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25 April 2024

OXFORD

Green technologies and firms' market value: a micro-econometric analysis of European firms

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Abstract

This paper investigates the impact of the generation of green (environmental) technologies on the market value (MV) of a sample of listed companies. The analysis is grounded on the combination of two different theoretical approaches, that is the one focusing on the relationship between MV and innovation and the one pertaining to the economic effects of eco-innovation. Environmental regulation, based on the regulatory push–pull effect, induces firms to cope with more stringent rules through innovation efforts, and this eventually leads to the emergence of new markets for the suppliers of green technologies (GTs). Our main hypothesis is that firms able to generate GTs can be expected to show better stock market performances in this framework, because of the prospects of regulation-driven profitability gains. The empirical analysis has been carried out on a sample of listed firms from France, Germany, Italy, the Netherlands, and the UK observed over the 1985–2011 time span, and it is based on the implementation of the most recent version of the MV equation, corrected for selection bias. Results are consistent with those of previous literature and highlight the positive impact of innovation on MV. When narrowing the focus to firms operating in sectors with a high propensity to generate GTs, we have found that the stringency of the environmental regulatory framework also yields a positive a significant impact, as does the stock of GTs vis-à-vis non-GTs. Moreover, environmental regulatory framework positively moderates the positive effect of the stock of GTs. Lastly, the quality of firms' own knowledge stocks is also found to positively influence firms' MV.

JEL classification: JEL classification: O33, Q55

1. Introduction

The estimation of market value (MV) returns of technological innovations has attracted increasing attention over the last few decades. A growing stream of literature has addressed core issues related to the value of patented inventions (Gambardella, 2013). Patents can generate value, because they grant exclusive property rights to the assignees, and hence make firms able to reap the benefits that arise from temporary monopoly power (Bessen, 2009). Moreover,

patents can be viewed as a signal of quality, and thus better performances can be anticipated on the stock markets (Hsu and Ziedonis, 2013).

This conceptual relationship has been investigated in detail. Starting with the seminal work by Griliches (1981), several works have related Tobin's *q* with the intangible capital that enables firms to generate technological knowledge. The main channel concerns the profitability gains that stem from the generation and exploitation of new technological and organizational knowledge (Cockburn and Griliches, 1988; Hall, 1993; Megna and Klock, 1993; Shane and Klock, 1997; Hall *et al.*, 2005; Coad and Rao, 2006; Bloch, 2008).

Empirical investigations have focused on industry- or technology-specific analyses of the MV of patented inventions. However, the literature has so far paid very little attention to how stock markets value the technological efforts of firms in the domain of green technologies (GTs), that is technologies that allow improvements to be made of the environmental performances of products, processes, and services.[1]

In fact, according to Porter and Van der Linde (1995), the introduction of GTs in response to stringent regulatory frameworks might have the twofold effect of improving both environmental and economic performances. Accordingly, most of the extant empirical studies have focused on the impact of "going green" strategies on firms' performances, by looking at firms that adopt green innovations or corporate socially responsible strategies. This literature, in short, analyzes the relationship between the shorter- and longer-term economic performances of firms and environmental strategies, including the adoption of eco-innovation or the implementation of corporate social responsibility approaches (Rennings and Rammer, 2009; Lanoie *et al.*, 2011; Ghisetti and Rennings, 2014; Rexhäuser and Rammer, 2014).

Very few systematic empirical analyses can instead be found about the impact of GTs on the economic performances of the firms that are responsible for their invention and which retain exclusive ownership. Some existing studies have consistently looked at the impact of firms' efforts to generate green knowledge on productivity or sales growth (Marin, 2014; Gagliardi *et al.*, 2016; Colombelli *et al.*, 2019; Leoncini *et al.*, forthcoming). To the best of the authors' knowledge, the framework for the investigation of the MV of innovating firms has rarely been applied to the analysis of the relationship between the patenting of green inventions and firms' MV.

Such a lack of attention seems surprising, in light of the fact that we contend that there is a double rationale behind the expected positive evaluation of stock markets of firms generating green patents. First, as for any kind of technology, the traditional arguments about the positive effects of innovation on MV also hold for GTs. Second, in the case of GTs, this effect should be even stronger, because of the key role played by environmental regulation in triggering the demand for these innovations. The derived demand for GTs, to either comply with environmental regulation or pursue socially responsible corporate strategies, is in turn likely to engender positive expectations concerning the profitability of those firms that generate GTs, thus leading to better evaluations by prospective stockholders.

This paper aims at filling this gap, by combining the conceptual and empirical frameworks that underlie the MV and innovation literature, with an analysis of the economic effects of eco-innovation. In particular, we have attempted to understand the effects of the generation of GTs (treated as a proxy for eco-innovations) on stock market evaluation.

