Research Paper 58 | **2018**

DO FINANCING CONSTRAINTS MATTER FOR THE DIRECTION OF TECHNICAL CHANGE IN ENERGY R&D?

Joëlle NOAILLY, Roger SMEETS

Do financing constraints matter for the direction of technical change in energy R&D?

Joëlle Noailly[a*] and Roger Smeets[b]

[a]Graduate Institute of International and Development Studies, Geneva, Switzerland

[b]Rutgers University, Newark (NJ), USA

December 2018

Abstract

The objective of this study is to examine the impact of firms' financing constraints on innovation activities in renewable (REN) versus fossil-fuel (FF) technologies. Our empirical methodology relies on the construction of a firm-level dataset for 1,300 European firms over the 1995-2009 period combining balance-sheet information linked with patenting activities in REN and FF technologies. We estimate the importance of the different types of financing (e.g. cash flow, long-term debt, and stock issues) on firms' patenting activities for the different samples of firms. We use count estimation techniques commonly used for models with patent data and control for a large set of firm-specific controls and market developments in REN and FF technologies. We find evidence for a positive impact of internal finance on patenting activities for the sample of firms specialized in REN innovation, while we find no evidence of this link for other firms, such as firms conducting FF innovation or large mixed firms conducting both REN and FF innovation. Hence, financing constraints matter for firms specialized in REN innovation but not for other firms. Our results have important implications for policymaking as the results emphasize that small innovative newcomers in the field of renewable energy are particularly vulnerable to financing constraints.

Keywords: R&D, financing constraints, renewable energy.

*Corresponding author: Joëlle Noailly, joelle.noailly@graduateinstitute.ch, Tel: +41229086222. Fax: +41229084225 Address: Center for International Environmental Studies, Graduate Institute of International and Development Studies, Voie-Creuse 16, CP 136, 1211 Geneve 21, Switzerland. Roger Smeets: rsmeets@business.rutgers.edu, Tel:+1 957 353 1647. Address: 1 Washington Park, Newark, NJ 07102. We acknowledge funding from the European Investment Bank (EIB) for this research and thank the EIB for providing us with the data. We thank participants at the "Workshop on Corporate Finance Alternatives in Europe", Luxembourg, a RWI research seminar in Berlin, EAERE Conference in Athens, EEA Conference in Lisbon and WCERE in Gothenburg for useful comments and suggestions.

1 Introduction

The ability to achieve sizeable greenhouse gases emissions reductions to address climate change without compromising future economic growth is linked to the deployment and development of clean technologies. The energy sector is key in this respect, as emissions from energy production are responsible for 40% of worldwide carbon emissions (IEA, 2015). Decarbonizing the energy sector implies shifting away from fossil-fuels, such as coal, oil and gas, which today still accounts for 70% of worldwide electricity production and 80% of global energy investments. Despite recent developments in renewable energy, in particular in wind and solar energy, experts worry that the current pace of innovation efforts in renewable technologies may not be sufficient to achieve the commitment of the Paris agreement to limit global temperature rise below 2 degrees Celsius (IEA, 2017). While technological advances are needed to improve further efficiency and reduce plant-level integration costs of renewables, the share of renewable (REN) energy in corporate energy R&D spending remains below 15% (FS, UNEP and BNEF, 2016) and most innovation efforts tend to be directed to existing incumbent fossil-fuel (FF) technologies.

Theoretically, several market failures explain why firms tend to underinvest in the development of renewable energy technologies. First, just like other forms of R&D, firms innovating in REN technologies cannot fully appropriate the returns on their innovation – this is the so-called 'knowledge externality'. Second, in the absence of environmental policy setting a price on carbon emissions, the 'environmental externality' implies that firms have no incentives to develop further these low-carbon technologies. Third, path-dependency in innovation leads technical change to be directed towards FF technologies, where most innovation took place historically (Acemoglu et al., 2012; Noailly and Smeets, 2015). Finally, an additional market failure that has received less attention in the energy R&D literature is the prevalence of credit constraints to finance R&D. Theoretically, all R&D investments are susceptible to financing constraints due to intrinsic characteristics of the R&D process (i.e. uncertain outcome of the R&D process, the lack of collateral values and information asymmetries between investors and innovating firms; Hall and Lerner (2010)). An open question, however, is whether financing constraints may be more severe for R&D in REN than in FF technologies, thereby affecting not only the rate but also the direction of innovation. There are several arguments why financing R&D may be more difficult for firms innovating in REN (vs. FF) technologies. First and foremost, the technologies present different characteristics substantiating distinct risk-profiles for investors: REN technologies are younger, less mature, and may require higher irreversible sunk costs than their fossil-fuel counterparts. In addition, due the presence of the environmental externality, renewable technologies are highly dependent on policy support, which tends to fluctuate over time thereby generating additional risks for investors.

In this paper, we aim to provide some novel empirical evidence on the impacts of financing constraints on innovation in REN and FF technologies. So far, the literature on energy R&D has mainly focused on the role of energy prices, market developments and environmental policies (Popp, 2002; Johnstone et al., 2010), and more recently on the impact of path-dependency on the number of patents in renewable technologies (Noailly and Smeets, 2015). By contrast, the role of financial constraints in commanding energy innovation has received little attention in previous research. In a recent contribution, Howell (2017) estimates the impact of being awarded an early-stage research grant by the US Department of Energy on revenues, innovation and survival of small high-tech firms in various sectors related to energy. She finds that firms awarded a grant were more likely to receive subsequent venture capital and to increase their patenting activities and revenues. She finds evidence of a larger effect for younger firms and for firms in less mature technology areas such as marine and ocean energy or electric vehicles compared to incumbent energy technologies in coal or gas, suggesting that immature clean technologies are particularly affected by financing constraints.

By studying how the availability of finance differentially affects R&D investments in renewable and fossil-fuel energy technologies, our study aims to contribute to a new research agenda on the role of financing constraints on the direction of innovation. So far, the evidence has remained mainly anecdotal and in sectors outside energy. Abraham (2011) note for instance that the pharmaceutical industry has become locked into innovation in drugs which are less complex and provide easier returns than other areas of research, such as diagnostics or life-style remedies. In a sector like energy where externalities are pervasive, understanding how financing constraints affect technological choices is crucial to design effective policies. Our analysis innovates compared to Howell (2017) by focusing on European firms rather than US companies. This is important as financial intermediation is not structured in the same way on the US and European markets and policies for REN technologies have been relatively more generous in

Europe over the last decades. Our study is also novel as it explicitly combines the environmental economics literature with the well-developed framework in corporate finance studying the role of finance for innovation. This literature generally finds that R&D is difficult to finance externally and that therefore debt and equity tend to be disfavoured sources of finance for R&D investment (Hall and Lerner, 2010; Bond et al., 2005; Brown and Petersen, 2009).

In line with the corporate finance literature, our econometric method will aim to detect financial constraints by comparing different groups of firms in terms of their R&D investments' sensitivity to internal financing (e.g. cash flows). Our analysis relies on an unique dataset combining balance-sheet data with data on firm-level innovation activities (as measured by patents) in renewable and fossil-fuel energy technologies for a sample of 1,300 European firms over the period 1995-2009. Our results suggest that small innovating firms specialized in renewable technologies face important financial constraints: their patenting activities are more sensitive to shocks in cash flows than other firms, suggesting that they mainly rely on internal finance to fund R&D. By contrast, firms innovating in fossil-fuel technologies are less financially constrained and can more easily resort to external financing.

Our study is structured as follows. Section 2 provides the conceptual framework underpinning our analysis. Section 3 gives a description of the data. Section 4 presents our empirical framework and results. Section 5 concludes.

2 Conceptual framework and related literature

2.1 Financing R&D

The theoretical literature in corporate finance predicts that innovation is difficult to finance externally (Hall and Lerner, 2010). This is explained by several factors.

First, the majority of R&D expenditures concerns wages of R&D workers, rather than capital investment. This implies that banks often cannot claim collaterals in return for R&D investment. First-time innovators will also often lack a valuable asset that can serve as collateral. As a result, the availability of external (debt) finance is either limited or very costly. Second, due to the highly uncertain nature of the outcome of the innovation process, so is its financial return. The high degree of uncertainty around innovation makes it always difficult to know in advance whether a firm will be successful at innovating or not. As a result, the risk premium charged on external sources of finance is often prohibitively high. Finally, market failures affecting investments also play a role for R&D investment. There exists asymmetric information between the provider of finance and the innovator, since the latter tends to have more information about potential success or failure. As a result, the high-success firms will tend to exit the market as they cannot signal their quality to financiers. Further, moral hazard may induce innovators to spend money on more risky projects than agreed upon ex-ante with the financier. Anticipating such behavior, financiers could limit the availability of external financing, or offer it at higher cost.

