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Is firm-level clean or dirty innovation valued more?

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Abstract

We examine how Tobin's Q - the ratio of market value of the firm to its book value of tangible assets - 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, United States and European patents, model specifications, sub-samples of firms and estimators adopted.

JEL Classification: G35, G32, C58
Keywords: Innovation, research and development, patents, citations, clean technologies, dirty technologies, market value

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1 Introduction

According to an Assessment Report by the Intergovernmental Panel on Climate Change, stabilising 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 this long-term decarbonisation 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 et al., 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 address this complex and important question, which pertains to the presence or not of an adequate economic incentive for clean 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 may redirect innovation away from fossil fuel towards low carbon technologies when faced with change in policies and energy prices. For instance, Calel and Dechezlepretre (2016) investigate the impact of the European Union Emissions Trading System on regulated companies using a matching method and report that among matched regulated companies there is a 30% increase in the amount of low-carbon technology innovation. Similarly, Newell et al. (1999) and Popp (2002) report a substantial increase in the production of energy-efficient technologies following increase in energy prices.

However, a limitation of existing studies of directed 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 et al., 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 determines 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 data set of United States patents, 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) of 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 (Chan et al., 2001; Deng et al., 1999; Gu, 2005) and efficiency variables (Hirshleifer et al., 2013).

We first verify, in our sample, the capital market value accorded to generic innovation productivity (Deng et al., 1999; Chan et al., 2001) and innovation efficiency (Hirshleifer et al., 2013). This work serves to extend, in the international arena, the non-linear least squares regression model findings in Hall et al. (2005).[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 - the ratio of market value of the firm to its book value of tangible assets - on firm-level clean and dirty innovation, together with other measures of innovation. To ascertain the expected economic performance of ‘clean’ and ‘dirty’ investment activities, we, specifically, follow Hall et al. (2005) and adopt a firm’s intangible stock of knowledge function. We dis-aggregate innovation productivity measures that are similar to those used in Deng et al. (1999) and Hirshleifer et al. (2013) innovation efficiency measures 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 the economic impact of generating a clean patent, per million dollars of book value, is 3.77%. The economic impact of generating a citation on a clean patent, per million dollars of book value, is 1.27%. Similarly, we infer that an economic impact of a citation on a clean patent, per million dollars of R&D expense, is 1% while noting that the comparable efficiency of R&D investments, in generating dirty patents, decreases the market

[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 et al. (2001) and Eberhart et al. (2004)).

value of the firm to the tune of 0.97% economic value. Our main finding is, thus, that 'clean' innovation is associated with an economically important and positive Tobin's Q association, 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 et al. (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) and a range of firm traits from the accounting based asset pricing literature (Ohlson, 1989, 1995; Hirshleifer et al., 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) and Dasgupta et al. (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 et al. (2007) and 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 '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 et al., 2001; Eberhart et al., 2004; Hall et al., 2005; Hirshleifer et al., 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 et al., 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 mechanisms, which can prevail, between investments in environmental innovation and financial performance.

[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), and show that the R&D-market value relationship is consistently positive (Ballardini et al., 2005).

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 et al., 2014), such innovation not only has generic research and development expenditure implications for future firm operating cash flows and risks (Hall, 2000) and (Czarnitzki et al., 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 et al., 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 (Corbett and Muthulingam, 2008; Russo and Fouts, 1997). More generally, (iv) environmental innovation can be regarded as a less risky investment (Narver, 1971; Shane and Spicer, 1983; Spicer, 1978). 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 (Nyborg and

Zhang, 2013; Brekke and Nyborg, 2008).

Second, climate change innovation can serve to mitigate risks of losses from crises or new regulation[3] (Reinhardt, 1999) and prevent expenses due to lawsuits and legal settlements (Karpoff et al., 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 et al., 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 et al., 1995). Climate change innovation can also, thus, be associated with a negative stock market valuation impact. Fisher-Vanden and Thorburn (2011) and Jacobs et al. (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.

[3]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.

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 et al., 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 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 capitalisation, capital expenditure, and earnings before interest, tax and amortisation. The final firm-count is 25,255 firms from Worldscope.

3.2 Firm-level patenting and clean and dirty innovation categories

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.

Our database in providing the identity of the patent applicants also facilitates matching clean and dirty patents with distinct patent applicants.[4] Our analysis focuses on a sample of published patents and citations, for listed firms for which we observe firm traits, filed by around 15,217 firms belonging to the top 12 country leaders in clean innovation[5] over the period 1995-2012. We primarily study the patents and citations that are published by the USPTO, however for

[4]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.

[5]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.

robustness we also conduct our analysis to the patents and citations published by the European Patent Office (EPO).

3.2.1 Clean and dirty patent categories

Our selection of patent classification codes for clean technologies relies on previous work by the OECD Environment Directorate.[6] 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 is 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.

[6] See www.oecd/environment/innovation

[Please insert Table 1 about here.]

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

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

where $Book$ is the book value of equity and $Market\_Value$ is the Market Capitalization.

3.3.2 Explanatory variables: Innovation productivity variables

Our innovation productivity variables are inspired by prior literature (Chan et al., 2001; Deng et al., 1999). We use R&D expense over book value of equity, $RDBE$ (worldscope # 05491 is book value per share) (Chan et al., 2001), patents over book value of equity, $Pat/Book$ (Deng et al., 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

$$RDBE_{i,t} = \frac{R\&D_{i,t}}{Book_{i,t}} \tag{2}$$

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

$$\frac{Pat_{i,t}}{Book_{i,t}} = \frac{Patents_{i,t}}{Book_{i,t}} \tag{3}$$

In constructing our citation productivity variable we ensure that the citations count is observable to investors in the market when they make investment decisions, Gu (2005) uses citations received in the year 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).[7] N_{t-j} is the total number of patents granted in year $t-j$ to firm i. This method for adjusting citations is in line with Gu (2005) and Hirshleifer et al. (2013). It is an attempt to adjust for citation propensity attributed to differences in technology fields, grant year and the year in which the citation occurs. We define Cit/Book as follows

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

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

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

where Clean Patents 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 rather we wish to also focus 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 et al. (2013). First, we study clean/dirty patents scaled by R&D capital, Pat_clean/RDC and Pat_dirty/RDC.[8] Second, we study adjusted clean/dirty patent citations scaled by R&D expenses, Cit_clean/RD

[7] Patent subcategories are defined based on the International Patent Classification.

[8] 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.

and Cit_dirty/RD. Hence, whereas Hirshleifer et al. (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

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

The R&D capital is the five year cumulative R&D expenses assuming an annual linear depreciation rate (Chan et al., 2001; Lev et al., 2005). In line with Lev and Sougiannis (1996), we assume a 5 year technology cycle with respect to the benefits of R&D.[9] The time lag between the innovation input (R&D capital) and output (patents) is to account for the average two year application to grant lag documented with respect to US patents (Hall et al., 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 et al. (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

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

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-

[9] 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.

grant time lag and that only R&D expenditure up to year $t-2$ contributes to successful patent applications which are granted 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 et al. (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 amortisation, 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 et al., 2013) and substantial R&D growth, RDG, (Eberhart et al., 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 (R&D expenditure is greater than 5% of total assets (worldscope # 02999) and of total sales (worldscope # 01001) 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. Eberhart et al. (2004) report significantly positive abnormal stock returns following substantial R&D expenditure growth. Finally, we include time and industry dummies in all our regression specifications.

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 published by the US Patent office. This Figure reports a slight increase in the number of dirty 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. Turning to Figure 2, it identifies the top 12 country leaders in clean and dirty innovation.[10] 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 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.

[Please insert Figure 1 and Figure 2 about here.]

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.

[Please insert Table 2 about here.]

[10]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.

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 et al. (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 et al. (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 et al. (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 et al., 2009). Simplifying the representation of the model by taking the natural logarithm on both sides of the equation and assuming that σ=1 we get the following model

$$logV_{i,t} = logb + log(A_{i,t}) + log(1 + \gamma \frac{K_{i,t}}{A_{i,t}}). \tag{10}$$

which further simplifies to

$$logQ_{i,t} = log(\frac{V_{i,t}}{A_{i,t}}) = logb + log(1 + \gamma \frac{K_{i,t}}{A_{i,t}}) \tag{11}$$

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/Book_{it} + \gamma_3 Cit/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it} \tag{12}$$

and

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/RDC_{it} + \gamma_3 Cit/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it} \tag{13}$$

We then disaggregate these variables as 'clean', 'dirty' and 'other' components and examine whether the stock market attaches any importance to these technology classes separately and analyze the relative importance of each productivity and efficiency variable. For this, we estimate the various specifications of following Models:

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it} \tag{14}$$

and

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it} \quad (15)$$

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

4.1.1 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.[11] 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:

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

where $M_{i,t}$ is the market value of the i^{th} 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 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 et al. (2013) as our vector of controls (RDG, Earning$_{abnormal}, invBE, CEME, Adverts, taxRDBE$[12]).

[11] This general asset pricing framework is also used in Barth et al. (1998); Sougiannis (1994); Ohlson (1995) and Hirshleifer et al. (2013) among others. It is recommended in Brennan's 1991 review paper (Brennan, 1991).
[12] See Table 3 of the definition of these variables.

