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

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Abstract

This paper investigates the determinants of directed technical change in the electricity generation sector. We use firm-level data on patents filed in renewable (REN) and fossil fuel (FF) technologies by about 7,000 European firms over the period 1978-2006. We separately study specialized firms, that innovate in only one type of technology during the sample period, and mixed firms, that innovate in both technologies. We find that for specialized firms the main drivers of innovation are fossil-fuel prices, market size, and firms' past knowledge stocks. Also, prices and market size drive the entry of new REN firms into innovation. By contrast, we find that innovation by mixed firms is mainly driven by strong path-dependencies since for these firms past knowledge stock is the major driver of the direction of innovation. These results imply that generic environmental policies that affect prices and energy demand are mainly effective in directing innovation by small specialized firms. In order to direct innovation efforts of large mixed corporations with a long history of FF innovation, targeted R&D policies are likely to be more effective.

Keywords: Directed technical change; Energy; Patents; Firms' 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, renewable combustibles and hydropower, can provide a clean alternative for electricity production. Yet despite rapid recent developments, renewable energy represents only 18% of world electricity (IEA, 2010). Price competitiveness is the most obvious barrier to the development of renewable energy. 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. Specifically, directing technological innovation away from fossil fuel technologies and towards renewable ones might be particularly effective in this respect.

Recent theoretical work on directed technical change in environmental economics has studied the factors affecting technological choices by firms (Smulders and Nooij, 2003; Di Maria and van der Werf, 2008; Acemoglu et al., 2012). These models aim to explain why firms keep on investing in dirty rather than in clean technologies, and how government policy might help to redirect technical change. A recent contribution by Acemoglu et al. (2012) emphasizes the role of three factors affecting the direction of technical change: first, the price effect, encouraging innovation in the sector with higher prices;[1] second, the market size effect, encouraging innovation in the sector for which there is 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

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

of giants": future innovations are building on the existing stock of knowledge or technology, thereby generating path-dependencies in knowledge creation.

This paper investigates the determinants of directed technical change in the sector of electricity generation. We use firm-level data on patents filed in renewable (REN) and fossil fuel (FF) technologies by about 7,000 European firms over the 1978-2006 period. We conduct separate estimations for specialized firms, which innovate in only one type of technology over the period 1978-2006, and mixed firms, which innovate in both technologies over the same period. This distinction is conceptually important. By construction, specialized firms conduct innovation in only one type of technology and do not switch between these different technologies over the sample period. In that case, the replacement of FF by REN technologies may occur via the entry of relatively more firms specialized in REN than in FF innovations. By contrast, mixed firms may switch between technologies over time and substitute FF for REN technologies, thereby redirecting their innovation efforts within the firm.

We find that for specialized firms the main drivers of innovation are energy prices, market size, and firms' past knowledge stocks. Also, prices and market size drive the entry of new REN firms into innovation. By contrast, we find that innovation by mixed firms is mainly driven by strong path-dependencies since for these firms past knowledge stock is the major driver of the direction of innovation. These results imply that generic environmental policies that affect prices and energy demand are mainly effective in directing innovation by small specialized firms. In order to direct innovation efforts of large mixed corporations that have a long history of FF innovation, targeted R&D policies are likely to be more effective.

Our study relates to the empirical literature on the determinants of environmental innovation using patent data. Much of this literature has been initiated by Popp (2002), who uses U.S. patent data in 11 energy-related technologies from 1970 to 1994 to study the effect of energy prices and knowledge stocks on energy-efficient innovations. He finds strong evidence for a positive effect of both energy prices and the quality of the stock of knowledge available to inventors on the share of successful energy patent applications. In particular, the price elasticity is estimated at 0.06 and that of the (instrumented) knowledge stock at 0.84. Taking into account average within-sample changes, this adds up to an average 2.1% increase in patent activity due to price increases, versus a 24.3% increase due to knowledge stock increases. Johnstone et al.

(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. The common feature of the studies by Popp (2002) and Johnstone et al. (2010) is that they focus only on clean or energy efficient technologies and they cannot therefore provide evidence on whether innovation is actually directed away from dirty sectors. By contrast, an important contribution of our study is to focus on the determinants of relative innovation, i.e. on what explains a shift towards clean technologies away from dirty ones.

Our paper shares many features with Aghion et al. (2010), who also study relative innovation at the firm-level, although they focus on another sector, namely the automobile industry. They study how carbon taxes and firms' past knowledge stocks induce firms to invest more in clean (e.g. electric and hybrid) than in dirty (e.g. internal combustion engine) technologies. They find evidence for path-dependency in the sense that firms that have conducted more clean innovation in the past also conduct more clean innovation today. Fuel taxes can stimulate clean technologies, but exactly how much depends on a firm's innovation history, with the effect being stronger for firms with a past history of dirty innovation. In contrast to their study, we conduct separate estimations for specialized and mixed firms, which allows us to study the factors affecting the replacement of FF innovations by REN ones via the entry of new specialized firms and via within-firm substitution by mixed firms. In addition, we also analyze the impact of (REN and FF) market size on innovation, which has been argued to be an important driver of directed technical change (Acemoglu et al., 2012).

The rest of this paper is organized as follows. Section 2 describes the data that we use in this paper. Section 3 presents a number descriptive statistics and patterns regarding the patent and firms' dynamics in our sample. Section 4 presents the empirical strategy and the main results. Finally, Section 5 concludes.

2 Data

In the framework of Acemoglu et al. (2012), incentives to engage in either REN or FF innovation are driven by three forces: first, there is the *price effect*. This effect mirrors Hicks' (1932) intuition that when a factor's price increases, firms will develop technologies that aim to reduce the use of this factor. In particular, when fossil fuel prices go up, we can expect innovations to be directed at REN technologies at the expense of FF technologies. However, as indicated before, to the extent that FF innovations improve the efficiency of FF technologies, an increase in fossil-fuel prices might also induce more FF innovation. The second effect is the *market size effect*, which pushes research towards applications for which there is a potentially large market. That is, if the market for renewable energy increases relative to the market for fossil fuels, we would expect innovation to be increasingly directed towards REN technologies, *ceteris paribus*. The third and final effect is the *direct productivity effect*, which pushes innovation towards technologies with a higher productivity or existing stock of knowledge. This force results from the ability to "build on the shoulders of giants": future innovations are building on the existing stock of knowledge or technology, i.e. current innovation levels depend on past innovation levels.

In this section, we describe the data that we will use to investigate how these three factors – prices, market size and knowledge stocks – affect directed technical change in the electricity sector.

Patents We use patent data to measure innovations in renewable and fossil-fuel technologies. The advantages and limitations of patents as a measure of innovation, have been discussed at length in the literature.[2] Since the pioneering work of Popp (2002), patents data have been widely used to study innovation in environmental technologies (Dekker et al., 2012; Verdolini and Galeotti, 2011). 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. Patents are extracted from the EPO/OECD World Patent Statistical Database (PATSTAT). Building on previous work by Lanzi et al. (2011) and Johnstone et al. (2010), we use International Patent Classification (IPC) codes to select patents in two different fields, namely: renewable energy generation, and fossil fuel energy generation.[3]

REN technology classes are aimed at creating and improving the generation of renewable energy. In particular, we consider innovations in six different technological classes: wind, solar,

[2] 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).

