between the FF technological areas and oil, gas or coal fuels as provided in Lanzi, Verdolini and Hascic (2011). For instance, technologies in the field of production of fuel gases by carburetting air are assigned to the market size of electricity output from coal.[24] For those FF innovations without such a correspondence, we assign the weighted average market size of all three fuel sources. Finally, we also compute firm-specific REN market sizes for firms innovating only in FF technologies since we include these in our estimations as explained in Section 4.2 below. To do so, we assign country-level market size averaged across all REN technologies, using the firm's relevant country-weights (w_{ic}). We proceed in a similar manner to assign FF market sizes to firms that innovate only in REN technologies. Figure 4 depicts the development of average firm-level REN

[23] We imputed missing values for installed capacity based on country-specific trends in electricity output data.
[24] See Table 1 on p.6 of Lanzi, Verdolini and Hascic (2011).

and FF market sizes over the sample period. The average FF market size is very stable and substantially higher than REN market size. However, the latter shows a remarkable increase since the early/mid 1990s. In addition to REN and FF technology market sizes, we use real GDP data from the World Bank Development Indicators for all the designation countries in our sample, and compute a firm-specific real GDP variable in a similar way as we compute firm-level prices (see above) to control for overall marketsize.

<< INSERT FIGURE 4 ABOUT HERE >>

Knowledge stock To proxy past productivity, we use cumulative patent counts to construct firm-specific knowledge stocks. We have to account for the fact that knowledge becomes obsolete as time progresses, for example due to the creation of new knowledge. We assume that knowledge stocks depreciate annually by 15% as is commonly assumed in the literature (Hall and Mairesse, 1995).[25] Knowledge stocks are computed using the perpetual inventory method as $KS_t = (1-\delta)KS_{t-1} + P_t$, where δ is the depreciation rate. Since we observe a long history of patenting for each firm, the initial knowledge stock for each firm is the cumulative knowledge stock in REN and FF technologies until 1978 (the first year of the sample period), or up until the first (observed) year of REN or FF innovation (if this is after 1978).

In addition, just as in Blundell, Griffith and van Reenen (1995) we include two variables to capture firms' capacity to innovate in the pre-sample period as explained in Section 4.2. We first compute the average pre-sample innovation count of every firm in all technologies, i.e. not only electricity generation technologies. This is the total count of all patents divided by the number of active innovation years in the period before the firms' first innovation in REN or FF technology. In addition, we add a dummy variable capturing whether a firm has innovated at all in the firm-specific pre-sample period. We will use this information in our estimations to control for unobserved firm heterogeneity as in Blundell, Griffith and van Reenen (1995).

4.2 Methodology

Our ultimate aim is to establish the impact of the energy prices, market size, and knowledge stocks on the direction of innovation. In order to do so, we first have to estimate how these

[25] Hall and Mairesse (1995) show in addition that the choice of depreciation rate for R&D makes little difference to estimate innovation production functions.

various factors affect firms' decisions to innovate in a given technology. An important issue that we need to address is firm's heterogeneity in innovation. As we show in Section 2 and as commonly found in the innovation literature, we have a large number of firms making few innovations while a small group is involved in higher and more diversified levels of innovation. These differences are unlikely to be all captured by observable differences across firms. In line with our conceptual framework in Section 3 some of the firm's heterogeneity is also explained by differences in firm's fixed and sunk costs for innovation reflecting their capacity to undertake R&D and break even on the innovation market. Other sources of heterogeneity may come from firm's propensity to patent or firm's (financial) capacity to innovate (for instance due to a better capacity to appropriate research efforts). In firm-level data, firm's heterogeneity is reflected in a larger number of zero innovation counts than a standard Poisson process would predict (Blundell, Griffith and van Reenen, 1995). In our analysis there are two different processes explaining a firm's zero patent count: (i) the 'structural' (excess) zeros stem from the fact that the firm has not find it profitable to undertake R&D (i.e. to enter the innovation market) in a given technology in that year (i.e. expected profits are not large enough to cover annual fixed costs), (ii) the 'standard' zeros are the realization of a standard Poisson process and reflect the fact that although the firm has entered the innovation market that year, innovation has not been successful (since innovation is an uncertain process). Accordingly, these two different processes capture firm's innovation decisions at the extensive and intensive margins as depicted in Section 3. To capture these two margins we estimate firm-level patenting behavior by a zero-inflated Poisson model. In this model, a logit distribution first determines whether the count variable (i.c. patent counts) has a zero or positive outcome. Then a second-stage Poisson distribution governs the actual realization of the outcome. Accordingly, the number of patents will follow a Poisson distribution, such that the intensive margin decision governing the rate of patenting is given by a log-linear Poisson model:

$$
\begin{aligned}
E(P_{ijkt}|X_{ijkt}, \eta_i, \upsilon_k, \nu_t) &= \log(\lambda_{ijkt}) \\
\text{s.t. } \lambda_{ijkt} &= \exp(\beta_0 + \beta_1 \log p_{it-1} + \beta_{2j} \log M_{ijt-1} + \beta_{3j} \log A_{ijt-1} + X_{it}\gamma \\
&\quad + \eta_i + \upsilon_k + \nu_t)
\end{aligned}
\tag{5}
$$

with i, j, k and t indexing firm, technology (REN (c) or FF (d)), country, and time respectively. The variable p denotes FF prices, M denotes market size, and A denotes knowledge stocks. η, υ and ν capture unobserved firm, country and time-specific heterogeneity, respectively. The vector $\mathbf{X}$ includes firm-specific levels of real (total) GDP. We lag the price and market size variables by one year to allow their impacts on patenting to be sluggish. To test the expectations depicted in Table 4, we include all REN and FF variables in both margins for both firm types when possible.[26] Regarding the extensive margin decision, in the zero-inflated Poisson model the likelihood of having a zero outcome for the count variable is estimated by a logit model:

$$\Pr(P_{ijkt} = 0) = \Lambda(\mu_{ijkt}) = \frac{e^{\mu_{ijkt}}}{1 + e^{\mu_{ijkt}}} \tag{6}$$

where $\mu_{ijkt} = \ln(\lambda_{ijkt})$ (as given in (5)) and Λ denotes the logistic distribution function.

The zero-inflated Poisson model allows us to separate the extensive and intensive innovation margin decisions, as it simultaneously estimates the two models in (5) and (6). In this regard, it is instructive to write the conditional mean of the model:

$$E(P_{ijkt}|X_{ijkt}, \eta_i, \upsilon_k, \nu_t) = (1 - \Lambda(\mu_{ijkt})) \times \lambda_{ijkt} \tag{7}$$

The first term on the RHS of (7) captures the probability that the binary process variable equals 1, implying a non-zero outcome (i.e. the extensive margin), whereas the second term on the RHS of (7) captures the level of patenting (i.e. the intensive margin).

Our motivation for the choice of zero-inflated Poisson estimation techniques presents many analogies with recent developments in the trade literature on how to deal with zero-value trade flows in gravity equations explaining bilateral trade activities (Helpman, Melitz and Rubinstein, 2008; Silva and Tenreyro, 2006; Anderson and van Wincoop, 2003; Burger, van Oort and Linders, 2009) in particular when estimations are disaggregated to the product level. In many cases, these zeros occur simply because some pairs of countries did not trade in a given period. The absence of trade can be explained by the presence of fixed costs to start trading, such as the lack of cultural or historical links between the two countries, and expected profits may simply not be large enough in the absence of demand for a given product. Hence in this literature - and

[26] As noted, we cannot include REN (FF) knowledge stocks in the models for specialized FF (REN) firms due to absence of such stocks for firms.

analogous to our modeling of innovation decisions - the same determinants that explains trade profits might thus affect both the extensive margin (decision to trade) and intensive margin (volume of trade) decisions.

