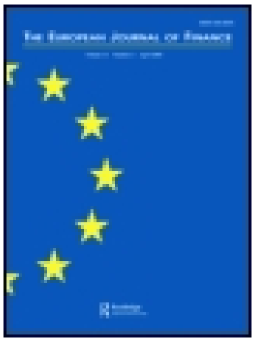

The European Journal of Finance

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rejf20

Is firm-level clean or dirty innovation valued more?

Antoine Dechezleprêtre , Cal B. Muckley & Parvati Neelakantan

THE EUROPEAN JOURNAL OF FINANCE
https://doi.org/10.1080/1351847X.2020.1785520

Is firm-level clean or dirty innovation valued more?

Antoine Dechezleprêtre[a], Cal B. Muckley[b] and Parvati Neelakantan[c]

[a]OECD, Science, Technology and Innovation Directorate, Grantham Research Institute on Climate Change and the Environment, London School of Economics London, UK; [b]UCD School of Business and Geary Institute, Michael Smurfit Graduate Business School, University College Dublin, Dublin, Ireland; [c]UCD School of Business, University College Dublin, Dublin, Ireland

ABSTRACT

We examine how Tobin's Q is linked to 'clean' and 'dirty' innovation and innovation efficiency at the firm level. Clean innovation relates to patented technologies in areas such as renewable energy generation and electric cars, whereas dirty innovation relates to fossil-based energy generation and combustion engines. We use a global patent data set, covering over 15,000 firms across 12 countries. We find strong and robust evidence that the stock market recognizes the value of clean innovation and innovation efficiency and accords higher valuations to those firms that engage in successful clean research and development activities. The results are substantively invariant across innovation measurement, model specifications, estimators adopted, select sub-samples of firms and United States and European patent offices.

ARTICLE HISTORY
Received 7 January 2019
Accepted 27 May 2020

KEYWORDS
Research and development; patents and citations; clean technology; dirty technology; market value

JEL CLASSIFICATIONS
G35; G32; C58

1. Introduction

According to an Assessment Report by the Intergovernmental Panel on Climate Change, stabilizing global carbon emissions in 2050 requires a 60% reduction in the carbon intensity of global GDP compared with a business-as-usual scenario (IPCC 2014). In order to achieve a decarbonization of the economy, while meeting growing global energy demands, the world needs to implement a radical change in the mix of technologies used to produce and consume energy. This, in turn, requires massive investments in research and development activities. For this reason, one of the most pressing challenges for climate change policies today is to ensure, in the context of multiple market failures associated with environmental externalities and R&D provision (Jaffe, Newell, and Stavins 2005), that there is an adequate economic incentive for firms to redirect innovation away from fossil fuel ('dirty') and towards low-carbon ('clean') technologies. In this paper, we avail of capital market price signals to assess the presence and magnitude of economic incentives for clean innovation relative to dirty innovation. We examine whether firms conducting clean innovation trade at a premium or a discount relative to firms which conduct dirty innovation.

Understanding the determinants of clean technological change is a lively research area, both on the theoretical (Acemoglu et al. 2012) and on the empirical side (Aghion et al. 2016). Several studies have shown evidence that firms redirect innovation away from fossil fuel towards low-carbon technologies when faced with a change in policies or market conditions. For instance, Calel and Dechezlepretre (2016) investigate the impact of the European Union Emissions Trading System - the largest carbon market in the world – on regulated companies using a matching method and report that the policy caused regulated companies to increase patenting activity in low-carbon technology by 30%. Similarly, Newell, Jaffe, and Stavins (1999) and Popp (2002) report a substantial increase in the production of energy-efficient technologies following an increase in energy prices.

CONTACT Cal B. Muckley cal.muckley@ucd.ie

Supplemental data for this article can be accessed here. https://doi.org/10.1080/1351847X.2020.1785520

However, a limitation of existing studies of induced technological change towards clean innovation is that a multitude of drivers can determine companies' decisions to conduct R&D activity. These drivers include the relative prices of production factors (Hicks 1932; Popp 2002; Acemoglu et al. 2012) but also the quality of environmental policy instruments (Johnstone, Haščič, and Popp 2010) and the extent of a path-dependency in knowledge creation and market demand (Acemoglu et al. 2012; Aghion et al. 2016), which can all influence the prospective economic returns of clean and dirty innovation. Critically, a variety of policies and drivers can coexist in a given jurisdiction – for example, carbon markets, fuel taxes, energy efficiency standards and renewable energy mandates – making it difficult to measure the overall impact of these policies and drivers taken together or considered in isolation. An additional complication is that it is the expected realization of these policies and drivers which determine innovation decisions, rather than current observed realizations. But these expectations are inevitably not directly observed and may vary markedly across firms. A major advantage of our approach, relative to extant studies, is that the stock market evaluation of patented innovation in clean and dirty technologies can reveal market expectations with respect to the prospective economic performance of these complex investments.

Our analysis avails of a global firm-level patent data set, covering 15,217 firms across 12 countries. Our patent data are drawn from the World Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO). Our database reports the name of patent applicants, which allows us to match clean and dirty patents with distinct patent holders. The global nature of the database means that we can test our hypothesis on several measures of patenting activity, including patents taken out in the world's major patents offices such as the United States Patents and Trademark Office (USPTO) or the European Patent Office (EPO), irrespective of the jurisdiction of the innovating firm. Our data also includes information on patent citations, allowing us to address the well-known issue of heterogeneity in patent value. We associate 'dirty' innovation with fossil-based energy generation and ground transportation, and 'clean' innovation with renewable energy generation, electric vehicles and energy efficiency technologies in the buildings sector. The clean and dirty innovation categories allow us to, specifically, develop and study insightful dis-aggregated versions of well-known innovation productivity (Deng, Lev, and Narin 1999; Chan, Lakonishok, and Sougiannis 2001; Gu 2005) and efficiency variables (Hirshleifer, Hsu, and Li 2013).

We first verify, in our sample, the capital market value accorded to generic innovation productivity (Deng, Lev, and Narin 1999; Chan, Lakonishok, and Sougiannis 2001) and innovation efficiency (Hirshleifer, Hsu, and Li 2013). This work serves to extend, in the international arena, the non-linear least squares regression model findings in Hall (2000).[1] To determine if there is an economic incentive for firms to direct innovation away from fossil fuel ('dirty') and towards low-carbon ('clean') technologies, we regress firm-level Tobin's Q on firm-level clean and dirty innovation, together with innovation in other technologies. To ascertain the expected economic performance of 'clean' and 'dirty' investment activities, we, specifically, follow Hall, Jaffe, and Trajtenberg (2005) and adopt a firm's intangible stock of knowledge function. We dis-aggregate innovation productivity measures and innovation efficiency measures that are similar to those used in Deng, Lev, and Narin (1999) and Hirshleifer, Hsu, and Li (2013) to account for 'clean' and 'dirty' innovation production and efficiency, respectively.

Our main findings are as follows. Consistent with the view that the capital market evaluates clean innovation positively, we find that an additional clean patent, per million dollars of book value, is associated with an increment of 3.77% in Tobin's Q. We also find that generating a citation on a clean patent, per million dollars of book value, is associated with an increment of 1.27% in Tobin's Q. We also note that the comparable efficiency of R&D investments, in generating dirty patents, reduces the market value of the firm to the tune of 0.97% of its economic value. Our main finding is, thus, that 'clean' innovation is associated with an economically important and positive Tobin's Q relation, especially relative to the inferred association with dirty innovation.

We implement a series of robustness tests. These checks are based on a variety of dimensions: (i) we test, following Hirshleifer, Hsu, and Li (2013), if the findings are invariant to an alternative estimator, the Fama-Macbeth two-step regression estimator (Fama and MacBeth 1973), (ii) we test if the results are robust to examining only those firms which conduct both clean and dirty innovation, (iii) we test if the results can be accounted for by including emerging technology innovation in our main regression equations, (iv) we check the sensitivity of the results to including a range of firm traits from the accounting based asset pricing literature (Ohlson 1989, 1995; Hirshleifer, Hsu, and Li 2013), (v) we conduct a Heckman two-stage analysis (Heckman 1979) to account for sample selection concerns, (vi) we test if our main findings hold when we examine European patents, as opposed to United States patents. Our main findings are substantively unchanged across all these tests.

Our paper relates to the extensive literature that links firm-level environmental performance with its financial performance. Earlier papers including Gupta and Goldar (2005) show that capital markets can create financial and reputational incentives for pollution control in both developed and emerging market economies (see also Hamilton 1995; Dasgupta, Laplante, and Mamingi 2001). More recent papers such as that of Guenster et al. (2011) show that eco-efficiency relates positively to operating performance and market value (see also, Ziegler, Schröder, and Rennings 2007; Von Arx and Ziegler 2014). Prior studies, however, suffer from several problems including small samples and the lack of objective environmental performance criteria. We do not rely on subjective analysis to characterize environmental performance. Instead, we study the documented environmental patenting activity and the efficiency of this patenting activity of publicly traded firms around the world. In addition, this prior literature, unlike our paper, does not look at the critically important performance criterion of environmentally friendly patented innovation (IPCC 2014), with a view to improving the mix of technologies used to produce and consume energy. It does not, hence, examine whether this type of environmental performance can be related to financial performance and capital market values.

The remainder of the paper is organized as follows. Section 2 presents a discussion of possible mechanisms which can inter-relate market valuations and environmentally coherent innovation. Section 3 presents our data sources and characterizes our sample. Section 4 presents our econometric methodology. Section 5 presents our results and robustness tests. Section 6 concludes.

2. Theoretical background: market evaluation of innovation and 'green' business decisions

Our point of departure is the well-established notion that stock markets can provide useful information on the value and expected performance of R&D investments (Griliches 1981; Chan, Lakonishok, and Sougiannis 2001; Eberhart, Maxwell, and Siddique 2004; Hall, Jaffe, and Trajtenberg 2005; Hirshleifer, Hsu, and Li 2013).[2] Assuming efficient capital markets, traded security prices can provide an unbiased estimate of the present value of discounted future cash flows. There exists, however, significant differences in the market value of R&D investments across time, sectors and countries (Grandi, Hall, and Oriani 2009). What we examine in this paper, which has not been studied previously, is whether clean firm-level innovation productivity and efficiency are valued in capital markets around the world, in particular compared to dirty innovation productivity and efficiency. The literature identifies two potentially countervailing outcomes, which can prevail, between investments in environmental innovation and financial performance.

2.1. Clean innovation and positive stock market evaluation

Low-carbon and more generally environmental innovation by firms can be evaluated positively in the capital market as it can increase expected firm-level cash-flows (revenues less costs) and/or reduce the risk of these cash flows. There is a variety of potential mechanisms which can link firm-level environmental innovation and financial performance. Due to the plethora of emissions trading systems, climate and energy policies around the world (Ellerman, Marcantonini, and Zaklan 2014), such innovation not only has generic research and development expenditure implications for future firm operating cash flows and risks (Hall 2000; Czarnitzki, Hall, and Oriani 2006). It also reflects recipient firms' expected environmental taxes and subsidies and financial penalties for environmental policy violations.

First, to the extent that environmental innovation is a measure of environmental performance, investors can link pro-active environmental innovation to lower firm risk. For instance, environmental performance can proxy for (i) high-skilled management (Bowman and Haire 1975) and labour conditions at the firm and thus the firm's capacity to attract high-quality employees (Turban and Greening 1997) and increasing employee morale and productivity (Dowell, Hart, and Yeung 2000); (ii) operational efficiency (Porter and Van der Linde 1995); and (iii) sales benefits in existing markets (Klassen and McLaughlin 1996) and in new markets (Porter and Van der Linde 1995) due to improved corporate and brand reputation with regulators, employees and the public (Russo and Fouts 1997; Corbett and Muthulingam 2008). More generally, (iv) environmental innovation can be regarded as a less risky investment (Narver 1971; Spicer 1978; Shane and Spicer 1983). There is also evidence that firms with high commitments towards corporate social responsibility offer lower wage and enjoy higher employee productivity due to better recruitment, higher intrinsic motivation (many employees prefer a socially responsible employer and will accept a lower wage to achieve this), and a more effort-promoting corporate culture (Brekke and Nyborg 2008; Nyborg and Zhang 2013).

It is also possible that the life-cycle of the technology sector of a clean patent can account for it being associated with a positive stock market evaluation.[3] Essentially, early stage life-cycle technology can be associated with potential for high growth albeit also high risk. If initially assets are valued above their replacement cost, competition in the marketplace will erode this mark-up over time (Tobin 1969). Depending on the shape of this trajectory, innovation at a mature stage (e.g. internal combustion engines) will typically be valued less, relative to replacement cost, than innovation in relation to new technologies (e.g. energy generation through renewable energy sources). In a similar vein, this life-cycle argument can lead to smaller effects of incremental patenting on Tobin's q for a given technology over time (i.e. radical innovations are likely to precede incremental innovations in time). As a result, effects on Tobin's q for new technologies can be expected to be greater than for existing technologies that are in the refinement phase of their life cycle, and are facing stronger competition. A life-cycle mechanism can potentially account for a clean innovation premium.

Third, climate change innovation can serve to mitigate risks of losses from crises or new regulation[4] (Reinhardt 1999) and prevent expenses due to lawsuits and legal settlements (Karpoff, Lott, and Wehrly 2005). Investors can, hence, assign a lower discount rate to firms which are high environmental performers which would accord the firm a higher market value (and lower expected stock returns). Finally, climate change innovation can attract funds from ethical investors who can prefer firms with good track records of environmental performance (Heinkel, Kraus, and Zechner 2001). This interest on the part of ethical investment funds can reduce the cost of capital for the firm when it seeks to raise finance in the capital markets.

2.2. *Clean innovation and negative stock market evaluation*

To the contrary, it is also possible that corporate investment in environmental innovation can deteriorate a firm's financial performance (Walley and Whitehead 1994; Palmer, Oates, and Portney 1995). Climate change innovation can also, thus, be associated with a negative stock market valuation impact. Fisher-Vanden and Thorburn (2011) and Jacobs, Singhal, and Subramanian (2010) show that emissions reductions can be associated with significant negative market reactions. In particular, the stock market may respond negatively to such innovation due to the possibility that the capital budget of the firm is deteriorated by such investment. For instance, it may be interpreted by participants in the capital market that pertinent environmental legislation is binding at present or in the future. Environmental subsidies which are sought or the avoidance of financial penalties in respect to the emission of pollutants, which has motivated the environmental patenting activity, can also be ascribed a lower probability by capital market participants, than by firm management.