We run non-linear least squares regressions in line with Hall et al. (2005) as well as Fama-MacBeth (1973) annual cross-sectional regressions at the firm level. Our robustness tests regression specifications are derived from the following models:

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \gamma_4 RDG_{it} + \gamma_5 invBE_{it} \\ + \gamma_6 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \\ \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it} \quad (17)$$

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \gamma_4 RDG_{it} + \gamma_5 invBE_{it} \\ + \gamma_6 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \\ \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it} \quad (18)$$

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \gamma_4 RDG_{it} + \gamma_6 invBE_{it} \\ + \gamma_5 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \\ \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it} \quad (19)$$

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \gamma_4 RDG_{it} + \gamma_6 invBE_{it} + \\ \gamma_5 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \\ \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it} \quad (20)$$

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 to 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 et al. (2005). We first determine the impact of the innovation productivity and efficiency variables on a firm's Tobin's Q (Table 3), and, then, disaggregate these variables into clean, dirty and other components to assess their distinctive impact on a firm's Tobin's Q (Table 4). All our model specifications include time and industry dummies. Since R&D productivity is highly correlated with the firm's individual effect, we exclude firm-fixed effect to sidestep overcorrection (Hall et al., 2005).

Table 3 reports the results for specifications derived from equations (12) and (13). The results suggest that on an average, R&D, patent and citation productivity ($RDBE$, $Pat/Book$ and $Cit/Book$) positively correlate to Tobin's Q. In the light of the new international data, this corroborates the main findings reported in Hall et al. (2005). We also assess the impact of the efficiency of R&D investments in generating patents and citations on the Tobin's Q (Hirshleifer et al., 2013) to find that innovation efficiency variables (Pat/RDC, Cit/RD) are also positively associated with Tobin's Q. To determine the economic impact of these variables, 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 is associated with an increment of 1.1% ($\epsilon^{.1073}$) 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 at an economic impact of approximately 1% ($\epsilon^{.0030}, \epsilon^{.0109}$).[13]

[Please insert Table 3 about here.]

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. For the first specification reported in Table 4, the clean patents over book ($Pat\_clean/Book$) is positively associated with the Tobin's Q at an economic impact of 3.77%. We also find that the clean citation over book ($Cit\_clean/Book$) is positively associated with Tobin's Q at an economic impact 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 impact 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 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). 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 cita-

[13] Please refer Table B1 in the Internet Appendix B.

tions 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 4 and t-test can be found in Tables B2 and B6 (Panel A) in the Internet Appendix B, respectively.

[Please insert Table 4 about here.]

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

We also adopt the Fama-MacBeth estimator to assess the Models in Table 4 and this confirms the clean innovation premium reported in Table 4. The economic impact of clean innovation productivity and efficiency is similar to those derived from Table 4, with the exception of clean patent productivity ($Pat\_clean/Book$), which is three fold of the corresponding clean patent productivity ($Pat\_clean/Book$) derived from Table 4.

[Please insert Table 5 about here.]

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, as mentioned above, 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 intrinsic differences in the type of firms conducting clean or dirty innovation. Therefore, we estimate the models reported in Table 4 for the sub-sample of firms producing both clean and dirty technologies. 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%.[14] 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 statistically different from zero at a 5% level. Also, the difference 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 t-test can be found in Tables B3 and B6 (Panel B) in the Internet Appendix B, respectively.

[Please insert Table 6 about here.]

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

We are skeptical of the results reported in Table 4 as it possible that the estimates of clean innovation productivity and efficiency may be relaying the effect of emerging technologies on the firm's Tobin's Q. 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,[15]

[14]We estimate our baseline Models for the sample of firms with non-zero patents (See Tables D2 and D3 in the Internet Appendix D). 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.

[15]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.

and we extend the Models reported in Table 4 to include the patent and citation productivity ($Pat\_emtech/Book$, $Cit\_emtech/Book$) in emerging technologies and the corresponding efficiency variables (Pat_emtech/RDC, Cit_emtech/RD) as controls. We find no substantial change in the estimates of clean innovation productivity and innovation efficiency. This substantiates the results reported in Table 4.[16] 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 t-test can be found in Tables B4 and B6 (Panel C) in the Internet Appendix B, respectively[17].

[Please insert Table 7 about here.]

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

As a robustness test, 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 et al. (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

[16] 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 D5 in the Internet Appendix D). 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 D4 in the Internet Appendix D).

[17] We also adopt the Fama-MacBeth estimator to assess these Models. We find that the economic impact of clean innovation productivity and efficiency is similar to those derived from Table 7. Please refer Table E2 in the Internet Appendix E.

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 impact of 1.04% on the 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 t-test can be found in Tables B5 and B6 (Panel D and E) in the Internet Appendix B, respectively.

[Please insert Table 8 about here.]

Further, these Models are estimated using the Fama-MacBeth estimator and our main results of the stock market that yield significantly more value to clean as opposed to dirty innovation productivity and innovation efficiency remain unchanged.[18] [19]

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 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 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.[20]

[18]Please refer Table E3 in the Internet Appendix E.

[19]The main results hold even when we construct the innovation productivity and efficiency variables with respect to the grant date instead of publication date.

[20]Please refer Table D1 in the Internet Appendix D.

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). 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 $Emtech\_firm$,[21] $Total\_assets$, $EPSlag1 - EPSlag6$, the full set of control variables, year and industry dummies.

$$Clean\_firm = \alpha + \gamma_1 Emtech\_firm_i + \gamma_2 RDG_{it} + \gamma_3 invBE_{it} + \gamma_4 taxRDBE_{it} + \gamma_5 CEME_{it} \quad (21)$$

$$+\gamma_6 Earning_{\text{abnormal it}} + \gamma_7 Adverts_{it} + \gamma_8 Total\_assets + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

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.

[Please insert Table 9 about here.]

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 ($Pat\_clean/Book$) and Tobin's Q and this result is statistically significant at 5%. We also find a negative and significant association between dirty citation

[21] 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.

productivity ($Cit\_dirty/Book$) and efficiency variables (Cit_dirty/RD) with the Tobin's Q.[22]

To check if clean innovation and innovation efficiency are biased upwards, we include the patent and citation productivity and efficiency with respect to emerging technologies and find that the results do not change substantially.[23] These Models were estimated using Non-linear least squares method.

Additionally, we estimate these Models using 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 impact of generating clean patents and the efficiency with which these clean patents are generated.[24]

Further, we estimate the influence of 'clean' and 'dirty' innovation productivity and efficiency variables on the 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 et al. (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.

6 Conclusion

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

[22]Please refer Table C2 in the Internet Appendix C.
[23]Please refer Table C3 in the Internet Appendix C.
[24]Please refer Tables C5 and C6 in the Internet Appendix C.

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 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. 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 et al. (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 Deng et al. (1999); Chan et al. (2001) innovation productivity measure and Hirshleifer et al. (2013) innovation efficiency measures 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 association, 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 firm traits frequently used in respect to asset pricing.

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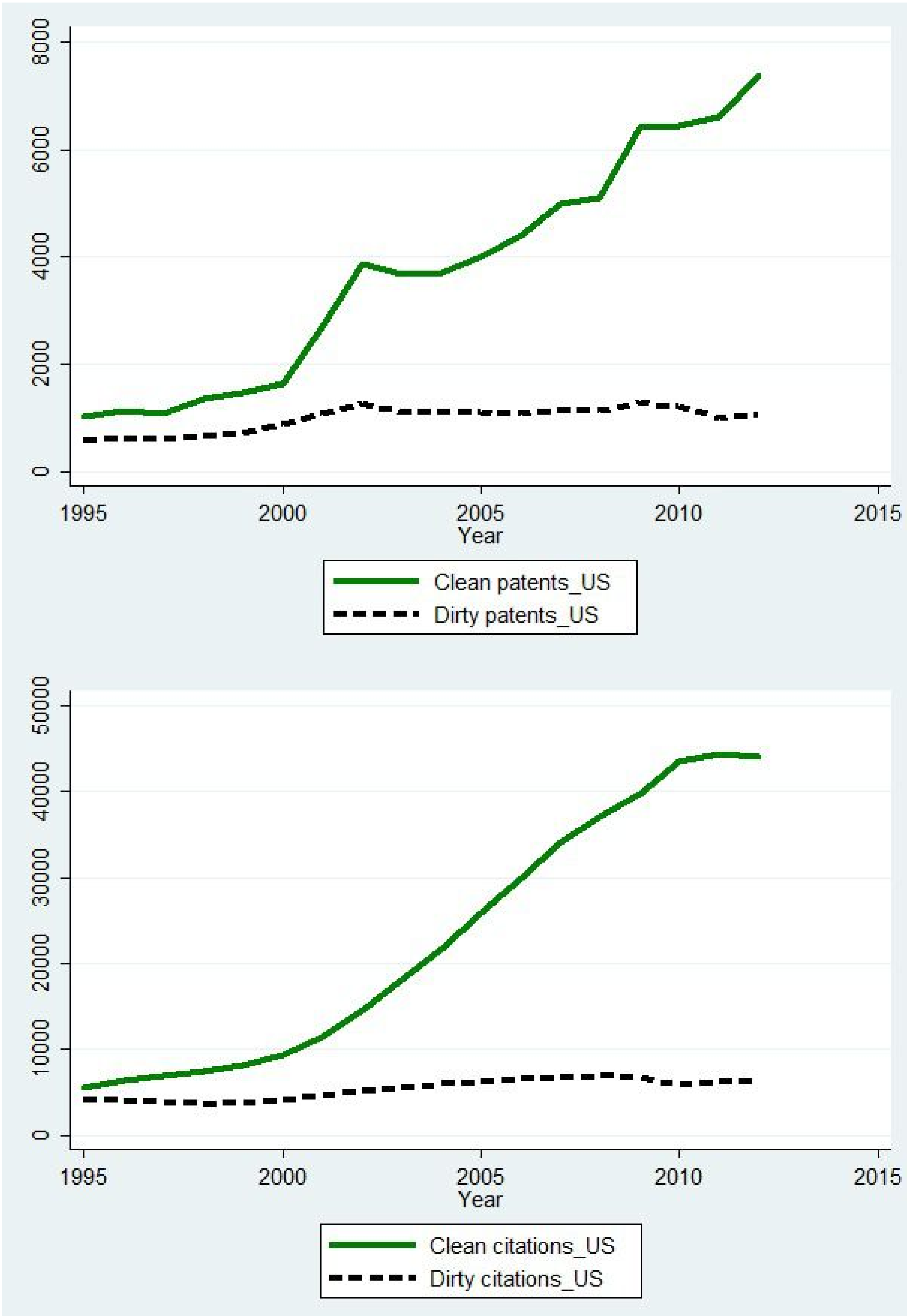
Table 1: Variable Definitions