The contribution of the paper to the literature is twofold. First, it contributes to the literature in the field of innovation economics by looking at the specific stock market evaluation of firms that generate GTs. Second and even more importantly, it allows one to extend the traditional framework, based on Porter's hypothesis, according to which

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1   Some empirical investigations have focused more on the impact of firms' environmental performances on market value, by showing, in most of the cases, that negative environmental performances, like toxic chemical releases or oil spills, engender negative performances on the stock markets (Spicer, 1978; Mahapatra, 1984; Jaggi and Freedman, 1992; Konar and Cohen, 2001). However, in recent years, increasing attention has been paid to the analysis of determinants and the effects of eco-innovations, understood as new products, process, or organizational and institutional arrangements that lead to environmental improvements. Within the framework of the natural resource-based view approach (Hart, 1995), many studies have investigated to what extent it pays, or not, to "be green," or, in other terms, whether firms are missing (obtaining) economic opportunities to improve (not improve) their environmental performances (Ambec and Lanoie, 2008). Positive effects (Russo and Fouts, 41997; Dowell *et al.*, 2000; Al-Tuwaijri et al., 2004), and also negative ones (Sarkis and Cordeiro, 2001); and nonsignificant correlations (Jaggi and Freedman, 1992; Elsayed and Paton, 2005; Telle, 2006) have been found in empirical works aimed at assessing the links between green strategies and economic implications.

strict regulatory frameworks trigger the introduction of cleaner technologies and also drive firms' productivity gains. Our paper focuses on the generation rather than on the adoption of environmental (or eco-) innovations by positing that either policymakers, by setting severe targets, in terms of environmental performance or socially responsible corporate strategies, stimulate the demand for GTs. The prospective increasing demand for a firm to generate eco-innovations leads agents operating on the stock market to improve their evaluation. In other words, environmental policies can have an indirect effect, not only on the productivity of adopters, but also on the stock market performances of firms that make eco-innovations available.

The rest of the paper is articulated as it follows. Section 2 presents the MV equation and discusses the main methodological issues. The dataset and the variables used in the empirical analysis are discussed in Section 3. The main results are discussed in Section 4. Section 5 concludes the paper.

2. Environmental regulation, GTs, and MV

An increasing body of literature investigating the determinants and effects of green technological change and eco-innovation,[2] has emerged in the last few years (see Barbieri et al., 2016 for an extensive survey). The motivation for such an interest lies in the expected role of GTs diffusion and eco-innovations adoptions in the decoupling of economic growth from environmental degradation.

Economic literature considers GTs and environmental regulation as being closely intertwined, due to two distinct but related arguments. On one hand, GTs suffer from the so-called "double externality" problem (Rennings, 2000). As for any kind of innovation, one source of externality is due to the public good nature of technological knowledge, and the consequent appropriability problems that keep private investments in innovation activities below the social optimum. The positive environmental impact driven by these technologies represents a further source of externality, because of the social benefits for which firms are not rewarded. In this context, the "regulatory push–pull" effect suggests that policy intervention seems unavoidable to keep investments in GTs at appropriate levels (Frondel et al., 2008; Rennings and Rammer, 2009; Horbach et al., 2012 for a review see Lanjouw and Mody, 1996; Jaffe and Palmer, 1997; Popp, 2002, 2003; Brunnermeier and Cohen, 2003; Del Rìo, 2009).

On the other hand, regulation is deemed to be crucial, due to the well-known Porter hypothesis, according to which stringent environmental regulation yields the twofold impact of triggering eco-innovation and improving firms' environmental and economic performances (Porter and Van der Linde, 1995). A "weak" and a "strong" version of this hypothesis can be identified in the literature, the former being related only to the incentive to eco-innovate, while the latter is also related to the joint effect on economic performance (Jaffe and Palmer, 1997).

The basic mechanism behind these dynamics is based on the inducement effect engendered by stringent environmental regulation. In a similar way to the framework set forth by Hicks (1932), stringent environmental regulation leads to an increase in the production costs of polluting firms. The latter can save polluting costs engendered by regulation, by introducing innovations that allow for the improvement of the environmental impact of production processes (Johnstone et al., 2012; Ghisetti and Quatraro, 2013).[3] The empirical testing of this hypothesis has led to mixed results (Costantini and Mazzanti, 2012; Rexhäuser and Rammer, 2014; Rubashkina et al. 2015; Franco and Marin, 2017), where evidence of positive effects has been found, and also of nil effects or negative ones. This can also be dependent on the endogeneity of the regulation itself, which is correlated with the unobserved determinants of the outcome for example competitiveness (Dechezleprêtre and Sato, 2017). Overall, although mixed evidence is depicted in the literature, it is possible to state that, on one hand, there is evidence that environmental regulation exerts a stimulus on innovation, while relatively less clear-cut support is found for the competitiveness returns of such regulation.

2   We are fully aware of the limitations of using patent applications to proxy for innovations, which are mainly associated with the evidence that not all the patent applications got developed and enter the market becoming real innovations and that not all the relevant innovations are technological and can be patented. Still, we retain that patents are a reliable approximation for knowledge and innovation as discussed into relevant literature (Hall et al., 1986; Acs et al., 2002). Furthermore, in this work our main interest is precisely in the generation (rather than in the adoption) of environmental technologies, thus supporting for the appropriateness of this choice.