Two additional results, from the broad empirical R&D and market valuation literature, which can bias our inferences away from a clean innovation premium, should be highlighted. First, firms' market share positively impacts on the valuation of R&D (Blundell, Griffith, and Van Reenen 1999), and firms conducting 'dirty' innovation are typically large incumbents, while firms engaged in clean innovation are more likely to be new entrants. New firms are often the vehicle through which radical, game-changing innovations enter the market. Our sample of listed firms is over-representative of large firms, but even within listed firms, clean innovators might be smaller than dirty innovators. Second, a decreasing relationship between market uncertainty and the valuation of R&D investments has been observed (Oriani and Sobrero 2008). Since the demand for clean innovation fundamentally depends upon environmental policies, which are inherently uncertain, this could lower the premium associated with pursuing environmental clean R&D investments.

3. Data and variables

This section presents our sample of firm and patenting data, including a discussion of clean and dirty patent categories. It also presents our key variables of interest: Tobin's Q, innovation productivity and efficiency variables and control variables. Finally, it presents descriptive statistics in respect to the evolution of clean and dirty innovation globally.

3.1. Our sample of firms

Our sample of firms is obtained from the Worldscope Database, which presents information on the largest firms internationally. The original sampled data comprises 47,420 listed firms in 40 countries. From the original sample of firms, we eliminate firms for which the ISIN No. is missing, and we retain firms in the home market where the ISIN No. is the same for two firms in two different markets. Next, we drop firms with negative total assets, market capitalization or common cash dividend paid. We also drop firms for which we have less than 5 consecutive firm-year observations between 1995 and 2012 across a subset of firm-level variables – year-end market capitalization, capital expenditure, and earnings before interest, tax and amortization. The final firm-count is 25,255 firms from Worldscope.

3.2. Firm-level patenting and clean and dirty innovation categories

3.2.1. The PATSTAT database

We use patent data to identify innovation in clean and dirty technologies. To construct our innovation variables, we have drawn data from the World Patent Statistical Database (PATSTAT) maintained by the European Patent Office. PATSTAT is the largest international patent database, including all of the major offices such as the United States Patent and Trademark office (USPTO) and the European patent office. In PATSTAT, patent documents are categorized according to the new Cooperative Patent Classification system (CPC), the International Patent Classification (IPC) and national classification systems. For each patent we know at which date it was filed (the application date), when it was first published (the publication date) and, if it was ever granted by the patent office, when the granted patent was published. In our study, we focus on patent publication date as it is reasonable to expect that capital market participants will become aware of the new patents at this date.

The use of patent data has gained popularity in the recent empirical literature. An advantage of patent data is that they focus on outputs of the inventive process (Griliches 1990). Furthermore, they provide a wealth of information on the nature of the invention and the applicant. Most importantly, they can be disaggregated to specific technological areas.

Patents also suffer from a number of limitations. The first limitation is that for protecting innovations, patents are only one of several means, along with lead-time, industrial secrecy, or purposefully complex specifications (Cohen, Nelson, and Walsh 2000; Frietsch and Schmoch 2006). However, a large fraction of the most economically significant innovations appear to have been patented (Dernis, Guellec, and van Pottelsberghe 2001). Moreover, in several sectors of which many clean and dirty technologies originate, such as automotive or special purpose machinery, patents are perceived as an effective means of protection against imitation (Cohen, Nelson, and Walsh 2000).[5] A second limitation is that the propensity to patent (e.g. the number of patents filed per USD of R&D) differs across industries and jurisdictions, making it difficult to use patent metrics for comparisons across sectors and countries. This problem can be alleviated in the econometric analysis by including industry and country fixed effects. Time fixed effects control for changes in the propensity to patent across time. A final problem is that patent values are highly heterogeneous, with most patents having a low valuation (Griliches 1998). This problem is partly addressed by invoking the law of large numbers, since our large dataset (over 15,000 companies across 12 countries) enables us to analyse average differences in the association between patenting and Tobin's Q across technologies. In addition, we employ citation-adjusted patent counts in our models. It is widely accepted that citations received by patents are an indication of the economic significance of an innovation (Harhoff, Scherer, and Vopel 2003).

Our database in providing the identity of the patent applicants also facilitates matching clean and dirty patents with distinct patent applicants.[6] Our analysis focuses on a sample of published patents and citations, for listed firms for which we observe firm traits, filed by 15,217 firms belonging to the top 12 country leaders in clean innovation[7] over the period 1995–2012. We primarily study the patents and citations that are published by the USPTO, however for robustness we also conduct our analysis to the patents and citations published by the European Patent Office (EPO).

3.2.2. Clean and dirty patent categories

Our selection of patent classification codes for clean technologies relies on previous work by the OECD Environment Directorate.[8] We examine areas of clean patenting activity related to energy generation from renewable and non-fossil sources (wind, solar, hydro, marine, biomass, geothermal and energy from waste), combustion technologies with mitigation potential (for example combined heat and power), other technologies with potential contribution to emissions mitigation (in particular energy storage), electric and hybrid vehicles and energy conservation in buildings. We refer to these areas as climate change mitigation innovation or in short 'clean' innovation. The patent classification codes used to extract clean patents from the database is presented in Table A1 in the Internet Appendix A.

Our selection of patent classification codes for dirty technologies relies on Noailly and Smeets (2015) for electricity generation technologies and on Aghion et al. (2016) for the automobile industry. Our dirty environmental innovation pertains to IPC codes in different technological classes, including steam engine plants, gas turbine plants, combustion engines, steam generation, combustion apparatus and furnaces. The patent classification codes used to extract dirty patents from the database are presented in Table A2 in the Internet Appendix A.

3.3. Key variables of interest and control variables

Our dependent variable, Tobin's Q, and independent variables, innovation productivity and efficiency variables, as well as control variables (i.e. firm trait variables) are described in this sub-section. Concise definitions are provided in Table 1.

3.3.1. Dependent variable

The dependent variable in all our Model specifications is the natural logarithm of Tobin's Q ratio which is the market value of firm i in year t to its replacement cost:

$$\text{Tobin's } Q = Q = \frac{\text{Total\_assets} - \text{Book} + \text{Market\_Value}}{\text{Total\_assets}} \tag{1}$$

where *Book* is the book value of equity and *Market_Value* is the Market Capitalization. The meaning we ascribe to Tobin's Q is consistent with its interpretation in Hall and Oriani (2006). It indicates the 'market value' of the innovating firm.

3.3.2. Explanatory variables: innovation productivity variables

Our innovation productivity variables are inspired by prior literature (Deng, Lev, and Narin 1999; Chan, Lakonishok, and Sougiannis 2001). We use R&D expense over book value of equity, *RDBE* (worldscope # 05491 is book value per share) (Chan, Lakonishok, and Sougiannis 2001), patents over book value of equity, *Pat*/*Book* (Deng, Lev, and Narin 1999) and adjusted patent citation (Gu 2005) over book value of equity, *Cit*/*Book*, as our innovation productivity variables.

RDBE is defined as the ratio of the R&D expense of firm i in year t scaled by the book value of equity in year t

$$\text{RDBE}_{i,t} = \frac{\text{R\&D}_{i,t}}{\text{Book}_{i,t}} \tag{2}$$

Similarly, we define Pat/Book as the ratio of firm i's patents published in year t scaled by the book value of equity

$$\frac{\text{Pat}_{i,t}}{\text{Book}_{i,t}} = \frac{\text{Patents}_{i,t}}{\text{Book}_{i,t}} \tag{3}$$

In constructing our citation productivity variable, we ensure that the citations count is observable to investors in the market when they make investment decisions. Following Gu (2005), we use citations received in the year

Table 1. Variable definitions.

Variable	Definition
Measures of firm value	
Tobin's Q	Market value of the firm to the book value of tangible assets $(Total\_assets - Book + Market\_Value)/(Total\_assets)$.
Total_assets (millions of $)	Total Assets represents the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.
Market_Value	Total market value of the company based on year end price and number of shares outstanding converted to U.S. dollars using the year end exchange rate.
Book (millions of $)	Book value of equity.
Measure of R&D Productivity	
RDBE	Research and Development expense divided by Book.
Measures of Innovation Productivity	
Pat/Book	Number of US patents of the firm, in any patent category, divided by Book.
Pat*/Book	As per Pat/Book but US patent category is *: clean, dirty, other or emerging technologies.
Cit/Book	The numerator is the number of citations received in year t by US patent k, granted in year $t-j$ $(j = 1-5)$ scaled by the average number of citations received in year t by all patents of the same subcategory granted in year $t-j$ $(j = 1-5)$. This number is summed over the total number of patents granted in year $t-j$ to firm i. The numerator is divided by the book value of equity.
Cit*/Book	As per Cit/Book but US patent category is *: clean, dirty, other or emerging technologies.
Measures of Innovation Efficiency	
Pat/RDC	Number of US patents of the firm divided by the 5-year cumulative R&D expenses, observed in year $t-2$, assuming a depreciation rate of 20% per annum.
Pat*/RDC	As per Pat/RDC but US patent category is *: clean, dirty, other or emerging technologies.
Cit/RD	The numerator is the number of citations received in year t by US patent k, granted in year $t-j$ $(j = 1-5)$ scaled by the average number of citations received in year t by all patents of the same subcategory granted in year $t-j$ $(j = 1-5)$. This number is summed over the total number of patents granted in year $t-j$ to firm i. The numerator is divided by the summation of R&D expenses in years $t-3$ to $t-7$.
Cit*/RD	As per Cit/RD but US patent category is *: clean, dirty, other or emerging technologies.
Firm traits	
invBE	Inverse of Book.
CEME	Capital expenditure (funds used to acquire fixed assets other than those associated with acquisitions) to Market Value of Equity.
Adverts	Advertising expenditure to Market Value of Equity.
RDG	R&D growth; An episode of R&D growth (RDG) is captured in a dummy variable which is equal to one if there is an episode of growth (R&D expenditure is greater than 5% of total assets and of total sales and there is a growth of at least 5% in R&D expenditure and a growth of at least 5% in R&D expenditure scaled by total assets relative to the prior year) and is zero otherwise (Total sales measured in millions of $, is the gross sales and other operating revenue less discounts, returns and allowances).
$\text{Earning}_{\text{abnormal}}$	Abnormal earnings; earnings before interest tax depreciation and amortization, E, is adjusted by the corporate income tax rate, $\tau_{i,t}$ on firm earnings and the annualized risk free rate, r_t, multiplied by the book value of equity is deducted.
taxRDBE	Tax shelter associated with R&D expenditure
Regulation	
EPS	Environmental Policy Stringency Index (Botta and Koźluk 2014); This index takes the value from 0 (least stringent) to 6 (most stringent) and is a country-specific stringency measure.

t with respect to patents granted in the previous five years. C_{ik}^{t-j} is the number of citations received in year t by patent k for firm i which is granted in year $t-j$ (j = 1 . . . 5). This number is scaled by the average number of citations received in year t by all patents of the same subcategory granted in year $t-j$ (j = 1 . . . 5).[9] N_{t-j} is the total number of patents granted in year $t-j$ to firm i. This method for adjusting citations propensity to differences in technology fields, grant year and the year in which the citation occurs is in line with Gu (2005) and Hirshleifer, Hsu, and Li (2013). We define Cit/Book as follows:

$$\frac{\text{Cit}_{i,t}}{\text{Book}_{i,t}} = \frac{\sum_{j=1}^{T}\sum_{k=1}^{N_{t-j}} C_{ik}^{t-j}}{\text{Book}_{i,t}} \tag{4}$$

We further dissaggregate our patent and citation productivity variables as 'clean', 'dirty' and 'other'. For example 'clean' patent productivity is defined as follows:

$$\frac{\text{Pat\_clean}_{i,t}}{\text{Book}_{i,t}} = \frac{\text{Clean Patents}_{i,t}}{\text{Book}_{i,t}} \tag{5}$$

where $CleanPatents_{i,t}$ denote the number of clean patents of firm i published in year t.

3.3.3. Explanatory variables: innovation efficiency variables

We do not wish to focus exclusively on clean or dirty innovation productivity variables, but also on the efficiency with which research and development (*R&D*) expenditure is used to generate that output. We use two proxies for the measurement of clean/dirty innovation efficiency which are tailored variants on those proxies used in Hirshleifer, Hsu, and Li (2013). First, we study clean/dirty patents scaled by R&D capital, Pat_clean/RDC and Pat_dirty/RDC.[10] Second, we study adjusted clean/dirty patent citations scaled by R&D expenses, Cit_clean/RD and Cit_dirty/RD. Hence, whereas Hirshleifer, Hsu, and Li (2013) study innovation efficiency, we focus on clean and dirty innovation efficiency.

Pat_clean/RDC is defined as the ratio of firm i's clean patents published in year t, scaled by its R&D capital in year $t-2$. It can be defined as:

$$\frac{\text{Pat\_clean}_{i,t}}{\text{RDC}_{i,t-2}} = \frac{\text{Clean Patents}_{i,t}}{\text{R\&D}_{i,t-2} + 0.8 * \text{R\&D}_{i,t-3} + 0.6 * \text{R\&D}_{i,t-4} + 0.4 * \text{R\&D}_{i,t-5} + 0.2 * \text{R\&D}_{i,t-6}} \tag{6}$$

The R&D capital is the five year cumulative R&D expenses assuming an annual linear depreciation rate (Chan, Lakonishok, and Sougiannis 2001; Lev, Sarath, and Sougiannis 2005). In line with Lev and Sougiannis (1996), we assume a 5 year technology cycle with respect to the benefits of R&D.[11] The time lag between the innovation input (R&D capital) and output (patents) is to account for the average two year application to publication lag documented with respect to US patents (Hall, Jaffe, and Trajtenberg 2001). The use of cumulative R&D expenses in this innovation efficiency measurement is informed by R&D expenses over the preceding five years contributing to successful patent applications in $t-2$.