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 Intensity	
RDBE	Research and Development expense divided by Book.
Measures of Innovation Intensity	
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 Kozluk, 2014); This index takes the value from 0 (least stringent) to 6 (most stringent) and is a country-specific stringency measure.

Figure 1: Clean and dirty patents and citations



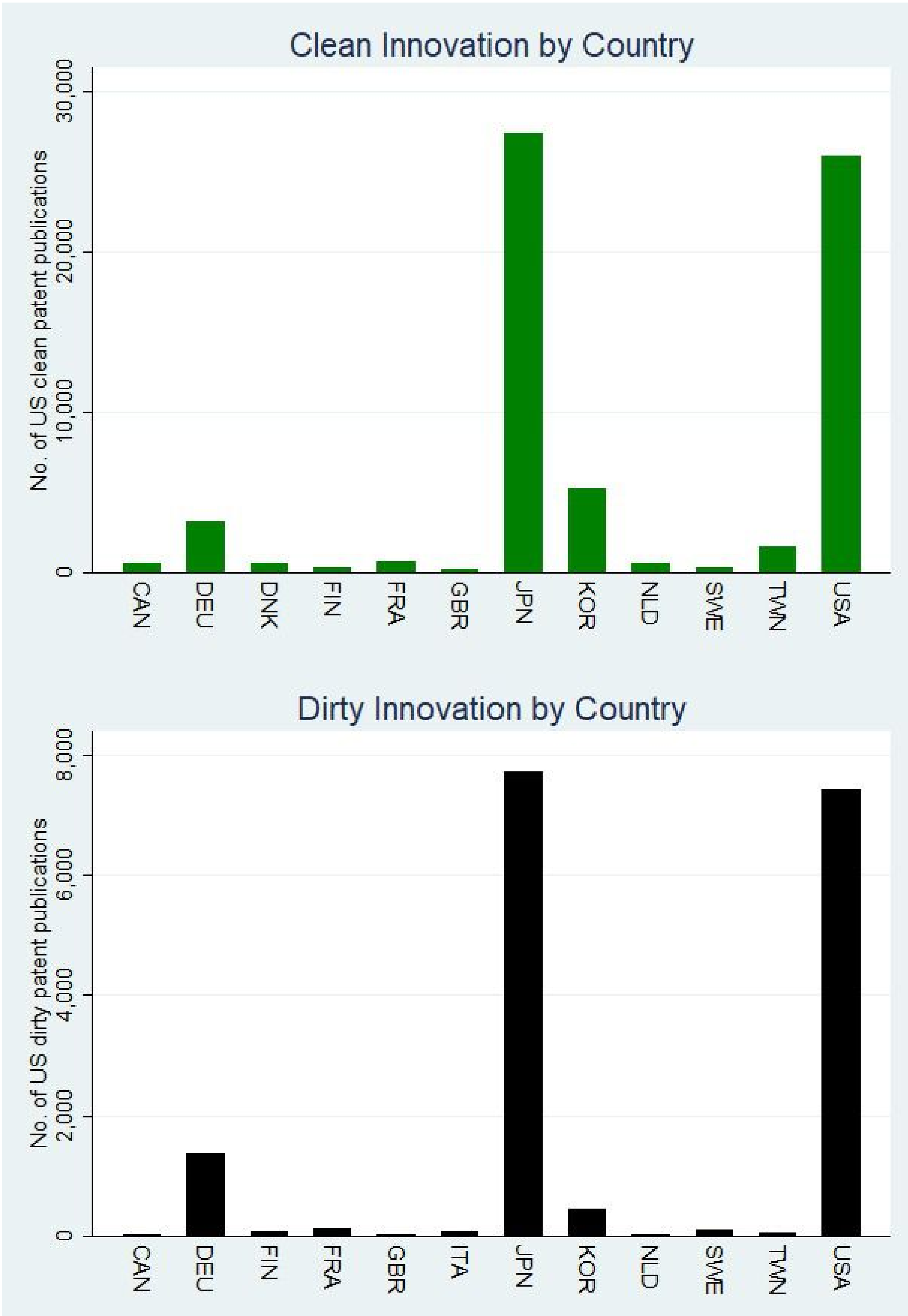
Notes. The Figure shows, over time, the number of published patents in clean and dirty technologies in the US (upper Panel) and shows related citations, accumulated in a 5-year window, in regard to clean and dirty innovations (lower Panel). We refer to Clean (Dirty) patents_US as the total number of 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.

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

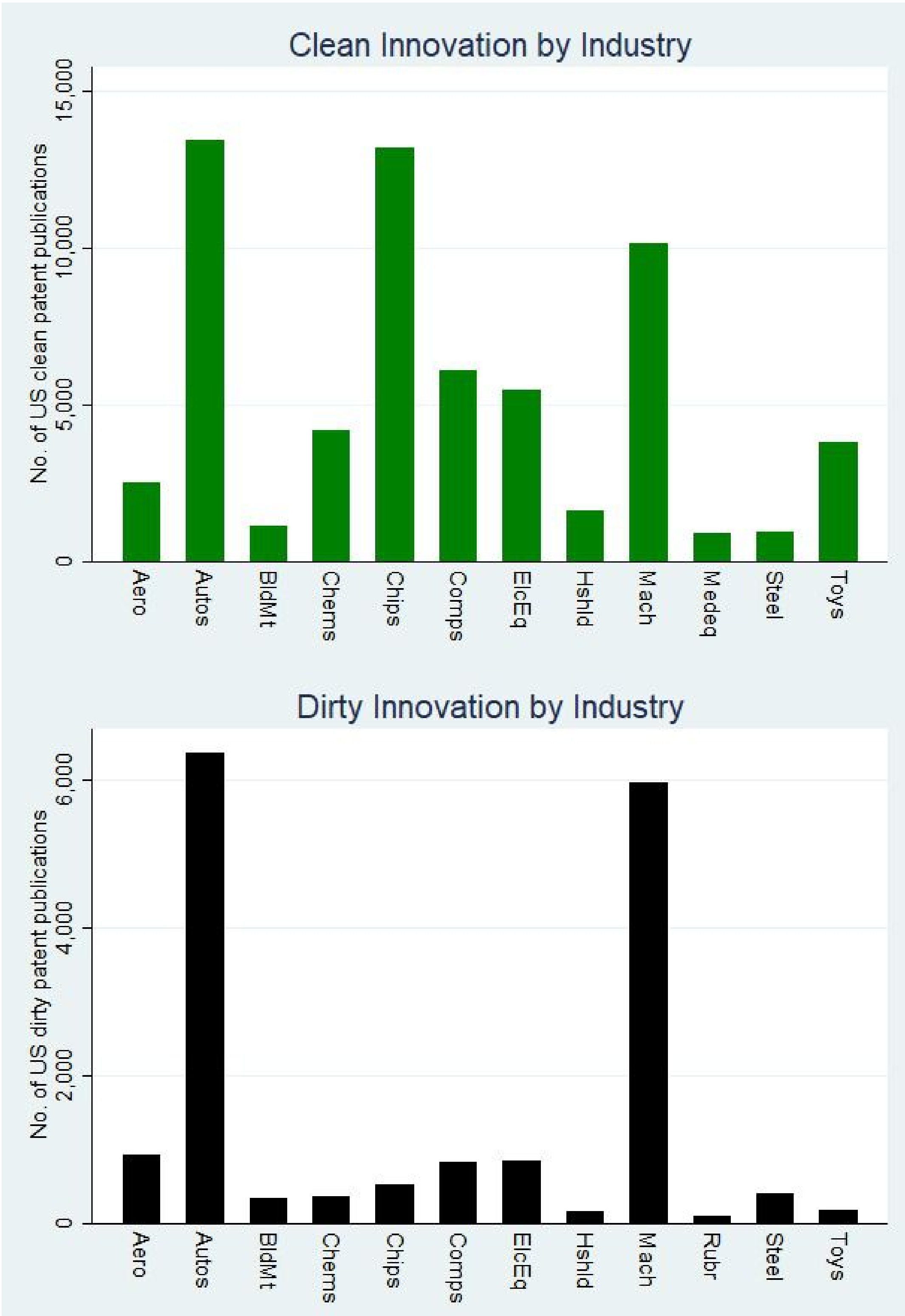
Notes. The Table presents summary statistics for Innovation productivity variables (RDBE, Pat/Book, Pat*/Book, Cit/Book and Cit*/Book), Innovation efficiency variables (Pat/RDC, Pat*/RDC, Cit/RD and Cit*/RD) and variables controlling for firm traits (Hirshleifer et al., 2013) during the period 1995-2012.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

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.