3   These arguments are consistent with the literature on innovation studies that is based on the "failure-inducement" hypothesis (Antonelli, 1989) and on the role of creative response to explain a firm's decision to innovate.

The inducement effect also yields an important effect related to the increase or creation of demand-driven incentives for the generation of GTs (Ghisetti and Quatraro, 2013). An undisputable effect of demand-pull deployment policies concerns the creation of new markets for both final and intermediate goods embodying new GTs. The size of these markets is also affected by policy-driven demand, so that prospects for the growth of inventing firms are boosted by policy-induced market growth (Nemet, 2009; Hoppmann *et al.*, 2013; Colombelli *et al.*, 2019).

The literature discussed so far suggests that, by means of inducement dynamics, regulation strengthens existing markets, or creates new market niches for the suppliers of GTs. Not only those firms that adopt green innovation are expected to gain benefits, but also those involved in their generation.

The combination of the literature about the relationship between firms' MV and innovation with that on the analysis of the economic effects of eco-innovation can be far reaching in this respect. This literature originates from the seminal contribution in Griliches' hedonic price model (Griliches, 1981). In this framework, firms are considered as bundles of assets that cannot easily be disentangled and separately priced on the market. Technological knowledge is one of these assets, and specifically one of a firm's intangible assets. The theory assumes that financial markets assign a value to the bundle of a firm's assets, which is equal to the present discounted value of its future cash flows. In other words, if knowledge stock is expected to contribute positively to the future net cash flows of a firm, then the size of this stock should be reflected in the observed MV of the firm[4] (Griliches, 1981; Hall, 1993; Hall *et al.*, 2005; Hall and Oriani, 2006; Bloch, 2008).

Most empirical investigations have used firms' patent applications to derive an approximation of their knowledge stock. Patents show well-known limitations as economic indicators (Griliches, 1990). However, from the theoretical viewpoint, patents seem to be well suited to appreciate how financial markets evaluate a firm's knowledge assets. Several studies have in fact stressed that patents, by approximating a firm's R&D competences, provide signals to external investors that mitigate information asymmetries on financial markets and derive probabilities for the success of R&D-active firms (Henderson and Cockburn, 1994; Harhoff *et al.*, 1999; Arora *et al.*, 2001; Long, 2002; Hottenrott *et al.*, 2015).

The positive evaluation of a firm's patent stock on financial markets is based on the fact that patents raise the prospects of future cash flows and protect firms—at least to some extent—against competition, thus raising the expected profit margins in the future (Levitas and McFadyen, 2009). As discussed above, the prospects for future cash flows for firms involved in the generation of green patents are closely related to the inducement effect played by environmental regulation, and the consequent emergence of new markets for GTs.

The arguments presented so far lead us to set out our basic working hypothesis. Financial markets positively evaluate a firm's knowledge assets, which are deemed to positively affect its future cash flows. Patents can be considered a good proxy for firms' knowledge assets, as they can act as signaling devices that allow information asymmetries to be reduced, by providing investors with the necessary information to make decisions. Firms involved in the generation of GTs might be facing institutional contexts featured by weak uncertainty, insofar as environmental regulation is characterized by strong stringency. Stringent policies in fact induce polluting firms to improve their environmental performances by eco-innovating. This introduces important effects for those upstream firms in the value chain that are suppliers of GTs, in terms of the extension of existing markets or the creation of new ones. Therefore, in contexts shaped by stringent environmental policies, the suppliers of GTs and their green knowledge assets are expected to be positively evaluated by financial markets.

3. Model specification: the MV equation

The model used in this paper is based on that of Cockburn and Griliches (1988). This model assumes that financial markets evaluate the firm by considering both its tangible assets[5] and its knowledge capital, namely its command of technological and organizational knowledge that enables the introduction and subsequent exploitation of

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4 See Hall (1999) for an extensive review of the literature about the relationship between MV and innovation.

5 These assets are referred to as tangible capital or tangible assets in Cockburn and Griliches (1988) and subsequent works. Hall *et al.* (2005) instead named them physical capital. Therefore, different approaches are used in empirical analyses to compute this variable: Cockburn and Griliches (1988) used the total fixed assets; Hall *et al.* (2005) used the net plant and equipment, inventories and investments in unconsolidated subsidiaries, intangibles, and others;

technological and organizational innovations. Thus, if the relationship between single assets is purely additive, the MV function can be written as follows:

$$V_{i,t} = b_t(A_{i,t} + \gamma KC_{i,t})^\sigma, \tag{1}$$

where V_{it} is the MV of firm i at time t, A_{it} and KC_{it} are its tangible assets and knowledge capital, respectively, b_t is the average multiplier of the MV relative to the replacement cost of the total assets and γ is the shadow price of knowledge capital relative to the tangible assets of the firm. The parameter σ allows for nonconstant scale effects in the value function.