[3] The IPC codes for REN and FF patents are borrowed from Johnstone et al. (2010) and Lanzi et al. (2011), respectively.

hydro, 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 combusion-product positive displacement engine, steam generation, combustion apparatus, furnaces and improved compressed-ignition engines.[4] The definition of these general classes of fossil-fuel technologies is described in more detail in Lanzi et al. (2011). 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).

Using the OECD HAN (Harmonised Applicants Names) database, we can link patent applications to firms. This database provides a dictionary with applicants' names, corrected for variations in spelling, which might in turn be linked with business register data. The HAN database covers applicants' names for patents filed at the EPO and via the Patent Cooperation Treaty (PCT). We focus on a sample of approximately 7,000 European firms that we could match with the HAN database and that have filed at least one renewable or fossil-fuel patent over the 1978-2006 period. We count the number of patent applications filed by these firms at the European Patent Office (EPO) and at 17 national patent offices of the EU-15 countries, Switzerland and Norway.[5] In order to select the most valuable patents, we only select 'claimed priorities', i.e. patent applications that have been registered in at least two offices. Our dataset is thus biased towards highly valuable inventions, worthwhile to patent in at least two countries.

Knowledge stock We use cumulative patent counts to construct firm-specific knowledge stocks. At the same time, we have to account for the fact that knowledge becomes obsolete as

[4] In the remainder, we coin the REN technologies as follows: *wind*, *solar*, *hydro*, *geo*, *waste/biomass*, respectively, and the FF technologies as: *coal*, *engines*, *turbines*, *hotgas*, *steam*, *burners*, *furnaces* and *ignition*, respectively.

[5] 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.

time progresses, for example due to the creation of new knowledge. We assume that knowledge stocks depreciate annually by 15%. We also assume that the pre-sample growth of the knowledge stock was 15% and also depreciated at the same rate. That is, we compute the knowledge stock at $t = 0$ as $KS_0 = P_0/(g + \delta)$ where KS is knowledge stock, P is the patent count, g is the pre-sample growth rate, and δ is the depreciation rate. Subsequent knowledge stocks are then computed using the perpetual inventory method as $KS_t = (1 - \delta)KS_{t-1} + P_t$.

In addition, we have data on the pre-sample knowledge stock of every firm. This is the total count of all patents (not only renewable or fossil-fuel) filed over the 1950-1978 period. We will use this information in our estimations to control for unobserved firm heterogeneity as in Blundell et al. (1995). Although the period before 1978 is prior to the existence of EPO, we are able to track our firms in the other 17 European patent bureaus for this period. Again, we only count claimed priorities, i.e. highly valuable inventions filed in at least two patent offices before 1978.

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. 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. Unfortunately, price data for energy generation for the various fuel sources, coal, gas and oil, are subject to a large number of missing values. Since the price of gas and oil tend to be highly correlated[6] and since coal prices have been relatively stable over the whole period as shown in Figure 1, in the remainder of the analysis we will focus on the impact of oil prices.

In order to make fossil-fuel prices firm-specific, we take into account the fact that firms might be exposed to both domestic and foreign prices to different degrees as in Aghion et al. (2010). 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, for each patent in a firm's portfolio we consider in which different countries this patent has been validated[7]. For each firm i we compute a weight w_{ik} which captures the share of country k in the firm's overall patent validation portfolio. In

[6] In our sample, the correlation between oil and gas prices is of 0.75.

[7] Once granted by the European Patent Office, a European patent is a bundle of national patents, which must be validated at the national patent office of the designated states.

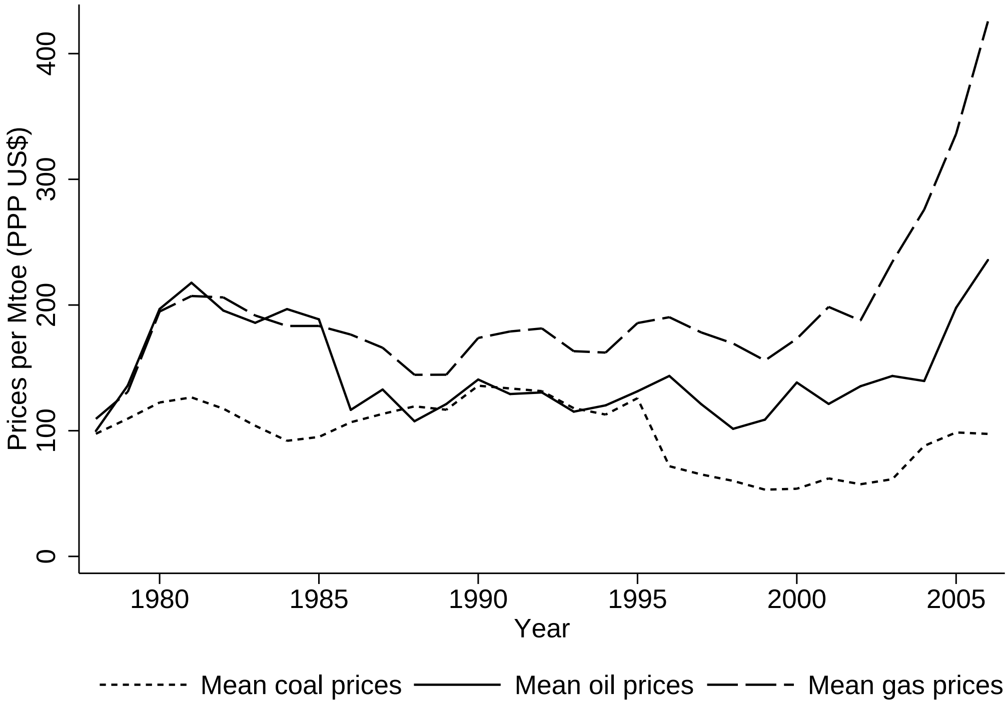


Figure 1: Firm-level price developments per type of fuel (in constant PPP US$ per Mtoe)

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:

$$p_{it} = \sum_k w_{ik} \times p_{kt} \tag{1}$$

where p_{kt} is the oil price in country k in year t, $w_{ik} = \frac{P_{ik} \times M_{kFF}}{\sum_k P_{ik} \times M_{kFF}}$, where P_{ik} is the total number of patents filed by firm i in designation country k and M_{kFF} is the country's FF average market size.[8]

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,

[8]Our weights are fixed, i.e. we compute total patent counts P_{ik} and average market sizes M_{kFF} during our 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.

namely coal, gas, and oil. Renewable electricity output breaks down into geothermal, heat, hydro, waste, wind and solar. 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 (1), we use fixed firm-specific country weights w_{ik} to construct 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 mostely concerned with the market size for solar energy. Hence we compute:

$$M_{it} = \sum_{k=1}^{N} \sum_{s=1}^{S} w_{is} \times w_{ik} \times M_{kt} \tag{2}$$