Finally, although the zero-inflated Poisson model bears resemblance to the Heckman selection model, the zero-inflated Poisson is less restrictive as it does not rely on stringent normality assumptions and do not require an exclusion restriction or instrument for the second stage of the equation[27] Additionally, the Heckman model is not based on a count data process but on a logarithmic transformation of the explanatory variable, which is less suited for modeling patent counts.[28] As a result, the zero-inflated Poisson is our preferred estimation model.

Although the zero-inflated model accounts for unobserved heterogeneity in firms' sunk and fixed costs in innovation, there might be additional heterogeneity that cannot be captured by observable variables, such as the firm's financial ability to invest in innovation or other factors affecting the firm's capacity to innovate. Although the Orbis dataset includes some business and financial data at the firm level, the sample of firms for which these data are available is too small for reliable estimation. In addition, these data are only available for years after 2003 while our innovation panel runs for much earlier periods of time, raising the issue of endogeneity for these variables.

An additional complexity arises due to the fact that we include firm's knowledge stock on the right-hand side, which are not strictly exogenous, as they are based on the cumulative sum of lagged realizations of the dependent variable. This rules out an estimation of firms' fixed effect based on Hausman, Hall and Griliches (1984) conditional maximum likelihood estimation, since the later requires strict exogeneity and thus excludes the inclusion of a dynamic variable on the right hand side.[29] Instead or order to capture additional firm's heterogeneity, we rely on the pre-sample mean estimator developed by Blundell, Griffith and van Reenen (1995). They derive a proportional relationship (up to a constant) between a firm's average pre-sample innovation activity on the one hand, and unobserved firm heterogeneity on the other hand. The underlying assumption is that pre-sample innovation is a proxy for firm's propensity to

[27] In our case, this instrument should reflect a variable that influences the absence of innovation but is unrelated to the level of innovation - which would be hard to find.

[28] This is particularly true when studying patent counts at the firm level where there are only small absolute differences in the number of patents (which would become large differences after a logarithmic transformation).

[29] See Majo and van Soest (2011) for an example of zero-inflated fixed effect Poisson estimator based on conditional maximum likelihood estimation as in Hausman, Hall and Griliches (1984) and constructed for two time periods only, as standard routines for this model are not (yet) available in standard statistical packages.

innovation and firm's innovation search activity, which itself follows an AR1 process and is stationary. Hence, in our estimation we include for each firm its average pre-sample patent count, as well as a dummy variable equal to one if the firm ever innovated in the pre-sample period (cf. Blundell, Griffith and van Reenen, 1995).[30] The dummy will capture the fact that firms who have ever innovated in the past may be qualitatively different from firms who never innovated. Additionally, we control for unobserved country and time heterogeneity through the use of country and year dummies.

We include all the explanatory variables – including the proxies for unobserved firm heterogeneity – in both models. One limitation of our data is that we do not have data on firms' real entry and exit, only on its innovation (i.e. patenting) entry and exit. Hence, we are concerned that we might be trying to explain a firms' decision to invest into a R&D in periods where the firm did not even exist. To mitigate this issue, we only estimate our models on the firm's innovation period, i.e. between the first and last innovation years that we observe in our sample. Hence, our extensive margins estimates mainly reflect whether a firm expected profits in a given technology are large enough to cover the firm's fixed costs to innovate in a given year.

We estimate the empirical models in (5) and (6) separately for specialized and mixed firms. Using the estimated marginal impacts of each of the explanatory variables in the REN and FF models, we then compute the impact on aggregate directed technical change. That is, we compute the impact of the different model variables on the (relative) change in the FF-REN technology gap as formulated in (2), separating extensive and intensive margin impacts (the Appendix provides the technical details).

Table 5 shows some summary statistics and pairwise correlations of the variables in our model. In accordance with the descriptive evidence presented above, all the unconditional averages of the FF variables are higher than those of the REN variables. As can be seen, multicollinearity is not an issue in our sample.

<< INSERT TABLE 5 ABOUT HERE >>

[30]For firms that have zero pre-sample information, we use the logarithm of an arbitrary small constant and let the dummy estimates its level.

5 Estimation results

5.1 Baseline results

In Table 6 we present our baseline results. All models include full sets of country and year dummies (not reported). Columns (1) and (2) estimate the model for specialized REN and FF firms, respectively. Columns (3) and (4) estimate the two models for mixed firms. All models are estimated using the zero-inflated Poisson model described earlier. The top part of the table presents the coefficient estimates of the Poisson model on the number of patents (i.e. the intensive margin of innovation), whereas the bottom part of the table presents the coefficient estimates of the logit model in the inflation equation on the likelihood of observing (excess) zero patent counts. We interpret the results of the inflation equation as the impact on the extensive margin of innovation, i.e. the likelihood of participating into the innovation market (innovation 'entry'). A negative impact on the likelihood of (excess) zero patents is thus interpreted as a positive impact on the likelihood to undertake R&D. The Vuong test statistic reported in the bottom of the table suggests that the zero-inflated Poisson model performs significantly better than the general Poisson model in all of the estimated models in line with our reasoning that there are two different processes explaining zero patenting in our model.

Firm fixed effects are captured by the two pre-sample variables: (1) a dummy variable equal to one if the firm has innovated in the pre-sample period; (2) the firm's average innovation count in the pre-sample period in all technologies (i.e. not only patents in REN and FF technologies). While they reflect the innovation capacity of the firm and thus firms' heterogeneity, we do not have *a priori* expectations on the sign of generic pre-sample innovation on further specific innovation in REN or FF technologies. For specialized firms, the pre-sample variables tend to be mainly significant in the extensive margin models. Having patented in the pre-sample period is positively associated with the likelihood to conduct innovation both in REN and FF technologies. Yet the pre-sample level of patents is negatively associated with innovation entry in electricity generation. For mixed firms, we observe that having pre-sample innovation experience increases the rate of REN innovation, even though the level of pre-sample patents reduces it. Instead, pre-sample innovation decreases the rate of FF innovation by mixed firms.[31] Regardless

[31]These results suggest a subtle effect of general (as opposed to specific) innovation experience. Having some innovation experience by itself increases the probability of future REN innovation. However, the actual amount of innovation experience is not conducive to more REN innovation. This seems to imply that mixed firms in our

of the actual signs of the coefficients, the more important result is that either (or both) of the firm heterogeneity proxies are statistically significant in almost all models, suggesting that they indeed pick up (part of the) unobserved firm characteristics. The impact of overall market size as measured by firm-specific real GDP is hardly ever significant.

Column (1) conducts the analysis for firms that specialize in REN innovation only (consequently, the FF knowledge stock is dropped from the model, as these firms have not built up FF knowledge stocks). Regarding the factors affecting the rate of innovation (i.e. intensive margin decision) as shown in the upper panel of column (1), except for a positive effect of the firm's past REN knowledge stocks, none of the other variables significantly affect the rate of REN innovation. The drivers of innovation are, however, much more significant on the extensive margin as can be seen in the lower panel of column (1). The inflation equation shows a positive impact of both FF energy prices and REN market size on the likelihood of REN innovation. In a counter-intuitive way, larger REN knowledge stocks reduce this probability. Although unexpected, this result is consistent with our earlier observation that specialized firms are typically incidental (one-time) innovators. The knowledge stock of these firms turns positive only after their first innovation, yet often they do not re-enter the innovation market again, inducing a negative correlation between knowledge stocks and the likelihood of innovation.