In previous empirical works, the MV equation was estimated using various measures of knowledge capital, such as R&D investments, patent stocks, and patent citations. In this paper, we extend the model by including measures of the generation of GTs. Our knowledge capital measure is thus decomposed in two elements: the generation of green technologies (GT) and the generation of not-environmental technologies (NO_GT) (equation [1]). Equation (1) is therefore rewritten as it follows:

$$V_{i,t} = b_t(A_{i,t} + \gamma_1 GT_{i,t} + \gamma_2 NO_{GT}i,t)^\sigma. \tag{2}$$

Dividing equation (1) by A_{it}, transforming in logarithms and assuming constant returns to scale in the MV function ($\sigma = 1$), equation (2) becomes:

$$\log(q_{i,t}) = \log\left(\frac{V_{i,t}}{A_{i,t}}\right) = \log b_{i,t} + \log\left(1 + \gamma_1 \frac{GT_{i,t}}{A_{i,t}} + \gamma_2 \frac{NO_{GT}i,t}{A_{i,t}}\right), \tag{3}$$

where $\log(q)$ is the log of Tobin's q index and the intercept can be interpreted as an estimate of the logarithmic average of Tobin's q for each year. According to previous works, we also consider the approximation $\log(1+x) \approx x$ when x is small (Griliches, 1981; Jaffe, 1986; Cockburn and Griliches, 1988; Hall, 1993). The estimating equation thus becomes:

$$\log(q_{i,t}) = \log\left(\frac{V_{i,t}}{A_{i,t}}\right) = \log b_{i,t} + \gamma_1\left(\frac{GT_{i,t}}{A_{i,t}}\right) + \gamma_2\left(\frac{NO_{GT}i,t}{A_{i,t}}\right) \tag{4}$$

which can be estimated using ordinary least squares (OLS).

The estimation of equation (4) raises the econometric issues of selection bias. In fact, only few firms are engaged in (formal) R&D activities, so that studies restricted to these firms are prone to such bias.[6] We have taken care of the selection problems by using a two-stage procedure which implements two approaches: the Heckman and the Wooldridge procedures.

More precisely, two research equations have been analyzed in the first step, while the MV equation has been tested in the second step.

First, to describe the research behavior of a firm, we have assumed that firms decide on whether they perform R&D and, if so, by how much. Then, depending on the extent of their R&D and other factors, they achieve a certain performance on the market. Hence, our model consists of two groups of equations.

To the first group of research equations (R&D equations) belongs the following two steps:

1. A firm's decision to engage or not in R&D activities;
2. The determinants of the amount of investments in R&D activities of each firm.
   To the second group of research equations belongs the MV equation:

Megna and Klock (1993) used the sum of the property, plants and equipment, inventory, and net working capital; Hall and Oriani (2006) used the total tangible assets. In this paper, we use tangible fixed assets.

6 It should be noted that, because R&D is an independent variable in our equation rather than a dependent variable, if the process that generates the observed R&D is not related to the disturbance in the MV equation, no bias will be introduced into the equation as a result of the selection, even if it generates a nonrandom sample of observed R&D; there will merely be fewer observations on R&D, and those that are available may possibly span a smaller area in the independent variable space, thus implying less precise estimates of the coefficients and a different approximation to any nonlinearity in the model. A true selection bias will only occur when the disturbance in the presence of the R&D equation is correlated with the disturbance in the valuation equation.

3. The MV equation is a function of the estimated level of R&D.

The following section describes the econometric methodologies and the specifications used to estimate these three research equations.

3.1 R&D equations

To describe the research behavior of a firm, we have relied on a two equation models, where the first equation accounts for the fact that the firm is engaged in research activities, and the second one accounts for the intensity of these activities.

Let $D\_R\&D_{it}^*$ be the latent dependent variable pertaining to whether a firm invests in R&D or not, and $LnR\&D_{it}^*$ the latent or true intensity of R&D investment of firm i. $D\_R\&D_{it}$ and $LnR\&D_{it}$ are the corresponding observed variables.

The two-equation R&D investment model is written as follows:

$$D\_R\&D_{it}^* = \beta_1 x_{it}^1 + k_i^1 + u_{it}^1 \tag{5}$$

with $D\_R\&D_{it}=1$, if $D\_R\&D^*{}_{it}>0$, and $D\_R\&D_i=0$ otherwise.

$$LnR\&D_{it}^* \mid (D_R\&D_{it} = 1) = \beta_2 x_{it}^2 + k_i^2 + u_{it}^2 \tag{6}$$

with $LnR\&D_{it}= LnR\&D^*{}_{it}$, if $LnR\&D_{it}>0$, and $LnR\&D_{it}=0$ otherwise.

$x^1{}_{it}$ and $x^2{}_{it}$ are explanatory variables, β_1 and β_2 are the respective coefficients. $k^1{}_i$ and $k^2{}_i$ represent the unobserved characteristics that are fixed over time and $u^1{}_{it}$ and $u^2{}_{it}$ are the individual-specific unobserved disturbances. The $LnR\&D_{it}$ variable is only observable if $D_R\&D_{it} = 1$.