Taken together, these problems imply that external (to the firm) financing of innovation can be quite costly. This creates a hierarchy in the corporate financing of innovation (Hall and Lerner, 2010): firms will typically first deplete their internal cash flow (and possibly part of their cash stocks) before turning to external sources of financing. A corollary of this result is that firms that are relatively cash-constrained will be more sensitive to shocks in both the internal and external supply of financing, relative to their cash-replete counterparts. Figure 1 borrowed from Brown et al. (2012) plots the relationship between the quantity of funds (horizontal axis) and the marginal costs of finance (vertical axis). The supply of finance S exhibits first constant marginal costs as long as cash flows (CF) are being depleted. As cash flows are exhausted, the firm must resort to external finance which is more costly (the upward trending part of S). The equilibrium level of R&D is at the intersection between the demand for R&D (D_{RD}) and the supply of finance S. This equilibrium depends crucially on cash flows: a jump in cash flows for instance from CF to CF' (which shifts the supply of finance to S') raises the equilibrium level of R&D from RD to RD'. Hence, a shock in internal finance leads to more R&D.

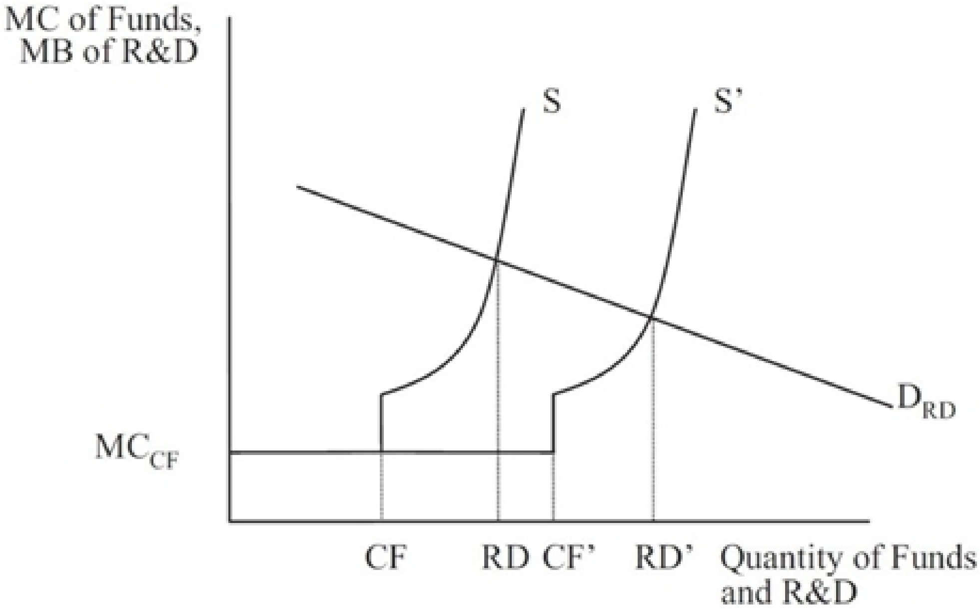

Figure 1: Financing hierarchy for R&D

A number of studies have tested empirically these theoretical insights. The standard approach for testing for financial constraints has been to examine the sensitivity of cash flows to R&D investments. In addition, recent research further stressed the importance of R&D smoothing. The empirical evidence finds that in particular small, young, and high-tech firms' R&D activities are sensitive to internal and external (equity) cash constraints, unlike large and mature firms (Brown and Petersen, 2009; Brown et al., 2012; Himmelberg and Petersen, 1994).

Another insight of this literature is that, when resorting to external sources of finance, equity financing trumps debt financing (Brown et al., 2012). Two important reasons for this are that, first, equity financing does not require collateral, and second, unlike providers of debt, equity investors share in the upside of the investment. This makes external equity cheaper than external debt. Indeed, Brown and Petersen (2009), Brown and Petersen (2011) and Brown et al. (2012) all demonstrate the sensitivity of small, young, and technology-intensive firms' R&D to external equity financing constraints. Given that large and mature firms typically do not rely on external equity for their marginal innovation financing needs, their R&D does not exhibit a significant elasticity with respect to such constraints.

However, there are a number of caveats to these established insights that are important for the purpose of the current study. First, the majority of the studies on the corporate financing of innovation are undertaken for US firms. It is not completely clear that their results translate one-to-one to the European context, given the substantial differences in the structure of capital markets.[1] Brown et al. (2012) study R&D and financing constraints in a number of European countries. However, their study is particular in the sense that they only study publicly listed firms. This constitutes the second caveat to the established literature in this field, which mostly focuses on samples of publicly traded firms. In this context, the typical definition of a small firm is one with less than 500 employees, whereas a young firm is one whose IPO took place less than 15 years ago.

In an implicit acknowledgement of these limitations, a more recent literature has developed that explicitly considers the importance of non-equity external financing for truly small (start-up) firms (Kerr and Nanda, 2015). One important insight from this literature is that for many small firms, debt financing is an important resource for innovation. Partly, this is due to the fact that innovation sometimes does produce some valuable collateral, such as patents (Sudheer et al., 2017), as well as the increased willingness and ability of (US) banks to monitor small and innovative corporate borrowers (Chava et al., 2013; Cornaggia et al., 2015). Yet in other part, it is also due to costs associated with being a publicly listed firm undertaking R&D that were not previously acknowledged. Risk-averse managers of public corporations, who recognize the highly skewed returns of innovation, as well as its stochastic failure, will not innovate or only engage in incremental innovation when confronted with short-term oriented stockholders. In this line of thinking, there is little symbiosis between public equity and innovation.

In a survey on the capital structure decision of new US firms, Robb and Robinson (2014) further uncover some interesting stylized facts of small-firm debt financing. Although their study is not specifically aimed at innovative or high-tech firms, the underlying survey is biased towards such firms. Two results stand out in particular: First, newly founded businesses rely heavily on formal outside debt financing, in the form of bank loans and business credit lines. This even holds for the relatively small number of start-ups that have access to (private) equity (such as venture capital, or angel investment). Second, many small entrepreneurs overcome the

[1] In particular, EIB (2015) quotes Mario Draghi as saying that 'in the United States 80% of credit intermediation goes via the capital markets. In the European situation it is the other way around; 80% of financial intermediation goes through the banking system' (p.110). This suggests that the importance of equity markets (vs. debt markets) may not be as prevalent in Europe as it is in the US.

lack of corporate collateral by leveraging their personal assets as collateral or guarantees for bank financing.

Taken together, the findings from the literature argue that the nature of the innovation process (lack of collateral, uncertainty, asymmetric information) inhibits the financing of innovation. The corporate finance literature sketches a financing hierarchy: first, internal cash flow is depleted, followed by external equity financing, possibly followed by external debt financing. As most of this work has been conducted in the context of US and/or publicly listed firms, this casts some doubts on the financing hierarchy relevant for European private firms. Given the limited importance of equity markets in (continental) Europe, equity financing is not likely to be a viable substitute. We can thus expect that European R&D firms will first deplete internal cash before resorting to debt and possibly equity financing. In addition, the literature has also firmly established that small, young, and technology-intensive firms are more sensitive to financial constraints than large and mature firms, so that the former are likely more sensitive to a shock in cash flows.

2.2 Financing energy R&D

While the previous section has established that financial frictions are particularly relevant for R&D, the nature of the problem may also differ across technologies. Energy technologies for instance present specific characteristics that make them largely dependent on external finance: they are highly capital-intensive, require large upfront investments, and these investments are often irreversible. By contrast to pharmaceuticals or IT, very large capital investments are required in the energy sector after the R&D phase in order to supply energy services using new energy technologies (Hartley and Medlock, 2017). This explains why investments in energy exhibit very different risk profiles than investments in other sectors.

Within the energy sector, REN and FF technologies also present distinct risk profiles, as investments in renewable energy face specific challenges. First, REN technologies still largely rely on policy support. Government intervention is justified in this sector by the environmental externality. Yet, the risk that policies supporting clean energy are subject to change makes it challenging for investors, who might hold an investment under successive governments. Looking at the determinants of venture capital financing in the renewable energy sector using data on deals in the 'clean tech' industry for 26 countries over the period 2005-2010, Criscuolo and Menon (2015) find that national policies designed with a long-term perspective (e.g. feed-in tariffs) are associated with higher investment levels compared to more short term fiscal policies (e.g. tax incentives, rebates).

Second, REN technologies present higher technological risks than traditional FF ones. Renewables usually require higher upfront capital investments. Nelson and Shrimali (2014) estimate that upfront capital costs represent 84-93% of total project costs for wind, solar and hydro energy (compared to 66-69% for coal and 24-37% for gas). More importantly, most of these technologies are still in an early stage of development, and failure rates are still high. Ghosh and Nanda (2010) and Nanda and Fleming (2015) discuss how entrepreneurs in renewables need risk capital, not only in early stages, but also later on to demonstrate that the technology can work at scale. This is less of a problem for FF technologies that are well-established in the sector. Howell (2017) also finds that it is mainly immature clean technologies in hydropower (wave and tidal), carbon capture and storage, building and lighting efficiency and electric vehicles that most benefit from an early-stage research grant, while coal, natural gas, biofuels and recycling technologies do not. Although biofuels and recycling are also clean technologies, they are older and more mature and thereby less affected by financing constraints.