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 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	79285	79285	79285	79284	79285	79284
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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/Book_{it} + \gamma_3 Cit/Book_{it} + \sum_{i=1996}^{2012} \kappa_i year_i + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 4-6)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/RDC_{it} + \gamma_3 Cit/RD_{it} + \sum_{i=2}^{17} \kappa_i year_i + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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	79285	79285	79284	79284
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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

and the Model (columns 3 and 4)

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

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.

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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)
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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et. al., 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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)
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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \gamma_4 RDG_{it} + \gamma_5 invBE_{it} + \gamma_6 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 \gamma_3 Cit^*/RD_{it} + \gamma_4 RDG_{it} + \gamma_5 invBE_{it} + \gamma_6 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 2005 and Hirshleifer et al., 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 * $p < 0.05$, **

Table 9: Heckman sample selection 2^{nd} 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 2^{nd} stage Heckman Model

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \gamma_4 RDG_{it} + \gamma_6 invBE_{it} + \gamma_5 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

The likelihood of a firm to conduct clean innovation is modeled in the 1^{st} stage of Heckman sample selection Model

$$Clean\_firm = \alpha + \gamma_1 Emtech\_firm_i + \gamma_2 RDG_{it} + \gamma_3 invBE_{it} + \gamma_4 taxRDBE_{it} + \gamma_5 CEME_{it} + \gamma_6 Earning_{\text{abnormal it}} + \gamma_7 Adverts_{it} + \gamma_8 Total\_assets + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

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 2^{nd} 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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Internet Appendices A-E (supplementary material) for "Is firm-level clean or dirty innovation valued more?"

Internet Appendix A

Table A1: Clean Patent classification codes

Patent code	Definition
Y02E	REDUCTION OF GREENHOUSE GAS [GHG] EMISSIONS, RELATED TO ENERGY GENERATION, TRANSMISSION OR DISTRIBUTION
Y02E10/00	Energy generation through renewable energy sources
Y02E20/00	Combustion technologies with mitigation potential
Y02E30/00	Energy generation of nuclear origin
Y02E40/00	Technologies for an efficient electrical power generation, transmission or distribution
Y02E50/00	Technologies for the production of fuel of non-fossil origin
Y02E60/00	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation
Y02E70/00	Other energy conversion or management systems reducing GHG emissions
Y02C	CAPTURE, STORAGE, SEQUESTRATION OR DISPOSAL OF GREENHOUSE GASES [GHG]
Y02C10/00	CO2 capture or storage
Y02C20/00	Capture or disposal of greenhouse gases [GHG] other than CO2
Y02T	CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO TRANSPORTATION
Y02T10/00	Road transport of goods or passengers
Y02T30/00	Transportation of goods or passengers via railways
Y02T50/00	Aeronautics or air transport
Y02T70/00	Maritime or waterways transport
Y02T90/00	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation
Y02B	CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO BUILDINGS, e.g. HOUSING, HOUSE APPLIANCES OR RELATED END-USER APPLICATIONS
Y02B10/00	Integration of renewable energy sources in buildings
Y02B20/00	Energy efficient lighting technologies
Y02B30/00	Energy efficient heating, ventilation or air conditioning [HVAC]
Y02B40/00	Technologies aiming at improving the efficiency of home appliances
Y02B50/00	Energy efficient technologies in elevators, escalators and moving walkways
Y02B70/00	Technologies for an efficient end-user side electric power management and consumption
Y02B80/00	Architectural or constructional elements improving the thermal performance of buildings
Y02B90/00	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation

Table A2: Dirty Patent classification codes

Patent code	Definition
C10J	PRODUCTION OF PRODUCER GAS, WATER-GAS, SYNTHESIS GAS FROM SOLID CARBONACEOUS MATERIAL, OR MIXTURES CONTAINING THESE GASES; CARBURETTING AIR OR OTHER GASES
F01K	STEAM ENGINE PLANTS; STEAM ACCUMULATORS; ENGINE PLANTS NOT OTHERWISE PROVIDED FOR; ENGINES USING SPECIAL WORKING FLUIDS OR CYCLES
F02C	GAS-TURBINE PLANTS; AIR INTAKES FOR JET-PROPULSION PLANTS; CONTROLLING FUEL SUPPLY IN AIR-BREATHING JET-PROPULSION PLANTS
F02G	HOT GAS OR COMBUSTION-PRODUCT POSITIVE-DISPLACEMENT ENGINE PLANTS; USE OF WASTE HEAT OF COMBUSTION ENGINES; NOT OTHERWISE PROVIDED FOR
F22	STEAM GENERATION
F23	COMBUSTION APPARATUS; COMBUSTION PROCESSES
F27	FURNACES; KILNS; OVENS; RETORTS
F02B	INTERNAL-COMBUSTION PISTON ENGINES; COMBUSTION ENGINES IN GENERAL

Table A3: Emerging Technologies Patent classification codes

Patent code	Definition
Nanotechnology	
B82	NANOTECHNOLOGY
GMO	
C12N/15	Mutation or genetic engineering; DNA or RNA concerning genetic engineering, vectors, e.g. plasmids, or their isolation, preparation or purification; Use of hosts therefor
3D	
H04N/13	Stereoscopic video systems; Multi-view video systems; Details thereof
Wireless	
H04W	WIRELESS COMMUNICATION NETWORKS
Robots	
B25J	MANIPULATORS; CHAMBERS PROVIDED WITH MANIPULATION DEVICES
IT	
G06 (excl G06Q)	COMPUTING; CALCULATING; COUNTING
G10L	SPEECH ANALYSIS OR SYNTHESIS; SPEECH RECOGNITION; SPEECH OR VOICE PROCESSING; SPEECH OR AUDIO CODING OR DECODING
Biotechnology	
C07G	COMPOUNDS OF UNKNOWN CONSTITUTION
C07K	PEPTIDES
C12M	APPARATUS FOR ENZYMOLOGY OR MICROBIOLOGY
C12N	MICROORGANISMS OR ENZYMES; COMPOSITIONS THEREOF
C12P	FERMENTATION OR ENZYME-USING PROCESSES TO SYNTHESISE A DESIRED CHEMICAL COMPOUND OR COMPOSITION OR TO SEPARATE OPTICAL ISOMERS FROM A RACEMIC MIXTURE
C12Q	MEASURING OR TESTING PROCESSES INVOLVING ENZYMES, NUCLEIC ACIDS OR MICROORGANISMS; COMPOSITIONS OR TEST PAPERS THEREFOR; PROCESSES OF PREPARING SUCH COMPOSITIONS; CONDITION-RESPONSIVE CONTROL IN MICROBIOLOGICAL OR ENZYMOLOGICAL PROCESSES
C12R	MICROORGANISMS

Internet Appendix B

Table B1: Semi-elasticities for determining the impact of aggregated Innovation productivity and efficiency variables on Tobin's Q for the Models reported in Table 3

	(1)	(2)	(3)	(4)	(5)	(6)
RDBE	.8350	.7970	.7900	.9362	.9265	.9267
	(.0490)	(.0494)	(.0494)	(.0500)	(.0493)	(.0493)
Pat/Book	.5302		.1533			
	(.0884)		(.0790)			
Cit/Book		.1281	.1073			
		(.0188)	(.0199)			
Pat/RDC				.0030		.0005
				(.0012)		(.0005)
Cit/RD					.0109	.0108
					(.0020)	(.0020)
Observations	79285	79285	79285	79284	79285	79284

Notes. The Table presents the semi-elasticities with respect to Innovation productivity and efficiency variables for various specifications (columns 1-3) of the Model

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/Book_{it} + \gamma_3 Cit/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 4-6)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/RDC_{it} + \gamma_3 Cit/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 2005. Our dependent variable is the natural logarithm of Tobin's Q and we report standard errors estimated using delta method in parentheses. All the variables are defined in Table 1.