As the number of citations made to a firm's clean/dirty patents can reflect the patents' technological or economic importance, we also follow Hirshleifer, Hsu, and Li (2013) to define a new variable which is adjusted clean/dirty patent citations scaled by R&D expenses, Cit_clean/RD and Cit_dirty/RD. Specifically, Cit_clean/RD is defined as

$$\frac{\text{Cit\_clean}_{i,t}}{\text{RD}_{i,t}} = \frac{\sum_{j=1}^{T}\sum_{k=1}^{N_{t-j}} C_{ik}^{t-j}}{(\text{R\&D}_{i,t-2} + \text{R\&D}_{i,t-3} + \text{R\&D}_{i,t-4} + \text{R\&D}_{i,t-5} + \text{R\&D}_{i,t-6})} \tag{7}$$

C_{ik}^{t-j} is defined above. The denominator, RD, is the summation of R&D expenses in years $t-2$ to $t-6$. This denominator is informed by the assumption that there is a 2-year application-publication time lag and that only R&D expenditure up to year $t-2$ contributes to patent applications which are published in year t.

Pat_dirty/RDC and Cit_dirty/RD are defined similarly, focusing on dirty patents only.

3.3.4. Control variables: firm traits

The adopted set of control variables comprises firm traits that can play a role in the market's accordance of stock price value. The set of firm trait variables includes the inverse of book equity, $1/BE$, capital expenditure (Worldscope # 04601) to market value, *CEME* and advertisement expenditure to market value, *Advert* (Worldscope # 01101). We control for capital expenditure and advertising expenditure because they are found to explain firm operating performance (e.g. Lev and Sougiannis 1996; Pandit, Wasley, and Zach 2011). The set of firm trait variables also includes *abnormal* earnings, $Earning_{abnormal}$ (the earnings, E is defined as earnings before interest tax depreciation and amortization, Worldscope # 18198). To obtain abnormal earnings, $Earning_{abnormal}$, earnings, E, is adjusted by the corporate income tax rate, $\tau_{i,t}$ (Worldscope # 08346) on firm earnings and the annualised risk free rate, r_t (Datastream annualised 90/91 day annualised Treasury bill rate), multiplied by the book value of equity (Ohlson 1995).

We also include the tax shelter associated with R&D expenditure, *taxRDBE*, as a control variable (Hirshleifer, Hsu, and Li 2013) and substantial R&D growth, *RDG*, Eberhart, Maxwell, and Siddique (2004). An episode of R&D growth (*RDG*) is captured in a dummy variable which is equal to one if there is an episode of growth of at least 5% in R&D expenditure and a growth of at least 5% in R&D expenditure scaled by total assets relative to the prior year) and is zero otherwise. Eberhart, Maxwell, and Siddique (2004) report significantly positive abnormal stock returns following substantial R&D expenditure growth. Finally, we include time and industry

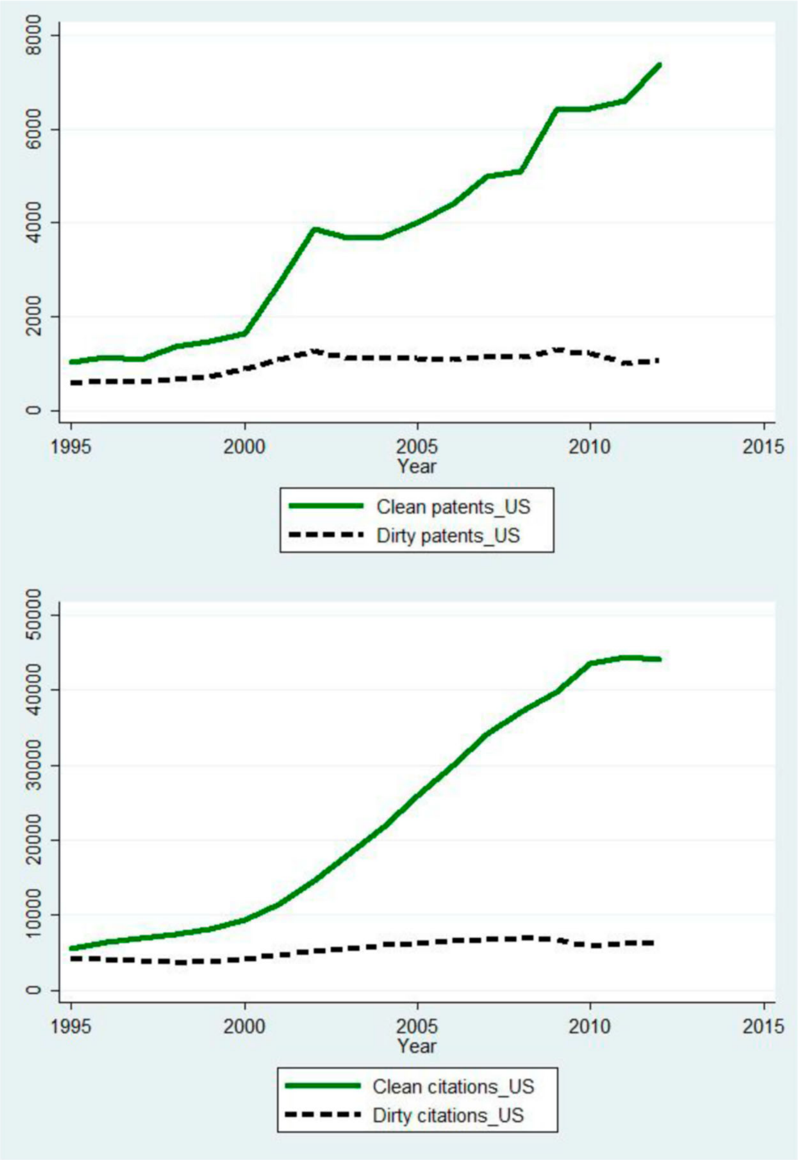

Figure 1. Clean and dirty patents and citations.

Notes. The Figure shows, over time, the number of published patents in clean and dirty technologies in the US (upper Panel) and shows related citations, accumulated in a 5-year window, in regard to clean and dirty innovations (lower Panel). We refer to Clean (Dirty) patents_US as the total number of clean (dirty) patents published by the USPTO during the period 1995–2012. We refer to Clean (Dirty) citations_US as the number of clean (dirty) patent citations of the firm, related to patents granted in the past 5 years by the USPTO.

fixed effects in all our regression specifications. We have employed the 48 Fama-French industry classification codes to generate industry dummies. The codes were obtained from Kenneth R. French's website.[12]

3.4. Descriptive statistics: growth in clean and dirty innovation globally

The global rate of growth of production of environmentally friendly 'clean' technologies, vis-a-vis 'dirty' technologies, can be observed in Figure 1, which compares the aggregate clean and dirty patents (and citations made to such patents) published by the US Patent office.[13] This Figure reports a slight increase in the number of dirty

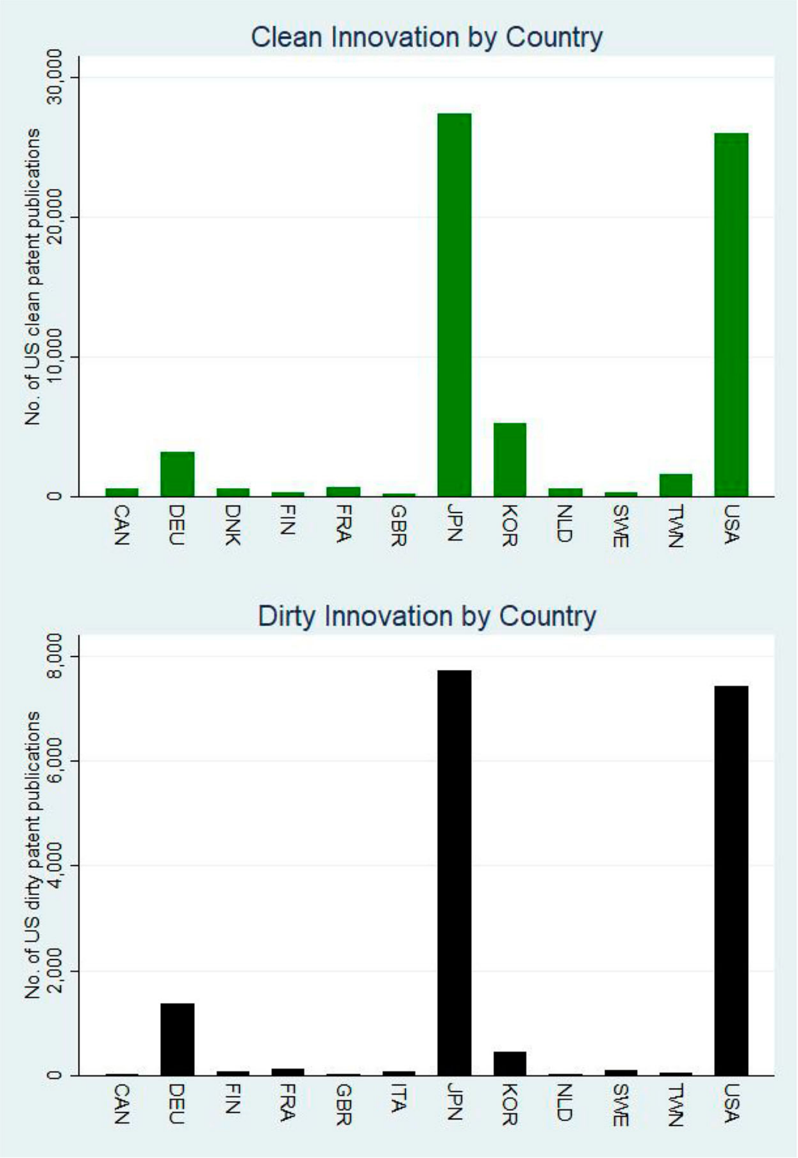

Figure 2. Clean and dirty patent productivity by country.

Notes. The Figure shows the number of published patents in clean and dirty technologies held by 12 leading clean technology producing countries (upper Panel) and 12 leading dirty technology producing countries (lower Panel). The top 12 clean innovation producing countries in descending order are: Japan, USA, Korea, Germany, Taiwan, France, Denmark, Netherlands, Canada, Sweden, Finland and Great Britain. The top 12 dirty innovation producing countries in descending order are: Japan, USA, Germany, Korea, France, Sweden, Finland, Italy, Taiwan, Great Britain, Canada, Netherlands.

patents published during the period 1995–2002, though there is no substantial change in the number of patents published yearly from 2002 to 2012. In contrast, there is a considerable increase in the number of clean patents published with an average growth of 13.58% per year. Figure 2[14] identifies the top 12 country leaders in clean and dirty innovation.[15] These countries are ranked based on the number of clean and dirty patents published by the US Patent office. All the dirty technology producing countries, except Italy, are also among the top clean technology producing countries. So, if there is a high level of innovation both dirty and clean innovation tend

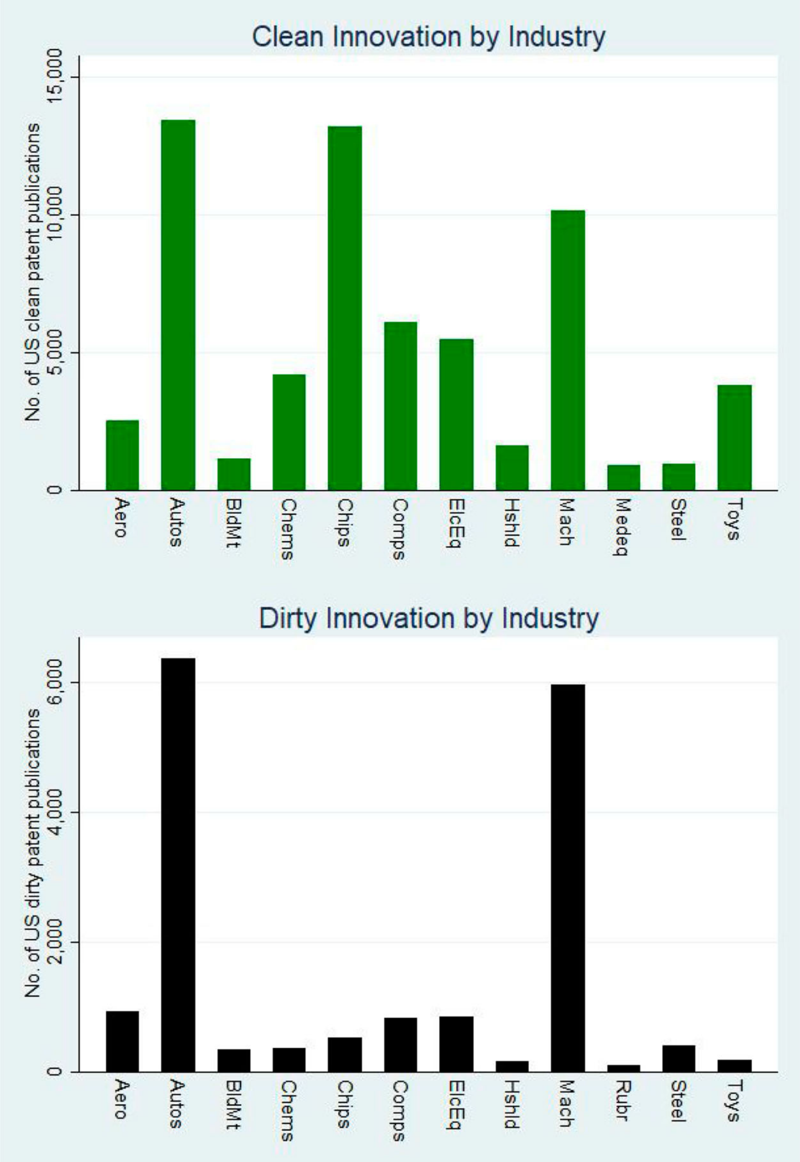

Figure 3. Clean and dirty patent productivity by industry.

Notes. The Figure shows the top 12 leading clean technologies producing industries (upper Panel) and the top 12 leading dirty technologies producing industries (lower Panel) in the 12 leading clean technology producing countries. The top 12 clean innovation producing industries in descending order are: Autos (Automobile), Chips (Electronic equipment), Mach (Machinery), Comps (Computers), ElcEq (Electrical equipment), Chems (Chemicals), Toys (Recreation), Aero (Aircraft), Hshld (Consumer goods), BldMt (Construction materials), Steel (Steel) and Medeq (Medical equipment). The top 12 dirty innovation producing industries in descending order are: Autos (Automobile), Mach (Machinery), Aero (Aircraft), ElcEq (Electrical equipment), Comps (Computers), Chips (Electronic equipment), Steel (Steel), Chems (Chemicals), BldMt (Construction materials), Toys (Recreation), Hshld (Consumer goods) and Rubr (Rubber and Plastic).

Table 2. Summary statistics.