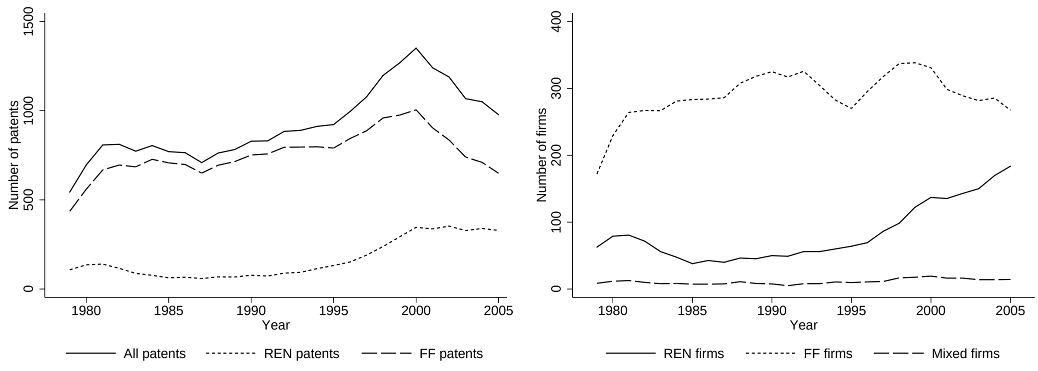
with $w_{ik} = \frac{P_{ik}}{\sum_k P_{ik}}$ and $w_{is} = \frac{P_{is}}{\sum_s P_{is}}$. To compute FF technology weights w_{is} we use a correspondence between the FF technological areas and oil, gas or coal fuels as provided in Lanzi et al. (2011). For instance, technologies in the field of production of fuel gases by carburetting air are assigned to the market size of electricity output from coal. [9] 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. To do so, we assign country-level market size averaged across all REN technologies, also using the relevant country-weights (w_{ik}). We proceed in a similar manner to assign FF market sizes to (specialized) REN firms.

3 Descriptive statistics

Our analysis focuses on a sample of 26,269 patents filed by 6,934 firms. The REN and FF patents represent 18% and 82% of the patents, respectively. As shown in Figure 2a, the total number of patents applied for by the firms in our sample generally increases up until 2000, after which it decreases. This overall trend is mainly driven by patent applications in FF technologies. REN patents experienced a small peak in the early '80s, an acceleration between 1995-2000, after which the count stabilizes somewhat.

We make a distinction between so-called 'specialized' versus 'mixed' firms. Specialized firms

[9] See Table 1 on p.6 of Lanzi et al. (2011).



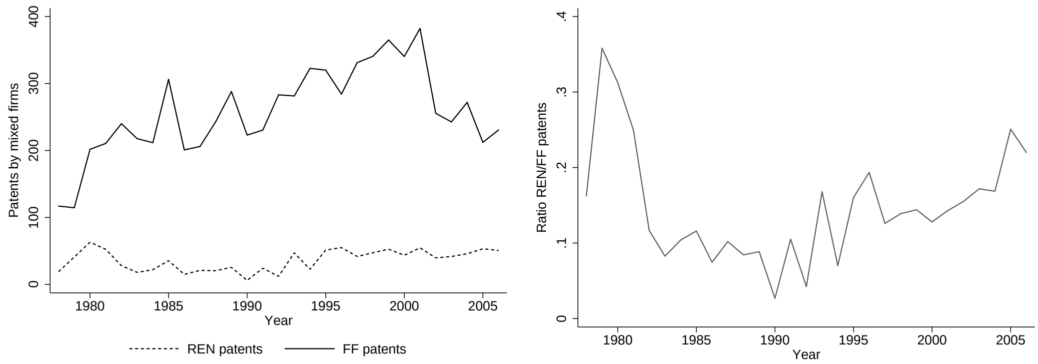
(a) Patent counts　　　　(b) Firm counts

Figure 2: Number of patents and firms (three-year moving averages

are firms that patent in one technology (e.g REN) in the 1978-2006 period and do not patent in the other technology (i.e. FF) over the same period. Mixed firms are firms that patent in both REN and FF technologies over the 1978-2006 period. We classify firms after observing *e*xpost their innovation activities over the sample period. Our sample contains 361 mixed firms (5%), 2,009 (30%) specialized REN and 4,202 (65%) specialized FF firms. Figure 2b counts the number of firms that applied for patents in each sample year, and breaks them down into specialized firms and mixed firms. The development in the number of REN firms mirrors the developments of the corresponding patent count in Figure 2a. To a lesser extent this also holds for the FF firm count, although the dip around 1995 is not present in the FF patent count. The number of patenting mixed firms is relatively constant over time.

Since we are also concerned about relative innovation, i.e. how REN patents replace FF patents over time, Figure 3 gives the evolution of REN and FF patents and the evolution of the ratio of REN over FF patents by mixed firms, respectively. As shown in Figure 3a, mixed firms patent much more in FF than in REN technologies. The number of REN patents by mixed firms has been slowly increasing since the mid 1990s but remains far below the level of FF innovations. Figure 3b shows that the ratio of REN over FF innovation by mixed firms decreased sharply between 1980 and the beginning of the 1990s and has been increasing slowly afterwards, suggesting that mixed firms increasingly conduct relatively more REN innovation, in particular after 2000.

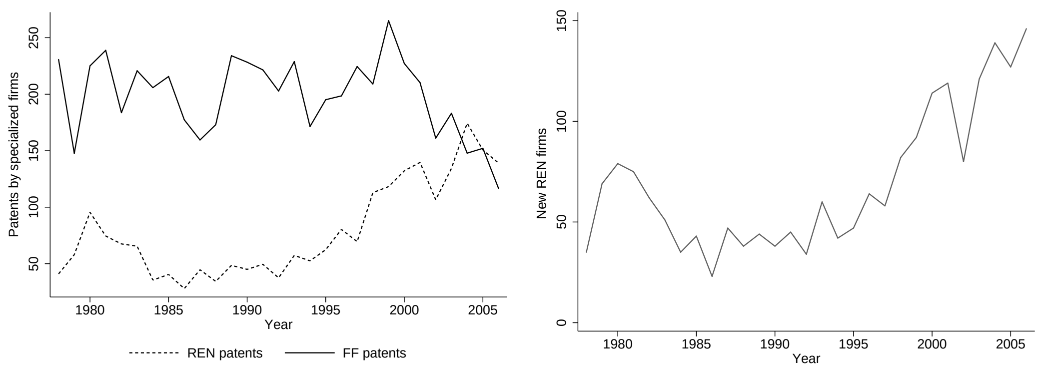
Figure 4a gives the evolution of REN and FF patents by specialized firms only. From 2004 on, REN firms file more patents than FF firms. In the case of specialized firms a relative increase



(a) Patent counts by mixed firms

(b) Ratio

Figure 3: Patents by mixed firms



(a) Patent counts by specialized firms

(b) Entry by REN firms

Figure 4: Patents and entry by specialized firms

in REN innovation, i.e. the replacement of FF by REN patents, can only occur via the entry of new firms. Figure 4b plots the number of new REN entrants over time. The trend closely follows the number of REN patents, suggesting that REN firms file relatively few patents per firm.

As suggested above, the patents are not equally distributed among the different types of firms. Specialized firms account for 78% and 64% of REN and FF patents, respectively. Mixed firms comprise approximately 5% of the total firm sample, yet they account for approximately 22% of REN patents, and for 36% of FF patents. Figure **??** illustrates how these shares develop over the sample period. Each panel in the figure distinghuishes between mixed *versus* specialized firms, where we also split both firm types into those that innovate only once during the sample period ('single'-innovators) and those that innovate multiple times ('multi'-innovators).[10] The

[10]Since we define single innovators *ex post* as firms that have innovated only once over the 1978-2006 period,

Table 1: Years of innovation by different firm and technology types

Firmtype	Mean	St. Dev.	Min.	Med.	Max.
FF	1.8	2.1	1	1	28
REN	1.2	0.8	1	1	12
Mixed	6.2	5.9	1	4	29
	Innovation in mixed firms				
FF	5.2	6	1	3	29
REN	1.9	1.8	1	1	14

bars in the graphs denote the share of total patents of a particular technology type that have been applied for by a particular firm type.