Column (2) repeats the analysis in column (1) for firms that specialize in FF innovation only (consequently, the REN knowledge stock is dropped from the model). A rise in FF prices is associated with a marginally significant positive impact on the rate of innovation by specialized FF firms. We find the opposite effect of FF prices in the inflation equation: here a rise in FF prices is associated with a negative effect on the likelihood of innovation entry. As with specialized REN firms, FF knowledge stocks also have a negative impact on the likelihood of FF innovation entry, again reinforcing the notion that specialized firms are incidental innovators.

<< **INSERT TABLE 6 ABOUT HERE** >>

Column (3) looks at REN innovation in mixed firms. The top panel in column (3) shows how the various factors affect the intensive margin decisions of mixed firms. First, FF energy prices have a positive and significant impact on the rate of REN innovation by mixed firms. We also find a positive significant effect of the firm's past REN knowledge stock. FF market

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sample have developed generic innovation experience that is not relevant to REN innovation.

size further has a negative and significant impact on REN patenting, as expected. However, FF knowledge stocks also have a positive and significant impact, suggesting complementarities between REN and FF innovation in mixed firms. Regarding mixed firms decisions to undertake REN innovation in every period, i.e. the extensive margin decision, results of the inflation equation given in the lower part of column (3) suggest that a large REN knowledge stock increases the likelihood of REN innovation entry, whereas a larger FF knowledge stock reduces it.

Finally, column (4) shows that the rate of FF innovation in mixed firms is driven by changes in FF prices, FF market size and FF knowledge stocks. As in column (3), an increase in FF prices also raises FF innovation. Together with the positive effect of FF prices on REN patents, this suggests that mixed firms are not substituting one type of innovation for the other as we expected, but rather increasing both simultaneously.[32] Finally, the results in the inflation equation suggests a significant positive impact of FF market size and FF knowledge stocks on the FF innovation probability.

Summarizing these results, we find mixed support for the expectations formulated in Table 4. Innovation by specialized firms is mainly affected by the model variables through the extensive margin. For firms specializing in REN innovation, we find that FF prices and REN market size encourage firms to enter REN technologies, while high FF prices also discourage firms to enter FF technologies, all as expected. Contrary to mixed firms, innovation by specialized firms tends to be very incidental and cannot be sustained over time, as demonstrated by the fact that larger knowledge stocks reduce the likelihood of innovation. Once specialized firms have entered, their level of innovation is mainly affected by their past knowledge stock.[33] Mixed firms tend to increase both REN and FF innovation in equal proportion as a response to a rise in FF prices, which goes against our hypothesis of within-firm substitution. A larger FF market further induces substitution from REN to FF innovation. Also, these firms experience complementarities in innovation, as the past stock of FF innovation positively affects REN patenting.

[32] Results of a Wald test show however that there is no significant difference between the two coefficients (cf. Table 7), suggesting that mixed firms will respond to a rise in FF prices by increasing both types of innovation in equal proportions.

[33] Although we do find a marginally significant positive impact of FF prices on the rate of innovation by specialized FF firms, this effect is not always robust for alternative specifications (see Section 5.3).

5.2 Impact on the technology gap

The overarching motive of our study is to establish whether developments in prices, market size, and knowledge stocks are able to direct innovation from FF towards REN technologies in the sector of electricity generation. In order to assess to what extent this is the case, we conduct additional computations – combining the estimated elasticities of Table 6 with the actual average yearly changes in our model variables[34] – to draw conclusions on the magnitude of the effects on the direction of technical change in electricity generation. We compute the relative change in the FF-REN technology gap at the aggregate level, following the average yearly change in one of the model variables (while keeping the others constant). Ultimately, we want to assess which variables have the largest impact on closing this gap (i.e. on reducing the difference between the total number of FF and REN patents in our sample of firms). As stated in equation (2), the technology gap at the sector level varies with the number of firms active in the two technologies and with the average number of patents by firm. A technical explanation of our computations is relegated to the Appendix.

Table 7 presents the results. Columns (1) to (4) in Table 7, labeled "firm-level impact", show the impact of an average yearly change[35] in each of the explanatory variables on the firm-level intensive and extensive margins of innovation. These impacts are presented for the different subsamples, using the coefficients estimated in Table 6. As an illustration, we find that for specialized REN firms an average yearly change in the firm past REN knowledge stock is associated with a 5.78% increase in the rate of REN patents.

<< **INSERT TABLE 7 ABOUT HERE** >>

Columns (5) and (6), labeled "aggregate FF-REN technology gap", present the resulting changes in the technology gap at the aggregate level. Since this is our metric of interest, we only focus from now on on the implications of the results in columns (5) and (6). Figures presented in bold indicate that there is a significant difference (below the 5% significance level) between the coefficient estimates for the REN and FF models in Table 6.[36]

[34] See Popp (2002) for a similar approach to interpreting marginal impacts.

[35] In the remainder of this subsection, an increase in a explanatory variable thus always refers to an average yearly increase of the given variable.

[36] We conduct Wald tests for differences in coefficients between the two models (i.e. REN and FF, for both specialized and mixed firms) in a seemingly unrelated regressions framework.

A first look at the top panel of column (5) shows that knowledge stocks are the main significant drivers of the technology gap on the intensive margin for specialized firms. As shown in column (6), knowledge stocks are only important drivers for mixed firms. For both specialized and mixed firms, we see that REN knowledge stocks have a significant effect on closing the technology gap, whereas FF knowledge stocks widen it. The impact generated by specialized firms is substantially stronger than that by mixed firms. An increase in REN knowledge stocks in specialized firms reduces the innovation gap by 4.35%, while it only reduces it by 0.15% for mixed firms. Similarly, an increase in FF knowledge stocks in specialized firms widens the innovation gap by 7.67%, while for mixed firms the impact is smaller (2.79%). Also, the relative difference between the impacts of REN and FF knowledge stocks is much larger for mixed firms than for specialized firms. This is in line with our earlier observation that mixed firms tend to have a long history of FF innovation and only innovate occasionally in REN technologies. Besides knowledge stocks, other factors are less important for mixed firms. While we did find that FF prices have a significant effect on the rate of REN and FF innovation in Table 6, they do not affect REN innovation in a significantly different way than FF innovation. As a result, FF prices in this case have no effect on the aggregate technology gap. FF market size marginally increases the innovation gap through mixed firms' innovation by 0.003%.

The bottom panel in Table 7 shows that several different variables affect the drivers of the aggregate technology gap on the extensive margin in particular for specialized firms. Indeed, for these firms both FF prices and REN market size help to reduce the gap in the REN-FF innovation probabilities, by 0.4%-points and 2.6%-points, respectively. An increase in REN knowledge stocks increases the gap by 8.1%-points, whereas an increase in FF knowledge stocks reduces it by 0.9%-points. These latter impacts again reflect the incidental nature of innovation in specialized firms. Finally, in mixed firms we see that increases in FF market size and FF knowledge stocks widen the innovation probability gap by 0.001%-points and 0.84%-points, respectively.