Table B2: Semi-elasticities for determining the impact of disaggregated Innovation productivity and efficiency variables on Tobin's Q for the Models reported in Table 4

	(1)	(2)	(3)	(4)
RDBE	.7888	.7889	.9267	.9253
	(.0494)	(.0494)	(.0493)	(.0493)
Pat_clean/Book	1.3270			
	(.4504)			
Pat_dirty/Book	-.7156			
	(.4055)			
Pat_other/Book	.1251			
	(.0800)			
Cit/Book	.1061			
	(.0200)			
Cit_clean/Book		.2370		
		(.0854)		
Cit_dirty/Book		-.0645		
		(.0770)		
Cit_other/Book		.1022		
		(.0211)		
Pat/Book		.1588		
		(.0796)		
Pat_clean/RDC			.0434	
			(.0276)	
Pat_dirty/RDC			-.0261	
			(.0101)	
Pat_other/RDC			.0004	
			(.0005)	
Cit/RD			.0106	
			(.0020)	
Cit_clean/RD				.0372
				(.0173)
Cit_dirty/RD				-.0041
				(.0035)
Cit_other/RD				.0100
				(.0019)
Pat/RDC				.0004
				(.0005)
Observations	79285	79285	79284	79284

Notes. The Table presents the semi-elasticities with respect to Innovation productivity and efficiency variables for various specifications (columns 1-2) of the Model

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 2005. Our dependent variable is the natural logarithm of Tobin's Q and we report standard errors estimated using delta method in parentheses. All the variables are defined in Table 1.

Table B3: Semi-elasticities for determining the impact of disaggregated Innovation productivity and efficiency variables on Tobin's Q for the Models reported in Table 6

	(1)	(2)	(3)	(4)
RDBE	.0381	.0103	.0773	.0731
	(.0525)	(.0354)	(.0443)	(.0423)
Pat_clean/Book	1.9078			
	(.8606)			
Pat_dirty/Book	-.3194			
	(.6613)			
Pat_other/Book	-.1221			
	(.1640)			
Cit/Book	.0738			
	(.0312)			
Cit_clean/Book		.3870		
		(.0720)		
Cit_dirty/Book		-.0022		
		(.0276)		
Cit_other/Book		.0476		
		(.0259)		
Pat/Book		-.0311		
		(.0910)		
Pat_clean/RDC			.0078	
			(.0180)	
Pat_dirty/RDC			-.0205	
			(.0096)	
Pat_other/RDC			.0051	
			(.0075)	
Cit/RD			.0038	
			(.0056)	
Cit_clean/RD				.0544
				(.0416)
Cit_dirty/RD				-.0095
				(.0031)
Cit_other/RD				-.0010
				(.0027)
Pat/RDC				-.0016
				(.0025)
Observations	6593	6593	6593	6593

Notes. The Table presents the semi-elasticities with respect to Innovation productivity and efficiency variables for various specifications (columns 1-2) of the Model

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 2005. Our dependent variable is the natural logarithm of Tobin's Q and we report standard errors estimated using delta method in parentheses. All the variables are defined in Table 1.

Table B4: Semi-elasticities for determining the impact of disaggregated Innovation productivity and efficiency variables, including emerging technology variants of Innovation productivity and efficiency variables on Tobin's Q for the Models reported in Table 7

	(1)	(2)	(3)	(4)
RDBE	.7891	.7885	.9254	.9192
	(.0494)	(.0494)	(.0493)	(.0492)
Pat_clean/Book	1.3177			
	(.4437)			
Pat_dirty/Book	-.6945			
	(.4174)			
Pat_emtech/Book	.4700			
	(.2611)			
Pat_other/Book	.0611			
	(.0791)			
Cit/Book	.1043			
	(.0199)			
Cit_clean/Book		.2332		
		(.0831)		
Cit_dirty/Book		-.0604		
		(.0792)		
Cit_emtech/Book		.1837		
		(.0601)		
Cit_other/Book		.0852		
		(.0243)		
Pat/Book		.1528		
		(.0793)		
Pat_clean/RDC			.0339	
			(.0295)	
Pat_dirty/RDC			-.0248	
			(.0096)	
Pat_emtech/RDC			.1440	
			(.0316)	
Pat_other/RDC			.00002	
			(.00034)	
Cit/RD			.0091	
			(.0019)	
Cit_clean/RD				.0348
				(.0167)
Cit_dirty/RD				-.0038
				(.0036)
Cit_emtech/RD				.0560
				(.0116)
Cit_other/RD				.0061
				(.0018)
Pat/RDC				.0004
				(.0005)
Observations	79,285	79,285	79,284	79,284

Notes. The Table presents the semi-elasticities with respect to Innovation productivity and efficiency variables for various specifications (columns 1-2) of the Model

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 2005. Our dependent variable is the natural logarithm of Tobin's Q and we report standard errors estimated using delta method in parentheses. All the variables are defined in Table 1.

Table B5: Semi-elasticities for determining the impact of disaggregated Innovation productivity and efficiency variables, including emerging technology variants of Innovation productivity and efficiency variables on Tobin's Q for the Models reported in Table 8

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RDBE	.2976	.2978	.2150	.2148	.2966	.2978	.2137	.2134
	(.0311)	(.0311)	(.0245)	(.0245)	(.0310)	(.0311)	(.0244)	(.0245)
Pat_clean/Book	.5948				.5940			
	(.4461)				(.4439)			
Pat_dirty/Book	.4501				.4525			
	(.8513)				(.8524)			
Pat_emtech/Book					.2797			
					(.2480)			
Pat_other/Book	.2027				.1895			
	(.0857)				(.0862)			
Cit/Book	.0568				.0567			
	(.0148)				(.0147)			
Cit_clean/Book		.1316				.1317		
		(.0803)				(.0803)		
Cit_dirty/Book		-.0139				-.0139		
		(.0387)				(.0386)		
Cit_emtech/Book						.0536		
						(.0385)		
Cit_other/Book		.0545				.0547		
		(.0152)				(.0178)		
Pat/Book		.2161				.2161		
		(.0851)				(.0854)		
Pat_clean/RDC			.0396				.0296	
			(.0263)				(.0291)	
Pat_dirty/RDC			-.0204				-.0190	
			(.0137)				(.0131)	
Pat_emtech/RDC							.1351	
							(.0289)	
Pat_other/RDC			.0009				.0002	
			(.0008)				(.0005)	
Cit/RD			.0062				.0050	
			(.0016)				(.0015)	
Cit_clean/RD				.0418				.0401
				(.0195)				(.0194)
Cit_dirty/RD				-.0015				-.0014
				(.0006)				(.0006)
Cit_emtech/RD								.0369
								(.0090)
Cit_other/RD				.0058				.0031
				(.0015)				(.0013)
Pat/RDC				.0010				.0010
				(.0008)				(.0008)
Observations	87,800	87,800	87,799	87,799	87,800	87,800	87,799	87,799

Notes. The Table presents the semi-elasticities with respect to Innovation productivity and efficiency variables for various specifications (columns 1, 2, 5 and 6) of the Model

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \gamma_4 RDG_{it} + \gamma_5 invBE_{it} + \gamma_6 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \gamma_4 RDG_{it} + \gamma_5 invBE_{it} + \gamma_6 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 2005. Our dependent variable is the natural logarithm of Tobin's Q and we report standard errors estimated using delta method in parentheses. All the variables are defined in Table 1.

Table B6: The Table reports the nonlinear hypothesis for the coefficients from the Models reported in Tables 4, 6, 7, and 8

t Test for Non-linear least squares estimation	Chi^2	$Prob > Chi^2$
Pat_clean/Book - Pat_dirty/Book = 0	8.58	0.0034
Cit_clean/Book - Cit_dirty/Book = 0	6.28	0.0122
Pat_clean/RDC - Pat_dirty/RDC = 0	6.36	0.0116
Cit_clean/RD - Cit_dirty/RD = 0	5.81	0.0160

(a) Panel A: Test for Non-linear hypotheses after estimation for the Models reported in Table 4

t Test for Non-linear least squares estimation	Chi^2	$Prob > Chi^2$
Pat_clean/Book - Pat_dirty/Book = 0	3.75	0.0528
Cit_clean/Book - Cit_dirty/Book = 0	26.19	0.0000
Pat_clean/RDC - Pat_dirty/RDC = 0	2.50	0.1141
Cit_clean/RD - Cit_dirty/RD = 0	2.38	0.1233

(b) Panel B: Test for Non-linear hypotheses after estimation for the Models reported in Table 6

t Test for Non-linear least squares estimation	Chi^2	$Prob > Chi^2$
Pat_clean/Book - Pat_dirty/Book = 0	8.38	0.0038
Cit_clean/Book - Cit_dirty/Book = 0	5.99	0.0144
Pat_clean/RDC - Pat_dirty/RDC = 0	3.44	0.0638
Cit_clean/RD - Cit_dirty/RD = 0	5.41	0.0201

(c) Panel C: Test for Non-linear hypotheses after estimation for the Models reported in Table 7

t Test for Non-linear least squares estimation	Chi^2	$Prob > Chi^2$
Pat_clean/Book - Pat_dirty/Book = 0	0.02	0.8822
Cit_clean/Book - Cit_dirty/Book = 0	2.62	0.1057
Pat_clean/RDC - Pat_dirty/RDC = 0	5.74	0.0166
Cit_clean/RD - Cit_dirty/RD = 0	4.90	0.0268

(d) Panel D: Test for Non-linear hypotheses after estimation for the Models (1-4) reported in Table 8

t Test for Non-linear least squares estimation	Chi^2	$Prob > Chi^2$
Pat_clean/Book - Pat_dirty/Book = 0	0.02	0.8848
Cit_clean/Book - Cit_dirty/Book = 0	2.62	0.1054
Pat_clean/RDC - Pat_dirty/RDC = 0	2.78	0.0957
Cit_clean/RD - Cit_dirty/RD = 0	4.57	0.0326