Panel *a* in the figure demonstrates that specialized firms are responsible for the big majority of REN patents, and increasingly so over time. Within the group of specialized firms, a notable shift has occurred from single innovators – that dominated the REN patent count during the first half of our sample – to multiple innovators. Panel *b* shows a somewhat different pattern for FF technologies. Here mixed firms apply for a substantially bigger share of patents, yet this has been relatively stable over time. Moreover, within the group of specialized FF firms, the shares of single and multiple innovators have also been rather stable, with single innovators being much less important compared to their REN counterparts. Unsurprisingly, mixed single innovators are much less important in both panels, which testifies of the fact that they are relatively large.

Table 1 illustrates the differences in innovation frequency. The top panel shows the years of active innovation for the different firm types, i.e. the years in which they had a positive number of patent counts. Mixed firms have an average of 6.2 active innovation years, relative to 1.8 and 1.2 years for specialized FF and REN firms, respectively.[11] The bottom panel of Table 1 decomposes mixed firms' innovation into FF and REN technologies. This shows that mixed firms spend most of their time innovating in FF technologies.

To identify possible complementarities between REN and FF patents in the technology portfolio of mixed firms, we compute pairwise correlations between each pair of REN and FF

firms that entered at the end of the period are more likely to be a single innovator compared to firms that entered early in the period.

[11] These results mirror those reported for UK firms in Geroski et al. (1997), who show that between 70% and 87% of their sample of firms innovate only once.

Table 2: Pairwise correlations between REN and FF technologies (mixed firms)

	wind	solar	geo	marine	hydro	waste&bio
coal	-0.05	0.08	0.97	0.07	0.05	0.2
	(11)	(27)	(1)	(3)	(7)	(30)
engines	0.25	0.05	-0.03	0.29	0.28	0.18
	(9)	(17)	(2)	(6)	(9)	(17)
turbines	0.19	0.08	0.97	0.17	0.1	0.08
	(24)	(32)	(1)	(6)	(14)	(24)
hotgas	0.02	0.11	0.26	0.09	0.15	0.07
	(16)	(34)	(1)	(5)	(9)	(22)
steam	0.08	0.15	-0.03	0.36	0.12	0.13
	(13)	(32)	(2)	(3)	(12)	(34)
burners	0.05	0.1	0.31	0.04	0.06	0.28
	(36)	(127)	(7)	(7)	(20)	(113)
furnaces	0.08	0.07	0.97	0.02	0.08	0.15
	(23)	(88)	(1)	(6)	(19)	(66)
ignition	0.01	0.02	-0.04	-0.04	0.01	0.21
	(13)	(41)	(3)	(4)	(9)	(16)

Note: The number of mixed firms active in a particular REN-FF combination is shown within parentheses.

technologies. The results are reported in Table 2. In particular, each cell depicts the Pearson correlation coefficient, as well as the number of firms that engage in a particular combination of FF and REN innovation (within parentheses). We find that a large proportion of mixed firms combine FF technologies in burners with REN technologies in waste/biomass (correlation coefficient of 0.28, N=113), suggesting complementarities between these technologies, as indeed burners can not only be used for oil, coal and gas but also for biomass. Generally speaking, the correlation coefficients between waste and biomass and many of the FF technologies are relatively high. Many mixed firms also combine solar energy technologies with burners, furnaces, and ignition technologies.

Next we investigate whether the patterns of innovation by specialized and mixed firms are affected by technology characteristics. According to Table 3, solar is the largest category and represents 43% of REN patents, followed by wind (41%) and waste and biomass (10%). Looking at the distribution of the different types of firms across REN technologies in Table 3, we find that mixed firms file 49% of their REN patents in solar energy, 21% in waste and biomass and 16% in wind. Instead, specialized firms file 42% of their patents in wind, 36% in solar and 7% in waste and biomass. Mixed firms tend thus to be more specialized in solar and waste and

Table 3: Specialized and mixed firms per REN technology type

	Solar	Wind	Hydro	Waste & Bio	Geothermal	Marine	Total
Specialized firms	36%	42%	5%	7%	2%	8%	78%
Mixed firms	49%	16%	8%	21%	2%	4%	22%
Total	43%	41%	6%	10%	2%	8%	100%

Table 4: Specialized and mixed firms per FF technology type

	Coal	Engine	Turb.	Hotg.	Steam	Burn.	Furnac.	Ignit.	Total
Specialized firms	3%	2%	7%	2%	6%	38%	33%	9%	65%
Mixed firms	4%	2%	12%	2%	6%	39%	27%	9%	35%
Total	3%	2%	8%	2%	6%	38%	31%	9%	100%

biomass technologies than specialized firms, which instead tend to innovate more in wind and marine technologies.

Over the 1978-2006 period, Table 4 shows that burners and furnaces represent 38% and 31% of all FF patents, respectively. Looking at the distribution of specialized versus mixed firms in FF innovation shown in Table 4, it appears that the patterns of technology specialization are similar for specialized and mixed firms in FF technologies. The two largest FF technology groups are burners and furnaces for both specialized and mixed firms, with mixed firms innovating relatively more in turbines than specialized firms.

In summary, we observe that FF patents make up the lion share of our total energy patent counts, whereas REN patents have been less important. Only from the mid 1990s onwards do we observe a relatively rapid increase in REN patents. Moreover, small and specialized firms are mainly responsible for REN innovations, whereas specialized firms with multiple innovations and mixed firms account for substantial shares in FF innovations. We have also demonstrated that mixed firms are much larger than specialized firms, and that they are more frequent and persistent innovators. Given their revealed comparative advantage in FF technologies, this might imply that their technological paths are already firmly locked into these technologies, and that directing research away from FF and towards REN technologies might be rather difficult for these firms. We now turn to a more formal analysis of these issues.

4 Empirical strategy and results

4.1 Empirical strategy

Building on the framework described in Acemoglu et al. (2012), the first empirical question that we aim to answer deals with the factors affecting the rate of REN and FF innovations by firms. We measure the rate of innovation by means of firm-level patent counts in FF and REN technologies as described in Section 2. This means that we have to rely on count data-techniques in our empirical strategy, since the number of patents are nonnegative integers. As is standard, we assume that patent counts follow a Poisson distribution, so that we can estimate a log-linear Poisson regression:

$$E(P_{ijkt}|X_{ijkt}, \eta_i, \upsilon_k, \nu_t) = \log(\lambda_{ijkt})$$
$$\text{s.t. } \lambda_{ijkt} = \exp(\beta_{0i} + \beta_1 \log p_{idt-1} + \beta_{2j} \log M_{ijt-1} + \beta_{3j} \log A_{ijt-1} + \eta_i + \upsilon_k + \nu_t) \tag{3}$$

where i, j, k and t index firm, technology (REN or FF), country, and time respectively. P is the annual firm-level patent count, p is the fossil-fuel price, M is market size, proxied by REN and FF electricity consumption, A is productivity proxied by the existing knowledge stock, and η, υ and ν capture unobserved firm, country and time-specific heterogeneity, respectively. As demonstrated by the subscripted beta coefficients, we will add REN and FF explanatory variables simultaneously to the RHS of (3) to already probe their effects on the direction of technical change. Since the number of patents is a nonnegative integer, we use count data estimation techniques. Yet, the presence of unobserved firm heterogeneity in model (3) introduces additional complexity. Hausman et al. (1984) suggest to use conditional ML estimation so that the β's can be estimated directly without estimating individual firm fixed effects.[12] However, consistency of this estimator hinges on the (strict) exogeneity of the RHS variables. In our case, in particular market size M and knowledge stocks A are unlikely to be strictly exogenous. Blundell et al. (1995) suggest an alternative estimator, in which they interpret the unobserved firm heterogeneity to reflect entry level innovation. Specifically, they use the pre-sample mean of