Summarizing, the following patterns emerge. First, in both the intensive and extensive margins of innovation, the marginal impacts of average yearly changes in our model variables on the aggregate FF-REN innovation gap are generally larger in an absolute sense for specialized firms than for mixed firms. This is consistent with the observation in the previous section that

FF-REN innovation convergence has been induced mainly by specialized firms. Second, the impact of variables external to the firm (prices and REN market size) is particularly strong in affecting the extensive margin of innovation - i.e. the innovation entry and exit - in specialized firms. This is consistent with the observed pattern of convergence between the number of innovating REN and FF firms during the latter part of our sample period (cf. Figure 1(b)), when both FF energy prices (cf. Figure 3) and the REN market size (cf. Figure 4) were also rising. Third, the incidental nature of innovation in specialized REN firms forms a strong impediment to stronger convergence between FF and REN innovation probabilities.

5.3 Robustness analysis

In this section we report on a number of robustness tests. To economize on space, we only provide a discussion of the outcomes and refer the reader to the online Appendix of this paper for a detailed overview of all the estimation results. All together, these tests indicate that the main results presented in Table 6 are robust to different changes in model specification. In particular, our conclusions drawn from Table 7 on the main significant drivers of directed technical change at the aggregate level remain robust.

First, we consider the role of the firms' fixed effects captured by the pre-sample variables by dropping them from our baseline estimation. As explained earlier, we believe that these fixed effects mainly capture the firms' capacity to innovate. Excluding the pre-sample variables mainly results on a lower impact of FF prices on the incentives for REN innovation: the impacts of prices on specialized REN firms' decision to conduct R&D and on mixed firms' rate of REN innovation loose significance. This might be explained by a negative correlation between FF prices and firms' fixed effects with regard to REN innovation. A potential explanation is that when FF prices are high only firms with a high capacity to innovate will choose to invest in REN innovation, while other firms with lower capacity to innovate will instead choose a less risky innovation path and focus on improving FF technologies. A log-likelihood ratio test confirms that the baseline specification including firms' fixed effects is to be preferred over the specification without fixed-effects for all models (at the 1% level).

Second, we further investigate the positive impact of FF energy prices on FF innovation. This effect is intuitive insofar as FF innovation is aimed at improving the efficiency of methods

FF energy generation. On the other hand, to the extent that FF innovation is more aimed at e.g. developing alternative methods of FF energy generation, the positive price effect is not necessarily straightforward, as we should expect substitution towards REN innovation in mixed firms. Following Lanzi, Verdolini and Hascic (2011) we make a distinction between energy-efficient FF (EFF) versus traditional FF (TFF) innovation. As FF energy prices increase, it seems reasonable to assume that in particular EFF innovation increases. The results partly support this expectation. FF prices indeed have a positive and significant effect (at the 5% level) on the rate of EFF innovation but no significant effect on the rate of TFF innovation by specialized FF firms. For mixed firms, however, we still find a positive impact of FF prices on the rate of both EFF and TFF (as well as REN) innovation, although the impact is more significant for EFF than for TFF innovation.

Third, we consider the impact of knowledge spillovers on innovation by including external knowledge stocks in the model. In particular, using the patent portfolio of each firm in our sample, we established the distribution of inventors across different countries.[37] We then construct overall REN and FF knowledge stocks in these countries (excluding the focal firm's patents) and computed firm-specific external knowledge stocks using inventor-country weights as well as technology-weights (similar to the weights used to construct market size in equation (4)). For specialized firms, we find that the size of the external knowledge stock has a positive impact on the likelihood of innovation entry by specialized FF firms. Also, a larger external FF knowledge stock tends to marginally decrease the rate of innovation by specialized REN firms. Yet, we do not find any significant impact of the external REN knowledge stock on innovation by specialized REN firms. Regarding mixed firms, the size of the external REN knowledge stock has a positive impact on the likelihood of REN innovation, although we also find a positive impact on the rate of FF innovation by mixed firms (but this effect is only marginally significant). Higher external FF knowledge stocks increase the rate of FF innovation by mixed firms. Hence, a striking result is that there is no evidence for spillover effects from REN technologies (except for a marginally significant impact on mixed firms decision to innovate in REN technologies). Our intuition is that the stock of REN innovation is still relatively small in almost all countries to have a sensible impact.

[37] We only considered inventors from either one of the 17 home countries in our sample, as well as the United States, Japan, and Canada. This accounts for more than 93% of all inventors in the sample.

Fourth, we consider dropping the (very) large (i.e. innovative) firms from our model to rule out any biasing influence of outliers. Following Aghion et al. (2012) we identified the top 1% of firms (in terms of total innovation activity) in each of the subsamples and re-estimated the models in Table 6 excluding these firms. Most of our main results carry over, except for the fact that REN knowledge stocks are no longer positive and significant in the intensive margin model for specialized REN firms, suggesting that this effect is mainly due to large firms with a history of REN innovation (as expected). Also, the positive impact of FF prices on the rate of innovation by specialized FF firms now drops out.

Fifth, in Table 6 we include both (FF) prices and market size simultaneously. However, these variables are likely to influence each other. In particular, as FF prices increase we might expect REN (FF) market size to increase (decrease). Indeed, the correlations in Table 5 suggest that this is the case, although the correlations are very small. Therefore, it would be informative to establish the unconditional impact of both prices and market size. To this end, we re-estimated the models in Table 6, excluding either FF prices or REN and FF market size from the model. All our main significant results carry over.

Sixth, we may be concerned about the issue of endogeneous market size. Indeed, innovation may also have an impact on the level of electricity output produced in a given country from a given technology type. Since we conduct the analysis at the firm level, the issue of endogeneity of market size is mainly likely to be relevant for mixed firms that are large enough to have an impact on a country's market. To address this issue, we check the robustness of our results using installed capacity data– i.e. the installation of new REN and FF power plants, measured in terms of megawatt-hours. Using installed capacity might go some way towards addressing the potential endogeneity of electricity output as a measure of market size, since the building of power plants is arguably a long-term process, the plans for which are made further back in time. As such, it is less likely to be influenced by current innovation. Using installed capacity leaves our main significant results reported in Table 6 intact, with two exceptions: First, REN market size now reduces the likelihood of innovation entry by specialized FF firms ($p<0.01$). Second, the positive impact of FF market size on the likelihood of FF innovation by mixed firms now drops out. Additionally, we also find a positive impact of REN market size on the rate of innovation by specialized REN firms, but this effect is only marginally significant. Additionally, we also conducted the analysis using longer lags for market size (2 and 3 years lags for both electricity output and installed capacity data) to address the issue of endogeneous market size and found that all our results carry over; market size coefficients are hardly affected.[38]

Finally, we also conduct estimations for an alternative set of patents. As explained earlier, our baseline results include patents granted at the EPO as well as the 17 national patent offices in the different home-countries of our sample firms. In order to select only high-quality patents, we instead select the set patents that have been filed in at least two additional patent offices. As explained earlier, a main disadvantage of selecting only the highest quality patents is that we are biasing our sample towards large internationally active firms that can afford to file their patents in multiple patent offices. As expected, the sample of REN patents is reduced and our results for specialized firms are particularly affected by this selection process. We find that FF prices do not have any significant impact anymore on the likelihood of innovation entry by specialized REN firms. Also, the positive impact of FF prices on the rate of innovation by specialized FF firms is now significant below the 1% significance level. This implies that in these settings the impact of price signals on specialized firms will tend to widen the technology gap towards FF innovation.[39] Regarding mixed firms, the effects of FF prices on both rates of REN and FF innovation loose significance but there is still no statistical difference between the impact of prices on REN and FF innovation. Also, REN knowledge stocks have no significant impact anymore on REN innovation by mixed firms. Accordingly, the impact of mixed firms on closing the aggregate technology gap still remains very limited.[40]

6 Conclusion

This paper uses firm-level data on patents filed in renewable (REN) and fossil fuel (FF) technologies by 5,261 European firms over the period 1978-2006 to investigate directed technical change in the electricity sector. The paper focuses on the determinants of firm-level innovation and the role of firm dynamics in driving the replacement of FF technologies by REN technologies. In our analyses, we make a distinction between specialized firms – that innovate only in

[38] Results available on request.