(e) Panel E: Test for Non-linear hypotheses after estimation for the Models (5-8) reported in Table 8

Internet Appendix C

Robustness tests for the patents and citations published by the European Patent Office (EPO). We study the influence of the innovation productivity and efficiency variables on the Tobin's Q of firms. The firms in this study have their headquarters in any of the top 12 clean innovation producing countries

Table C1: Tobin's Q as a function of aggregated Innovation productivity and efficiency variables

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.2420***	0.2390***	0.2410***	0.2440***	0.2430***	0.2440***
	(0.0361)	(0.0359)	(0.0360)	(0.0369)	(0.0370)	(0.0369)
RDBE	0.6480***	0.8090***	0.7160***	0.261***	0.2600***	0.2610***
	(0.0432)	(0.0545)	(0.0502)	(0.0199)	(0.0199)	(0.0199)
Pat/Book	1.9310***		1.5550***			
	(0.1860)		(0.2410)			
Cit/Book		0.1060***	0.0282*			
		(0.0121)	(0.0139)			
Pat/RDC				0.0262***		0.0255***
				(0.0059)		(0.0058)
Cit/RD					0.0016	0.0007
					(0.0009)	(0.0008)
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	87800	87800	87800	87800	87800	87800
Adjusted R^2	0.2040	0.2000	0.2040	0.1900	0.1900	0.1900

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/Book_{it} + \gamma_3 Cit/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 4-6)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/RDC_{it} + \gamma_3 Cit/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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 C2: Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables

	(1)	(2)	(3)	(4)
Intercept	0.2410***	0.2410***	0.2440***	0.2440***
	(0.0360)	(0.0360)	(0.0369)	(0.0369)
RDBE	0.7150***	0.7300***	0.2610***	0.2610***
	(0.0503)	(0.0514)	(0.0199)	(0.0199)
Pat_clean/Book	3.3150*			
	(1.3620)			
Pat_dirty/Book	0.8690			
	(1.1040)			
Pat_other/Book	1.5020***			
	(0.2430)			
Cit/Book	0.0301*			
	(0.0139)			
Cit_clean/Book		0.0011		
		(0.0024)		
Cit_dirty/Book		-0.0624***		
		(0.0102)		
Cit_other/Book		0.0330*		
		(0.0148)		
Pat/Book		1.5030***		
		(0.2430)		
Pat_clean/RDC			0.0304	
			(0.0239)	
Pat_dirty/RDC			-0.0336	
			(0.0448)	
Pat_other/RDC			0.0259***	
			(0.0062)	
Cit/RD			0.0008	
			(0.0008)	
Cit_clean/RD				0.0004
				(0.0025)
Cit_dirty/RD				-0.0011***
				(0.0001)
Cit_other/RD				0.0011
				(0.0010)
Pat/RDC				0.0253***
				(0.0057)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	87800	87800	87800	87800
Adjusted R^2	0.2040	0.2040	0.1900	0.1900

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C3: 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	0.2410***	0.2410***	0.2440***	0.2440***
	(0.0360)	(0.0360)	(0.0369)	(0.0369)
RDBE	0.7140***	0.7360***	0.2600***	0.261***
	(0.0503)	(0.0524)	(0.0199)	(0.0199)
Pat_clean/Book	3.2350*			
	(1.3590)			
Pat_dirty/Book	0.8810			
	(1.1200)			
Pat_emtech/Book	2.2050***			
	(0.6400)			
Pat_other/Book	1.3570***			
	(0.2540)			
Cit/Book	0.0354*			
	(0.0144)			
Cit_clean/Book		0.0012		
		(0.0024)		
Cit_dirty/Book		-0.0623***		
		(0.0101)		
Cit_emtech/Book		0.0029		
		(0.0304)		
Cit_other/Book		0.0345*		
		(0.0152)		
Pat/Book		1.4970***		
		(0.2430)		
Pat_clean/RDC			0.0282	
			(0.0218)	
Pat_dirty/RDC			-0.0265	
			(0.0435)	
Pat_emtech/RDC			0.1660**	
			(0.0630)	
Pat_other/RDC			0.0196***	
			(0.0058)	
Cit/RD			0.0003	
			(0.0008)	
Cit_clean/RD				0.0003
				(0.0024)
Cit_dirty/RD				-0.0011***
				(0.0001)
Cit_emtech/RD				0.0016*
				(0.0008)
Cit_other/RD				0.0008
				(0.0016)
Pat/RDC				0.0253***
				(0.0057)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	87800	87800	87800	87800
Adjusted R^2	0.2040	0.2040	0.1910	0.1900

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C4: Tobin's Q as a function of aggregated Innovation productivity and efficiency variables, estimated using Fama-MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0381	0.0382	0.0381	0.0381	0.0381	0.0381
	(0.0249)	(0.0249)	(0.0249)	(0.0249)	(0.0249)	(0.0249)
RDBE	0.0867***	0.0868***	0.0860***	0.0879***	0.0878***	0.0879***
	(0.0177)	(0.0188)	(0.0177)	(0.0189)	(0.0189)	(0.0189)
Pat/Book	0.3430***		0.4060***			
	(0.1150)		(0.1350)			
Cit/Book		0.0251***	-0.0020			
		(0.0060)	(0.0103)			
Pat/RDC				0.0089***		0.0095***
				(0.0022)		(0.0023)
Cit/RD					0.0004	-9.45e-05
					(0.0005)	(0.0005)
Industry FE	YES	YES	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO	NO	NO
Observations	87,800	87,800	87,800	87,800	87,800	87,800
avg. R-squared	0.1810	0.1770	0.1820	0.1770	0.1760	0.1770

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

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat/Book_{it} + \gamma_3 Cit/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

and the Model (columns 4-6)

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

that are estimated using Fama-MacBeth method. These Models test whether the knowledge creation process acts as a continuum from R&D to patents and citations and tests 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 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.

Table C5: Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables, estimated using Fama-MacBeth regressions

	(1)	(2)	(3)	(4)
Intercept	0.0381	0.0381	0.0381	0.0381
	(0.0249)	(0.0249)	(0.0249)	(0.0249)
RDBE	0.0860***	0.0862***	0.0879***	0.0879***
	(0.0177)	(0.0177)	(0.0188)	(0.0189)
Pat_clean/Book	4.1090***			
	(1.3970)			
Pat_dirty/Book	0.7770			
	(0.9080)			
Pat_other/Book	0.4100***			
	(0.1340)			
Cit/Book	-0.0029			
	(0.0101)			
Cit_clean/Book		0.1970		
		(0.1430)		
Cit_dirty/Book		-0.2280		
		(0.2300)		
Cit_other/Book		-0.0013		
		(0.0107)		
Pat/Book		0.4210***		
		(0.1380)		
Pat_clean/RDC			0.1520*	
			(0.0855)	
Pat_dirty/RDC			0.0870	
			(0.0954)	
Pat_other/RDC			0.0102***	
			(0.0029)	
Cit/RD			-1.04e-06	
			(0.0006)	
Cit_clean/RD				-0.0093
				(0.0069)
Cit_dirty/RD				-0.0145
				(0.0161)
Cit_other/RD				0.0002
				(0.0006)
Pat/RDC				0.0101***
				(0.0027)
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	87,800	87,800	87,800	87,800
avg. R-squared	0.1830	0.1830	0.1780	0.1770

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

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

and the Model (columns 3 and 4)

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

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.

Table C6: Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables, including emerging technology variants of Innovation productivity and efficiency variables estimated using Fama-MacBeth regressions

	(1)	(2)	(3)	(4)
Intercept	0.0380	0.0380	0.0380	0.0381
	(0.0249)	(0.0249)	(0.0249)	(0.0249)
RDBE	0.0883***	0.0870***	0.0879***	0.0879***
	(0.0171)	(0.0176)	(0.0188)	(0.0189)
Pat_clean/Book	4.0970***			
	(1.3810)			
Pat_dirty/Book	0.6930			
	(0.9070)			
Pat_emtech/Book	0.7940**			
	(0.3010)			
Pat_other/Book	0.3890**			
	(0.1380)			
Cit/Book	0.0033			
	(0.0106)			
Cit_clean/Book		0.1860		
		(0.1420)		
Cit_dirty/Book		-0.2280		
		(0.2300)		
Cit_emtech/Book		0.0959**		
		(0.0403)		
Cit_other/Book		-0.0111		
		(0.0107)		
Pat/Book		0.4310***		
		(0.1390)		
Pat_clean/RDC			0.1450*	
			(0.0823)	
Pat_dirty/RDC			0.0922	
			(0.0961)	
Pat_emtech/RDC			0.0750**	
			(0.0276)	
Pat_other/RDC			0.0097***	
			(0.0031)	
Cit/RD			-0.00027	
			(0.000612)	
Cit_clean/RD				-0.0106
				(0.0073)
Cit_dirty/RD				-0.0140
				(0.0151)
Cit_emtech/RD				0.0028**
				(0.0012)
Cit_other/RD				-0.0003
				(0.0007)
Pat/RDC				0.0103***
				(0.0028)
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	87,800	87,800	87,800	87,800
avg. R-squared	0.1850	0.1830	0.1780	0.1770

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

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

and the Model (columns 3 and 4)

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

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.