[12]In particular, this requires a sufficient (observed) statistic, conditioning on which eliminates the dependence of a firm's likelihood contribution on the (unobserved) firm-specific effect. In the case of a Poisson model, this statistic is a weighted average of a firm's average values on P and $\mathbf{X}$, with weights $\lambda_{it}/\overline{\lambda}_i$.

innovations for each firm to control for unobserved firm heterogeneity. We adopt this approach in our estimation, while controlling for unobserved country and time heterogeneity through the use of country and year dummies.

A final issue concerns the very high incidence of zero patent counts in our sample. In all of our estimation samples, the incidence of zeroes ranges between 70%-90%. The standard Poisson model can generate biased estimates in the presence of such a high number of zeroes in the dependent variable. Therefore, we estimate the model in (3) using a zero-inflated Poisson model (ZIP). This model decomposes the estimation in two stages, one which estimates the probability of observing zero patent counts (the "inflation equation"), and one estimating the standard Poisson model. We include knowledge stocks variables in the inflation equation as we expect larger knowledge stocks to reduce the probability of zero patents.[13]

In terms of expectations, we expect energy prices to have a positive impact on REN patent counts. The impact of prices on FF innovation is ambiguous. On the one hand if FF innovations aim to improve the fuel efficiency of technologies, we should expect that higher prices would lead to more innovation in these technologies. On the other hand, higher energy prices might lower the incentives to innovate in FF technologies, in particular if these can be easily substituted by REN technologies. An increase in the market size for REN inputs is expected to increase the rate of REN innovation due to increased demand. The market size for FF inputs should have a positive impact on FF innovations. Finally, REN knowledge stocks should have a positive impact on REN innovation, and similarly for FF knowledge stocks on FF innovations. We estimate (3) for both specialized and mixed firms. For mixed firms, we can in addition estimate "cross-technology" impacts of knowledge stocks (i.e. the impact of REN stocks on FF innovation and vice versa) since by definition mixed firms have built a knowledge stock in both technologies, which is not the case for specialized firms.

The second empirical question that we aim to answer relates to the factors influencing not only the rate but also the direction of innovation. In this case, we are concerned about the factors inducing a shift away from FF towards REN innovation, i.e. how REN innovation can replace FF innovation. By construction, we only observe *within-firm* substitution between REN and FF innovation for mixed firms, which conduct both types of innovation.[14] For specialized

[13]We tested the inclusion of additional additional variables in the inflation equations but these always turned out insignificant.

[14]Recall that we qualify firms as specialized or mixed *ex post*, i.e. after having observed them throughout the

firms, substitution from FF by REN innovation only occur *between firms*: a relative increase in REN innovation can only occur via relatively more entry and more patenting by REN firms compared to FF firms. To study the factors affecting entry into REN innovatin, we estimate for specialized firms the probability to be a new innovator in REN technologies (versus a new innovator in FF) as follows:

$$Pr(REN_{ikT} = 1|X_{ijkt}, \eta_i, \upsilon_k, \nu_T) = \Phi(\alpha_0 + \alpha_1 \log p_{iT-1} + \alpha_{2j} \log M_{ijT-1} + \eta_i + \upsilon_k + \nu_T) \quad (4)$$

where, as before, i and k index firms and countries, T denotes the first year of innovation of a specialized firm, and Φ is the cumulative normal distribution. REN is a binary variable taking the value 1 if the new innovator is a REN firm and 0 if the new innovator is a FF firm. Thus note that the sample underlying model (4) in principle is a cross-section. However, because different firms innovate for the first time in different years T, we also have to account for (unobserved) heterogeneity over time. As before, p is the fossil-fuel price and M is market size. Since we consider the innovation entry-decision of REN innovators (versus FF innovators), these firms have not innovated in REN of FF technologies in the past and hence we cannot include knowledge stock variables in the model.

Equation (4) is estimated as a probit model with robust standard errors clustered at the country level, and includes a full set of year and country dummies. Even though the cross-sectional nature of this particular model does not allow us to properly control for unobserved firm heterogeneity (η_i), we include as before the average number of pre-sample patent applications of the firm as a control Blundell et al. (1995).[15] We expect to find that the probability to be a new REN innovator is positively associated with high energy prices ($\alpha_1 > 0$) and a larger REN market size ($\alpha_{2,REN} > 0$), but is negatively associated with FF market size ($\alpha_{2,FF} < 0$).

For mixed firms, substitution between REN and FF technologies within the firm may occur, so that we can directly estimate the factors affecting relative innovation, i.e. the ratio of REN

sample period. Therefore, we only observe that specialized firms *have not* switched technologies. That is, apart from their relatively small size (cf. Section 3) there is nothing that we can observe which might prevent these firms from switching between technologies. They just have not done so.

[15] Note that we are considering innovation-entry into either REN or FF activities. Hence, these firms may already have innovated in the past and hence have pre-sample patent applications.

Table 5: Summary statistics and pairwise correlations

		Mean	St. Dev.	1	2	3	4	5	6
1	P_{REN}	0.02	0.55	1					
2	P_{FF}	0.11	0.92	0.03	1				
3	p_{FF}	5.06	0.29	0.01	0.01	1			
4	$Marketsize_{REN}$	6.44	2.40	0.01	-0.06	0.11	1		
5	$Marketsize_{FF}$	11.1	1.40	-0.01	0.04	0.00	0.02	1	
6	Pre-sample patents	0.00	0.00	0.01	0.21	0.01	-0.12	-0.00	1
1	$Prob_{REN}$	0.29	0.45	1					
2	p_{FF}	5.06	0.27	0.1	1				
3	$Marketsize_{REN}$	6.57	2.14	0.34	0.09	1			
4	$Marketsize_{FF}$	11.2	1.31	-0.27	0.02	0.04	1		
5	Pre-sample patents	0.13	0.63	-0.07	-0.02	-0.08	-0.02	1	

The top panel is based on N=183,666. The bottom panel is based on N=5,907.

over FF innovation. We estimate the following model for mixed firms:

$$\log\left(\frac{P_{REN,kt}}{P_{FF,kt}}\right) = \gamma_0 + \gamma_1 \log p_{it-1} + \gamma_{2j} \log M_{ijt-1} + \gamma_{3j} \log A_{ijt-1} + \varepsilon_{ikt}$$
$$\text{s.t. } \varepsilon_{ikt} = \eta_i + \upsilon_k + \nu_t + \epsilon_{ikt} \tag{5}$$

where the indices and independent variables are as before. The dependent variable (P_{REN}/P_{FF}) measures the (log) ratio of REN over FF patents. Accordingly, the estimated γ's tell us something about the direction of technical change. For instance, if $\gamma_1 > 0$, we know that an increase in the price of FF energy induces an increase in the innovation rate of REN technologies relative to FF technologies. That is, innovation in REN technologies increases faster than innovation in FF technologies, which implies that technical change is indeed directed. A similar reasoning applies to the other coefficients. We estimate the model in (5) by means of a (feasible) GLS FE estimator, including year dummies to account for unobserved time heterogeneity.[16]

Table 5 presents some summary statistics and pairwise correlations for the different variables in our sample. The top panel presents statistics and correlations for the Poisson models and the linear model, whereas the bottom panel give statistics for the probit model. Due to the significantly higher number of observations in the top panel (N=183,666 vs. N=5,907) these correlations are substantially smaller than those in the bottom panel.