The independent variable that first explains the probability of engaging in R&D activities as well as the intensity of these activities, is intangible assets. Moreover, we have included a measure of firm size in the selection equation (5). Finally, both equations include a set of industry and time dummies to capture the market and cycle conditions. The following section provides a detailed specification of all the variables.

We have estimated equations (5) and (6) according to two approaches. The first approach is the Heckman two-step sample selection procedure (Heckman, 1979). Hence, the first equation has been estimated using a probit model; the second equation has been estimated in levels by means of pooled OLS and it includes the Inverse Mill's Ratio (IMR) as an explanatory variable to correct for any possible selection bias. However, with panel data, the OLS estimates on the selected subsample are inconsistent if the selection is nonrandom, and/or if correlated individual heterogeneity is present. We have therefore also adopted the estimation method proposed by Wooldridge (1995), which can be used in a panel setting to take into account that there may be some unobserved time-variant factors that can affect the selection and influence the R&D levels through the error term. In this approach, the time-invariant effects are assumed to be linked to x_{it}^1 through a linear function of k_i^1 of the time averages of x_{it}^1 (denoted with $\bar{x}_i^1$) and an orthogonal error term $a_{i,}$ which exhibits no variation over time and is independent of x_{it}^1 and u_{it}^1:

$$k_i^1 = \bar{x}_i^1 + a_i.$$

Hence equation (5) can be rewritten as:

$$D\_R\&D_{it}^* = \beta_1 x_{it}^1 + \gamma_1 \bar{x}_i^1 + v_{it}^1 \tag{7}$$

with the composite error term $v_{it}^1 = u_{it}^1 + a_i$ being independent of x_{it}^1, and normally distributed with a zero mean and variance σ^2. In this approach, a standard probit of the selection (equation [7]) is estimated for each t to obtain estimates for IMR.

In this approach, equation (6) can be rewritten as:

$$LnR\&D_{it}^* \ (D\_R\&D_{it} = 1) = \beta_1 x_{it}^2 + \gamma_2 \bar{x}_i^2 + \zeta \lambda_{it}^2 + v_{it}^2, \tag{8}$$

where λ_{it}^2 is the IMR and v_{it}^2 is an orthogonal residual.

Wooldridge (1995) proposed estimating equation (6) by including the t IMRs obtained from the selection equation for each time period along with the regressors. Moreover, as the error term is allowed to be correlated with the

IMRs, equation (8) can consistently be estimated by pooled OLS. We followed the procedure described by Wooldridge (2010) and calculated the panel bootstrapped standard errors clustered by firm. This allows standard errors to be obtained that are corrected for first stage probit estimates and robust to heteroskedasticity and serial correlation.

The two approaches, the one by Heckman and the one by Wooldridge, allow the potential R&D to be predicted for nonreporting firms. Given the panel nature of our data, we decided to include the estimated levels of R&D obtained by applying the second method[7] in the MV equation.

4. Data and variables

4.1 Data
To test the validity of our hypothesis, we constructed a dataset of firm-level information for firms listed on stock markets and merged it with patent applications.

The Bureau van Dijk—ORBIS dataset provided data that had been extracted from the balance sheets of firms, mainly concerning R&D expenditures, sales, tangible, and intangible assets and market capitalization, and it indicated the sector in which the firms operate.

To gather information on patents and the IPC(s) of such listed firms, we drew on the OECD REGPAT dataset, which has been merged with balance sheet data through the OECD HAN dataset. We extracted patent applications to the European patent office from 1985 to 2011. The IPC codes were used to label patent applications as "environmental" according to two alternative international classifications of GTs: the World Intellectual Property Organization (WIPO) "IPC Green Inventory" and the OECD "EnvTech." We decided to apply both classification schemes to ensure all the appropriate firms were included.

We restricted the analysis to manufacturing and knowledge intensive services both because of their innovation potential and because of their environmental pressure, and we concentrated on the five largest and comparable European countries—with respect to the number of operating enterprises: France, Germany, Italy, the Netherlands, and the UK.

The overall dataset is a balanced panel of firms listed on the main European stock markets over a period of 10 years (2002–2011) and consists of 4.449 firms for which information is available on all the variables of interest. The sample raises up to 11.007 observations when we estimated the R&D expenditures for nonreporting firms. However, to provide consistency to our analysis, as later explained, the core of the analysis is centered on a filtered sample that only includes those sectors with the largest shares of generation of GTs. The three selected sectors do cover about 80% of patent applications in GTs in our sample and are: Manufacture of chemical and chemical products, Manufacture of computer, electronic and optical products, and Manufacture of motor vehicles, trailers and semitrailers, and other transport equipment (Nace Revision 2: CE, CI, and CL).