Finally, firms active in renewables tend to be relatively small, both in the R&D and deployment stage (Noailly and Smeets, 2015; Donovan, 2015). As a consequence, REN projects are often small (compared to nuclear or gas for instance) and small companies do not have an institutional track record to secure debt financing. Incumbents, by contrast, are large companies that often remain specialized in FF technologies. For such firms, shifting to REN often implies cannibalizing their core business. As a result, energy producing firms and utilities are far from active in acquiring promising clean energy startups, thus limiting the available exit options for REN firms (Ghosh and Nanda, 2010; Gaddy et al., 2016).

Altogether, these factors explain why REN investments have an unattractive risk/return profile compared to FF investments.[2] In the realm of REN innovation, this implies a twofold

[2]The specificities of the REN sector also explain why project financing is so popular, compared to other sources of financing. Project financing is mainly used for the deployment stage (i.e. construction of REN generating facilities, such as solar or wind turbines) and is less suited for R&D investment, which is why we abstract from project financing in this paper. This form of financing provides a fixed-income which relies solely on the ability of the project cash flows to repay the amounts borrowed; it typically involves the creation of a project company (Special Purpose Vehicle) which is the legal owner of the project assets and which has contractual agreements with a number of other parties that include off takers, operators, suppliers, insurers and so on. About 30% of the

financial 'squeeze': first, compared to FF innovation, REN innovation is more uncertain, making external financing more difficult. Second, REN innovation is typically undertaken by small and young firms, which only have limited internal funds. Hence, we can expect in particular small firms specialized in REN innovation to face important financial constraints, as reflected in a higher sensitivity of patenting activities to internal cash flows. Small firms specialized in FF innovation should be less financially constrained than REN firms. Finally, we would expect large mature firms, predominantly innovating in FF technologies, to show no evidence of financial constraints, while there might be some weak evidence that internal finance matters for their REN innovation activities (although to much lower extent than for small firms specialized in REN).

3 Data and empirical strategy

3.1 Data sources and descriptives

Patents data We measure innovation in REN and FF technologies using patent data, following the literature on low-carbon innovation (**?**Johnstone et al., 2010). There are several advantages and limitations to working with patent data, which have been discussed at length in the literature.[3] We extract patents from the Orbis dataset provided by Bureau van Dijk, which has recently been linked to the European Patent Office's (EPO) PATSTAT dataset. The main advantage of using the Orbis-PATSTAT dataset to extract relevant patents is that it provides us with an unique firm's identifier that allows us to match firm-level patents to firms' balance sheet and income statement data.

We extract data on firms' patenting activities in REN and FF technologies using International Patent Classification (IPC) codes to select patents in REN and FF technologies. REN patents include patents in wind, solar, hydro, marine, biomass, geothermal and waste energy technologies (Johnstone et al., 2010), while FF patents include patents related to production of

total new investment deployed into large scale REN projects over the 2003-2013 period was financed by project finance debt (Alonso, 2014).

[3]A main caveat of working with patents is that not all inventions are patented, as for strategic reasons firms may prefer not to disclose valuable information. The value of patents is also very heterogeneous: only a few patents will lead to successful commercial applications. Despite these limitations, the link between patents and inventions has been clearly established in the literature (Griliches, 1990) as patents are correlated with other indicators of innovative activity, such as R&D expenditures or new product introductions. For our purpose, the main advantage of patent data is that they are highly disaggregated and are available at the firm and technology level.

fuel gases by carbureting air, steam engine plants, gas turbine plants, hot-gas or combustion-product positive displacement engine, steam generation, combustion apparatus, furnaces and improved compressed-ignition engines (Lanzi et al., 2011).

Just as in Noailly and Smeets (2015), we focus on firms that have been granted at least one REN or FF patent at the EPO and 17 national patent offices (EU-15, Switzerland and Norway). We count the number of granted patents per firm per year over the 1980-2009 period, including only priority patents and excluding equivalent patent filings. The fact that we focus on granted patents of firms' registered in Orbis implies that our sample is not likely to include the lowest quality patents.[4] We use 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. We compute the annual count of REN and FF patents per firm as well as firm-specific REN and/or FF knowledge stocks, which are the cumulated number of patent counts over the period.[5]

The firms in our sample have been granted a total of 21,487 patents during the period 1980-2009. 16,854 (78%) of these apply to FF innovations, whereas the remaining 4,633 (22%) apply to REN innovations.[6]. The total patent count in this period is 12,377, with 8,384 (68%) allocated to FF innovation and 3,953 (32%) to REN innovation.

The strong bias towards FF innovation in the sample as a whole masks the fact that REN innovation has caught up with FF innovation spectacularly since the second half of the 1990s, as witnessed in Figure 2. Whereas the average gap between FF and REN innovation before 1995 was around 500 patents, by 2009 the total number of granted REN patents at European patent offices has actually overtaken the number of granted FF patents.

[4]In addition, we restrict our analysis to firms that could be linked to the Orbis dataset, therefore excluding patents from individuals, which may be of lower value.

[5]Knowledge stocks are calculated using the perpetual inventory method, assuming an annual depreciation rate of 15%.

[6]We focus on the 1980-2009 period for descriptive purposes, although in the econometric analysis we later restrict our analysis to the 1995-2009 period, due to limited availability of firm-level financial data before 1995

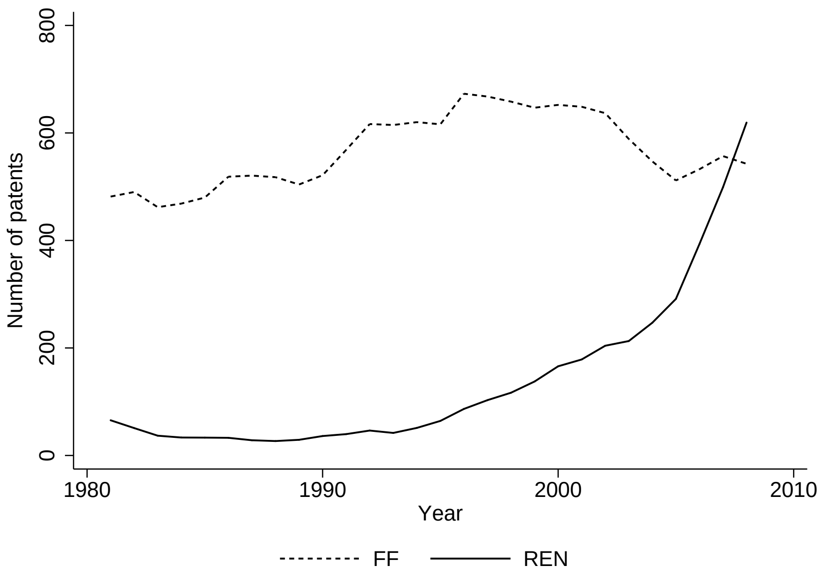

Figure 2: The development in FF and REN patents (3-year moving averages)

Further investigation shows that our dataset is composed of three types of firms: (1) firms that specialize solely in REN innovation (REN firms), (2) firms that specialize solely in FF innovation (FF firms), and (3) firms that engage in both types of innovation (mixed firms) over the observed period.[7] Table 1 presents a number of descriptive statistics regarding the relative importance of these three firm types in our sample, as well as their share of total innovation.

The majority of firms in our sample are FF firms (62%), whereas mixed firms are the clear minority (5%). However, mixed firms' patent counts in the sample are highly disproportional. Overall, they are responsible for 37% of all patents. Splitting this out further between REN and FF innovation, mixed firms capture 24% of the former and 40% of the latter. This implies that mixed firms are much larger in terms of innovation, but as we will see below, also in other

[7]We do not have information on firms' actual market entry and exist but instead we focus on the patterns of firms' technological entry and exit across energy technologies. A firm is defined as active if it has entered REN or FF innovation and not exited yet. There are several concerns with our definition of REN, FF and mixed firms. Our first concern is that some of our specialized firms may 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 and we could mistakenly classify young firms as specialized. However, Noailly and Smeets (2015) show that on average, initial REN and FF innovations in mixed firms tend to be clustered together in time. As such, we are not overly worried that our classification of specialized and mixed firms is driven by the sample period. An additional 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. We extracted information on the Global Ultimate Owner (GUO) of firms using information on the total percentage of ownership, and assign a GUO dummy to firms that are owned by another firm with a direct percentage higher than 50%. We found that only 10% of specialized REN firms are part of a larger corporate network that also incorporates specialized FF subsidiaries. For specialized FF firms this percentage is only 12%.