[16] As the firms in our sample never switch countries k applying the FE transformation also takes care of the unobserved country-level heterogeneity.

4.2 Baseline results

In Table 6 we present our baseline results. In columns (1) and (2) we study the rate of REN innovation, in columns (3) and (4) the rate of FF innovation, and in columns (5) and (6) the direction of innovation between REN and FF patenting activities. The first four columns are all estimated using zero-inflated Poisson, with standard errors clustered at the firm-level. Column (5) is estimated using the probit model, and column (6) is estimated using the FE GLS specification, clustering standard errors at the country-level in both cases.

In column (1), we give the results on the rate of REN innovation for specialized firms. Fossil-fuel prices have a positive significant effect on patenting by REN firms. A 1% price increase is associated with a 0.98% increase in the number of patents by REN firms. The stock of REN patents also has a positive significant effect on patenting activities by REN firms. A 1% increase in the stock yields 0.76% more patents by REN firms. At last, a larger market for renewable energy also has a positive significant effect on patenting by REN firms, although the effect is small (0.09%). The market size of fossil-fuel energy has no significant impact on the level of innovation by specialized REN firms. Results are somewhat different for mixed firms in column (2). The most important determinants of REN innovation in this case are past REN and FF knowledge stocks, which both have a positive and significant impact on REN patenting activities. A 1% increase in the FF knowledge stock is associated with a 0.16% increase in REN patenting activities by mixed firms. This suggests complementarity between past FF innovation and future REN innovation in mixed firms, a result already found in Table 2 that showed for instance that mixed firms innovating in burners also tend to innovate in waste and biomass technologies. Further, the market size for FF energy has a moderately negative impact on REN innovation by mixed firms. Finally, the coefficients on knowledge stocks in the inflation equations always have the expected negative signs. Increased knowledge stocks tend to reduce the probability of zero REN patents, but only significantly so for mixed firms.

Columns (3) and (4) In Table 6 show the estimation results of similar models for FF innovation. We find that prices have a positive significant effect on patenting activities by specialized FF firms in column (3). A 1% increase in the past fossil-fuel price is associated with a 0.64%

increase in innovative activities by FF firms. Regarding the effect of the past knowledge stock, we find that a 1% increase in the firm's past FF knowledge stock is associated with 0.66% additional patenting activities by FF firms. In addition, we find that the size of the market for fossil-fuel energy has a small positive effect on FF innovation (0.09%), but the REN market size coefficient is insignificant. For mixed firms in column (4), results are again somewhat different. As in column (2), past knowledge stocks are the main factors driving current FF innovation. A 1% increase in past FF knowledge stocks is associated with a 0.74% increase in FF patenting activities by mixed firms. In this case however, an increase in REN knowledge stocks reduces the expected level of FF innovation, suggesting substitution. A 1% increase in past REN knowledge stocks is associated with a 0.23% decrease in FF patenting activities by mixed firms.

The estimates in columns (5) and (6) in Table 6 pertain to relative innovation, i.e. to whether innovation is not only towards REN innovation but also away from FF innovation. The probit model in column (5) applies to specialized firms, and analyzes the likelihood that a firm files its first innovation in REN rather than in FF technologies, capturing *between-firm* substitution of REN and FF innovation at the industry level. We focus on a cross-sectional sample of 5,907 specialized firms innovating for the first time over the 1978-2006 period. Fossil-fuel prices show the expected positive effect, indicating that a 1% increase increases the likelihood of REN versus FF innovation entry by 0.37%-points. REN market size is positive and significant, indicating that a 1% increase in REN market size increases the probability of a REN vs. a FF innovation entry by 0.23%-points. For FF market size this is exactly the reverse, since a 1% increase reduces this probability by 0.46%-points.

Finally, column (6) shows how the ratio of REN over FF patent applications, capturing *within-firm* substitution of REN and FF innovation, in mixed firms is affected. We find that fossil-fuel prices have no significant effect on relative innovation. A higher FF knowledge stock on the other hand is significantly associated with a lower ratio of REN over FF patents. The impact of REN knowledge stocks and REN and FF market sizes are not significant.

Summarizing, we find that prices, knowledge stocks, and market size are all important determinants of the rate of innovation in specialized (REN and FF) firms. For mixed firms on the other hand, only knowledge stocks are of key importance. Here we also find that the rate of REN

Table 6: Baseline results for specialized and mixed firms

	REN patents		**FF patents**		**REN/FF patents**	
	(1) Specialized ZIP	(2) Mixed ZIP	(3) Specialized ZIP	(4) Mixed ZIP	(5) Specialized Probit	(6) Mixed GLS
FF price	0.983***	0.316	0.636***	-0.321	0.374***	0.091
	(0.356)	(0.671)	(0.183)	(0.823)	(0.142)	(0.065)
REN knowledge stock	0.761***	0.258***		-0.230***		-0.017
	(0.029)	(0.087)		(0.072)		(0.015)
FF knowledge stock		0.161**	0.663***	0.747***		-0.191***
		(0.070)	(0.026)	(0.069)		(0.041)
REN market size	0.085***	0.031	0.002	-0.014	0.230***	-0.005
	(0.013)	(0.022)	(0.014)	(0.019)	(0.043)	(0.007)
FF market size	-0.019	-0.096*	0.093***	0.122	-0.458***	0.021
	(0.045)	(0.051)	(0.014)	(0.096)	(0.110)	(0.029)
Presample patent stock	0.071	-0.038	-0.050***	-0.054**	-0.163***	
	(0.060)	(0.031)	(0.018)	(0.022)	(0.039)	
Constant	-7.257***	-1.742	-6.050***	-0.044	0.770	-0.636*
	(1.929)	(3.993)	(1.094)	(4.930)	(0.958)	(0.325)
Inflation equation:						
REN knowledge stock	-0.049	-0.362***		0.002		
	(0.199)	(0.133)		(0.121)		
FF knowledge stock		-0.220***	-0.648***	-0.790***		
		(0.056)	(0.030)	(0.064)		
Constant	1.816***	2.187***	2.112***	1.870***		
	(0.143)	(0.115)	(0.043)	(0.159)		
Observations	50070	9501	117175	9501	5907	9501
Log Likelihood	-10393	-2803	-34952	-7835	-2791	
(Pseudo) Rsq					0.22	0.072

All models include a full set of year and country dummies. The probit model includes 5-year dummies since in this specific sample the price data show relatively little within-year variation compared to between-year variation. This could imply that the inclusion of year dummies absorbs all the relevant variation of energy prices. Robust standard errors are clustered at the firm level. All explanatory variables are expressed in logarithm 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. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

innovation is positively affected by past FF knowledge stocks, suggesting complementarities between REN and FF activities, whereas the rate of FF innovation is negatively affected by past REN knowledge stocks, suggesting that mixed firms with past experience in REN innovation are less likely to file FF patents in the future. Regarding the direction of innovation, we find that lower FF market size, and higher FF prices and REN market size stimulate entry into REN innovation *vis-a-vis* FF innovation (between-firm substitution). (Re)directing innovation within mixed firms appears much harder, as only a decrease in FF knowledge stocks stimulates a relatively more important increase in REN than in FF activities. In other words, mixed firms with a large existing stock of FF patents will find it more difficult to substitute FF by REN innovations.