4.2 Variables
Our empirical analysis has relied on the estimation of two groups of equations: R&D equations and the MV equation.

In Section 3.1, we have outlined the steps to obtain the R&D equation. The variables upon which equations are built are the following. For what concerns the dependent variables, in the selection equation (equation [5]) $D\_R\&D$ is a dummy taking value 1 if firm's R&D expenditures are positive, 0 otherwise. In equation (6) the variable $LnR\&D$ represents the log-transformed amount of deflated R&D expenditures of each firm i at time t. As for the independent variables, *Intangible assets* are included (in logarithm terms) along with country, sector, and time fixed effects as explanatory variables in equation (5). Moreover, in the Heckman selection equation, we also include the size of the firm. Following Corrado *et al.* (2005, 2006, 2009) and Antonelli and Colombelli (2011, 2015, 2017), *intangible assets* are identified as a specific component of the total assets. The book value of intangible assets is taken by firms' balance sheets. It includes goodwill, patents, copyrights, trademarks, and also other expenses such as organizational and capitalized advertising cost. Goodwill represents assets arising from the acquisition of other companies and is

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7   The results of the first equation used to predict R&D values are available upon request.

measured as the excess cost paid for the assets purchased over the book value ascribed in the acquiring firm's balance sheet. Data are gathered from the Bureau van Dijk ORBIS database.

As of the MV equation, it was built by drawing on existing previous literature (Cockburn and Griliches, 1988; Hall *et al.*, 2005). The core dependent variable is a measure of the firms' MV through a Tobin's *q* index, that is a ratio between market capitalization over tangible fixed assets, log transformed. Knowledge stock has been captured through R&D intensity (*R&D/Asset*) and the patent yield of R&D (*PAT_R&D*) (as in Hall *et al.*, 2005).

To construct PAT_R&D, since we possessed information on patent applications since 1985, we have first constructed the knowledge stock of patent applications (*PAT_STOCK*) by applying a perpetual inventory method (PIM) that assumes a yearly depreciation rate (σ) of 15% (Hall, 1999), as in equation (9):

$$\text{PAT\_STOCK}_{it} = \text{PAT}_{it} + (1 - \sigma)\text{PAT\_STOCK}_{it-1}. \tag{9}$$

Then we calculated the stock of real R&D. As no R&D expenditures before 2002 were available in our dataset, we first have built the 2002 R&D stock assuming an annual growth rate of 8% of knowledge capital (*g*) and a depreciation rate (σ) of 15%, as in equation (10).

$$\text{R\&D\_STOCK}_{i,t(t<2008)} = \frac{1+g}{g+\sigma}\text{R\&D}_{i,t}. \tag{10}$$

When R&D was missing in the first year, the initial R&D stock was constructed for the subsequent year, if available, otherwise for the first year available until 2007.[8] We have then constructed R&D_STOCK by applying a PIM to past R&D expenditures, with a yearly depreciation rate of 15%, and then divided the thus obtained R&D stock by the value of the firm's intangible assets.

After having calculated PAT_STOCK *and* R&D_STOCK, we have divided the former by the latter to obtain the patent yield of R&D, as in equation (11):

$$\text{PAT\_R\&D}_{it} = \frac{\text{PAT\_STOCK}_{it}}{\text{R\&D\_STOCK}_{it}}. \tag{11}$$

The R&D_STOCK has also been used to calculate the variable *R&D/Asset*.

A stock of GTs (GT_STOCK) was included to test our main research hypothesis according to two alternative methods. The identification of green patents was made considering the WIPO Green IPC Inventory together with the OECD EnvTech classifications. We augmented the MV equation with the green patents yield of R&D, obtained by applying the PIM to the subset of patents classified as green, divided by the R&D_STOCK, as in equation (12):

$$\text{GT\_R\&D}_{i,t} = \frac{\text{GT\_stock}_{it}}{\text{RD\_stock}_{it}}. \tag{12}$$

Similarly, we created the stock of patents that are not environmental (though not necessarily dirty) by applying the same equation, that is, (12) to the patents that are not assigned to any GT field:

$$\text{NOGT\_R\&D}_{i,t} = \frac{\text{NOGT\_stock}_{it}}{\text{RD\_stock}_{it}}. \tag{13}$$

Coherently with existing literature we also extended the MV equation to account for the quality of the firm's knowledge stock (Sandner and Block, 2011), allowing to reflect the technological importance of the patent, and the economic value of inventions (Trajtenberg, 1990; Hall *et al.*, 2005). To this aim we exploited the OECD patent quality indicators (Squicciarini *et al.*, 2013) and in particular the forward citations a patent has received in a 5 years window. We then augmented the MV equation by two variables: (i) the stock of citations to all the patents of the firm since 1985 deflated using the PIM with a depreciation rate of 15% divided by the count of patent applications of the firm in each year and (ii) the stock of citations to environmental patents of each firm since 1985 (deflated) divided by the count of green patent applications of the firm in each year.