Table 1: Innovation by firm type

	Firms (N)	Firms (%)	REN pats (N)	REN pats (%)	FF pats (N)	FF pats (%)
REN firms	1,776	33	3,524	76	-	-
FF firms	3,392	62	-	-	10,031	60
Mixed firms	265	5	1,108	24	6,823	40
Total	5,433	100	4,633	100	16,854	100

respects than specialized firms.

Figure 3 tracks the firm-dynamics in our sample over the period 1980-2009. Three aspects are notable. First, the increase in the active number of REN firms closely tracks the development of REN patents in Figure 2. This suggests that the increase in REN patents after the mid-1990s is strongly driven by the extensive margin (i.e. new firms patenting) rather than the intensive margin (i.e. existing firms patenting more). Although REN specialized firm are small and innovate only occasionally, the fact that many new specialized firms have become active REN innovation ('innovation entry') in the last fifteen years is the main cause of the surge in REN patents since the mid-1990s. Second, the trend in firm dynamics of firms specialized in FF innovation (FF firms) also mirrors the trend in their patenting behavior, although the absolute numbers are slightly more different, suggesting that the intensive margin is a relatively more important driver of patenting. Finally, the number of mixed firms has remained stable over time. As shown in Table 1 they are much bigger and more persistent innovators than any of the two types of specialized firms.

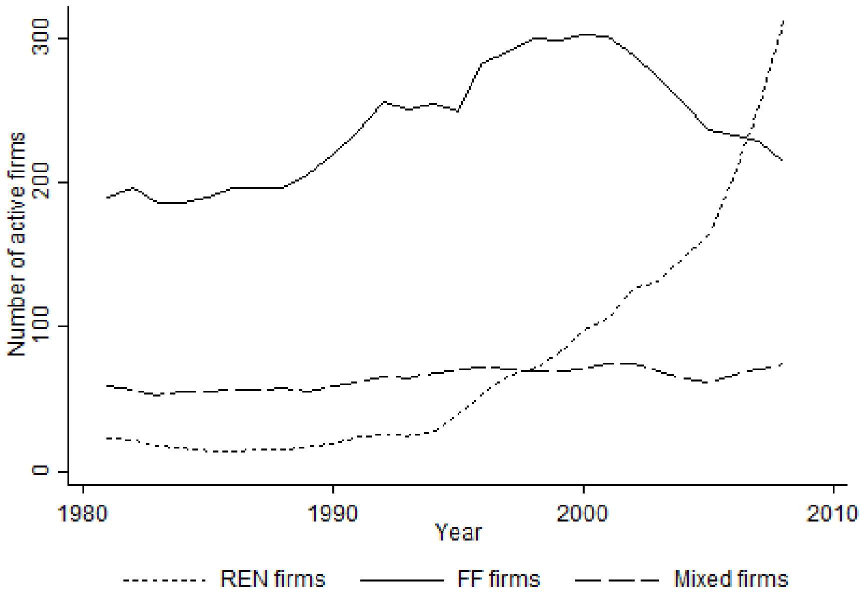

Figure 3: Active firm dynamics (3-year moving averages)

Balance sheets' data Using the financial database of Orbis, we have access to data on firms' (consolidated) balance sheets and income statements. We match our set of firms with patents in REN and FF technologies with the financial database of Orbis. Unfortunately, our sample of firms is reduced after the matching as: 1) not all firms can be found back in the financial database 2) data availability is severely limited before 1995. We conduct a series of consistency checks as in Kalemli-Ozcan et al. (2015) recommended when working with financial variables in Orbis (see Appendix) and we trim the 1% tails of all regression variables. We are left with a sample of 1,300 firms (about 400 REN firms, 800 FF firms and 90 mixed firms) over the 1995-2009 period for which we can exploit balance sheets data. We consider the following indicators of financing sources:

- *Cash flow:* computed as total cash flow (including depreciation), divided by the end-of-last-period stock of total assets.
- *Long-term debt:* computed as the annual change in total long-term debt, divided by the end-of-last-period stock of total assets.
- *Stock issues:* computed as the annual change in outstanding issued share capital, divided by the end-of-last-period stock of total assets.

All variables are measured in 100,000 USD, using the exchange rate data from the International Energy Agency to convert the financial variables into US dollars. We further include a number of firm-level control variables also borrowed from the financial database of Orbis and include (net) sales[8], the number of employees and the age of the firm.

In addition, we also include a control for the change in firm-level stocks of cash (and cash equivalents). This variable aims to capture so-called 'R&D smoothing' (Brown and Petersen, 2011). As firms face high R&D adjustment costs, whenever they need to reduce R&D due to financing constraints, they would need to fire R&D workers with a lot of intrinsic knowledge, which has high (opportunity) costs. As a result, firms have a tendency to smooth R&D investment over time, which they typically do using cash holdings. In particular, during downturns such stocks are depleted to maintain a basis level of R&D, whereas in upswings they are replenished from excess cash flow. As a result, failing to control for the change in cash stocks may lead us to underestimate the relationship between innovation and financial constraints.

Table 2 presents summary statistics of financial variables for the different types of firms. The bottom part of the table confirms what we already observed in the previous subsection: both specialized REN and FF firms are significantly smaller in terms of their patents counts than mixed firms. In addition, REN firms tend to be younger on average than FF firms, and both types of specialized firms are significantly younger than mixed firms. On average, REN firms have a smaller number of employees than FF firms but the difference is not significant, while both types of firms are significantly smaller in terms of employees than mixed firms.

The top part of the table considers a number of financial variables. We can observe that mean stock issues to assets ratios (Stk) and mean debt to assets ratios (Dbt) are always smaller than the mean cash flow ratios (CF), showing the importance of cash as a source of funding. Median values of debt and stock issues are close to zero. The fact that stock issues do not appear as a very large source of funding could be due to the fact that we look at European firms, as the literature which is mostly focused on American firms generally finds higher levels of equity finance. Average cash holdings ratios (Cash) are also large showing that firms have some important stocks of liquidity to be able to smooth R&D during transitory shocks.

Looking at differences across firms, we find no significant difference in terms of cash flows or cash holdings between specialized and mixed firms. Instead, average stock issues ratios for

[8]Sales are computed as the ratio of net sales to end-of-last period total assets.

Table 2: Summary Statistics

	REN firms			FF firms			Mixed firms		
	Mean	Std. Dev	Median	Mean	Std. Dev	Median	Mean	Std. Dev	Median
CF_{t-1}	0.135	0.448	0.096	0.129	1.056	0.085	0.146	0.448	0.096
Dbt_{t-1}	0.045^{b}	0.268	0.002	0.020	0.180	0.000	0.098	0.268	0.002
Stk_{t-1}	0.024^{a}	0.079	0.004	0.021	0.100	0.004	0.015	0.079	0.004
$Cash_{t-1}$	0.160	0.280	0.076	0.148	0.532	0.064	0.132	0.336	0.056
$\Delta Cash_{t-1}$	0.048	0.213	0.008	0.033	0.512	0.003	0.052	0.213	0.008
$Sales_{t-1}$	2.091^{b}	2.610	1.592	1.669	2.936	1.369	2.006	7.172	1.110
Age	$14^{a,b}$	26	6	23^{a}	32	13	39	39	31
Employees	1607^{a}	15779	60	2071^{a}	10060	116	20022	55604	1301
REN patents	0.2^{a}	0.6	0.1	-	-	-	0.3	0.6	0.1
FF patents	-	-	-	0.2^{a}	0.4	0.1	1.2	0	0
All patents	$1.8^{a,b}$	8.4	0.2	2.8^{a}	17.9	0.3	51.8	8.4	0.2

^{a} indicates significant difference with Mixed firms, ^{b} indicates significant difference (below 10%) with FF firms. All balance sheets data (except age and number of employees) are scaled by beginning of the year ratios to total assets. Number of observations: REN firms (N=403), FF firms (N=813), Mixed firms (N=90).

REN firms are significantly larger than for mixed firms, while there is no significant difference in terms of stock issues between REN and FF firms. Stock issues are used primarily in the early stage of the firm's life cycle, so the relative importance of stock issues for REN firms could be explained by the fact that these firms are less mature. Finally, mixed firms show the highest average levels of debt-to-assets-ratio, which is significantly larger than for REN firms. Overall, there are mostly no significant differences in terms of funding sources between FF and mixed firms.

Other control variables Finally, we also consider variables that aim to capture changes in the macro-economic environment of the firm in particular with respect to the market and policy environment affecting REN and FF technologies in Europe over the last decades. These variables are included as additional controls in our regressions. As our focus is on interpreting the impact of financial variables, we refer to Noailly and Smeets (2015) for a more extensive discussion of how these other control variables affect REN and FF innovation. Table 6 in the Appendix provides specific definitions of all these variables and their data sources.