Variables	*N*	Mean	Standard deviation
Innovation intensity			
RDBE	283,254	0.0426	1.4510
Pat/Book	186,710	0.0267	2.2100
Pat_clean/Book	186,710	0.0010	0.1870
Pat_dirty/Book	186,710	0.0001	0.0060
Pat_emtech/Book	186,710	0.0062	0.7180
Pat_other/Book	186,710	0.0256	2.0390
Cit/Book	186,710	0.1320	7.8290
Cit_clean/Book	186,710	0.0048	0.4940
Cit_dirty/Book	186,710	0.0006	0.0298
Cit_emtech/Book	186,710	0.0330	3.5470
Cit_other/Book	186,710	0.1270	7.5040
Innovation efficiency			
Pat/RDC	283,253	0.0855	7.8890
Pat_clean/RDC	283,254	0.0022	0.1180
Pat_dirty/RDC	283,254	0.0006	0.0595
Pat_emtech/RDC	283,254	0.0073	0.2500
Pat_other/RDC	283,253	0.0827	7.8860
Cit/RD	283,254	0.2100	8.5060
Cit_clean/RD	283,254	0.0079	0.4680
Cit_dirty/RD	283,254	0.0023	0.3460
Cit_emtech/RD	283,254	0.0263	0.9760
Cit_other/RD	283,254	0.2000	8.4510
Firm traits			
RDG	283,254	0.0377	0.1900
invBE	283,254	−0.0078	0.9450
taxRDBE	283,254	0.1360	1.2250
CEME	283,254	−0.0167	0.9440
$\text{Earning}_{\text{abnormal}}$	283,254	−0.0029	0.9390
Adverts	283,254	0.2570	2.6650

Notes. The Table presents summary statistics for Innovation productivity variables (RDBE, Pat/Book, Pat*/Book, Cit/Book and Cit*/Book), Innovation efficiency variables (Pat/RDC, Pat*/RDC, Cit/RD and Cit*/RD) and variables controlling for firm traits (Hirshleifer, Hsu, and Li 2013) during the period 1995–2012. The Variables are defined in Table 1.

to prevail. A comparison of the aggregate clean and dirty patents published in these countries underscores the rising importance of environmentally friendly technologies in these nations.

To assess whether firms have a net incentive or disincentive to produce clean technologies, we construct our innovation productivity (*RDBE*, *Pat*/*Book* and *Cit*/*Book*) and innovation efficiency variables (*Pat*/*RDC* and *Cit*/*RD*) and further disaggregate these variables into 'clean', 'dirty' and 'other' components for investigating their distinct influences on the Tobin's Q of the firm. The descriptive statistics for these variables are shown in Table 2.

For our dataset, firms on average allocate 4% of their book value of equity to R&D investments. Also, the clean and dirty innovation relative to book value of equity and R&D is a small fraction of total innovation. For instance, while clean and dirty patents over book value of equity account for 3.74% and 0.49%, these same patents over R&D Capital account for 2.62% and 0.68% respectively.

4. Econometric methodology

In this section, we describe the principal methodologies adopted to elicit the capital market evaluation of clean and dirty innovation. In particular, we describe the extension of the (Hall, Jaffe, and Trajtenberg 2005) firm's intangible stock of knowledge function, to account for dis-aggregated clean and dirty innovation productivity and efficiency measures. We also describe Ohlson's accounting based asset valuation model (Ohlson 1989, 1995), which serves to inform our Fama-Macbeth two stage (Fama and MacBeth 1973) estimator work in the robustness tests.

4.1. Estimation of the firm-level market-value stock of knowledge function including innovation productivity and efficiency variables

We follow Hall, Jaffe, and Trajtenberg (2005) and adopt the firm-level market-value model to evaluate the relationship between R&D investment and the market value of the firm. The chief novelty in our approach consists in the way we apply the model to assess if the stock market recognizes the value of innovation productivity and efficiency in the production of 'clean' and 'dirty' technologies. The market-value model used in Hall, Jaffe, and Trajtenberg (2005), Hall and Oriani (2006) and many other studies on valuation of R&D investments assumes that a firm is valued as a combination of both tangible and intangible assets by the stock market. However, the intangible assets that are created by the R&D investments are often not factored in the computation of the dependent variable, Tobin's Q. The model represents the market value, V, of the firm i at a time t as a function of book value of tangible assets, $A_{i,t}$, replacement value of firm's knowledge assets, $K_{i,t}$, and the replacement value of the other intangible assets, $I^{j}_{i,t}$ and can be represented as below.

$$V_{i,t} = V(A_{i,t}, K_{i,t}, I^{1}_{i,t}, \ldots, I^{n}_{i,t}) \tag{8}$$

Assuming assets can be written in an additive and linearly separable fashion and neglecting the other intangible assets, the market-value model is expressed as

$$V_{i,t} = b(A_{i,t} + \gamma K_{i,t})^{\sigma} \tag{9}$$

where σ accounts for the non-constant scale effects in the market-value function, γ represents the shadow value of knowledge assets relative to a firm's tangible assets and b denotes the average market valuation coefficient of total assets of a firm and can be interpreted to account for a firm's monopoly position and its differential risk (Grandi, Hall, and Oriani 2009). Simplifying the representation of the model by taking the natural logarithm on both sides of the equation and assuming that $\sigma = 1$ we get the following model

$$\log V_{i,t} = \log b + \log(A_{i,t}) + \log\left(1 + \gamma \frac{K_{i,t}}{A_{i,t}}\right) \tag{10}$$

which further simplifies to

$$\log Q_{i,t} = \log\left(\frac{V_{i,t}}{A_{i,t}}\right) = \log b + \log\left(1 + \gamma \frac{K_{i,t}}{A_{i,t}}\right) \tag{11}$$

where $Q_{i,t}$ stands for Tobin's Q. From the above model, one can estimate the average effect of a unit currency invested in knowledge assets on the firm's market value.

In creating our innovation productivity and efficiency variables, we consider that the full value of R&D investments can be captured from investment in R&D to creation of patents to efficiency of R&D investment in generating patents, to the generation of citation and finally the efficiency of R&D investment in creating citations. So, in our specifications we use R&D over book value of equity (*RDBE*) as a proxy for R&D productivity; patents over book value of equity ($Pat/Book$) and patents over R&D Capital (Pat/RDC) as proxies for patent productivity and efficiency; and citations over book value of equity ($Cit/Book$) and citations over RD (Cit/RD) as proxies for citation productivity and efficiency. We further disaggregate these variables into 'clean', 'dirty' and 'other' components to determine their relative importance in assessing the market value of the firm.

We first assess the impact of each individual innovation productivity and efficiency variable on the Tobin's Q of the firm by estimating various specifications derived from the Models

$$\log Q_{it} = \alpha + \log\Bigg(1 + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat/Book}_{it} + \gamma_3 \mathrm{Cit/Book}_{it} + \sum_{l=1996}^{2012} \kappa_l \mathrm{year}_l + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j\Bigg) + \epsilon_{it} \tag{12}$$

and

$$\log Q_{it} = \alpha + \log\Bigg(1 + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat/RDC}_{it} + \gamma_3 \mathrm{Cit/RD}_{it} + \sum_{l=1996}^{2012} \kappa_l \mathrm{year}_l + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j\Bigg) + \epsilon_{it} \tag{13}$$

Year and industry dummies represent time and industry fixed effects. We dis-aggregate the main innovation variables into 'clean', 'dirty' and 'other' components and examine whether the stock market attaches any importance to these technology classes separately. We also analyse the relative importance of each of the innovation productivity and efficiency variable. For this, we estimate various specifications of the following Models:

$$\log Q_{it} = \alpha + \log\Bigg(1 + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat}^*/\mathrm{Book}_{it} + \gamma_3 \mathrm{Cit}^*/\mathrm{Book}_{it} + \sum_{l=1996}^{2012} \kappa_l \mathrm{year}_l + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j\Bigg) + \epsilon_{it} \tag{14}$$

and

$$\log Q_{it} = \alpha + \log\Bigg(1 + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat}^*/\mathrm{RDC}_{it} + \gamma_3 \mathrm{Cit}^*/\mathrm{RD}_{it} + \sum_{l=1996}^{2012} \kappa_l \mathrm{year}_l + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j) + \epsilon_{it} \tag{15}$$

where Pat^* and Cit^* denote the 'clean', 'dirty' or 'other' knowledge asset.

4.2. Estimation of market value as a function of innovation productivity and efficiency stocks using Ohlson's accounting based asset valuation model

We adapt the Ohlson (1989) accounting-based asset valuation model to examine whether, and, if so, to what extent, the stock market assimilates the information content in clean and dirty innovation production and efficiency.[16] This model allows a test of whether clean and dirty innovation expenses explain market value and of any difference between their market value contributions. Ohlson (1989) derives the following valuation equation:

$$M_{i,t} = BE_{i,t} + \beta_0[E_{i,t}(1-\tau_{i,t}) - r * BE_{i,t}] + \beta_1[\tau_{i,t}\mathrm{RD}_{i,t}] + \alpha * Z_{i,t} \tag{16}$$

where $M_{i,t}$ is the market value of the ith firm at time t. $[E_{i,t}(1-\tau_{i,t}) - r * BE_{i,t}]$ is a measure of abnormal earnings discussed above and initially defined in Ohlson (1989); $[\tau_{i,t}RD_{i,t}]$ accounts for the tax shelter associated with $R\&D$ expenditure; $Z_{i,t}$ is a vector of other information variables. Other variables are as defined above.

In our adaptation of this accounting-based asset valuation model, we use the natural logarithm of Tobin's Q as the dependent variable and we include 'clean', 'dirty' and 'other' innovation productivity and efficiency variables, and the control variables used in (Hirshleifer, Hsu, and Li 2013) as our vector of controls (RDG, $\text{Earning}_{\text{abnormal}}$, invBE, CEME, Adverts, taxRDBE[17]).

We run non-linear least squares regressions in line with Hall, Jaffe, and Trajtenberg (2005), see Equations (17) and (18), as well as Fama and MacBeth (1973) annual cross-sectional regressions at the firm level, see Equations (19) and (20). We specify and estimate Equations (19) and (20) following Hirshleifer, Hsu, and Li (2013), to test if our findings are invariant to an alternative estimator: the Fama and MacBeth (1973) estimator. Our robustness tests regression specifications are derived from the following models:

$$\begin{aligned}\log Q_{it} &= \alpha + \log\Bigg(1 + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{Book}_{it} + \gamma_3 \text{Cit}^*/\text{Book}_{it} + \gamma_4 \text{RDG}_{it} + \gamma_5 \text{invBE}_{it}\\ &\quad + \gamma_6 \text{taxRDBE}_{it} + \gamma_7 \text{CEME}_{it} + \gamma_8 \text{Earning}_{\text{abnormal it}} + \gamma_9 \text{Adverts}_{it}\\ &\quad + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j\Bigg) + \epsilon_{it} \end{aligned} \tag{17}$$

$$\begin{aligned}\log Q_{it} &= \alpha + \log\Bigg(1 + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{RDC}_{it} + \gamma_3 \text{Cit}^*/RD_{it} + \gamma_4 \text{RDG}_{it} + \gamma_5 \text{invBE}_{it}\\ &\quad + \gamma_6 \text{taxRDBE}_{it} + \gamma_7 \text{CEME}_{it} + \gamma_8 \text{Earning}_{\text{abnormal it}} + \gamma_9 \text{Adverts}_{it}\\ &\quad + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j\Bigg) + \epsilon_{it} \end{aligned} \tag{18}$$

$$\begin{aligned}\log Q_{it} &= \alpha + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{Book}_{it} + \gamma_3 \text{Cit}^*/\text{Book}_{it} + \gamma_4 \text{RDG}_{it} + \gamma_6 \text{invBE}_{it}\\ &\quad + \gamma_5 \text{taxRDBE}_{it} + \gamma_7 \text{CEME}_{it} + \gamma_8 \text{Earning}_{\text{abnormal it}} + \gamma_9 \text{Adverts}_{it}\\ &\quad + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j + \epsilon_{it} \end{aligned} \tag{19}$$

$$\begin{aligned}\log Q_{it} &= \alpha + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{RDC}_{it} + \gamma_3 \text{Cit}^*/\text{RD}_{it} + \gamma_4 \text{RDG}_{it} + \gamma_6 \text{invBE}_{it}\\ &\quad + \gamma_5 \text{taxRDBE}_{it} + \gamma_7 \text{CEME}_{it} + \gamma_8 \text{Earning}_{\text{abnormal it}} + \gamma_9 \text{Adverts}_{it}\\ &\quad + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j + \epsilon_{it} \end{aligned} \tag{20}$$

*Pat**, and *Cit**, are 'clean', 'dirty' or 'other' patents and citations.

5. Empirical findings

This section presents our baseline empirical results. It then presents results of robustness tests on a variety of dimensions: alternative estimators, sub-samples of firms which have conducted both clean and dirty innovation, accounting for firm traits and emerging technology innovation and tests for whether comparable findings hold for European patents. We discuss the baseline results in Subsection 5.1. The results of the robustness tests are discussed in Subsections 5.2–5.7.

5.1. Baseline regressions: association between Tobin's Q and innovation productivity and efficiency variables

Tables 3 and 4 report the results for the non-linear regression specifications which are derived from the firm-level market value model and are similar to those reported in Hall, Jaffe, and Trajtenberg (2005). We first determine the innovation productivity and efficiency variables' association with a firm's Tobin's Q (Table 3), and, then, disaggregate these variables into clean, dirty and other components to assess their distinctive associations with a firm's Tobin's Q (Table 4). All our model specifications include time and industry fixed effects. Since R&D productivity is highly correlated with the firm's individual effect, we exclude firm fixed effects to sidestep over-correction (Hall, Jaffe, and Trajtenberg 2005).