Table C7: 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, estimated using Fama-MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.1610***	0.1610***	0.1610***	0.1610***	0.1610***	0.1610***	0.1610***	0.1610***
	(0.0319)	(0.0319)	(0.0319)	(0.0319)	(0.0319)	(0.0319)	(0.0319)	(0.0319)
RDBE	0.0550***	0.0553***	0.0610***	0.0610***	0.0569***	0.0561***	0.0610***	0.0610***
	(0.0145)	(0.0146)	(0.0155)	(0.0155)	(0.0144)	(0.0146)	(0.0155)	(0.0155)
Pat_clean/Book	3.4130***				3.4330***			
	(1.0530)				(1.0430)			
Pat_dirty/Book	0.7030				0.6430			
	(0.7740)				(0.7680)			
Pat_emtech/Book					0.8110***			
					(0.1950)			
Pat_other/Book	0.3880***				0.3850***			
	(0.1160)				(0.1220)			
Cit/Book	-0.0040				-0.0005			
	(0.0103)				(0.0105)			
Cit_clean/Book		0.1910				0.1810		
		(0.1360)				(0.1340)		
Cit_dirty/Book		0.0905				0.0917		
		(0.2450)				(0.2450)		
Cit_emtech/Book						0.0719*		
						(0.0397)		
Cit_other/Book		-0.0033				-0.0111		
		(0.0110)				(0.0103)		
Pat/Book		0.3970***				0.4070***		
		(0.1200)				(0.1200)		
Pat_clean/RDC			0.1190*				0.1140*	
			(0.0657)				(0.0634)	
Pat_dirty/RDC			0.0924				0.0962	
			(0.0810)				(0.0816)	
Pat_emtech/RDC							0.0581**	
							(0.0220)	
Pat_other/RDC			0.0092***				0.0092***	
			(0.0025)				(0.0029)	
Cit/RD			-3.31e-05				-0.0003	
			(0.0006)				(0.0006)	
Cit_clean/RD				-0.0110				-0.0117
				(0.0078)				(0.0081)
Cit_dirty/RD				0.0062				0.0074
				(0.0104)				(0.0107)
Cit_emtech/RD								-0.0005
								(0.0014)
Cit_other/RD				2.31e-05				-0.0003
				(0.0006)				(0.0007)
Pat/RDC				0.0091***				0.0092***
				(0.0023)				(0.0024)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	87,800	87,800	87,800	87,800	87,800	87,800	87,800	87,800
avg. R-squared	0.3030	0.3030	0.2990	0.2980	0.3040	0.3030	0.2990	0.2980

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

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \gamma_4 RDG_{it} + \gamma_6 invBE_{it} + \gamma_5 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

and the Model (columns 2, 4, 7 and 8)

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \gamma_4 RDG_{it} + \gamma_6 invBE_{it} + \gamma_5 taxRDBE_{it} + \gamma_7 CEME_{it} + \gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

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.

Internet Appendix D

This appendix presents additional robustness tests. All the patents and citations are published by USPTO. We study the influence of disaggregated innovation productivity and efficiency variables on the Tobin's Q of firms. The firms in this study have their headquarters in any of the top 12 clean innovation producing countries

Table D1: 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	0.0375	-0.3850***	-0.3040***	-0.3170***
	(6412.6000)	(0.0466)	(0.0469)	(0.0469)
RDBE	0.2910	1.0990***	0.4260***	0.4300***
	(1864.3000)	(0.0853)	(0.0376)	(0.0381)
Pat_clean/Book	-0.3010			
	(1930.8000)			
Pat_dirty/Book	2.7940			
	(17910.6000)			
Pat_emtech/Book	-0.0812			
	(520.2000)			
Pat_other/Book	-0.0397			
	(254.8000)			
Cit/Book	0.0097			
	(61.9500)			
Cit_clean/Book		0.2350		
		(0.2060)		
Cit_dirty/Book		-0.0579		
		(0.4590)		
Cit_emtech/Book		0.1690		
		(0.0916)		
Cit_other/Book		0.2510***		
		(0.0454)		
Pat/Book		0.7520***		
		(0.1990)		
Pat_clean/RDC			0.0617	
			(0.0591)	
Pat_dirty/RDC			-0.0369	
			(0.0265)	
Pat_emtech/RDC			0.3820***	
			(0.0747)	
Pat_other/RDC			0.0003	
			(0.0010)	
Cit/RD			0.0110***	
			(0.0031)	
Cit_clean/RD				0.0771*
				(0.0370)
Cit_dirty/RD				-0.0029*
				(0.0011)
Cit_emtech/RD				0.1110***
				(0.0242)
Cit_other/RD				0.0068*
				(0.0027)
Pat/RDC				0.0021
				(0.0018)
EPSlag1-EPSlag6	0.8310	1.0480***	1.1440***	1.1530***
	(5328.1000)	(0.1970)	(0.1910)	(0.1930)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	66697	66697	66696	66696
Adjusted R^2	0.1880	0.2120	0.1980	0.1980

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \gamma_4(EPSlag1 - EPSlag6) + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \gamma_4(EPSlag1 - EPSlag6) + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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. The Innovation productivity and efficiency variables are defined in Table 1 and we refer to EPSlag1 and EPSlag6 as the one year and six year lag of EPS. And we use the following significance stars * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D2: Tobin's Q as a function of aggregated Innovation productivity and efficiency variables for firms having non-zero patents during the period 1995-2012

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.3040***	0.3070***	0.3070***	0.3010***	0.3030***	0.3030***
	(0.0648)	(0.0645)	(0.0645)	(0.0649)	(0.0659)	(0.0659)
RDBE	0.8380***	0.7720***	0.7620***	0.9800***	0.9790***	0.9800***
	(0.0848)	(0.0830)	(0.0824)	(0.0926)	(0.0929)	(0.0930)
Pat/Book	0.5590***		0.1450			
	(0.1100)		(0.0922)			
Cit/Book		0.1420***	0.1230***			
		(0.0240)	(0.0249)			
Pat/RDC				0.0021*		0.0002
				(0.0011)		(0.0005)
Cit/RD					0.0107***	0.0107***
					(0.0025)	(0.0025)
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	49343	49343	49343	49342	49343	49342
Adjusted R^2	0.2270	0.2300	0.2300	0.2220	0.2250	0.2250

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/Book_{it} + \gamma_3 Cit/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 4-6)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat/RDC_{it} + \gamma_3 Cit/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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. In the above regression models the sample is the firms having non-zero patents during the period 1995-2012. 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 D3: Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables for firms having non-zero patents during the period 1995-2012

	(1)	(2)	(3)	(4)
Intercept	0.3060***	0.3070***	0.3030***	0.3030***
	(0.0645)	(0.0645)	(0.0658)	(0.0658)
RDBE	0.7600***	0.7610***	0.9800***	0.9780***
	(0.0822)	(0.0823)	(0.0929)	(0.0928)
Pat_clean/Book	1.7810**			
	(0.5670)			
Pat_dirty/Book	-0.8650			
	(0.5120)			
Pat_other/Book	0.1050			
	(0.0924)			
Cit/Book	0.1210***			
	(0.0250)			
Cit_clean/Book		0.3190**		
		(0.1140)		
Cit_dirty/Book		-0.0718		
		(0.0936)		
Cit_other/Book		0.1150***		
		(0.0260)		
Pat/Book		0.1510		
		(0.0930)		
Pat_clean/RDC			0.0526	
			(0.0351)	
Pat_dirty/RDC			-0.0291*	
			(0.0127)	
Pat_other/RDC			0.0002	
			(0.0005)	
Cit/RD			0.0105***	
			(0.0024)	
Cit_clean/RD				0.0449*
				(0.0213)
Cit_dirty/RD				-0.0051
				(0.0043)
Cit_other/RD				0.0097***
				(0.0023)
Pat/RDC				0.0002
				(0.0005)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	49343	49343	49342	49342
Adjusted R^2	0.2310	0.2310	0.2260	0.2260

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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 having non-zero patents during the period 1995-2012. 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 D4: Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables, including emerging technology variants of Innovation productivity and efficiency variables for firms having non-zero patents during the period 1995-2012

	(1)	(2)	(3)	(4)
Intercept	0.3060***	0.3070***	0.3030***	0.3050***
	(0.0645)	(0.0645)	(0.0657)	(0.0654)
RDBE	0.7610***	0.7600***	0.9790***	0.9670***
	(0.0824)	(0.0823)	(0.0927)	(0.0918)
Pat_clean/Book	1.7710**			
	(0.5600)			
Pat_dirty/Book	-0.8490			
	(0.5220)			
Pat_emtech/Book	0.3900			
	(0.3010)			
Pat_other/Book	0.0532			
	(0.0914)			
Cit/Book	0.1190***			
	(0.0248)			
Cit_clean/Book		0.3140**		
		(0.1110)		
Cit_dirty/Book		-0.0682		
		(0.0955)		
Cit_emtech/Book		0.1870**		
		(0.0681)		
Cit_other/Book		0.0991***		
		(0.0294)		
Pat/Book		0.1460		
		(0.0924)		
Pat_clean/RDC			0.0413	
			(0.0377)	
Pat_dirty/RDC			-0.0280*	
			(0.0121)	
Pat_emtech/RDC			0.1360***	
			(0.0355)	
Pat_other/RDC			-0.0001	
			(0.0003)	
Cit/RD			0.0093***	
			(0.0023)	
Cit_clean/RD				0.0423*
				(0.0207)
Cit_dirty/RD				-0.0048
				(0.0043)
Cit_emtech/RD				0.0540***
				(0.0128)
Cit_other/RD				0.0060**
				(0.0021)
Pat/RDC				0.0002
				(0.0005)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm-level controls	NO	NO	NO	NO
Observations	49343	49343	49342	49342
Adjusted R^2	0.2310	0.2310	0.2270	0.2280