[39] Relative to the baseline, the changes are that (1) there is now a significant difference between price effects in the specialized firm level equation; (2) the significant difference in price effects in the specialized firm inflation equation drops out.

[40] We find that neither knowledge stocks are significantly different anymore in the mixed firm level equation (i.e. only FF market size has a significantly different impact).

REN or FF technologies – and mixed firms – that innovate in both.

We find that the three factors – prices, market size and past knowledge stocks – as described in Acemoglu et al. (2012*a*) affect firms' decision to innovate at both the extensive and intensive margins. Yet, we demonstrate that the impact of these factors on closing the aggregate FF-REN technology gap is stronger for specialized firms than for mixed firms. This is mainly explained by the fact that specialized firms' dynamics (innovation entry and exit) are particularly responsive to price and market signals. Past knowledge stocks are also significant drivers affecting the aggregate REN-FF technology gap since we find that higher firm-level REN knowledge stocks and lower FF knowledge stocks will tend to close the technology gap in both specialized and mixed firms. Yet, further innovation by specialized firms appears to be limited by the incidental nature of innovation in these firms. Although we do find that mixed firms respond to market and price incentives, their impact on the aggregate technology gap is much more limited. This is mainly due to the fact that prices and market size variables do not significantly shift mixed firms' innovation towards REN technologies relative to FF ones. In addition, mixed firms' past knowledge stock in REN innovation is still too low (and complementarities between the REN and FF knowledge stocks too limited) to significantly counterbalance path-dependencies effect in FF innovation due to the long history of mixed firms with FF innovation.

Metaphorically, specialized firms are the small ships in an ocean of innovation. They change their course more explicitly in the face of changes in (external and internal) drivers of innovation, yet they also go under more easily. Mixed firms on the other hand are the big ships. Their course is more difficult to change, yet they command a comparatively large share of the ocean and stay afloat much longer. The (policy) challenge thus is twofold: first, to encourage small specialized firms to start and sustain innovation in REN technologies; second, to make mixed firms more responsive to drivers of REN technical change. There are several options for policymaking to encourage additional innovation entry into REN technologies, ranging from providing venture capital for REN start-up firms (Criscuolo and Menon, 2011), to providing firm-size dependent R&D subsidies (Akcigit, 2011).[41] Further research should also explore how to prevent premature

[41] Due to the important contributions of small firms to aggregate technological innovations and growth, Akcigit (2011) argues for size-dependent R&D policies which would provide higher subsidies to smaller firms. Our results show that such subsidies should not only be one-shot transfers to encourage small firms into REN innovation; they should be temporarily continued to help these firms *continue* their innovation, up until the point where the productivity-effect (i.e. knowledge stock) becomes innovation-reinforcing. This reasoning is similar to the conclusions of Arque-Castells and Mohnen (2012), who model both an innovation entry and an innovation continuation subsidy threshold.

innovation exit of small specialized REN firms, for instance by investigating the role of a stable environmental policy regime.

Making large mixed firms more responsive to drivers of REN technical change seems more involved. What appears to be hindering directed technical change towards REN innovation in these firms is the large stock of FF innovation that they have built up in the past as this reinforces FF innovation in the future. Nonetheless, our empirical results also suggest some degree of complementarity between the FF knowledge stock and REN innovation in these firms. As such, policies might be configured to leverage the large stock of FF innovation in mixed firms by subsidizing research that develops complementarities between existing FF innovations and new REN innovations. As the resulting REN innovation add to the REN knowledge stocks, such policies should eventually become self-reinforcing and could thus be only temporary.

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Appendix

Change in the technology gap

In order to derive the marginal impacts in the zero inflated poisson model, it is useful to again write the conditional mean of the dependent variable as in (7):

$$E(P_{ijkt}|X) = (1 - \Lambda(0|\mu_{ijkt})) \times \lambda_{ijkt} \tag{A.1}$$

where Λ is the logistic distribution and μ and λ are defined as in equations (5) and (6). Accordingly, a change in this conditional mean is given by:

$$\Delta E(P_{ijkt}|X) = \lambda_{ijkt} \times \Delta(1 - \Lambda(0|\mu_{ijkt})) + (1 - \Lambda(0|\mu_{ijkt})) \times \Delta\lambda_{ijkt} \tag{A.2}$$

The first term on the RHS of (A.2) is the change in the probability of observing a non-zero patent count (i.e. the extensive margin) whereas the second term is the change in the patent count itself (i.e. the intensive margin).

In our computations, we separate intensive and extensive margin impacts, as well as specialized and mixed firms. For the intensive margin, using (A.1) we first compute the average number of FF and REN patents per firm. Aggregating over the total number of (REN and FF) firms in our sample, we then derive the FF(d)-REN(c) technology gap:

$$\sum_i E(P_{id}) - \sum_i E(P_{ic}) = \overline{P}_d - \overline{P}_c \tag{A.3}$$

We then compute the intensive margin change in these averages by setting $\Lambda(0|\mu_{ijkt})$ in (A.1) to 0 (i.e. ignoring the fact that some firms do not innovate in some period) so that the RHS in (A.2) is reduced to $\Delta\lambda_{ijkt}$. Using the estimated coefficients in the level equations of Table 6, we compute the (expected) change in the number of patents in each technology, following the change in each of the model variables *ceteris paribus*. That is, we compute the marginal impact of each model variable x_k (prices, market size, or knowledge stock) on the average innovation rate in sector j, keeping the others constant:

$$\begin{aligned}\Delta\overline{P}_j &= \frac{\partial\overline{P}_j}{\partial x_k}\times\Delta x_k^j \\ &= \beta_k^j\times\exp(X_j'\beta)\times\Delta x_k \\ &= \beta_k^j\times\overline{P}_j\times\Delta x_k\end{aligned}\tag{A.4}$$

where β_k^j is the estimated coefficient of variable x_k in the level equation of Table 6 in sector j, and Δx_k^j is the average within-sample change in that variable.[42] These results are reported in columns (1)-(4) in the top panel of Table 7.

Taken together, the impact on the relative change in the innovation rate gap – as reported in columns (5) and (6) in the top panel of in Table 7 – is then computed as:

$$\frac{\Delta\overline{P}_d-\Delta\overline{P}_c}{\overline{P}_d-\overline{P}_c}=\frac{\beta_k^d\Delta x_k^d\overline{P}_d-\beta_k^c\Delta x_k^c\overline{P}_c}{\overline{P}_d-\overline{P}_c}\tag{A.5}$$

For the extensive margin, we proceed in a similar fashion. We first compute the average innovation probability in FF and REN technologies for each firm i in sector j, i.e. $(1-\Lambda(0|\mu_{ij}))$. We then compute the aggrate averages of these probabilities in the FF (d) and REN (c) sector to compute the aggregate FF-REN innovation probability gap:

$$\frac{\sum_i(1-\Lambda(0|\mu_{id}))}{\mathbb{N}_d}-\frac{\sum_i(1-\Lambda(0|\mu_{ic}))}{\mathbb{N}_c}=\pi_d-\pi_c\tag{A.6}$$

where $\mathbb{N}$ denotes the total number of firms (rather than the total number of active firms N).