Energy prices: we extract data from the Energy Prices and Taxes database of the International Energy Agency on country-level prices of the different fossil-fuel energy sources, namely:

oil, gas and coal.[9] To make FF prices firm-specific, we weight FF prices according to the firm's distribution of patent filings across countries using information on patent families as in Noailly and Smeets (2015) and Aghion et al. (2016). Since energy prices include taxes, this variable can proxy for carbon pricing policies.

Market size: we extract data from the Energy Statistics database from the IEA on electricity output from REN and FF sources per country in total number of gigawatt hours generated by power plants. For FF energy, we use data on electricity output in oil, gas and coal, while for REN energy we have access to disaggregated data on electricity output from solar, wind, hydro, marine, geothermal, biomass and waste energy. Market size variables also capture demand-pull policies, such as feed-in tariffs, put in place in specific countries. We compute firm-specific market size by using designation country weights as well as technology weights in each firm's patent portfolio (see Appendix). Market size variables are likely to capture demand-pull policies (e.g. guaranteed tariffs, investment and production tax credits) that aim to increase the market for renewables.

3.2 Empirical strategy

Rate of innovation In order to investigate the impact of the various financial constraints on the patenting activity of the firms in our sample, we follow the literature on the corporate financing of R&D (Brown and Petersen, 2009, 2011; Brown et al., 2012) and estimate the relationship between innovative activities (here measured as patents) and internal and external financing flows as follows:

$$P_{ict} = \beta_0 + \beta_1 CF_{it-1} + \beta_2 DB_{it-1} + \beta_3 STK_{it-1} + \beta_4 \Delta CashHold_{it-1} + X_{ict} + \nu_c + \tau_t + \epsilon_{ict} \quad (1)$$

where subscripts i, c, and t denote firm, country, and year; P captures (REN or FF[10]) patent counts; CF are cash flows; DB is long-term debt; $\Delta CashHold$ is the growth in cash holdings; X is a vector of control variables (including firms' ratio of sales to total assets, firm's age and number of employees); ν and τ capture unobserved country, and time heterogeneity,

[9] These are prices paid at the power plant for electricity generation, i.e. prices paid by electricity facilities for a certain type of fuel (including taxes).

[10] We do not have enough observations to provide a more refined analysis per specific REN - e.g. solar, wind, etc - or FF technology type.

respectively; and ϵ is an IID error term. The theoretical prediction is that financially constrained firms should exhibit a positive coefficient on cash flow and a negative coefficient on cash holdings growth, since a reduction in cash holdings releases cash for innovation activities.

As discussed earlier, all financial variables are normalized by end-of-previous-period total asset stocks. Lagged realizations of the financial variables are included to allow for dynamic adjustments of innovation to cash constraints. Patenting at time t corresponds to the application year of the patent, which is the year most closely related to the date of invention (rather than the granting date).

Using the absolute patent count as the dependent variable, we use negative binomial regression models:

$$\begin{aligned} E(P_{ict}|X_{ict}, \theta_i, \nu_c, \tau_t) = \lambda_{ict} \\ s.t.\ \lambda_{ict} = exp(\Omega_{ict}) \end{aligned} \tag{2}$$

where Ω_{ict} denotes the model in (1). As is well known, compared to the Poisson model, the negative binomial model does not impose equidispersion (i.e. the equivalence of the conditional mean and variance). In robustness analysis, we will also consider the Poisson model.

Identification As noted by Brown and Petersen (2009), one concern may be that all financial variables, including stocks, long-term debt, cash flows and cash holdings may be endogenous to innovation activities.[11] Such endogeneity could come from several factors. First, although we capture unobserved country and time heterogeneity that may affect patenting activities by the inclusion of country and year dummies, there may be time-varying factors (for example, a change in a country's R&D policy) that boost patenting and also triggers more financial resources for firms. Second, our estimation could also be affected by reverse causality between financing variables and patenting: firms could use patents as a signal to attract external funding. Finally, patents and financing could be jointly determined due to unobserved firm's heterogeneity: cash-rich firms may be more likely to patent as this is a costly process, or some firms may be more able to attract funding than others. All these factors could imply that financial variables are correlated with the error term of the regression and yield inconsistent estimates.

[11] Brown et al (2009) use lagged financial variables as instruments when estimating a GMM for dynamic panel data.

Our dataset presents several limitations to address these identification issues. First, for specialized firms, our sample contains only a few years per firm as these firms only innovate occasionally. Hence, we are left with insufficient time variance to include firms' fixed effects. Instead, we will rely on the host of firm-level variables to capture the majority of cross-firm heterogeneity. We correct for age, level of employment, sales and past innovation activities. Although there might be other unobserved firm-level variables that are correlated with both financing sources and patenting, we have no reason to believe that the endogeneity bias between patenting and our financial variables may be differently distributed across REN or FF firms. Second, for mixed firms, although we usually have longer time series, we are limited by the relatively small size of the sample of mixed firms (N=90). For the case of mixed firms, we can however introduce additional firm's fixed effects by using the pre-sample estimator of Blundell et al. (2002).[12]

Still, due to the limited degrees of freedom, we cannot perform any non-linear instrumental variable estimation for patenting activities. We then test for endogeneity of the right-hand side variables. We regress each lagged financial variable on its own (second) lags and other exogenous variables. Residuals of all these first stages regression are then introduced afterwards in equation (2) and both a Wald test and a likelihood-ratio test for joint significance of all residuals are implemented to provide a diagnosis of endogeneity. The null hypothesis of joint significance is rejected in all our models. Nonetheless, in our baseline we report a double set of estimates for each specification: a negative binomial on first lagged values of financial variables, completed by another one relying on the mean of second and third lagged values of financial variables.[13]

Innovation entry Along our analysis, we also aim to estimate the impact of financial factors on the extensive margin of innovation, i.e. innovation entry, as Figure 3 showed that the rise in REN patenting in recent years was mainly caused by the entry of specialized REN firms. We can expect that small firms specialized in REN face important financial constraints at the innovation entry stage, i.e. before their first innovation (when they cannot use patents as collateral for instance). In this case, the decision to enter innovation should be particularly sensitive to a shock in cash flows. Hence, in our empirical strategy, we will conduct additional estimations in

[12]Firms' fixed effects for mixed firms are captured by the firm's average innovation count in the presample period (1950-1994) in all technologies (i.e.,not only patents in REN and FF technologies).

[13]We take the mean of both periods, mainly to avoid dropping too many observations.

which we make a distinction between the extensive margin of innovation (i.e. a firm's decision to enter a specific type of innovation) and the intensive margin of innovation (conditional on positive entry decision, firms make a decision regarding how much to innovate). In the data, these two different processes (intensive vs. extensive margins) can be reflected into a firm's zero patent counts. First, there are structural (excess) zeros which stems from the fact that the firm has not found it profitable to undertake R&D (i.e. to enter the innovation market). Second, the standard zeros are the realization of a Poisson process and reflect the fact that after entry, innovation has not been successful that year (as innovation is an uncertain process). To capture these two margins, we will consider additional specifications, namely zero-inflated Poisson models, in which in a first step a logit distribution first determines the extensive margin decision, i.e. the likelihood of having a zero outcome (i.e. no innovation entry) for the count variable, estimated as:

$$Pr(P_{ict} = 0) = \Delta(\nu_{ict}) = \frac{e^{ict}}{1 + e^{ict}} \tag{3}$$

Where Δ denotes the logistic distribution function and $_{ict} = log(\lambda_{ict})$ as in (2). Note that the interpretation of the coefficients is based on the likelihood of (excess) zero patents (i.e. no entry). Then, a second stage Poisson distribution governs the actual realization of the outcome. Hence, the intensive margin decision is given by a log-linear Poisson model as in (2). We expect financially constrained firms to exhibit a negative coefficient on cash flows - to be interpreted as a positive impact on the likelihood of innovation entry in the inflation equation.

4 Results

4.1 Baseline

In Table 3, we present the baseline results of estimating equation (1) by negative binomial models for the sample of specialized REN (columns (1) and (2)) and FF firms (columns (3) and (4)). All models include full sets of country and year dummies (not reported). The dependent variable in every column is the number of patents (either REN or FF) per firm i and year t.

Regarding the impact of financial factors, we expect to find a stronger link between the financial variables and R&D in the groups of firms most likely to be financially constrained. For the sample of firms that specialize in REN innovation only, we find that the coefficient for lagged cash flows is positive and significant in both column (1) (at 5% levels) and column (2) (at 10% levels, where we include the mean of second and third lags for financial variables). Instead, cash flow coefficients are positive but insignificant for FF firms (in columns (3) and (4)). This result confirms our hypothesis that REN firms in particular are financially constrained. FF firms, although younger and smaller than mixed firms, do not appear to be financially constrained.