4.3 Robustness analysis

In order to test the robustness of our baseline results in Table 6 we conduct a number of robustness tests. First, we consider the possible non-linear effect of fossil-fuel prices. As we explained above, the effect of prices on FF innovation is ambiguous. On the one hand, an increase in prices might stimulate more FF innovation that is aimed at a more efficient use of FF energy. On the other hand, it might also redirect innovation towards REN and away from FF innovation, as REN energy becomes relatively cheaper.

Table 7 repeats the analyses in Table 6 while adding a quadratic term for prices. In columns (1) and (2), we find that the quadratic price term has no significant effect on REN patenting activities by specialized and mixed firms.[17] On the other hand, in column (3) we find evidence of a significant non-linear effect of prices on FF innovation by specialized firms.[18] Hence, when fossil-fuel prices are low, an additional increase in prices is associated with a rise in innovation by FF firms. Firms will innovate in order to save on the expensive fossil-fuel factor of production. Yet, when fossil-fuel prices are high, an additional price increase will be associated with lower patenting activities by FF firms. There is thus a threshold price beyond which FF innovators

[17] Due to the addition of a quadratic term, the coefficients in Table 7 cannot be directly interpreted and compared to the ones in Table 6.

[18] A likelihood ratio test rejects the null hypothesis that the model in column (3) of Table 6 is to be preferred to the model in column (3) of Table 7 at $p<0.01$.

Table 7: Robustness - non-linear prices

	REN patents		**FF patents**		**REN/FF patents**	
	(1) Specialized ZIP	(2) Mixed ZIP	(3) Specialized ZIP	(4) Mixed ZIP	(5) Specialized Probit	(6) Mixed GLS
FF price	9.130*	12.909	15.681***	1.738	-9.896***	-0.698
	(5.467)	(11.652)	(3.478)	(16.715)	(3.273)	(1.205)
FF price sq	-0.800	-1.250	-1.490***	-0.203	1.006***	0.078
	(0.530)	(1.166)	(0.342)	(1.615)	(0.321)	(0.116)
REN knowledge stock	0.765***	0.258***		-0.230***		-0.017
	(0.029)	(0.087)		(0.072)		(0.015)
FF knowledge stock		0.162**	0.666***	0.748***		-0.190***
		(0.070)	(0.026)	(0.069)		(0.041)
REN market size	0.084***	0.030	-0.003	-0.014	0.228***	-0.005
	(0.013)	(0.022)	(0.014)	(0.019)	(0.044)	(0.007)
FF market size	-0.024	-0.093*	0.092***	0.122	-0.458***	0.020
	(0.044)	(0.050)	(0.014)	(0.096)	(0.111)	(0.029)
Presample patent stock	0.072	-0.036	-0.051***	-0.055**	-0.166***	
	(0.060)	(0.031)	(0.018)	(0.022)	(0.040)	
Constant	-27.570**	-32.747	-43.173***	-5.169	26.907***	1.329
	(13.992)	(28.582)	(8.728)	(42.732)	(8.484)	(2.910)
Inflation equation:						
REN knowledge stock	-0.045	-0.360***		0.002		
	(0.199)	(0.133)		(0.121)		
FF knowledge stock		-0.219***	-0.646***	-0.790***		
		(0.056)	(0.030)	(0.064)		
Constant	1.807***	2.182***	2.107***	1.869***		
	(0.141)	(0.117)	(0.043)	(0.159)		
Observations	50070	9501	117175	9501	5907	9501
Log Likelihood	-10390	-2803	-34936	-7834	-2777	
(Pseudo) Rsq					0.22	0.072

All models include a full set of year and country dummies. The probit model includes 5-year dummies. Robust standard errors are clustered at the firm level. All explanatory variables are expressed in logarithm 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. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

do not find it profitable anymore to innovate in these technologies.[19] Interestingly, we also find a non-linear impact of FF prices on the entry of specialized firms in column (5). This implies that as prices increase, specialized firms tend to enter initially into FF rather than REN innovation, but as prices pass a threshold[20] new innovators tend to enter into REN rather than FF innovation. We do not find for a non-linear effect of prices on relative innovation by mixed firms in column (6). Finally, the effects of the other variables in the regressions remain robust.

A second robustness test that we conduct considers the possible impact of knowledge spillovers external to the firm. While so far, we assumed that firm's innovation only builds up on the firm's past knowledge stock, there is a large literature that emphasizes that firms can (partly) appropriate knowledge spillovers from other firms and use them as inputs in their own innovation efforts. The fact innovation, research and development create externalities to other firms is due to the public good nature of knowledge. (e.g. Romer, 1990; Keller, 2004). In order to test whether the firms in our sample also benefit from knowledge spillovers, we construct sector-wide knowledge stocks of REN and FF technologies. We again account for the fact that firms may be active in multiple countries, and hence that all these countries' knowledge stocks might affect a firm's innovation. Hence external knowledge stocks are computed similarly as prices in (1), except that p_{kt} now becomes K_{kt}^{REN} or K_{kt}^{FF}. Table 8 presents the results. We include the external knowledge stocks both in the level equations, as well as in the inflation equations (for the Poisson models).

Columns (1) and (2) in Table 8 show that sector-wide REN knowledge stocks do not have any impact on REN patenting activities, neither for specialized firms nor for mixed firms. However, the results in the inflation equation show that increased external REN knowledge stocks decrease the likelihood of zero REN patents, whereas the opposite is the case for external FF knowledge stocks in column (2). Columns (3) and (4) show the impact of external knowledge stocks on FF patenting. For specialized firms in column (3), there appears to be a positive spillover effect of the external FF knowledge stock on the rate of innovation by FF firms. For mixed firms in

[19] The coefficient estimates imply that the "ceiling" price is approximately US$ 192. The marginal effect of a variable in the Poisson model is given by $\partial E(y_i|x_i)/\partial x_{ik} = \beta_k \exp(x_i'\beta)$. Hence, in this case, $\partial E(P_{ijkt}|X_{ijkt})/\partial \ln p_{ijkt} = (15.681 - 2 \times 1.49 \times \ln p_{ijkt}) \exp(X_{ijkt}'\beta)$. Equating this to 0 yields $\ln p_{ijkt} = 5.26$, or $p_{ijkt} = 192$.