Table 3 reports the results for specifications derived from equations (12) and (13). The results suggest that, on average, R&D, patent and citation productivity (*RDBE*, *Pat*/*Book* and *Cit*/*Book*) positively correlate to Tobin's Q.[18] In the light of the new international data examined, this corroborates the main findings reported in Hall, Jaffe, and Trajtenberg (2005). We also assess the association between the efficiency of R&D investments in generating patents and citations with the Tobin's Q (Hirshleifer, Hsu, and Li 2013) to find that innovation efficiency variables (*Pat*/*RDC*, *Cit*/*RD*) are also positively associated with Tobin's Q. To determine the association of these variables with the Tobin's Q, we estimate the corresponding semi-elasticities, the results of which can be found in Table B1 in the Internet Appendix B. For example, the semi-elasticities with respect to citation over book (*Cit*/*Book*) for specification 3 suggest that an additional citation per million dollars of book value of equity

Table 3. Tobin's Q as a function of aggregated Innovation productivity and efficiency variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1930***	0.1950***	0.1950***	0.1920***	0.1950***	0.1950***
	(0.0393)	(0.0393)	(0.0393)	(0.0392)	(0.0391)	(0.0391)
RDBE	1.1330***	1.0820***	1.0730***	1.2690***	1.2570***	1.2580***
	(0.0785)	(0.0781)	(0.0778)	(0.0822)	(0.0814)	(0.0814)
Pat/Book	0.7190***		0.2080			
	(0.1230)		(0.1080)			
Cit/Book		0.1740***	0.1460***			
		(0.0264)	(0.0276)			
Pat/RDC				0.0041*		0.0006
				(0.0017)		(0.0007)
Cit/RD					0.0147***	0.0146***
					(0.0028)	(0.0028)
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO	NO	NO
Observations	79,285	79,285	79,285	79,284	79,285	79,284
Adjusted R^2	0.2130	0.2150	0.2150	0.2090	0.2120	0.2120

Notes. The Table presents the regression results of various specifications (columns 1–3) of the Model

$$\log Q_{it} = \alpha + \log\left(1 + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat/Book}_{it} + \gamma_3 \mathrm{Cit/Book}_{it} + \sum_{i=1996}^{2012} \kappa_i \mathrm{year}_i + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j\right) + \epsilon_{it}$$

and the Model (columns 4–6)

$$\log Q_{it} = \alpha + \log\left(1 + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat/RDC}_{it} + \gamma_3 \mathrm{Cit/RD}_{it} + \sum_{i=2}^{17} \kappa_i \mathrm{year}_i + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j\right) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall, Jaffe, and Trajtenberg (2005). Models 1–3 test whether the knowledge creation process acts as a continuum from R&D to patents to citations. And Models 4-6 test the efficiency in the knowledge creation process, from investment in R&D to efficiency of R&D investment in generating patents and citations. In our specifications we use RDBE as a proxy for R&D productivity; Pat/Book as a proxy for patent productivity; Cit/Book as a proxy for citation productivity; Pat/RDC as a proxy for patent efficiency; and Cit/RD as a proxy for citation efficiency. Our dependent variable is the natural logarithm of Tobin's Q and we report clustered standard errors in parentheses. All the variables are defined in Table 1 and we use the following significance stars * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables.

	(1)	(2)	(3)	(4)
Intercept	0.1950***	0.1950***	0.1950***	0.1950***
	(0.0393)	(0.0393)	(0.0391)	(0.0391)
RDBE	1.0720***	1.0720***	1.2580***	1.2560***
	(0.0778)	(0.0779)	(0.0814)	(0.0813)
Pat_clean/Book	1.8030**			
	(0.6150)			
Pat_dirty/Book	−0.9720			
	(0.5520)			
Pat_other/Book	0.1700			
	(0.1090)			
Cit/Book	0.1440***			
	(0.0277)			
Cit_clean/Book		0.3220**		
		(0.1170)		
Cit_dirty/Book		−0.0876		
		(0.1050)		
Cit_other/Book		0.1390***		
		(0.0291)		
Pat/Book		0.2160*		
		(0.1080)		
Pat_clean/RDC			0.0588	
			(0.0375)	
Pat_dirty/RDC			−0.0355**	
			(0.0137)	
Pat_other/RDC			0.0005	
			(0.0007)	
Cit/RD			0.0144***	
			(0.0028)	
Cit_clean/RD				0.0505*
				(0.0236)
Cit_dirty/RD				−0.0055
				(0.0048)
Cit_other/RD				0.0136***
				(0.0027)
Pat/RDC				0.0006
				(0.0007)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	79,285	79,285	79,284	79,284
Adjusted R^2	0.2150	0.2150	0.2120	0.2120

Notes. The Table presents the regression results of various specifications (columns 1–2) of the Model

$$\log Q_{it} = \alpha + \log\left(1 + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{Book}_{it} + \gamma_3 \text{Cit}^*/\text{Book}_{it} + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j\right) + \epsilon_{it}$$

and the Model (columns 3–4)

$$\log Q_{it} = \alpha + \log\left(1 + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{RDC}_{it} + \gamma_3 \text{Cit}^*/\text{RD}_{it} + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j\right) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall, Jaffe, and Trajtenberg (2005). Models 1 and 2 test whether the knowledge creation process acts as a continuum from R&D to clean patents to clean citations. And Models 3 and 4 test the efficiency in the knowledge creation process, from investment in R&D to efficiency of R&D investment in generating clean patents and citations. In our specifications we use RDBE as a proxy for R&D productivity; Pat/Book as a proxy for patent productivity; Cit/Book as a proxy for citation productivity; Pat/RDC as a proxy for patent efficiency; and Cit/RD as a proxy for citation efficiency. Our dependent variable is the natural logarithm of Tobin's Q and we report clustered standard errors in parentheses. All the variables are defined in Table 1 and we use the following significance stars * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

is associated with an increment of 1.1% ($e^{.1073}$) in Tobin's Q, respectively. Similarly, for specification 4 and 5, we find that the patents over R&D capital (*Pat/RDC*) and citations over RD (*Cit/RD*) are positively associated with the Tobin's Q with an economic relation of approximately 1% ($e^{.0030}$, $e^{.0109}$).[19]

To determine whether the capital markets incentivize clean innovation vis-a-vis dirty innovation, we disaggregate patents over book (*Pat/Book*), citations over book (*Cit/Book*), patents over R&D capital (*Pat/RDC*), and citations over RD (*Cit/RD*) into clean, dirty and other components. We estimate the semi-elasticities for each specification reported in Table 4 with respect to the dis-aggregated innovation and innovation efficiency variables to determine their association with the Tobin's Q. For the first specification reported in Table 4, we find that the clean patents over book (*Pat_clean/Book*) is positively associated with the Tobin's Q at an economic value of 3.77% ($e^{1.3270}$). We also find that the clean citation over book (*Cit_clean/Book*) is positively associated with Tobin's Q at an economic value of 1.27% (specification 2 of Table 4). Additionally, we disaggregate our innovation efficiency variables and find that the clean citations over RD (*Cit_clean/RD*) is positively related to the dependent variable with an economic value of 1% (specification 4 of Table 4). We find that the clean patents over R&D capital (*Pat_clean/RDC*) is positively related to Tobin's Q, though this result is not statistically significant (specification 3 of Table 4). However, efficiency of R&D investments in generating dirty patents decreases the market value of the firm to the tune of 0.97% economic value (specification 3 of Table 4).[20] Significantly, the t-test for the difference between coefficients of clean and dirty patents over book ($Pat\_clean/Book - Pat\_dirty/Book = 0$), patents over R&D capital ($Pat\_clean/RDC - Pat\_dirty/RDC = 0$), citations over book ($Cit\_clean/Book - Cit\_dirty/Book = 0$), and citations over RD ($Cit\_clean/RD - Cit\_dirty/RD = 0$) are all statistically different from zero at a 5% level. The results for semi-elasticities for Table 4 are consistent and t-tests can be found in Tables B2 and B6 (Panel A) in the Internet Appendix B.[21]

5.2. *Do the main results hold using a Fama-Macbeth two-step estimator?*

As an alternative econometric approach to the firm-level market value model used in Hall, Jaffe, and Trajtenberg (2005) and other studies on valuation of R&D investments, we adopt the popular Fama-MacBeth estimator (Fama and MacBeth 1973) to assess the Models in Table 4 and this confirms the prevalence of a clean innovation premium. The economic upshot of clean innovation productivity and efficiency is similar to that reported in Table 4, with the exception of clean patent productivity (*Pat_clean/Book*), which is three times higher than the corresponding clean patent productivity (*Pat_clean/Book*) association reported in Table 4.[22]

5.3. *Do the main results hold using a sub-sample of firms which produces both clean and dirty technologies?*

A potential issue is that in the sector of electricity generation, dirty firms tend to be large incumbents while clean firms are typically smaller entrants. In the absence of firm fixed effects, the results could therefore be driven by unobserved intrinsic and time-invariant differences in the type of firms conducting clean or dirty innovation which are not controlled for in the regressions. Therefore, we estimate the models reported in Table 4 for the sub-sample of firms producing both clean and dirty technologies. This allows us to assess if there is clean innovation premium *within* firms producing both clean and dirty technologies.

The results are reported in Table 6. We find that our results are robust with respect to clean patent (*Pat_clean/Book*) and citation (*Cit_clean/Book*) productivity variables, respectively. We also find that the efficiency of R&D investments in generating dirty patents (*Pat_dirty/RDC*) and citations (*Cit_dirty/RD*) decrease the Tobin's Q of the firm to the tune of 0.98%.[23] Further, the difference between coefficients of clean and dirty patent ($Pat\_clean/Book - Pat\_dirty/Book$) and citation productivity ($Cit\_clean/Book - Cit\_dirty/Book$) and the difference between clean and dirty coefficients of citation efficiency ($Cit\_clean/RD - Cit\_dirty/RD$) variables are positive and statistically different from zero at a the 5% level. Also, the difference in the premia associated with the efficiency with which R&D investments generate clean and dirty patents ($Pat\_clean/RDC - Pat\_dirty/RDC$) is statistically different from zero at 10%. The results for semi-elasticities for Table 6 and related t-tests can be found in Tables B3 and B6 (Panel B) in the Internet Appendix B.

Table 5. Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables, estimated using Fama-MacBeth regressions.

	(1)	(2)	(3)	(4)
Intercept	0.0409*	0.0410*	0.0362	0.0365
	(0.0219)	(0.0219)	(0.0228)	(0.0227)
RDBE	0.2890***	0.2880***	0.3090***	0.3090***
	(0.0267)	(0.0264)	(0.0365)	(0.0365)
Pat_clean/Book	2.3190**			
	(0.9300)			
Pat_dirty/Book	−0.3290			
	(1.2590)			
Pat_other/Book	0.0690			
	(0.0783)			
Cit/Book	0.0324*			
	(0.0164)			
Cit_clean/Book		0.2890**		
		(0.1040)		
Cit_dirty/Book		−0.1150		
		(0.2520)		
Cit_other/Book		0.0321*		
		(0.0165)		
Pat/Book		0.0770		
		(0.0739)		
Pat_clean/RDC			0.1210**	
			(0.0455)	
Pat_dirty/RDC			0.0181	
			(0.0327)	
Pat_other/RDC			0.0019*	
			(0.0011)	
Cit/RD			0.0039***	
			(0.0011)	
Cit_clean/RD				0.0224**
				(0.0092)
Cit_dirty/RD				−0.0099
				(0.0086)
Cit_other/RD				0.0042***
				(0.0012)
Pat/RDC				0.0025*
				(0.0014)
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	79,285	79,285	79,284	79,284
avg. R-squared	0.1930	0.1920	0.1880	0.1880

Notes. The Table presents the regression results of various specifications (columns 1 and 2) of the Model

$$\log Q_{it} = \alpha + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{Book}_{it} + \gamma_3 \text{Cit}^*/\text{Book}_{it} + \sum_{j=2}^{48} \beta_j \text{Industry}_j + \epsilon_{it}$$

and the Model (columns 3 and 4)

$$\log Q_{it} = \alpha + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{RDC}_{it} + \gamma_3 \text{Cit}^*/\text{RD}_{it} + \sum_{j=2}^{48} \beta_j \text{Industry}_j + \epsilon_{it}$$

that are estimated using Fama-MacBeth method. These Models test whether the knowledge creation process acts as a continuum from R&D to clean patents and clean citations and tests the efficiency in the knowledge creation process, from investment in R&D to efficiency of R&D investment in generating clean patents and citations. In our specifications we use RDBE as a proxy for R&D productivity; Pat/Book as a proxy for patent productivity; Cit/Book as a proxy for citation productivity; Pat/RDC as a proxy for patent efficiency; and Cit/RD as a proxy for citation efficiency. Our dependent variable is the natural logarithm of Tobin's Q and we report standard errors in parentheses. All the variables are defined in Table 1 and we use the following significance stars $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

We conclude from this test that the result is not simply driven by unobserved heterogeneity between firms conducting clean or dirty innovation, but that a clean innovation premium holds *within* diversified firms conducting both types of innovation.

Table 6. Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables for firms which conduct both clean and dirty innovation.

	(1)	(2)	(3)	(4)
Intercept	1.4960***	1.5050***	1.4810***	1.4830***
	(0.0173)	(0.0130)	(0.0156)	(0.0150)
RDBE	0.0123	0.0033	0.0256	0.0240
	(0.0171)	(0.0114)	(0.0150)	(0.0142)
Pat_clean/Book	0.6160*			
	(0.2770)			
Pat_dirty/Book	−0.1030			
	(0.2140)			
Pat_other/Book	−0.0394			
	(0.0529)			
Cit/Book	0.0238*			
	(0.0100)			
Cit_clean/Book		0.1240***		
		(0.0221)		
Cit_dirty/Book		−0.0007		
		(0.0088)		
Cit_other/Book		0.0152		
		(0.0082)		
Pat/Book		−0.0100		
		(0.0291)		
Pat_clean/RDC			0.0026	
			(0.0060)	
Pat_dirty/RDC			−0.0068*	
			(0.0033)	
Pat_other/RDC			−0.0017	
			(0.0025)	
Cit/RD			0.0013	
			(0.0019)	
Cit_clean/RD				0.0179
				(0.0136)
Cit_dirty/RD				−0.0031**
				(0.0010)
Cit_other/RD				−0.0003
				(0.0009)
Pat/RDC				−0.0005
				(0.0008)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	6593	6593	6593	6593
Adjusted R^2	0.2150	0.2180	0.1970	0.2040

Notes. The Table presents the regression results of various specifications (columns 1–2) of the Model

$$\log Q_{it} = \alpha + \log\left(1 + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat}^*/\mathrm{Book}_{it} + \gamma_3 \mathrm{Cit}^*/\mathrm{Book}_{it} + \sum_{l=1996}^{2012} \kappa_l \mathrm{year}_l + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j\right) + \epsilon_{it}$$

and the Model (columns 3–4)

$$\log Q_{it} = \alpha + \log\left(1 + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat}^*/\mathrm{RDC}_{it} + \gamma_3 \mathrm{Cit}^*/\mathrm{RD}_{it} + \sum_{l=1996}^{2012} \kappa_l \mathrm{year}_l + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j\right) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall, Jaffe, and Trajtenberg (2005). Models 1 and 2 test whether the knowledge creation process acts as a continuum from R&D to clean patents to clean citations. And Models 3 and 4 test the efficiency in the knowledge creation process, from investment in R&D to efficiency of R&D investment in generating clean patents and citations. In our specifications we use RDBE as a proxy for R&D productivity; Pat/Book as a proxy for patent productivity; Cit/Book as a proxy for citation productivity; Pat/RDC as a proxy for patent efficiency; and Cit/RD as a proxy for citation efficiency. Our dependent variable is the natural logarithm of Tobin's Q and we report clustered standard errors in parentheses. In the above regression models the sample is the firms producing both clean and dirty technologies. All the variables are defined in Table 1 and we use the following significance stars $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

5.4. Do the main results hold explicitly accounting for emerging technologies in our regressions?

We are concerned that the estimates of clean innovation productivity and efficiency may be relaying the effect of emerging technologies more generally on the firm's Tobin's Q.[24] Emerging technologies are new and disruptive innovations such as Information technologies, robots or nanotechnologies, that are likely positively associated with both the firm's Tobin's Q as well as with clean technologies, if some firms specialize in emerging technologies in general, which encompass clean technologies. Hence, the omission of emerging technologies may upwardly bias the estimates of clean innovation productivity and innovation efficiency. The patent classification codes used to extract emerging patents from the database is presented in Table A3 in the Internet Appendix A.