Regarding long-term debt, the evidence is mixed and inconclusive. For REN firms, the coefficient for long-term debt is positive significant in column (2) but not in column (1). Somewhat puzzling, we find a significant negative coefficient of long-term debt on patenting by FF firms in column (3)[14], but not in column (4). We do not find any positive significant impact of stock issues in the various samples of firms. Finally, the lagged coefficient on cash holdings growth are negative as expected in most specifications, but not significant. Cash holdings growth was expected to be negatively associated with R&D as reductions in cash holdings at the firm level free liquidity for R&D smoothing.

Regarding firm-levels controls, we find no impact of the sales ratio on patenting activities. Firm's age tend to have a negative impact on firms' innovation and larger firms, as measured by the number of employees, tend to patent more. Finally, the impact of firm's knowledge stocks and other macroeconomic variables is in line with previous results found in Noailly and Smeets (2015): 1) there is evidence for within-firm path-dependency as firm's specific past knowledge stock in REN (FF) technology firms, 2) REN (FF) market size has a positive (negative) impact on REN innovation, 3) higher FF prices can either encourage or discourage both types of innovation.[15]

In Table 4, we present the estimation results for mixed firms. Due to the limited number of firms, we face convergence issues when taking second and third lags of financial variables as this reduces our sample of firms so we only report the results for the first lags variables. In columns (1) and (2), we report the same specifications as columns (1) and (2) for specialized firms in Table 3. In columns (3) and (4), we control for additional firm's fixed effects by including a

[14]This would imply that FF firms might rely on long-term debt financing for other activities, such as investment in physical capital, which might crowd out R&D.

[15]Higher FF prices might encourage firms to innovate more in FF technologies (to develop more efficient and cheaper technologies) but could also encourage firms to develop alternative technologies such as REN technologies. Note that the negative impact of FF prices on FF innovation in column (3) is not robust to other specifications, such as Poisson model (see Table 7).

Table 3: Baseline Specialized firms- Negative Binomial Results

VARIABLES	REN firms REN patents (1)	REN firms REN patents (2)	FF firms FF patents (3)	FF firms FF patents (4)
CF_{t-1}	1.079**[a]		0.059	
	(0.546)		(0.164)	
$CF_{(t-2,t-3)}$		1.139*		0.124
		(0.655)		(0.409)
Dbt_{t-1}	-0.198[a]		-0.762**	
	(0.177)		(0.296)	
$Dbt_{(t-2,t-3)}$		1.188*		0.746
		(0.711)		(0.573)
Stk_{t-1}	-1.538		0.173	
	(1.051)		(0.552)	
$Stk_{(t-2,t-3)}$		0.073		-0.542
		(1.993)		(0.908)
$\Delta Cashholdings_{t-1}$	-0.318		0.008	
	(0.222)		(0.258)	
$\Delta Cashholdings_{(t-2,t-3)}$		-0.723		-0.094
		(0.967)		(0.731)
$Sales_{t-1}$	0.029	0.072	-0.058	-0.023
	(0.043)	(0.050)	(0.054)	(0.054)
$Log(Age)_t$	-0.312***	-0.306***	-0.155***	-0.191***
	(0.089)	(0.087)	(0.056)	(0.062)
$Log(Employees)_t$	0.084**	0.103***	0.094***	0.100***
	(0.035)	(0.037)	(0.025)	(0.027)
Log(REN knowledge stock)$_{t-1}$	0.606***	0.625***		
	(0.153)	(0.191)		
Log(FF knowledge stock)$_{t-1}$			0.871***	0.844***
			(0.075)	(0.077)
Log (FF prices)$_{t-1}$	-0.285	-0.419	-0.299*	-0.124
	(0.277)	(0.312)	(0.176)	(0.166)
Log (REN market size)$_{t-1}$	0.050**	0.024	0.013	0.020
	(0.025)	(0.024)	(0.048)	(0.041)
Log (FF market size)$_{t-1}$	-0.023	0.033	0.060	0.074
	(0.043)	(0.052)	(0.052)	(0.056)
Year FE[b]	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	2,093	1,933	4,811	4,455
Number of firms	403	369	813	780
Log Likelihood	-1027	-928	-2436	-2251

[a] indicates a significant difference between the REN and FF model at $p \leq 0.1$ for financial variables (CF, Dbt, Stk, ΔCashholdings). We conduct Wald tests to establish statistically significant differences in coefficients between the two models in a Seemingly Unrelated Regressions(SUR) framework. [b] Due to convergence issues based on a small number of observations, in column (4) we use 2-years dummies rather than individual year dummies. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Robust standard errors are clustered at the firm level. Fossil fuel price and market size variables are constructed by using firm-specific weights reflecting the firms' patent portfolio and designation countries as in Noailly and Smeets (2015). The dependent variable in every column is the number of patents per firm i and year t.

variable that captures a firms' capacity to innovate, namely the number of patents filed by the firm over the presample period 1950-1994 (see **?**). In column (4), we find evidence that the presample number of patents only significantly affects the number of FF patents by mixed firms. Other coefficients remain mostly unaffected by adding firms' fixed effects. Overall and as expected, for mixed firms the fact that none of the financial factors are statistically significant in all models is consistent with our hypothesis of no financial constraints for these large mature firms predominantly innovating in FF technologies. Cash holdings growth is only significant in column (1) which considers specifically REN patenting activities by mixed firms. This indicates that mixed firms may rely on cash holdings to smooth REN R&D, i.e. use their stock of liquidity as a buffer to finance their REN activities, although the coefficient is not significant anymore in column (2) when including firm's fixed effects. Finally, in the sample of mixed firms, firm's size has no significant impact on mixed firms's patenting activities. Older firms tend to patent less, but this is only significant for FF patents.

All our results are robust to a Poisson estimation as shown in Table 7 in Appendix.

4.2 Innovation entry

In a second step, we estimate equations (2) and (3) using a zero-inflated Poisson model. The results for specialized firms are presented in Table 5.[16] The top panel of the table presents the coefficient estimates of the Poisson model for the number of patents (level equation, intensive margin), while the bottom panel presents the coefficient estimates of the logit model in the inflation equation for the likelihood of observing (excess) zero patent counts. To save on space, we only report the results for the balance sheet and income statement variables. We interpret the results of the inflation equation as the impact on the extensive margin of innovation, i.e. the likelihood of participating in 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 enter into REN or FF innovation. The Vuong test statistic reported at the bottom of Table 5 suggests that the zero-inflated Poisson model performs better than the standard Poisson model for specialized firms.

We investigate the positive impact of cash flow on REN innovation and in particular on

[16]Due to a limited number of observations for mixed firms (N=90), we do not report the results for mixed firms as the zero-inflated models face convergence issues in this specific sample.

Table 4: Baseline Mixed firms - Negative Binomial Results

VARIABLES	Mixed firms REN patents (1)	Mixed firms REN patents (2)	Mixed firms FF patents (3)	Mixed firms FF patents (4)
CF $_{t-1}$	0.785	0.768	0.324	0.218
	(0.877)	(0.903)	(0.784)	(0.782)
Dbt$_{t-1}$	-0.247	-0.199	0.014	0.163
	(0.700)	(0.557)	(0.360)	(0.384)
Stk$_{t-1}$	-7.228	-5.226	-0.441	-0.630
	(5.888)	(4.984)	(2.616)	(2.679)
ΔCashholdings$_{t-1}$	-2.878*	-2.258	-0.012	-0.028
	(1.498)	(1.424)	(0.373)	(0.382)
Sales$_{t-1}$	0.100	0.104	-0.181	-0.157
	(0.141)	(0.128)	(0.182)	(0.171)
Log(Age)$_t$	0.234	0.211	-0.235**	-0.219*
	(0.154)	(0.160)	(0.118)	(0.116)
Log (Employees)$_t$	-0.045	-0.045	-0.061	-0.060
	(0.052)	(0.048)	(0.046)	(0.046)
Log(REN knowledge stock)$_{t-1}$	0.555***	0.528***	-0.268*	-0.226
	(0.171)	(0.188)	(0.152)	(0.148)
Log(FF knowledge stock)$_{t-1}$	0.652***	0.644***	1.180***	1.139***
	(0.149)	(0.151)	(0.103)	(0.102)
Log (FF prices)$_{t-1}$	-2.364**	-1.984**	0.466	0.739
	(1.055)	(0.832)	(0.640)	(0.653)
Log (REN market size)$_{t-1}$	0.130**	0.140**	0.045	0.043
	(0.056)	(0.054)	(0.036)	(0.037)
Log (FF market size)$_{t-1}$	-0.438***	-0.432***	0.017	0.034
	(0.073)	(0.074)	(0.067)	(0.063)
Presample (Firm FE)		-0.372		-1.654***
		(0.391)		(0.231)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	536	536	536	536
Number of firms	90	90	90	90
Log Likelihood	-291	-300	-481	-477

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Robust standard errors are clustered at the firm level. Fossil fuel price and market size variables are constructed by using firm-specific weights reflecting the firms' patent portfolio and designation countries as in Noailly and Smeets (2015). The dependent variable in every column is the number of patents per firm i and year t.

entry of firms into REN innovation. The inflation equation at the bottom panel of column (1) shows a positive and significant impact of cash flows ratios on the likelihood of REN innovation (recall that the inflation equation estimates the probability of zero innovation, so that a negative coefficient implies an increased likelihood of innovation). Hence, this suggests that REN firms are particularly constrained in their decisions to enter the REN innovation market. Instead, we do not find any impact of cash flows the innovation entry decisions of FF firms. Looking at the intensive margin in the top panel of Table 5, we do not find any more a positive impact of cash flows on the rate of innovation of REN specialized firms, which suggests that once they have entered and filed their initial patents, REN firms do not appear to be financially constrained. The inflation equation in column (2) also shows that a higher long-term debt is negatively associated with innovation entry of FF firms, although the coefficient is only marginally coefficient. This is in line with the results in Table 3: FF firms use long-term debt to finance other activities than innovation.