[20] (i.c. US$ 137)

Table 8: Robustness - knowledge spillovers

	REN patents		**FF patents**		**REN/FF patents**	
	(1) Specialized ZIP	(2) Mixed ZIP	(3) Specialized ZIP	(4) Mixed ZIP	(5) Specialized Probit	(6) Mixed GLS
FF price	1.020**	-0.128	0.627***	-0.241	0.198	0.090
	(0.399)	(0.748)	(0.185)	(0.750)	(0.223)	(0.067)
REN knowledge stock	0.772***	0.325***		-0.257***		-0.019
	(0.035)	(0.093)		(0.073)		(0.017)
FF knowledge stock		0.192***	0.663***	0.758***		-0.190***
		(0.066)	(0.026)	(0.070)		(0.042)
REN market size	0.082***	0.029	-0.013	-0.012	0.221***	0.018
	(0.014)	(0.022)	(0.015)	(0.019)	(0.049)	(0.036)
FF market size	-0.045	-0.123**	0.082***	0.151*	-0.486***	-0.008
	(0.051)	(0.054)	(0.014)	(0.078)	(0.126)	(0.034)
REN external knowledge stock	0.085	-0.421		0.323	0.241	-0.005
	(0.109)	(0.330)		(0.200)	(0.217)	(0.007)
FF external knowledge stock		0.460	0.130**	-0.270	0.081	0.020
		(0.286)	(0.061)	(0.179)	(0.137)	(0.029)
Presample patent stock	0.059	-0.045	-0.051***	-0.054***	-0.157***	
	(0.060)	(0.031)	(0.018)	(0.021)	(0.036)	
Constant	-7.489***	0.161	-6.481***	-0.694	0.677	-0.659*
	(2.188)	(4.712)	(1.165)	(4.611)	(1.281)	(0.314)
Inflation equation:						
REN knowledge stock	-0.025	-0.262**		-0.049		
	(0.199)	(0.129)		(0.130)		
FF knowledge stock		-0.219***	-0.646***	-0.774***		
		(0.054)	(0.030)	(0.064)		
REN external knowledge stock	-0.118**	-0.776***		0.363***		
	(0.055)	(0.237)		(0.126)		
FF external knowledge stock		0.608***	-0.021	-0.331**		
		(0.218)	(0.030)	(0.146)		
Constant	2.369***	1.754***	2.241***	2.343***		
	(0.306)	(0.637)	(0.204)	(0.575)		
Observations	50070	9501	117175	9501	5907	9501
Log Likelihood	-10382	-2783	-34940	-7809	-2766	
(Pseudo) Rsq					0.22	0.072

All models include a full set of year and country dummies. The probit model includes 5-year dummies. Robust standard errors are clustered at the firm level. All explanatory variables are expressed in logarithm 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. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

column (4), we do not find any significant effect of the sector-wide FF knowledge stocks on FF patenting activities. Also, external REN knowledge stocks increase the probability of zero FF patenting by mixed firms. Finally, there is no significant impact of external knowledge stocks on the direction of innovation in columns (5) and (6). Moreover, the other results are rather robust. The two notable changes are that FF market size becomes marginally significant in column (5), and the energy price loses significance in column (5). Overall, these results suggest that external knowledge stocks are not very significant drivers of REN and FF innovation, in particular compared to the firm's own knowledge base. The external REN knowledge stocks increase the likelihood of innovating in REN but their impact is not large enough to influence the level of REN innovation. [21]

We conducted two other robustness tests for which we will briefly summarize the results.[22] First, we dropped single (i.e. one-time) innovators in our sample. The main change relative to the baseline estimates in Table 6 is that the positive effect of fossil-fuel prices only shows up on REN patents by specialized firms (column (1)), whereas it becomes insignificant in columns (3) and (5) in Table 6. Including the non-linear price term as in Table 7 does not change this result. The effect of fossil-fuel prices on FF patenting activities appear thus to be mainly driven by single FF innovators.

Second, we split our sample period in two: 1978-1993 and 1994-2005. The reason is that, as we demonstrated in the previous section, the market for renewable energy and the related innovations only started to gain momentum during the second part of the 1990s. Hence, our results might be mainly driven by developments during the latter period. We indeed find that this is the case. In particular, the impact of prices and FF market size on patenting activities is more pronounced after 1994. Our main conclusions still hold.

5 Conclusion

In this paper we have investigated the determinants of directed technical change in the electricity generation sector, a sector particularly relevant for policymaking. We focused on three main

[21] A potential problem with the analyses in Table 8 is the fact that external knowledge stocks for REN and FF are strongly correlated with each other (0.88 in the total sample). This could yield problems when including them simultaneously in the mixed firm regressions. In order to investigate this further, we also ran the models in columns (2), (4) and (6) while including only external knowledge stocks (results are available upon request). This did not affect our results.

[22] The results tables are available from us upon request.

factors inducing energy innovation as described by Acemoglu et al. (2012): a price effect, a market size effect, and a productivity effect. The price effect implies that innovation will be directed towards innovation which saves on the use of the higher priced inputs. The market size effect predicts that innovation takes place in areas where the (potential) market is large. Finally, the productivity effect entails that innovation mainly builds on earlier innovations, and hence takes place in areas where there already is a large body of established research.

We use firm-level data on patents filed in renewable (REN) and fossil fuel (FF) technologies by about 7,000 European firms over the period 1978-2006 to test these effects. We also distinguish between (small) specialized firms – that only innovate in REN or FF technologies – and (large) mixed firms – that innovate in both REN and FF technologies. We find that for specialized firms the main drivers of REN and FF innovation are energy prices, market size, and firms' knowledge stocks. A differential impact arises for prices however, which has a positive and linear effect on REN innovation, but an inverted U-shaped effect on FF innovation. Second, prices and market size drive the entry of new REN firms (relative to new FF firms) into the industry. Third, we find that innovation by mixed firms is characterized by strong path-dependencies. Past knowledge stocks are the major driver of the direction of innovation. Mixed firms with a large existing stock of FF patents will find it more difficult to substitute REN innovations by FF innovations (and vice versa). Fourth, we do not find much evidence of knowledge spillovers from outside the firms' knowledge base. Sector-wide REN knowledge stocks mainly increase the probability of REN innovation, but not its level.

Our results have a number of policy implications. First, a short-term policy goal may be to increase FF innovations (to the extent that these also lower CO_2 emissions). Given the responsiveness of FF innovations to prices and market size, as well as its huge existing knowledge base, such a policy can be highly effective. In the longer term, however, a major policy question is how to break the path-dependency towards ever-increasing innovation in FF technologies. Our results suggest that policies are not likely to be "one size fits all".

The general impression that arises from our analyses is that it will be difficult to steer large mixed firms' innovations away from FF and towards REN technologies, as they have already specialized quite heavily in FF technologies. Our results show that innovation incentives by mixed firms, which are large and persistent innovators, are largely path-dependent. In this case, R&D policies specifically targetted to increase innovation in renewable energy may be useful to rebalance firms' R&D towards REN innovation. It will take time before sufficient critical mass has been accumulated that can match the existing expertise in FF innovation.

We also find that stimulating entry of new firms specialized in REN innovation can be effective in driving innovation towards REN technologies and away from FF technologies. Higher fossil fuel prices (or an equivalent carbon tax) and other policies aiming to increase the (relative) market for REN technologies, can encourage entry of new REN firms over FF firms and have a positive impact on the rate of innovation of these firms. Since the entry of small specialized REN firms has been key in driving REN innovation after the mid-1990s, policies should be cautiously designed not to deter entry and to enhance competition in this sector.

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