Therefore, we disaggregate the 'other patents' into 'emerging' and 'mature' technologies,[25] and we extend the Models reported in Table 4 to include the patent and citation productivity ($Pat\_emtech/Book$, $Cit\_emtech/Book$)

Table 7. Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables, including emerging technology variants of Innovation productivity and efficiency variables.

	(1)	(2)	(3)	(4)
Intercept	0.1950***	0.1950***	0.1950***	0.1960***
	(0.0392)	(0.0393)	(0.0390)	(0.0391)
RDBE	1.0710***	1.0690***	1.2520***	1.2420***
	(0.0778)	(0.0777)	(0.0810)	(0.0807)
Pat_clean/Book	1.7880**			
	(0.6050)			
Pat_dirty/Book	−0.9420			
	(0.5670)			
Pat_emtech/Book	0.6380			
	(0.3550)			
Pat_other/Book	0.0829			
	(0.1070)			
Cit/Book	0.1410***			
	(0.0275)			
Cit_clean/Book		0.3160**		
		(0.1130)		
Cit_dirty/Book		−0.0820		
		(0.1070)		
Cit_emtech/Book		0.2490**		
		(0.0819)		
Cit_other/Book		0.1150***		
		(0.0332)		
Pat/Book		0.2070		
		(0.1080)		
Pat_clean/RDC			0.0459	
			(0.0399)	
Pat_dirty/RDC			−0.0336*	
			(0.0131)	
Pat_emtech/RDC			0.1950***	
			(0.0431)	
Pat_other/RDC			0.00003	
			(0.00046)	
Cit/RD			0.0123***	
			(0.0027)	
Cit_clean/RD				0.0470*
				(0.0227)
Cit_dirty/RD				−0.0051
				(0.0048)
Cit_emtech/RD				0.0756***
				(0.0158)
Cit_other/RD				0.0082***
				(0.0024)
Pat/RDC				0.0005
				(0.0007)

(*continued*).

Table 7. Continued.

	(1)	(2)	(3)	(4)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	79285	79285	79284	79284
Adjusted R^2	0.2160	0.2150	0.2130	0.2130

Notes. The Table presents the regression results of various specifications (columns 1–2) of the Model

$$\log Q_{it} = \alpha + \log\left(1 + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{Book}_{it} + \gamma_3 \text{Cit}^*/\text{Book}_{it} + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j\right) + \epsilon_{it}$$

and the Model (columns 3–4)

$$\log Q_{it} = \alpha + \log\left(1 + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{RDC}_{it} + \gamma_3 \text{Cit}^*/\text{RD}_{it} + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j\right) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall, Jaffe, and Trajtenberg (2005). Models 1 and 2 test whether the knowledge creation process acts as a continuum from R&D to clean patents to clean citations. And Models 3 and 4 test the efficiency in the knowledge creation process, from investment in R&D to efficiency of R&D investment in generating clean patents and citations. In our specifications we use RDBE as a proxy for R&D productivity; Pat/Book as a proxy for patent productivity; Cit/Book as a proxy for citation productivity; Pat/RDC as a proxy for patent efficiency; and Cit/RD as a proxy for citation efficiency. Our dependent variable is the natural logarithm of Tobin's Q and we report clustered standard errors in parentheses. All the variables are defined in Table 1 and we use the following significance stars $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

in emerging technologies and the corresponding efficiency variables (Pat_emtech/RDC, Cit_emtech/RD) as controls. Table 7 reports the findings. We find no substantial change in the estimates of clean innovation productivity and innovation efficiency. This substantiates the results reported in Table 4.[26] We also find that the t-test for the difference between coefficients of clean and dirty patents over book ($Pat\_clean/Book - Pat\_dirty/Book = 0$), patents over R&D capital ($Pat\_clean/RDC - Pat\_dirty/RDC = 0$), citations over book ($Cit\_clean/Book - Cit\_dirty/Book = 0$), and citations over RD ($Cit\_clean/RD - Cit\_dirty/RD = 0$) are statistically different from zero at a 5% level. The results for semi-elasticities for Tables 7 and related t-tests can be found in Tables B4 and B6 (Panel C) in the Internet Appendix B.[27]

5.5. Do the main results hold explicitly accounting for accounting-based asset valuation firm-level traits in our regressions?

As a further robustness test to deal with a potential omitted variable bias in the absence of firm fixed effects, we extend the non-linear regression models reported in Table 4 by including firm traits in line with the Ohlson's accounting based asset valuation model cited in Hirshleifer, Hsu, and Li (2013). In this heavily parameterized setting, our main results hold well in respect to clean and dirty citations over RD (Cit_clean/RD, Cit_dirty/RD), as indicated in specification 4 of Table 8. We also include patent and citation productivity and efficiency with respect to emerging technologies (Specifications 5-8 of Table 8), and again find that our results are robust with respect to clean and dirty citations over RD (Cit_clean/RD, Cit_dirty/RD), as indicated in specification 8 of Table 8. The estimates of clean citation efficiency, Cit_clean/RD, reported in specifications 4 and 8 of Table 8 are similar to the one reported in Table 4 having the same economic association of 1.04% with a firm's Tobin's Q. We also find that the efficiency of R&D investments in generating dirty citations (Cit_dirty/RD) decreases the Tobin's Q of the firm to the tune of 0.99%. For specifications 4 and 8 we find that difference between coefficients of clean and dirty citations over RD ($Cit\_clean/RD - Cit\_dirty/RD = 0$) are statistically different from zero at a 5% level. The results for semi-elasticities for Table 8 and related t-tests can be found in Tables B5 and B6 (Panel D and E) in the Internet Appendix B.

Further, these Models are also estimated using the Fama-MacBeth estimator and our main result that the stock market accords significantly more value to clean as opposed to dirty innovation productivity and innovation efficiency remain unchanged.[28,29]

As demand in the market and generic government policies inform a firm's decision to innovate in a particular area, we posit that the 5-year change in the Environmental policy stringency score (Botta and Koźluk 2014) would proxy for the appetite, for clean innovation, of the investors and consumers. Therefore, we add the difference between one-year and six-year lag of Environmental policy stringency score of the US ($EPSlag1-EPSlag6$) and emerging technology variants of innovation productivity and efficiency variables to the baseline regression models (Models in Table 4) and find that there is still a clean innovation premium with respect to efficiency of R&D investment in generating citations. We argue that this finding is economically relevant as citations show the importance of a particular innovation and further propel innovation in that area.[30]

Table 8. Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables, controlling for firm traits and emerging technology variants of Innovation productivity and efficiency variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.2440***	0.2440***	0.2440***	0.2450***	0.2440***	0.2440***	0.2450***	0.2450***
	(0.0331)	(0.0331)	(0.0329)	(0.0330)	(0.0331)	(0.0331)	(0.0329)	(0.0330)
RDBE	0.3250***	0.3250***	0.2290***	0.2290***	0.3240***	0.3250***	0.2280***	0.2280***
	(0.0361)	(0.0361)	(0.0274)	(0.0274)	(0.0359)	(0.0361)	(0.0274)	(0.0274)
Pat_clean/Book	0.6490				0.6480			
	(0.4870)				(0.4850)			
Pat_dirty/Book	0.4910				0.4940			
	(0.9290)				(0.9300)			
Pat_emtech/Book					0.3050			
					(0.2720)			
Pat_other/Book	0.2210*				0.2070*			
	(0.0941)				(0.0945)			
Cit/Book	0.0620***				0.0619***			
	(0.0163)				(0.0162)			
Cit_clean/Book		0.1440				0.1440		
		(0.0877)				(0.0877)		
Cit_dirty/Book		−0.0151				−0.0151		
		(0.0423)				(0.0421)		
Cit_emtech/Book						0.0585		
						(0.0421)		
Cit_other/Book		0.0595***				0.0597**		
		(0.0167)				(0.0195)		
Pat/Book		0.2360*				0.2360*		
		(0.0936)				(0.0939)		
Pat_clean/RDC			0.0422				0.0316	
			(0.0281)				(0.0311)	
Pat_dirty/RDC			−0.0218				−0.0203	
			(0.0146)				(0.0140)	
Pat_emtech/RDC							0.1440***	
							(0.0313)	
Pat_other/RDC			0.0010				0.0002	
			(0.0009)				(0.0005)	
Cit/RD			0.0066***				0.0053***	
			(0.0017)				(0.0016)	
Cit_clean/RD				0.0446*				0.0429*
				(0.0209)				(0.0208)
Cit_dirty/RD				−0.0016*				−0.0015**
				(0.0006)				(0.0006)
Cit_emtech/RD								0.0394***
								(0.0097)
Cit_other/RD				0.0061***				0.0033*
				(0.0017)				(0.0014)
Pat/RDC				0.0011				0.0011
				(0.0009)				(0.0009)

(*continued*).

Table 8. Continued.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	87800	87800	87799	87799	87800	87800	87799	87799
Adjusted R^2	0.2480	0.2480	0.2440	0.2450	0.2480	0.2480	0.2450	0.2450

Notes. The Table presents the regression results of various specifications (columns 1, 2, 5 and 6) of the Model

$$\log Q_{it} = \alpha + \log\Bigg(1 + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{Book}_{it} + \gamma_3 \text{Cit}^*/\text{Book}_{it} + \gamma_4 \text{RDG}_{it} + \gamma_5 \text{invBE}_{it} + \gamma_6 \text{taxRDBE}_{it} + \gamma_7 \text{CEME}_{it} + \gamma_8 \text{Earning}_{\text{abnormal it}} + \gamma_9 \text{Adverts}_{it} + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j\Bigg) + \epsilon_{it}$$

and the Model (columns 3, 4, 7 and 8)

$$\log Q_{it} = \alpha + \log\Bigg(1 + \gamma_1 \text{RDBE}_{it} + \gamma_2 \text{Pat}^*/\text{RDC}_{it} + \gamma_3\gamma_3 \text{Cit}^*/\text{RD}_{it} + \gamma_4 \text{RDG}_{it} + \gamma_5 \text{invBE}_{it} + \gamma_6 \text{taxRDBE}_{it} + \gamma_7 \text{CEME}_{it} + \gamma_8 \text{Earning}_{\text{abnormal it}} + \gamma_9 \text{Adverts}_{it} + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j\Bigg) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall, Jaffe, and Trajtenberg (2005) and Hirshleifer, Hsu, and Li (2013) with the inclusion of firm-level control variables, year and industry fixed-effects. These Models test whether the knowledge creation process acts as a continuum from R&D to clean patents and clean citations and tests the efficiency in the knowledge creation process,from investment in R&D to efficiency of R&D investment in generating clean patents and citations. In our specifications we use RDBE as a proxy for R&D productivity; Pat/Book as a proxy for patent productivity; Cit/Book as a proxy for citation productivity; Pat/RDC as a proxy for patent efficiency; and Cit/RD as a proxy for citation efficiency. Our dependent variable is the natural logarithm of Tobin's Q and we report clustered standard errors in parentheses. All the variables are defined in Table 1 and we use the following significance stars $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

5.6. Do the main results hold explicitly accounting for a managerial selection bias?

In our study, sample selection bias may arise if managers choose to innovate in clean technologies more relative to dirty technologies. Therefore, to address sample selection we adopt the Heckman two stage 1979 regression approach (Heckman 1979). Table 9 reports the related findings. In the first stage, we model the likelihood of a firm to conduct clean innovation using a Probit model. The dependent variable for the first stage is *Clean_firm*, which is a dummy variable that takes the value 1 if a firm has a clean patent published by the USPTO during the period 1995–2012 and 0 otherwise. We regress *Clean_firm* on *Emtech_firm*,[31] *Total_assets*, *EPSlag*1−*EPSlag*6, the full set of control variables, year and industry dummies:

$$\textit{Clean\_firm} = \alpha + \gamma_1 \text{Emtech\_firm}_i + \gamma_2 \text{RDG}_{it} + \gamma_3 \text{invBE}_{it} + \gamma_4 \text{taxRDBE}_{it} + \gamma_5 \text{CEME}_{it} + \gamma_6 \text{Earning}_{\text{abnormal it}} + \gamma_7 \text{Adverts}_{it} + \gamma_8 \text{Total\_assets} + \sum_{l=1996}^{2012} \kappa_l \text{year}_l + \sum_{j=2}^{48} \beta_j \text{Industry}_j + \epsilon_{it} \tag{21}$$

For the second stage we use Models 1 and 2 of Tables 4 and 8 and include the inverse Mills ratio (bias correction term), obtained from the first stage, as an explanatory variable. We find that our inference of a clean innovation premium remains, despite this correction.

5.7. Do the main results hold for European patents?

To check if our results hold in a different jurisdiction, we run the robustness tests for the patents and citations published by the European Patent Office (EPO). We find a positive association between clean patent productivity

Table 9. Heckman sample selection 2nd stage Model: Tobin's Q as a function of disaggregated innovation productivity and efficiency variables.