We then compute the extensive margin change in these averages by setting λ_{ijkt} in (A.1) to 1 (i.e. ignoring the intensive margin) so that the RHS in (A.2) is reduced to $\Delta(1-\Lambda(0|\mu_{ijkt}))$. We then proceed as before, using the estimated coefficients in the inflation equations of Table 6 to compute the (expected) change in the average innovation probability, following the change

[42] Note that for specialized firms, $\Delta x_k^d \neq \Delta x_k^c$ since the two samples are disjoint. For mixed firms however, $\Delta x_k^d = \Delta x_k^c$.

in each of the model variables *ceteris paribus*.[43]

$$\begin{aligned}\Delta\pi_j &= -1 \times \frac{\partial \pi_j}{\partial x_k} \times \Delta x_k^j \\ &= -\beta_k^j \times [e^{(X_j'\beta)}/(1+e^{(X_j'\beta)})^2] \times \Delta x_k^j \\ &= -\beta_k^j \times [e^{\pi_j}/(1+e^{\pi_j})^2] \times \Delta x_k^j\end{aligned} \tag{A.7}$$

In each case, we evaluate the marginal impacts using the estimated coefficients in the bottom part of Table 6. These are the impacts reported in columns (1)-(4) in the lower panel of Table 7.

Taken together, the impact on the (percentage-point) change in the innovation probability gap – as reported columns (5) and (6) in the lower panel of Table 7 – is then computed as:

$$\Delta\pi_d - \Delta\pi_c = \beta_k^c[e^{\pi_c}/(1+e^{\pi_c})^2]\Delta x_k^c - \beta_k^d[e^{\pi_d}/(1+e^{\pi_d})^2]\Delta x_k^d \tag{A.8}$$

Based on the estimated marginal impacts of our model variables (depicted in the first four columns in the lower panel of Table 7), we then compute the expected change in the FF and REN innovation probabilities. Comparing the difference between the FF and REN innovation probabilies in both cases gives us an 'old' and a 'new' innovation probability gap. Comparing the relative change between these two yields the elasticities presented in columns (5) and (6) in the lower panel of Table 7.

[43] Since the inflation equations estimate the probablity of zero innovation ($\Lambda(0|\mu_{ijkt})$), but we are interested in estimating the impact on positive innovation ($(1-\Lambda(0|\mu_{ijkt}))$), we multiply each coefficient β_k by -1.

Table 1: Characteristics of specialized vs. mixed firms

Variable	Firmtype	Mean	St. Dev.	Min.	Med.	Max.	# Firms
A. (Log) turnover	REN	8.7	3.5	0.6	8.7	17.2	233
	FF	10.5	3.1	1.27	10.7	18.7	350
	Mixed	13.3	3.4	3.0	13.1	19.0	74
B. (Log) total assets	REN	7.9	3.4	-6.4	7.7	19.0	307
	FF	9.7	3.4	-5.7	9.5	16.9	419
	Mixed	13.4	3.5	3.49	13.7	19.3	69
C. (Log) Employees	REN	3.9	2.7	0.0	3.8	12.2	168
	FF	5.2	2.5	0.0	5.2	11.2	304
	Mixed	8.1	2.7	0.0	8.1	13.0	66
D. Age (years)	REN	17.1	25.4	1.0	9	136	513
	FF	26.1	31.2	1.0	15	187	725
	Mixed	45.9	41.0	1.0	33	159	99
E. Number of innovative years	REN	2.5	1.9	1.0	2.0	12.0	1,307
	FF	5.3	409	1.0	3.0	24.0	3,674
	Mixed	10.5	7.8	1.0	8.0	29.0	280

Table 2: Share of REN patents by specialized and mixed firms per technology type

	Biomass	Geo	Hydro	Marine	Solar	Waste	Wind	Total
Specialized firms	1.7	2.1	4.2	4.7	34.6	1.4	21	69.7
Mixed firms	0.6	1.3	1.8	1.4	19.9	1.1	4.3	30.3
Total	2.3	3.4	6	6.1	54.5	2.5	25.3	100

Table 3: Share of FF patents by specialized and mixed firms per technology type

	Ignition	Furnaces	Steam	Burners	Coal	Engines	Hotgas	Turbines	Total
Specialized firms	6.1	17.2	2.7	27.9	1.7	4.3	0.6	5	65.4
Mixed firms	5	7.1	0.9	11.6	1.3	3.2	0.3	5.3	34.6
Total	11.1	24.3	3.6	39.5	3	7.5	0.9	10.3	100

Table 4: Expected drivers of technical change

	Specialized firms				Mixed firms			
	REN innovation		FF innovation		REN innovation		FF innovation	
	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive
FF price	+	0	-	+	+	+	-	-
REN market size	+	+	-	0	+	+	-	-
REN knowledge stock	+	+	0	0	+	+	-	-
FF market size	-	0	+	+	-	-	+	+
FF knowledge stock	0	0	+	+	-	-	+	+

Note: + positive effect; 0 no effect; - negative effect on the likelihood (extensive margin) and the rate (intensive) of innovation

Table 5: Summary statistics and pairwise correlations

	Variable	Mean	St. Dev.	1	2	3	4	5	6	7	8	9
1	REN patents	0.18	0.72	1								
2	FF patents	1.29	3.29	-0.01	1							
3	FF price	4.86	0.3	-0.05	0	1						
4	REN marketsize	1.7	1.71	0.2	-0.12	-0.25	1					
5	FF marketsize	9.95	1.96	-0.08	0.03	-0.04	0.2	1				
6	REN knowledge stock	0.17	0.47	0.34	0.11	-0.01	-0.01	-0.33	1			
7	FF knowledge stock	0.92	1.12	-0.09	0.43	0.06	-0.24	0.05	0.1	1		
8	Real GDP	27.16	0.61	0.01	-0.01	-0.22	0.22	0.38	-0.01	-0.08	1	
9	Presample innovation	0.75	1.13	-0.01	0.22	0.07	-0.2	-0.13	0.17	0.42	-0.02	1
10	Presample dummy	0.53	0.5	-0.06	0.07	0.06	-0.13	-0.06	-0.02	0.21	0.02	0.63

Note: Statistics and correlations are based on N = 20,400. All variables except REN and FF patents and the pre-sample variables are expressed in logarithms. For all variables transformed into logarithm, when the variable is equal to zero we then use the log of one plus the variable.)