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et al., 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 having non-zero patents during the period 1995-2012. 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 D5: Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables, including emerging technology variants of Innovation productivity and efficiency variables for firms which conduct both clean and dirty innovation

	(1)	(2)	(3)	(4)
Intercept	1.5020***	1.5060***	1.4820***	1.4850***
	(0.0153)	(0.0128)	(0.0153)	(0.0147)
RDBE	0.0055	0.0020	0.0248	0.0230
	(0.0146)	(0.0112)	(0.0146)	(0.0137)
Pat_clean/Book	0.5490*			
	(0.2770)			
Pat_dirty/Book	-0.1550			
	(0.2020)			
Pat_emtech/Book	-0.1690*			
	(0.0778)			
Pat_other/Book	-0.0219			
	(0.0506)			
Cit/Book	0.0303**			
	(0.0112)			
Cit_clean/Book		0.1230***		
		(0.0220)		
Cit_dirty/Book		-0.0005		
		(0.0087)		
Cit_emtech/Book		0.0106		
		(0.0066)		
Cit_other/Book		0.0205		
		(0.0144)		
Pat/Book		-0.0148		
		(0.0287)		
Pat_clean/RDC			-0.0034	
			(0.0056)	
Pat_dirty/RDC			-0.0046	
			(0.0029)	
Pat_emtech/RDC			0.0339*	
			(0.0161)	
Pat_other/RDC			-0.0041	
			(0.0021)	
Cit/RD			0.0012	
			(0.0018)	
Cit_clean/RD				0.0182
				(0.0135)
Cit_dirty/RD				-0.0028**
				(0.0009)
Cit_emtech/RD				0.0064
				(0.0035)
Cit_other/RD				-0.0013
				(0.0006)
Pat/RDC				-0.0004
				(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	0.2160	0.2180	0.1990	0.2060

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

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

and the Model (columns 3-4)

$$logQ_{it} = \alpha + log(1 + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j) + \epsilon_{it}$$

that are estimated using non-linear least squares method and are in the vein of the Models reported in Hall et. al., 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Internet Appendix E

Table E1: Tobin's Q as a function of aggregated Innovation productivity and efficiency variables, estimated using Fama-MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0409*	0.0411*	0.0411*	0.0405*	0.0372	0.0362
	(0.0219)	(0.0219)	(0.0219)	(0.0218)	(0.0226)	(0.0228)
RDBE	0.2850***	0.2800***	0.2840***	0.3090***	0.3080***	0.3090***
	(0.0288)	(0.0284)	(0.0280)	(0.0364)	(0.0364)	(0.0364)
Pat/Book	0.1740***		0.0712			
	(0.0469)		(0.0676)			
Cit/Book		0.0390***	0.0341**			
		(0.0113)	(0.0159)			
Pat/RDC				0.0044***		0.0024
				(0.0015)		(0.0014)
Cit/RD					0.0037***	0.0037***
					(0.0011)	(0.0011)
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
avg. R-squared	0.1870	0.1890	0.1900	0.1850	0.1870	0.1870

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

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat/Book_{it} + \gamma_3 Cit/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

and the Model (columns 4-6)

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

that are estimated using Fama-MacBeth method. These Models test whether the knowledge creation process acts as a continuum from R&D to patents and citations and tests 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 standard errors in parentheses. All the variables are defined in Table 1 and we use the following significance stars *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table E2: Tobin's Q as a function of disaggregated Innovation productivity and efficiency variables, including emerging technology variants of Innovation productivity and efficiency variables estimated using Fama-MacBeth regressions

	(1)	(2)	(3)	(4)
Intercept	0.0410*	0.0410*	0.0363	0.0373
	(0.0219)	(0.0220)	(0.0226)	(0.0225)
RDBE	0.2880***	0.2880***	0.3080***	0.3080***
	(0.0266)	(0.0258)	(0.0364)	(0.0365)
Pat_clean/Book	2.3010**			
	(0.9200)			
Pat_dirty/Book	-0.3480			
	(1.2570)			
Pat_emtech/Book	0.3090*			
	(0.1600)			
Pat_other/Book	0.0422			
	(0.0724)			
Cit/Book	0.0357**			
	(0.0158)			
Cit_clean/Book		0.2860**		
		(0.1000)		
Cit_dirty/Book		-0.1170		
		(0.2520)		
Cit_emtech/Book		0.1640***		
		(0.0486)		
Cit_other/Book		0.0268		
		(0.0161)		
Pat/Book		0.0461		
		(0.0707)		
Pat_clean/RDC			0.1070**	
			(0.0478)	
Pat_dirty/RDC			0.0246	
			(0.0314)	
Pat_emtech/RDC			0.0787***	
			(0.0181)	
Pat_other/RDC			-0.0005	
			(0.0011)	
Cit/RD			0.0036***	
			(0.0010)	
Cit_clean/RD				0.0240**
				(0.0084)
Cit_dirty/RD				-0.0095
				(0.0085)
Cit_emtech/RD				0.0278**
				(0.0096)
Cit_other/RD				0.0026**
				(0.0009)
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	0.1940	0.1940	0.1890	0.1900

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

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

and the Model (columns 3 and 4)

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

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.

Table E3: 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, estimated using Fama-MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.1610***	0.1610***	0.1590***	0.1590***	0.1610***	0.1610***	0.1600***	0.1590***
	(0.0320)	(0.0320)	(0.0323)	(0.0323)	(0.0320)	(0.0320)	(0.0322)	(0.0323)
RDBE	0.0569***	0.0516***	0.0609***	0.0609***	0.0593***	0.0537***	0.0608***	0.0609***
	(0.0121)	(0.0120)	(0.0155)	(0.0155)	(0.0124)	(0.0128)	(0.0155)	(0.0155)
Pat_clean/Book	1.5640*				1.5490**			
	(0.7390)				(0.7260)			
Pat_dirty/Book	0.2340				0.0946			
	(1.2170)				(1.1950)			
Pat_emtech/Book					0.2910**			
					(0.1160)			
Pat_other/Book	0.1400***				0.1690**			
	(0.0670)				(0.0595)			
Cit/Book	0.0160				0.0146*			
	(0.0094)				(0.0078)			
Cit_clean/Book		0.2090**				0.2050**		
		(0.0979)				(0.0975)		
Cit_dirty/Book		0.0775				0.0688		
		(0.1790)				(0.1750)		
Cit_emtech/Book						0.0301**		
						(0.0138)		
Cit_other/Book		0.0153				0.0158		
		(0.0093)				(0.0095)		
Pat/Book		0.1420**				0.1430**		
		(0.0638)				(0.0599)		
Pat_clean/RDC			0.0976**				0.0888**	
			(0.0393)				(0.0397)	
Pat_dirty/RDC			0.0169				0.0208	
			(0.0421)				(0.0420)	
Pat_emtech/RDC							0.0499***	
							(0.0132)	
Pat_other/RDC			0.0028***				0.0008	
			(0.0009)				(0.0009)	
Cit/RD			0.0015***				0.0013***	
			(0.0004)				(0.0003)	
Cit_clean/RD				0.0172**				0.0177**
				(0.0065)				(0.0063)
Cit_dirty/RD				0.0036				0.0039
				(0.0109)				(0.0110)
Cit_emtech/RD								0.0110***
								(0.0037)
Cit_other/RD				0.0023**				0.0019***
				(0.0008)				(0.0006)
Pat/RDC				0.0031**				0.0029**
				(0.0011)				(0.0012)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	87,800	87,800	87,799	87,799	87,800	87,800	87,799	87,799
avg. R-squared	0.3050	0.3050	0.2990	0.2990	0.3060	0.3060	0.3000	0.3000

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

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/Book_{it} + \gamma_3 Cit^*/Book_{it} + \gamma_4 RDG_{it} + \gamma_6 invBE_{it} + \gamma_5 taxRDBE_{it} + \gamma_7 CEME_{it}$$
$$+\gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

and the Model (columns 2, 4, 7 and 8)

$$logQ_{it} = \alpha + \gamma_1 RDBE_{it} + \gamma_2 Pat^*/RDC_{it} + \gamma_3 Cit^*/RD_{it} + \gamma_4 RDG_{it} + \gamma_6 invBE_{it} + \gamma_5 taxRDBE_{it} + \gamma_7 CEME_{it}$$
$$+\gamma_8 Earning_{\text{abnormal it}} + \gamma_9 Adverts_{it} + \sum_{l=1996}^{2012} \kappa_l year_l + \sum_{j=2}^{48} \beta_j Industry_j + \epsilon_{it}$$

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.