Results on the extensive margin of innovation confirm thus what we had previously established, namely that there is evidence that REN firms are financially constrained, while this is not the case for FF firms. The results highlight that since specialized firms tend to innovate only occasionally and then exit the innovation scene rather quickly the entry stage is particularly problematic.

Table 5: Zero-inflated Poisson estimations

Zero-inflated Poisson VARIABLES	(1) REN firms REN patents	(2) FF firms FF patents
Intensive margin Level equation		
CF_{t-1}	0.150	0.157
	(0.129)	(0.588)
Dbt_{t-1}	0.209	0.351
	(0.527)	(0.571)
Stk_{t-1}	-5.764	-0.436
	(3.519)	(0.689)
$Cashholdings_{t-1}$	-0.140	-0.598
	(0.588)	(0.548)
$Sales_{t-1}$	0.016	-0.341***
	(0.075)	(0.106)
$Log(Age)_t$	-0.452***	-0.027
	(0.122)	(0.086)
$Log\ (Employees)_t$	0.156***	0.082**
	(0.053)	(0.039)
Extensive margin Inflation equation		
CF_{t-1}	-1.322**	0.012
	(0.672)	(0.403)
Dbt_{t-1}	0.614	2.031*
	(0.568)	(1.095)
Stk_{t-1}	-5.509	-2.115
	(6.381)	(2.117)
Δ $Cashholdings_{t-1}$	-0.113	-1.424
	(0.752)	(1.413)
$Sales_{t-1}$	-0.085	-0.481***
	(0.136)	(0.185)
$Log(Age)_t$	-0.248	0.229**
	(0.183)	(0.116)
$Log(Employees)_t$	0.064	-0.024
	(0.072)	(0.053)
Additional controls	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Observations	2,093	4,811
Number of firms	403	813
Log Likelihood	-1048	-2465
Vuong test	3.60***	5.60***

* $p \leq 0.1$, **$p \leq 0.05$, ***$p \leq 0.01$. Robust standard errors are clustered at the firm level. Fossil fuel price and market size variables are constructed by using firm-specific weights reflecting the firms' patent portfolio and designation countries as in Noailly and Smeets (2015). The dependent variable in every column is the number of patents per firm i and year t. Both level and inflation equations include additional controls for Log(patent stocks), FF prices, REN and FF market sizes as in Table 3.

5 Conclusions

This paper aimed to test the central hypothesis that firms specializing in REN innovation are more financially constrained than either FF or mixed firms. Compared to FF innovation, REN innovation is more uncertain and risky for investors, due to the lower maturity of the technologies and the larger reliance on (uncertain) policy support. Our descriptive analysis of firms' balance sheet data also confirms that the bulk of REN innovation tends to be undertaken by smaller and younger firms than firms conducting FF innovation. Using negative binomial and Poisson estimation techniques, we estimate the sensitivity of firms' patenting activities to three financing factors, namely cash flows, long-term debt and stock issues, controlling for R&D smoothing as well as other firms' and market characteristics. We find evidence that financing constraints matter for firms specialized in REN innovation but not for small FF firms or large mixed firms. Results from a two-stage zero-inflated Poisson models confirm that financing constraints are particularly relevant for the firm's decision to start innovating ('innovation entry').

Our results have important implications for policymaking. First, the results emphasize that small innovative newcomers in the field of renewable energy are particularly vulnerable to financing constraints, not solely because they are younger and less mature than other established firms, but mainly because they focus on new clean technologies that are still perceived as more risky by investors than the incumbent technologies based on fossil-fuels electricity generation. Government and policymakers should thus pay particular attention to ease financing constraints of start-up companies into renewable energy. Some options for policymaking include for instance providing venture capital for REN start-up firms or providing specific R&D subsidies for small innovating firms in renewable energy. Our results highlight thus the need for sector specific subsidies (rather than generic policies for all firms) and for the need to configure investment policies to steer investments towards clean technologies, for instance in the form of specific capital grants, venture and equity funds or low-interest loans for starters in clean energy. Public regulators can also more actively use the option to lend directly to the renewable energy sector via public investment banks on terms more favourable than those of the market.

Finally, while this work has presented a first empirical analysis of the role of financing constraints on the direction of innovation in the electricity generation sector, future work could take advantage of larger datasets to produce a more refined analysis, for instance to investigate variation across specific REN technologies. The impact of the financial crisis of 2008 on firms' financing constraints for REN vs. FF innovation, and the impact of government policies that followed the crisis to spur innovation in clean technologies, is also left for future research.

References

Abraham, J. 2011. 'Evolving sociological analyses of pharmaceuticalisation: a response to Williams, Martin and Gabe'. *Sociology of Health and Illness* 33(5), 726–728.

Acemoglu, Daron, Aghion, Philippe, Bursztyn, Leonardo and Hemous, David. 2012. 'The environment and directed technical change'. *The American Economic Review* 102(1), 131–166.

Aghion, P., Dechezlepretre, A., Hemous, D., Martin, R. and van Reenen, J. 2016. 'Carbon taxes, path dependency and directed technical change: Evidence from the auto industry'. *Journal of Political Economy* 124(1), 1–51.

Blundell, Richard, Griffith, Rachel and Windmeijer, Frank. 2002. 'Individual effects and dynamics in count data models'. *Journal of econometrics* 108(1), 113–131.

Bond, S., Harhoff, D. and van Reenen, J. 2005. 'Investment, R&D and Financial Constraints in Britain and Germany.'. *Annales d'Economie et de Statistique* 79/80, 433–460.

Brown, J. R., Martinsson, G. and Petersen, B. C. 2012. 'Do financing constraints matter for R&D?'. *European Economic Review* 56, 15121529.

Brown, J. R. and Petersen, B. C. 2009. 'Why has the investment-cash flow sensitivity declined so sharply? Rising R&D and equity market developments'. *Journal of Banking and Finance* 33(5), 971–984.

Brown, J. R. and Petersen, B. C. 2011. 'Cash holdings and R&D smoothing'. *Journal of Corporate Finance* 17(3), 694–709.

Chava, S., A., Oettl, A. and Subramanian, K. V. 2013. 'Banking deregulation and innovation'. *Journal of Financial Economics* 109(3), 759–774.

Cornaggia, J., Mao, Y., Tian, X. and Wolfe, W. 2015. 'Does banking competition affect innovation?'. *Journal of Financial Economics* 115(1), 189–209.

Criscuolo, C. and Menon, C. 2015. 'Environmental policies and risk finance in the green sector: Cross-country evidence'. *Energy Policy* 83, 38–56.

Donovan, C. W. 2015. *Renewable energy finance: powering the future*. World Scientific.

EIB. 2015. 'Investment and Investment finance in Europe: Investing in competitiveness'. European Investment Bank Report.

FS, UNEP and BNEF. 2016. 'Global trends in renewable energy investment 2016'. Report Frankfurt School- UNEP Centre/Bloomberg New Energy Finance.

Gaddy, B., Sivaram, V. and O'Sullivan, F. 2016. 'Venture Capital and Cleantech: The Wrong Model for Clean Energy Innovation'. Report MIT Energy Initiative.

Ghosh, S. and Nanda. 2010. 'Venture capital investment in the clean energy sector'. Working Paper No. 11-020, Harvard Business School.

Griliches, Z. 1990. 'Patent Statistics as Economic Indicators: A Survey'. *Journal of Economic Literature* 28(4), 1661–1707.

Hall, B.H. and Lerner, J. 2010. *Handbook of the Economics of Innovation*. Vol. 1. North Holland. chapter The Financing of R&D and Innovation, pp. 609–639.