Table 6: Baseline results for specialized and mixed firms

	Specialized firms		**Mixed firms**	
	(1)	(2)	(3)	(4)
	REN	FF	REN	FF
Intensive margin (Poisson)				
FF price	-0.132	0.166*	1.015***	1.743***
	(0.152)	(0.092)	(0.387)	(0.497)
REN market size	0.026	-0.005	-0.034	0.014
	(0.017)	(0.042)	(0.036)	(0.027)
FF market size	-0.025	-0.038	-0.116***	0.123***
	(0.078)	(0.024)	(0.031)	(0.040)
REN knowledge stock	0.264***		0.184***	-0.017
	(0.083)		(0.063)	(0.074)
FF knowledge stock		0.429***	0.352***	0.567***
		(0.035)	(0.062)	(0.042)
GDP	-0.136	0.015	-0.295*	0.328**
	(0.127)	(0.079)	(0.170)	(0.167)
Presample patent stock	0.019	-0.049*	-0.258***	0.093
	(0.062)	(0.029)	(0.047)	(0.065)
Presample innovation dummy	-0.121	0.008	0.461**	-0.337*
	(0.102)	(0.059)	(0.193)	(0.194)
Constant	4.898*	-0.729	3.074	-18.981***
	(2.799)	(2.094)	(5.072)	(5.431)
Extensive margin (inflation)				
FF price	-1.440**	0.644***	0.385	0.164
	(0.636)	(0.126)	(0.386)	(0.257)
REN market size	-0.431***	-0.002	-0.074	0.010
	(0.121)	(0.074)	(0.052)	(0.045)
FF market size	-0.136	-0.011	0.049	-0.118**
	(0.319)	(0.054)	(0.044)	(0.060)
REN knowledge stock	1.478***		-0.389**	-0.114
	(0.259)		(0.152)	(0.115)
FF knowledge stock		0.341***	0.355***	-0.416***
		(0.041)	(0.076)	(0.106)
GDP	0.206	-0.195*	-0.629***	0.021
	(0.690)	(0.113)	(0.186)	(0.168)
Presample patent stock	-2.727***	-0.206***	-0.381***	0.136
	-0.662	(0.063)	(0.100)	(0.088)
Presample innovation dummy	1.171*	0.529***	0.861***	-0.218
	(0.603)	(0.126)	(0.248)	(0.258)
Constant	0.457	0.886	15.099***	-0.080
	(15.558)	(2.638)	(5.314)	(5.090)
Observations	2,417	14,418	3,565	3,565
Log-likelihood	-3253	-22457	-2221	-6636
Vuong test	8.01***	22.7***	14.2***	10.4***

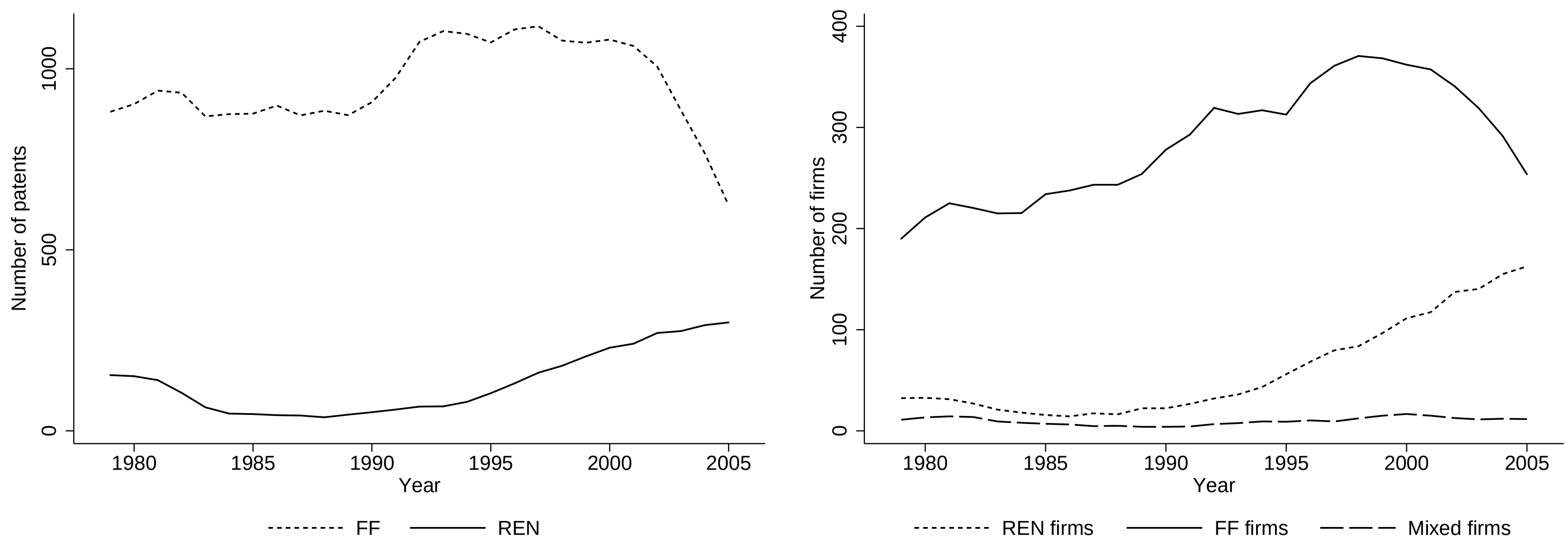
Note: All models include a full set of year and country dummies. Robust standard errors are clustered at the firm level. All explanatory variables are expressed in logarithms and are lagged by one year. Fossil fuel price and market size variables are constructed by using firm-specific weights reflecting the firms' patent portfolio and designation countries. . The dependent variable in each column is the number of patents per firm (i) and year (t), where for each firm we only include the years over the firms innovation period (i.e from the firms first to the last patent observed over 1978-2006)

[b] p<0.1; ** p<0.05; *** p<0.01

Table 7: Marginal impacts

	Firm-level impact				**Aggregate FF-REN gap**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Specialized REN	Specialized FF	Mixed REN	Mixed FF	Specialized	Mixed
Intensive margin (Poisson)						
FF price	-0.096	0.103	0.292	0.502	0.254	0.534
REN market size	0.629	-0.007	-0.186	0.077	-0.485	0.117
FF market size	-0.028	-0.013	-0.002	0.003	-0.002	**0.003**
REN knowledge stock	5.78	-	0.564	-0.051	**-4.35**	**-0.147**
FF knowledge stock	-	4.37	1.64	2.64	**7.67**	**2.79**
Extensive margin (inflation)						
FF price	0.261	-0.098	-0.025	-0.011	**-0.359**	0.014
REN market size	2.58	0.001	0.091	-0.013	**-2.58**	-0.103
FF market size	0.037	0.001	-0.000	0.001	-0.037	**0.001**
REN knowledge stock	-8.08	-	0.271	0.084	**8.08**	-0.188
FF knowledge stock	-	-0.850	-0.376	0.462	**-0.850**	**0.837**