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8   For instance, if R&D for 2002 was missing, the initial R&D stock was constructed for 2003. If the 2003 value was also missing, the R&D initial stock was built for 2004 and so on until 2007. This method was not adopted for firms with a first available value of R&D in 2008, 2009, 2010, or 2011 and these years were excluded from the analysis.

The OECD environmental policy stringency (EPS) indicator was used to control for the role of EPS across the considered countries (Botta and Koźluk, 2014). This is a composite indicator that bridges market-based environmental policies (taxes, trading schemes, feed-in tariffs, and deposit refund measures) and nonmarket-based ones (Standards and R&D subsidies). It ranges from 0 to 6 and it reports the stringency of existing environmental policies, where the stringency values depend on the explicit or implicit price of the produced environmental damage, mainly in the field of air and climate policies. Its appropriateness and quality has been confirmed by its high correlation with alternative policy indicators, such as the World Economic Forum's Executive Opinion Survey on the perception of EPS or the CLIMI Climate Laws, Institutions, and Measures Index produced by EBRD. The indicator focuses on the upstream sectors, namely energy and transport.

As pointed out in Albrizio et al. (2017), this choice limits the potential endogeneity of the policy variable in our model, given that those sectors (energy and transport) are not included directly in our analysis. More importantly, we retain EPS may be used as a valid proxy for a demand—pull stimulus of the policy. Our intuition is that upstream sectors—in our sample, those sectors that invest in environmental technologies—are both directly and indirectly stimulated by environmental regulation, that is, directly, as far as their own production is concerned and indirectly, because of the derived demand for GTs of downstream sectors. Direct and indirect regulatory effects are both expected to have a positive and significant effect on the MV returns of a firm developing GTs. We have followed the approach in Albrizio et al. (2017) by including a 3-year moving average for the change in EPS, that is an unweighted average of the first, second, and third lags of the changes in EPS.[9]

To test for main argument, we also account for the moderation effect of EPS on GTs' market returns to test whether the higher the growth in regulatory stringency the stronger the MV returns of GTs. This testing is conducted by means of two complementary analyses. At first an interaction term between the continuous values in EPS and GT/R&D is added to the analysis. At second, we investigated this moderation by constructing two symmetric dummies: EPS_above taking value 1 if the country faces an environmental regulation growth that is higher than the median value and EPS_below if it is lower than the median.[10] We then included directly in our estimates the interaction between GT/R&D and both EPS_above and EPS_below, to directly read the moderation effect of EPS on firms's MVs when the country reports a high versus a low stringency.[11]

We then controlled for the size of the firms, measured as the logarithm of firms' sales (SIZE).

The descriptive statistics of the main variables are reported in Table 1 and their correlation matrix is shown in Table 2.

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9   There is an ongoing and still unsolved debate on how to better measure environmental policy stringency in empirical analysis (Mazzanti et al., 2016) and there is agreement on the lack of good proxies available at disaggregated levels of analysis such as subnational or sectoral ones (Albrizio et al., 2017). We thus chose to rely to what is the best available proxy given our context and the aim of our analysis (the OECD EPS) and to avoid running the risk of exploiting possibly endogenous sectoral variables, such as those based on expenditures in environmental protection (as discussed in Brunel and Levinson, 2016). Still, this may constitute a limitation of this study due to the absence of an optimal sectoral based variable, although having restricted the analysis to only three main relevant sectors reduces such limitation.

10 As a robustness the same analysis is conducted when taking the "mean" value instead of the "median" value of the distribution. Results are robust to this alternative.

11 This strategy is equivalent to showing the effects for GT/R&D and its interactions with only $n-1$ interaction categories (i.e. in the form of differential impacts). We chose to display results also in this way, in addition to those into columns (3) and (4) pertaining the continuous variable for the EPS, as they directly show the impacts for GT at the two different EPS regimes: high, that is above the median value, and low. Algebraically, the coefficient associated with the interaction of GT/R&D*EPS_above (e.g. in Table 5, column 5: 0.7445) is equivalent to the sum of the coefficients of GT/R&D and GT/R&D*EPS_above we would have obtained in a model (not reported to avoid proposing twice the same evidence) that includes the three variables: GT/R&D, EPS_above, and GT/R&D*EPS_above. This approach is often preferred in empirical studies for more direct reading of the results (Benfratello and Sembenelli, 2006; Bianchini et al., 2017; Grinza and Quataro, 2019).