	(1)	(2)	(3)	(4)
Intercept	0.2930***	0.2930***	0.4760***	0.4750***
	(0.0641)	(0.0640)	(0.0575)	(0.0574)
RDBE	0.5010***	0.4770***	0.7760***	0.7660***
	(0.0443)	(0.0444)	(0.0408)	(0.0409)
PAT2c_book	0.3290		1.6270***	
	(0.3790)		(0.5020)	
PAT2d_book	0.1860		0.9730	
	(1.2320)		(1.1070)	
PAT2o_book	−0.1880***		−0.0957**	
	(0.0424)		(0.0394)	
CITE2_book	0.0409***		0.0354***	
	(0.0064)		(0.0057)	
CITE2c_book		0.4490***		0.4010***
		(0.0845)		(0.0801)
CITE2d_book		−0.1320		−0.0295
		(0.2450)		(0.2210)
CITE2o_book		0.0340***		0.0270***
		(0.0064)		(0.0059)
PAT2_book		−0.1830***		−0.0410
		(0.0307)		(0.0377)
Inverse Mills Ratio	−.0941***	−.0944***	−.0526***	−.0522***
	(.0072)	(.0072)	(.0068)	(.0068)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	YES	YES
Observations	78,577	78,577	78,577	78,577
Censored observations	68,103	68,103	68,103	68,103
Uncensored observations	10,474	10,474	10,474	10,474
Wald Chi^2	3048.39	3076.36	6391.84	6406.00
Prob > Chi^2	0.0000	0.0000	0.0000	0.0000
Rho	−0.23333	−0.23438	−0.14714	−0.14615
Sigma	.40330519	.40294769	.35750088	.35732054

Notes. The Table presents the regression results of various specifications of the 2nd stage Heckman Model

$$\log Q_{it} = \alpha + \gamma_1 \mathrm{RDBE}_{it} + \gamma_2 \mathrm{Pat}^*/\mathrm{Book}_{it} + \gamma_3 \mathrm{Cit}^*/\mathrm{Book}_{it} + \gamma_4 \mathrm{RDG}_{it} + \gamma_6 \mathrm{invBE}_{it} + \gamma_5 \mathrm{taxRDBE}_{it} + \gamma_7 \mathrm{CEME}_{it}$$
$$+ \gamma_8 \mathrm{Earning}_{\mathrm{abnormal\ it}} + \gamma_9 \mathrm{Adverts}_{it} + \sum_{l=1996}^{2012} \kappa_l \mathrm{year}_l + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j + \epsilon_{it}$$

The likelihood of a firm to conduct clean innovation is modelled in the 1st stage of Heckman sample selection Model

$$\mathrm{Clean\_firm} = \alpha + \gamma_1 \mathrm{Emtech\_firm}_i + \gamma_2 \mathrm{RDG}_{it} + \gamma_3 \mathrm{invBE}_{it} + \gamma_4 \mathrm{taxRDBE}_{it} + \gamma_5 \mathrm{CEME}_{it} + \gamma_6 \mathrm{Earning}_{\mathrm{abnormal\ it}}$$
$$+ \gamma_7 \mathrm{Adverts}_{it} + \gamma_8 \mathrm{Total\_assets} + \sum_{l=1996}^{2012} \kappa_l \mathrm{year}_l + \sum_{j=2}^{48} \beta_j \mathrm{Industry}_j + \epsilon_{it}$$

where Clean_firm and Emtech_firm are indicator variables that take the value 1 if a firm has a USPTO published patent and 0 otherwise. In our specifications we use RDBE as a proxy for R&D productivity; Pat/Book as a proxy for patent productivity; Cit/Book as a proxy for citation productivity; Pat/RDC as a proxy for patent efficiency; and Cit/RD as a proxy for citation efficiency. Our dependent variable in the 2nd stage Model is the natural logarithm of Tobin's Q and we report standard errors in parentheses. All the variables are defined in Table 1 and we use the following significance stars $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

(*Pat_clean*/*Book*) and Tobin's Q and this result is statistically significant at 5%. We also find a negative and significant association between dirty citation productivity (*Cit_dirty*/*Book*) and efficiency variables (*Cit_dirty*/*RD*) with the Tobin's Q.[32]

Following the test presented in Section 5.4, we also include the patent and citation productivity and efficiency with respect to emerging technologies and find that the results do not change substantially.[33] These Models were estimated using a non-linear least squares estimation method.

Additionally, we estimate these Models using a Fama-MacBeth estimator and find that our main results hold with regard to clean and dirty patent productivity and efficiency. We also extend these models to include a patent and citation productivity and efficiency with respect to emerging technologies (*Pat_emtech/Book*, *Cit_emtech/Book*, *Pat_emtech/RDC*, *Cit_emtech/RD*) and thus find that there is a positive and significant association between generating clean relative to dirty patents efficiently and Tobin's Q.[34]

Further, we estimate the association of clean and dirty innovation productivity and efficiency variables with Tobin's Q of the firm, while controlling for emerging technology variants of innovation productivity and efficiency variables and firm traits in line with the Ohlson's accounting based asset pricing model cited in Hirshleifer, Hsu, and Li (2013). In this heavily parameterized setting, our main results hold well in respect to clean and dirty patent productivity and efficiency (*Pat_clean/Book*, *Pat_dirty/Book*, *Pat_clean/RDC* and *Pat_dirty/RDC*), as indicated in specifications 1, 3, 5 and 7 of Table C7 in the Internet Appendix C.[35]

6. Conclusion and discussion

Innovation productivity is critically important for firm- and national-level competitiveness in international markets (Porter 1992). Innovation productivity to curtail, and ultimately reverse, environmental degradation (i.e. 'clean' innovation) can prove vital to establish a sustainable market economy around the world (Allen and Yago 2011; IPCC 2014). Such a sustainable market economy will mitigate market failures and serve to protect air, water, fisheries, wildlife, and biodiversity. In this paper, we raise the question of whether there is an economic incentive for firms to pursue strategies of clean environmentally-supportive innovation, as opposed to carbon-emitting dirty innovation activities.

We use a unique dataset covering 15,217 listed firms across 12 countries to measure the relationship between market value and innovation activity. We disaggregate annual patent counts by technology, distinguishing between clean, dirty and other technologies (including emergent technologies). Our dataset also includes patent citation data which is used to proxy for patent quality.

We start by verifying the value accorded by the capital market to generic innovation and innovation efficiency internationally, in the non-linear regression model setting of Hall, Jaffe, and Trajtenberg (2005). This serves to establish the validity of our data and empirical set-up.

Our main contribution is that we elicit capital market evaluations associated with the disaggregated innovation productivity measures (Deng, Lev, and Narin 1999; Chan, Lakonishok, and Sougiannis 2001) and innovation efficiency measures (Hirshleifer, Hsu, and Li 2013) to account for 'clean' and 'dirty' innovation production and efficiency. We report that 'clean' innovation efficiency is typically associated with an economically important and positive Tobin's Q, while the capital market ascribes no (or a negative) market value influence to 'dirty' innovation efficiency.

The relative Tobin's Q association of 'clean' vis-a-vis 'dirty' innovation is significant and economically important across innovation measurements. These main results are invariant with respect to a range of model specifications, a focus on European as opposed to United States patents, sub-samples of firms which conduct both clean and dirty innovation, estimation strategies, and controlling for firm traits frequently used in respect to asset pricing.

Our question is whether there is a clean innovation premium, consistent with the objective for a long-term de-carbonization of the international economy. We do not, thus, aim to discern, from the data, why a clean or dirty innovation premium can prevail. The question we raise is nonetheless important. Its resolution is also not straightforward. We, with novelty, avail of a compelling litmus test to resolve the raised question: the information content of equity market price signals. As such, we meaningfully address this complex and important question, and report strong and robust evidence of a clean innovation premium.

Several competing or complementary explanations can drive the existence of a clean innovation premium. A first possible explanation is that clean patents signal greater growth opportunities than dirty patents, in a world that is increasingly constrained by climate change mitigation policies. Clean investors might also need to invest more in the future to realise the value of their patent stock than firms producing dirty patents. A major competing candidate, however, is the existence of decreasing marginal returns to R&D, which could contribute to smaller effects of incremental patenting on Tobin's Q over time, as 'dirty' technologies are more mature than 'clean' innovations. It could also be that patents on 'clean' technologies are more difficult to produce than patents in 'dirty' technologies, which would be rewarded by the market (although this argument goes against the assumption of decreasing marginal returns from R&D efforts).

Therefore, an important avenue for research is to empirically investigate the drivers behind the clean innovation premium uncovered in this paper. This is left for future work.

Notes

1. The initial findings corroborate a large body of research which provides compelling evidence that the patent productivity of R&D and the citations received by these patents have a statistically and economically significant positive impact on firms' market value (e.g. Griliches 1981; Chan, Lakonishok, and Sougiannis 2001; Eberhart, Maxwell, and Siddique 2004).
2. As the returns to R&D investments will typically accrue over a number of years, stock prices or market value should provide, given market information efficiency arguments, useful information on their expected future benefits. Empirical studies analysing the relationship between R&D investments and market value typically model the market value relative to tangible assets (Tobin's Q) as a function of intangible assets (R&D capital), among other firm value determining variables, and show that the R&D-market value relationship is consistently positive (Ballardini et al. 2005).
3. We thank an anonymous reviewer for raising this point.
4. Calel and Dechezlepretre (2016) show that the European Union Emission's Trading System has had a quick causal impact on technological change in the form of new patenting activity.
5. Cohen, Nelson, and Walsh (2000) conducted a survey questionnaire administered to 1478 R&D labs in the U.S. manufacturing sector. They rank sectors according to how effective patents are considered as a means of protection against imitation, and find that the top three industries according to this criterion are medical equipment and drugs, special purpose machinery and automobile.
6. To link patent applicants with firms in Worldscope, we use the link provided by Bureau van Dijk's Orbis database in its 'IP' bundle, to which we have access through a commercial license. The matching algorithm is based not only on name matching but also on geographical information available from patent data (country, address, etc) as well as on extensive manual cleaning.
7. The top 12 clean innovation producing countries in descending order are: Japan, USA, Korea, Germany, Taiwan, France, Denmark, Netherlands, Canada, Sweden, Finland and Great Britain.
8. See www.oecd/environment/innovation.
9. Patent subcategories are defined based on the International Patent Classification.
10. Research and development expense represents all direct and indirect costs related to the creation and development of new processes, techniques, applications and products with commercial possibilities; Worldscope # 01201.
11. We set missing R&D to zero throughout but when we repeat our tests with variables with no missing R&D observations we obtain similar findings.
12. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
13. Clean technologies encompass a markedly larger number of categories than dirty technologies, in our sample. Internet Appendix A, Table A1 reports the list of clean technology categories sampled and Table A2 reports the list of categories for dirty technologies.
14. The top 12 clean innovation producing countries in descending order are: Japan, USA, Korea, Germany, Taiwan, France, Denmark, Netherlands, Canada, Sweden, Finland and Great Britain. The top 12 dirty innovation producing countries in descending order are: Japan, USA, Germany, Korea, France, Sweden, Finland, Italy, Taiwan, Great Britain, Canada, Netherlands.
15. Figure 3 shows the top 12 leading clean technologies producing industries (upper panel) and the top 12 leading dirty technologies producing industries (lower panel) in 12 leading clean technology producing countries.
16. This general asset pricing framework is also used in Barth, Beaver, and Landsman (1998), Sougiannis (1994), Ohlson (1995), and Hirshleifer, Hsu, and Li (2013) among others. It is recommended in Brennan's 1991 review paper (Brennan 1991).
17. See Table 3 of the definition of these variables.
18. Please refer to Table C1 in the Internet Appendix C which reports consistent findings for European patents, and Table D1 of the Internet Appendix D which shows consistent results from a Fama-Macbeth regression framework.
19. Please refer to Table B1 in the Internet Appendix B.
20. Please refer to Table C2 in the Internet Appendix C which reports consistent findings for European patents and Table D2 of the Internet Appendix D which shows consistent results from a Fama-Macbeth regression framework.
21. Tables E1 and E2 of Internet Appendix E, using a non-linear least squares estimator and a Fama-Macbeth regression specification, report consistent results with future operating profit, i.e. earnings before interest, taxes, depreciation, and amortization (EBITDA), as a response variable.
22. The first specification of Table 5 suggests that a unit increase in Pat_clean/Book is associated with an increase of 2.319 in the natural logarithm of Tobin's Q (log Q). So, a one unit increase in Pat_clean/Book is associated with an increase of 10.17% ($e^{2.319}$) in Tobin's Q. Since the non-linear estimation of the corresponding model (first specification of Table 4) suggests that

Pat_clean/Book is positively associated with Tobin's Q with an economic impact of 3.77%, we infer that the economic impact derived from Table 5 is approximately three-fold of the corresponding Pat_clean/Book derived from Table 4.

23. We estimate our baseline Models for the sample of firms with non-zero patents (See Tables F2 and F3 in the Internet Appendix F). We find a positive and statistically significant association between innovation productivity and efficiency variables with the Tobin's Q of the firm and further, find a positive and significant association between clean innovation productivity ($Pat\_clean/Book$, $Cit\_clean/Book$) variables and clean citation efficiency (Cit_clean/RD) variables with the Tobin's Q of the firm, respectively.
24. We thank a reviewer for highlighting that due to a life-cycle and a decreasing returns channel at the patent level, mature technologies (e.g. dirty innovation) can experience decreasing returns, and a weaker Tobin's Q association than clean innovation. This can potentially account for our main finding of a clean innovation premium. Table G1, of the Internet Appendix G, reports that for emergent technologies, presumably in the early phase of their life cycle, there is no clean innovation premium for patents (Column 1) but that a clean innovation premium is still evident for clean innovation citations (Column 2). This suggests some evidence in support of a patent technology category life-cycle mechanism to account for a clean innovation premium. Note that the paper is focused on establishing whether there is a clean innovation premium and does not claim to establish the drivers of such a premium – see the discussion in the concluding section.
25. For the sake of simplicity we denote 'mature' technologies as 'other' technologies when we include innovation productivity and efficiency variables with respect to emerging technologies in our Models.
26. We estimate the Models reported in Table 7 for the sample of firms producing both clean and dirty patents and find that our result of clean innovation premium holds with respect to patent and citation productivity (See Table F5 in the Internet Appendix F). We also estimate these Models for the sub-sample of firms with non-zero patents and find clean innovation premium with respect to innovation productivity variables and citation efficiency variables (See Table F4 in the Internet Appendix F).
27. We also adopt the Fama-MacBeth estimator to assess these Models. We find that the economic value of clean innovation productivity and efficiency is similar to those derived from Table 7. Please refer Table D2 in the Internet Appendix D.
28. Please refer to Table D3 in the Internet Appendix D.
29. The main results hold even when we construct the innovation productivity and efficiency variables with respect to the grant date instead of publication date.
30. Please refer Table F1 in the Internet Appendix F.
31. Emtech_firm is a dummy variable that takes the value 1 if a firm has an emerging technology patent published by the USPTO during the period 1995–2012 and 0 otherwise.
32. Please refer Table C2 in the Internet Appendix C.
33. Please refer Table C3 in the Internet Appendix C.
34. Please refer Tables C5 and C6 in the Internet Appendix C.
35. Please refer to Tables H1 to H7 in the Internet Appendix H, which report findings that the main results are invariant to time, industry, firm *and* country level control variables. Please refer to Tables I1 to I6 in the Internet Appendix I, which report findings that the main results are invariant to using book value of assets as opposed to the book value of equity as a denominator. We thank a reviewer and an Associate Editor for suggesting these latter tests of the robustness of our main findings.