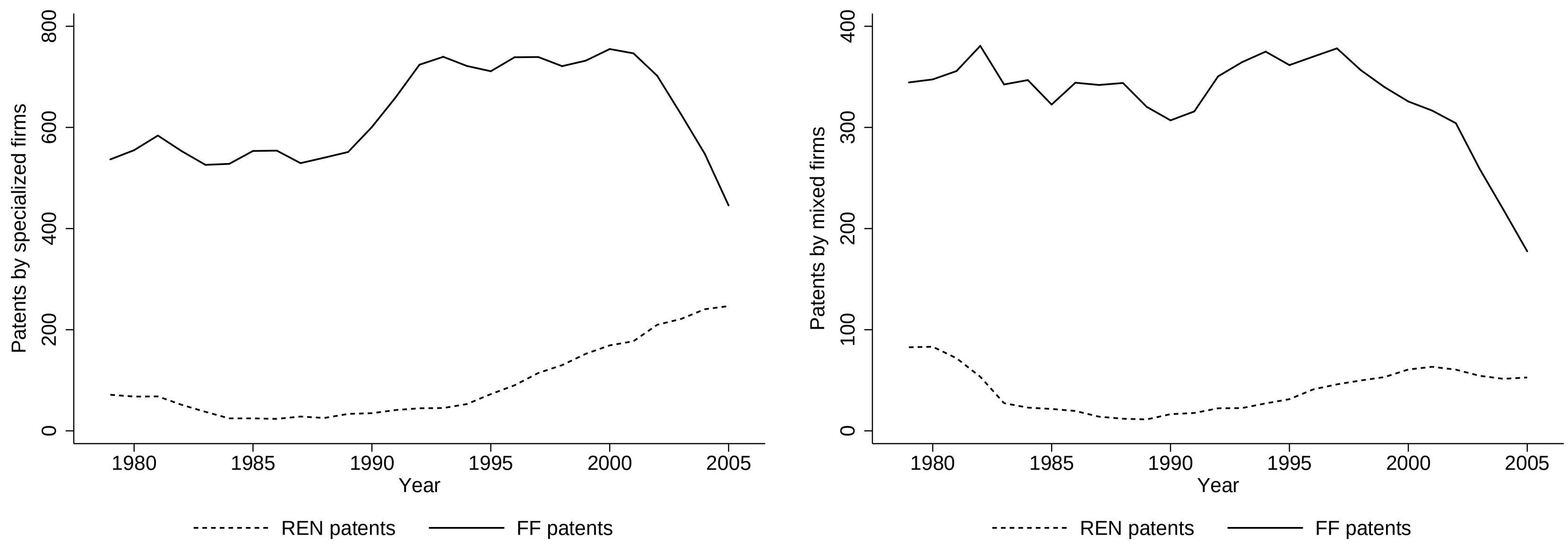
Notes: Columns (1) to (4) present the impact of the average yearly change in each variable on the percentage change in patenting (panel A), and the percentage-point change in the likelihood of patenting (panel B). Columns (5) and (6) present the impact of the average yearly change in each variable on the percentage change in the aggregate FF-REN patenting gap (panel A), and the percentage-point change in the aggregate FF-REN patenting likelihood gap (panel B). Numbers in bold indicate a statistically significant impact of the explanatory variable on the innovation gap (at $p<0.05$).



(a) Patent counts

(b) Firm counts

Figure 1: Number of patents and firms (three-year moving averages)



(a) Patent counts by specialized firms

(b) Patent counts by mixed firms

Figure 2: Patents by firm type (three-year moving averages)

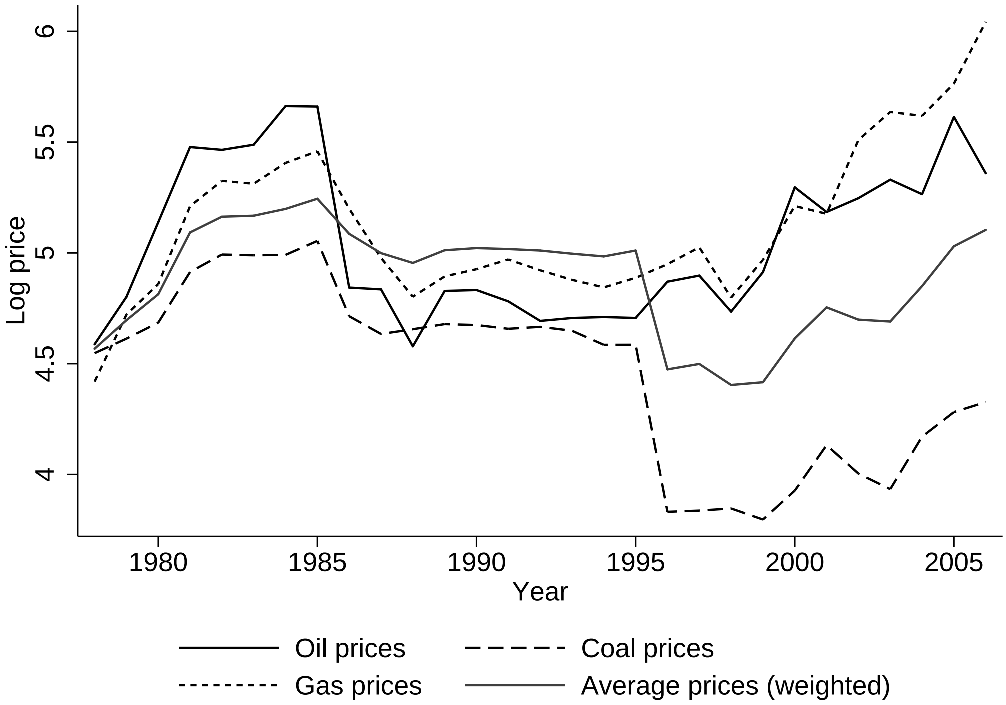


Figure 3: Firm-level price developments per type of fuel (in logs)

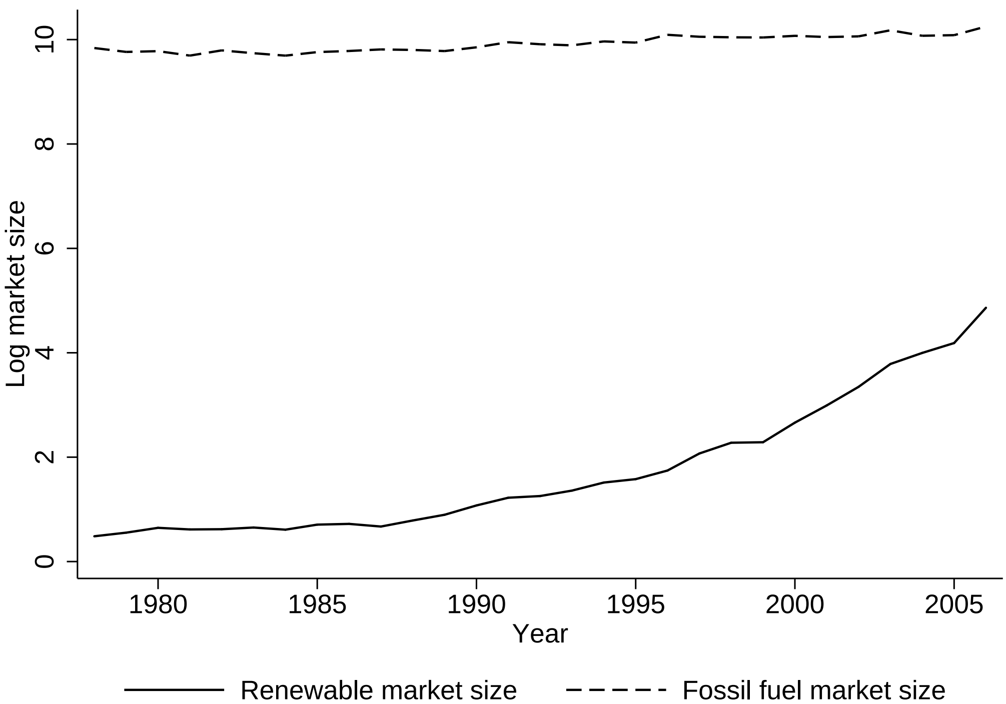


Figure 4: Firm-level market size developments per market type (in logs)