Hartley, P. R. and Medlock, K. B. 2017. 'The valley of death for new energy technologies'. *Energy Journal* 38(3), 33–61.

Himmelberg, C. P. and Petersen, B. C. 1994. 'R&D and internal finance: A panel study of small firms in high-tech industries'. *Review of Economics and Statistics* 76(1), 38–51.

Howell, S. T. 2017. 'Financing Innovation: Evidence from R&D Grants'. *American Economic Review* 107(4), 1136–64.

IEA. 2015. *World Energy Outlook*. IEA. Paris, France.

IEA. 2017. Tracking clean energy progress 2017. Technical report. IEA. Paris.

Johnstone, N., Hascic, I. and Popp, D. 2010. 'Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts'. *Environmental and Resource Economics* 45(1), 133–155.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V. and Yesiltas, S. 2015. 'How to Construct Nationally Representative Firm Level data from the ORBIS Global Database'. Working Paper No. w21558, National Bureau of Economic Research.

Kerr, W. R. and Nanda, R. 2015. 'Financing innovation'. *Annual Review of Financial Economics* 7(1), 445462.

Lanzi, E., Verdolini, E. and Hascic, I. 2011. 'Efficiency improving fossil fuel technologies for eletricity generation: Data selection and trends'. *Energy Policy* 39(11), 7000–7014.

Nanda, R., K. Younge and Fleming, L. 2015. *The Changing Frontier: Rethinking Science and Innovation Policy*. University of Chicago Press. chapter Innovation and Entrepreneurship in Renewable Energy, p. 199232.

Nelson, D. and Shrimali, G. 2014. 'Finance mechanisms for lowering the cost of renewable energy in rapidly developing countries'. *Report Climate Policy Initiative* .

Noailly, J. and Smeets, R. 2015. 'Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level data'. *Journal of Environmental Economics and Management* 72(C), 15–37.

Popp, D. 2002. 'Induced innovation and energy prices'. *American Economic Review* 92(1), 160–180.

Robb, A. M. and Robinson, D. T. 2014. 'The Capital Structure Decisions of New Firms'. *Review of Financial Studies* 27(1), 153–179.

Sudheer, C., Nanda, V. and Xiao, S. C. 2017. 'Lending to innovative Firms'. *Review of Corporate Finance Studies* 6(1), 234–289.

Appendix

5.1 Variables definitions

For a detailed description of the variable construction we refer to Noailly and Smeets (2015).

Table 6: Construction and sources of variables

Variable	Construction	Data source
Renewable (REN) patents	Count of patents in wind, solar, hydro, marine, biomass, geothermal, and waste energy technologies	Orbis-EPO (PATSTAT)
Fossil fuel (FF) patents	Count of patents in fuel gases by carbureting air, steam engine plants, gas turbine plants, hot-gas or combustion-product positive displacement engine, steam generation, combustion apparatus, furnaces, and improved compressed-ignition engines technologies	Orbis-EPO (PATSTAT)
Stock issues	$\frac{Capital_t - Capital_{t-1}}{TotalAssets_{t-1}}$	Orbis
Long-term debt	$\frac{LongTermDebt_t - LongTermDebt_{t-1}}{TotalAssets_{t-1}}$	Orbis
Cash flow	$\frac{CashFlow_t}{TotalAssets_{t-1}}$	Orbis
Sales	$\frac{Sales_t}{TotalAssets_{t-1}}$	Orbis
ΔCashHolding	$\frac{CashEquivalents_t - CashEquivalents_{t-1}}{TotalAssets_{t-1}}$	Orbis
Log employees	Log(Employees+1)	Orbis
Log age	Log(Year-Date of incorporation+ 1)	Orbis
Publicly listed	Publicly listed company	Orbis
Fossil fuel (FF) price	see below - Noailly and Smeets (2015)	IEA, PATSTAT, INPADOC
REN and FF market size	see below - Noailly and Smeets (2015)	IEA, PATSTAT, INPADOC
REN and FF knowledge stock	$(1-\delta)K_{it-1} + P_{it}$	Orbis, PATSTAT

The fossil-fuel price faced by firm i at time t is computed as:

$$\begin{aligned} p_{it} &= \sum_c w_{ic} \times p_{ct} \\ \text{s.t. } p_{ct} &= \sum_{f=\text{oil,coal,gas}} \frac{M_{fc}}{M_{FFc}} \times p_{fct} \end{aligned} \tag{4}$$

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 filed by firm i in designation country c and M_{FFc} is the country's FF average market size.[17]

As with prices in (4), 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:

$$M_{it} = \sum_{c} \sum_{s} w_{isc} M_{sct} \tag{5}$$

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 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 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. 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 firms that innovate only in REN technologies.

Knowledge stocks are computed using the perpetual inventory method as $KS_{it} = (1 - \delta)KS_{t-1} + P_{it}$, where δ is the depreciation rate and P_t is the total number of patents filed by firm i at time t.

5.2 Methodology and data cleaning of the Orbis dataset

To construct the firm-level financial variables, we follow the following steps for data cleaning as in Kalemli-Ozcan et al. (2015).

1. We check the consistency of accounting identities (ratio should not be larger than 10

    - fixedassets-tangiblefixedassets-intangiblefixedassets-otherfixedassets)/fixedassets

[17] 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.

- totalassets - fixedassets-currentassets)/totalassets
- noncurrentliabilities - longtermdebt - othernoncurrentliabilities)/noncurrentliabilities
- currentliabilities - loans - creditors - othercurrentliabilities)/currentliabilities
- totalsharehfundsliab-loans)/totalsharehfundsliab
- totalsharehfundsliab-longtermdebt)/totalsharehfundsliab

2. We drop the entire company (all years) if total assets is negative in any year.

3. We drop the entire company (all years) if sales is negative in any year.

4. We drop the entire company (all years) if tangible fixed assets (such as buildings, machinery, etc) is negative in any year

5. For some firms, there are some inconsistencies in the units of financial variables (as noted by Kalemli-Ozcan on p.29). The moment of switch in units coincides with an unreasonable" move of total assets, often clustered around the year 2000. To solve for this, we focus on firms with total assets above 1 million USD.

6. We also winsorize all financial variables by trimming the data at 1

5.3 Robustness results

Table 7: Robustness Poisson models

Poisson Estimation VARIABLES	(1) REN firms REN patents	(2) FF firms FF patents	(3) Mixed firms REN patents	(4) Mixed firms FF patents
CF_{t-1}	0.283**	0.078	0.617	0.632
	(0.124)	(0.132)	(0.877)	(1.006)
Dbt_{t-1}	-0.129	-0.747***	-0.236	-0.282
	(0.145)	(0.285)	(0.699)	(0.302)
Stk_{t-1}	-1.215	0.382	-8.420	-7.910
	(1.153)	(0.538)	(6.429)	(6.038)
$\Delta Cashholdings_{t-1}$	-0.204	0.017	-3.142*	0.654
	(0.173)	(0.213)	(1.623)	(0.429)
$Sales_{t-1}$	0.074*	-0.076	0.086	-0.158
	(0.041)	(0.056)	(0.148)	(0.169)
$Log(Age)_t$	-0.366***	-0.174**	0.216	-0.293***
	(0.124)	(0.073)	(0.157)	(0.080)
$Log(Employees)_t$	0.104***	0.093***	-0.062	-0.045
	(0.035)	(0.027)	(0.052)	(0.038)
$Log(\text{REN knowledge stock})_{t-1}$	0.884***		0.563***	1.263***
	(0.068)		(0.187)	(0.084)
$Log(\text{FF knowledge stock})_{t-1}$		0.907***	0.666***	0.566
		(0.075)	(0.155)	(0.647)
$Log(\text{FF prices})_{t-1}$	-0.220	-0.222	-2.297**	0.046
	(0.255)	(0.186)	(1.009)	(0.036)
$Log(\text{REN market size})_{t-1}$	0.074*	0.028	0.131**	-0.027
	(0.038)	(0.046)	(0.059)	(0.064)
$Log(\text{FF market size})_{t-1}$	-0.022	0.082	-0.425***	-0.280
	(0.048)	(0.061)	(0.078)	(0.160)
Constant	-1.297	-2.529**	12.606***	-3.038
	(1.866)	(1.260)	(4.587)	(3.554)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	2,093	4,811	536	536
Number of firms	403	813	90	90
Log Likelihood	-1138	-2596	-294	-511

[a] Due to convergence issues based on a small number of observations, in column (4) we use 2-years dummies rather than individual year dummies. [b] *$p \leq 0.1$, **$p \leq 0.05$, *** $p \leq 0.01$. Robust standard errors are clustered at the firm level. Fossil fuel price and market size variables are constructed by using firm-specific weights reflecting the firms' patent portfolio and designation countries as in Noailly and Smeets (2015). The dependent variable in every column is the number of patents per firm i and year t.