Acknowledgements

The authors would like to thank for suggestions Don Bredin, Matt Spiegel, Luca Taschini and Heather Tookes. We also thank the participants in seminars at Babson College finance department, University College Dublin's Geary Institute and College of Business, Dublin City University Business School, Loughborough University, the London School of Economics and the Organisation for Economic Co-operation and Development. Cal Muckley would like to acknowledge the financial support of Science Foundation Ireland under Grant Number 16/SPP/3347 and 17/SP/5447. This manuscript was substantively advanced while Cal Muckley was a CRH Fulbright scholar at Yale University and while he was a visiting researcher at the London School of Economics, Grantham Research Institute. This research has benefitted from the financial support of the Grantham Foundation for the Protection of the Environment and the UK Economic and Social Research Council through the Centre for Climate Change Economics and Policy. The usual disclaimer applies.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

Cal Muckley would like to acknowledge the financial support of Science Foundation Ireland under Grant Numbers 16/SPP/3347 and 17/SP/5447. This research has benefitted from the financial support of the Grantham Foundation for the Protection of the Environment and the UK Economic and Social Research Council through the Centre for Climate Change Economics and Policy under Grant Number ES/R009708/1.

References

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous. 2012. "The Environment and Directed Technical Change." *American Economic Review* 102 (1): 131–166.

Aghion, P., A. Dechezleprêtre, D. Hemous, R. Martin, and J. Van Reenen. 2016. "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence From the Auto Industry." *Journal of Political Economy* 124 (1): 1–51.

Allen, F., and G. Yago. 2011. "Environmental Finance: Innovating to Save the Planet." *Journal of Applied Corporate Finance* 23 (3): 99–111.

Ballardini, F., A. Malipiero, R. Oriani, M. Sobrero, and A. Zammit. 2005. "Do Stock Markets Value Innovation? A Meta-Analysis." *A Meta-Analysis* (January 2005).

Barth, M. E., W. H. Beaver, and W. R. Landsman. 1998. "Relative Valuation Roles of Equity Book Value and Net Income as a Function of Financial Health." *Journal of Accounting and Economics* 25 (1): 1–34.

Blundell, R., R. Griffith, and J. Van Reenen. 1999. "Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms." *Review of Economic Studies* 66 (3): 529–554.

Botta, E., and T. Koźluk. 2014. "Measuring Environmental Policy Stringency in OECD Countries."

Bowman, E. H., and M. Haire. 1975. "A Strategic Posture Toward Corporate Social Responsibility." *California Management Review* 18 (2): 49–58.

Brekke, K. A., and K. Nyborg. 2008. "Attracting Responsible Employees: Green Production As Labor Market Screening." *Resource and Energy Economics* 30 (4): 509–526.

Brennan, M. J. 1991. "A Perspective on Accounting and Stock Prices." *The Accounting Review* 66 (1): 67–79.

Calel, R., and A. Dechezlepretre. 2016. "Environmental Policy and Directed Technological Change: Evidence From the European Carbon Market." *Review of Economics and Statistics* 98 (1): 173–191.

Chan, L. K., J. Lakonishok, and T. Sougiannis. 2001. "The Stock Market Valuation of Research and Development Expenditures." *The Journal of Finance* 56 (6): 2431–2456.

Cohen, W. M., R. R. Nelson, and J. P. Walsh. 2000. *Protecting their Intellectual Assets: Appropriability Conditions and Why US Manufacturing Firms Patent (or Not)*. No. w7552. National Bureau of Economic Research.

Corbett, C., and S. Muthulingam. 2008. *An Empirical Investigation of the Depth of Adoption of the LEED Green Building Standards*. Technical Report, Working Paper, UCLA.

Czarnitzki, D., B. H. Hall, and R. Oriani. 2006. "The Market Valuation of Knowledge Assets in US and European Firms." *The Management of Intellectual Property*, 111–131. Cheltenham Glos.

Dasgupta, S., B. Laplante, and N. Mamingi. 2001. "Pollution and Capital Markets in Developing Countries." *Journal of Environmental Economics and Management* 42 (3): 310–335.

Deng, Z., B. Lev, and F. Narin. 1999. "Science and Technology as Predictors of Stock Performance." *Financial Analysts Journal* 55 (3): 20–32.

Dernis, H., D. Guellec, and B. van Pottelsberghe. 2001. "Using Patent Counts for Cross-country Comparisons of Technology Output". STI Review No. 27. Paris: OECD. www.oecd.org/dataoecd/26/11/21682515.pdf.

Dowell, G., S. Hart, and B. Yeung. 2000. "Do Corporate Global Environmental Standards Create Or Destroy Market Value?." *Management Science* 46 (8): 1059–1074.

Eberhart, A. C., W. F. Maxwell, and A. R. Siddique. 2004. "An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases." *The Journal of Finance* 59 (2): 623–650.

Ellerman, A. D., C. Marcantonini, and A. Zaklan. 2014. "The EU ETS: Eight Years and Counting." *Robert Schuman Centre for Advanced Studies Research Paper* (2014/04).

Fama, E. F., and J. D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (3): 607–636.

Fisher-Vanden, K., and K. S. Thorburn. 2011. "Voluntary Corporate Environmental Initiatives and Shareholder Wealth." *Journal of Environmental Economics and Management* 62 (3): 430–445.

Frietsch, R., and U. Schmoch. 2006. "Technological Structures and Performance as Reflected by Patent Indicators." In *National Systems of Innovation in Comparison*, 89–105. Dordrecht: Springer.

Grandi, A., B. H. Hall, and R. Oriani. 2009. "R&D and Financial Investors." *Evaluation and Performance Measurement of Research and Development*, 143–165. Cheltenham, UK: Edward Elgar.

Griliches, Z. 1981. "Market Value, R&D, and Patents." *Economics Letters* 7 (2): 183–187.

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

Griliches, Z. 1998. "Patent Statistics as Economic Indicators: A Survey." In *R&D and Productivity: The Econometric Evidence*, 287–343. Chicago: University of Chicago Press.

Gu, F. 2005. "Innovation, Future Earnings, and Market Efficiency." *Journal of Accounting, Auditing & Finance* 20 (4): 385–418.

Guenster, N., R. Bauer, J. Derwall, and K. Koedijk. 2011. "The Economic Value of Corporate Eco-Efficiency." *European Financial Management* 17 (4): 679–704.

Gupta, S., and B. Goldar. 2005. "Do Stock Markets Penalize Environment-Unfriendly Behaviour? Evidence From India." *Ecological Economics* 52 (1): 81–95.

Hall, B. H. 2000. "Innovation and Market Value." In *Productivity, Innovation and Economic Performance*, edited by R. Barro, G. Mason, M. O'Mahoney, 177–198. Cambridge: Cambridge University Press

Hall, B. H., A. B. Jaffe, and M. Trajtenberg. 2001. The NBER patent citation data file: Lessons, insights and methodological tools. No. w8498. National Bureau of Economic Research.
Hall, B. H., A. B. Jaffe, and M. Trajtenberg. 2005. "Market Value and Patent Citations." *RAND Journal of Economics* 36 (1): 16–38.
Hall, B. H., and R. Oriani. 2006. "Does the Market Value R&D Investment by European Firms? Evidence From a Panel of Manufacturing Firms in France, Germany, and Italy." *International Journal of Industrial Organization* 24 (5): 971–993.
Hamilton, J. T. 1995. "Pollution as News: Media and Stock Market Reactions to the Toxics Release Inventory Data." *Journal of Environmental Economics and Management* 28 (1): 98–113.
Harhoff, D., F. M. Scherer, and K. Vopel. 2003. "Citations, Family Size, Opposition and the Value of Patent Rights." *Research Policy* 32 (8): 1343–1363.
Heckman, J. J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47 (1): 153–161.
Heinkel, R., A. Kraus, and J. Zechner. 2001. "The Effect of Green Investment on Corporate Behavior." *The Journal of Financial and Quantitative Analysis* 36 (4): 431–449.
Hicks, J. R. 1932. *The Theory of Wages*. London: Macmillan.
Hirshleifer, D., P.-H. Hsu, and D. Li. 2013. "Innovative Efficiency and Stock Returns." *Journal of Financial Economics* 107 (3): 632–654.
IPCC. 2014. Climate change 2014: Synthesis Report. *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC, Geneva, Switzerland 151.
Jacobs, B. W., V. R. Singhal, and R. Subramanian. 2010. "An Empirical Investigation of Environmental Performance and the Market Value of the Firm." *Journal of Operations Management* 28 (5): 430–441.
Jaffe, A. B., R. G. Newell, and R. N. Stavins. 2005. "A Tale of Two Market Failures: Technology and Environmental Policy." *Ecological Economics* 54 (2–3): 164–174.
Johnstone, N., I. Haščič, and D. Popp. 2010. "Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts." *Environmental and Resource Economics* 45 (1): 133–155.
Karpoff, J. M., J. R. Lott, and E. W. Wehrly. 2005. "The Reputational Penalties for Environmental Violations: Empirical Evidence." *The Journal of Law and Economics* 48 (2): 653–675.
Klassen, R. D., and C. P. McLaughlin. 1996. "The Impact of Environmental Management on Firm Performance." *Management Science* 42 (8): 1199–1214.
Lev, B., B. Sarath, and T. Sougiannis. 2005. "R&D Reporting Biases and Their Consequences." *Contemporary Accounting Research* 22 (4): 977–1026.
Lev, B., and T. Sougiannis. 1996. "The Capitalization, Amortization, and Value-Relevance of R&D." *Journal of Accounting and Economics* 21 (1): 107–138.
Narver, J. C. 1971. "Rational Management Responses to External Effects." *Academy of Management Journal* 14 (1): 99–115.
Newell, R. G., A. B. Jaffe, and R. N. Stavins. 1999. "The Induced Innovation Hypothesis and Energy-Saving Technological Change." *The Quarterly Journal of Economics* 114 (3): 941–975.
Noailly, J., and R. Smeets. 2015. "Directing Technical Change From Fossil-Fuel to Renewable Energy Innovation: An Application Using Firm-Level Patent Data." *Journal of Environmental Economics and Management* 72: 15–37.
Nyborg, K., and T. Zhang. 2013. "Is Corporate Social Responsibility Associated with Lower Wages?" *Environmental and Resource Economics* 55 (1): 107–117.
Ohlson, J. A. 1989. "Accounting Earnings, Book Value, and Dividends: The Theory of the Clean Surplus Equation." Unpublished paper.
Ohlson, J. A. 1995. "Earnings, Book Values, and Dividends in Equity Valuation." *Contemporary Accounting Research* 11 (2): 661–687.
Oriani, R., and M. Sobrero. 2008. "Uncertainty and the Market Valuation of R&D Within a Real Options Logic." *Strategic Management Journal* 29 (4): 343–361.
Palmer, K., W. E. Oates, and P. R. Portney. 1995. "Tightening Environmental Standards: the Benefit-Cost Or the No-Cost Paradigm?" *Journal of Economic Perspectives* 9 (4): 119–132.
Pandit, S., C. E. Wasley, and T. Zach. 2011. "The Effect of Research and Development (R&D) Inputs and Outputs on the Relation Between the Uncertainty of Future Operating Performance and R&D Expenditures." *Journal of Accounting, Auditing & Finance* 26 (1): 121–144.
Popp, D. 2002. "Induced Innovation and Energy Prices." *American Economic Review* 92 (1): 160–180.
Porter, M. E. 1992. "Capital Disadvantage: America's Failing Capital Investment System." *Harvard Business Review* 70 (5): 65–82.
Porter, M. E., and C. Van der Linde. 1995. "Green and Competitive: Ending the Stalemate." In *The Dynamics of the Eco-Efficient Economy: Environmental Regulation and Competitive Advantage*. Vol. 33. Cheltenham: Edward Elgar
Reinhardt, F. L. 1999. "Bringing the Environment Down to Earth." *Harvard Business Review* 77 (4): 149–57.
Russo, M. V., and P. A. Fouts. 1997. "A Resource-Based Perspective on Corporate Environmental Performance and Profitability." *Academy of Management Journal* 40 (3): 534–559.
Shane, P. B., and B. H. Spicer. 1983. "Market Response to Environmental Information Produced Outside the Firm." *Accounting Review* 58: 521–538.
Sougiannis, T. 1994. "The Accounting Based Valuation of Corporate R&D." *Accounting Review* 69: 44–68.
Spicer, B. H. 1978. "Investors, Corporate Social Performance and Information Disclosure: An Empirical Study." *Accounting Review* 53: 94–111.
Tobin, J. 1969. "A General Equilibrium Approach to Monetary Theory." *Journal of Money, Credit and Banking* 1 (1): 15–29.

Turban, D. B., and D. W. Greening. 1997. "Corporate Social Performance and Organizational Attractiveness to Prospective Employees." *Academy of Management Journal* 40 (3): 658–672.
Von Arx, U., and A. Ziegler. 2014. "The Effect of Corporate Social Responsibility on Stock Performance: New Evidence for the USA and Europe." *Quantitative Finance* 14 (6): 977–991.
Walley, N., and B. Whitehead. 1994. "It's Not Easy Being Green." *Reader in Business and the Environment* 36 (81): 4.
Ziegler, A., M. Schröder, and K. Rennings. 2007. "The Effect of Environmental and Social Performance on the Stock Performance of European Corporations." *Environmental and Resource Economics* 37 (4): 661–680.