Table 1. Descriptive statistics and the main variables of the full sample

	Variable	N	Mean	SD	Min.	Max.
Full sample						
	lnTQ	4831	−4.74	1.765	−10.54	3.986
	EPS	4831	0.173	0.165	−0.136	0.576
	lnSize	4831	11.81	2.848	0.257	19.57
	GROUP (used in selection model)	4831	0.899	0.301	0	1
	lnINTASS (used for selection model)	4831	10.25	3.036	−0.0488	18.78
	R&D/Asset	4831	3.204	48.06	−0.00966	2799
	PAT/R&D	4831	0.255	2.203	0	63.45
	PAT_NOGT/R&D	4831	0.235	2.024	0	58.78
	GT/R&D	4831	0.055	0.733	0	21.81
	stockCIT_PAT	4831	28.19	246.6	0	5222
	stockCIT_GT	4831	5.68	56.38	0	1191
Filtered sample						
	lnTQ	1419	−5.009	1.667	−10.54	2.104
	EPS	1419	0.172	0.164	−0.136	0.576
	lnSize	1419	12.28	2.751	3.091	18.85
	GROUP (used in selection model)	1419	0.908	0.290	0	1
	lnINTASS (used for selection model)	1419	10.42	2.892	1.415	17.26
	R&D/Asset	1419	1.294	5.484	4.97e−05	107.1
	PAT/R&D	1419	0.404	3.534	0	63.45
	PAT_NOGT/R&D	1419	0.377	3.314	0	58.78
	GT/R&D	1419	0.103	1.057	0	21.81
	stockCIT_PAT	1419	76.08	444.8	0	5222
	stockCIT_GT	1419	16.80	102.5	0	1191
R&D predicted Heckman						
	R&D/Asset	2250	2.707	21.73	4.97e−05	845.2
	PAT/R&D	2250	0.172	1.245	0	31.04
	PAT_NOGT/R&D	2250	0.162	1.228	0	31.04
	GT/R&D	2250	0.0370	0.275	0	6.555
R&D predicted Wooldridge						
	R&D/Asset	2165	2.063	14.90	4.97e−05	561.8
	PAT/R&D	2165	0.187	1.322	0	31.04
	PAT_NOGT/R&D	2165	0.175	1.304	0	31.04
	GT/R&D	2165	0.0386	0.273	0	6.555

5. Estimation results

This paper has investigated the relationship between green patents and the stock market evaluation of firms that have generated these patents. For this reason, we implemented an empirical analysis based on the econometric framework of Cockburn and Griliches (1988), as discussed in Section 3.

The results of our estimations are presented in this section. We first estimated the MV equation, through OLS, but only on the sample of firms that have reported their R&D expenditures. The results of these estimations are given in Table 3. All regressions include sector and time fixed effects.

Column (1) reports the estimations of a baseline model including all firms' patents (including nonenvironmental ones) as regressor, for the sake of comparison with the extant literature. We have found that the coefficient of *R&D/Assets* is positive and significant. The same applies to the coefficient of the PAT/R&D variable. Overall, these results are in line with previous findings in most of the literature on MV and innovation, thus suggesting that stock markets tend to positively evaluate firm-specific investments in intangible assets.

We then extended the analysis by adding a GT stock variable (GT/R&D), as in equation (4), which was constructed using both the WIPO IPC GI and the OECD EnvTech to label patents as "green" (column [2]). The results suggest that our main research hypothesis cannot be rejected: green knowledge is positively evaluated by stock

Table 2. Pairwise correlation

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 lnTQ	1																	
2 EPS	0.10	1																
3 EPS above	0.05	0.72	1															
4 lnSize	−0.42	−0.02	0.02	1														
5 R&D/Asset	0.49	−0.02	−0.04	−0.30	1													
6 R&D(heck)/Asset	0.22	−0.05	−0.04	−0.16	0.94	1												
7 R&D(wool)/Asset	0.25	−0.05	−0.05	−0.18	0.92	0.99	1											
8 PAT/R&D	0.17	0.02	0.05	−0.14	0.00	0.16	0.28	1										
9 PAT/R&D(heck)	0.08	0.02	0.05	−0.07	0.00	0.00	0.01	0.58	1									
10 PAT/R&D(wool)	0.06	0.01	0.04	−0.05	0.00	−0.01	0.00	0.50	0.96	1								
11 PAT_NOGT/R&D	0.17	0.03	0.05	−0.15	0.00	0.16	0.27	1.00	0.61	0.53	1							
12 PAT_NOGT/R&D (heck)	0.08	0.02	0.04	−0.07	0.00	0.00	0.01	0.57	1.00	0.96	0.60	1						
13 PAT_NOGT/R&D (wool)	0.06	0.01	0.04	−0.06	0.00	−0.01	0.00	0.50	0.96	1.00	0.52	0.96	1					
14 GT/R&D	0.17	0.02	0.05	−0.14	0.00	0.15	0.28	0.95	0.40	0.31	0.94	0.39	0.30	1				
15 GT/R&D(heck)	0.09	0.01	0.04	−0.07	−0.01	0.00	0.01	0.56	0.77	0.71	0.57	0.76	0.70	0.56	1			
16 GT/R&D(wool)	0.07	0.00	0.04	−0.05	−0.01	−0.01	0.00	0.44	0.77	0.74	0.45	0.75	0.73	0.42	0.98	1		
17 stockCIT_PAT	−0.02	−0.07	−0.02	0.28	−0.03	−0.01	−0.02	0.00	0.03	0.02	0.00	0.03	0.02	0.00	0.02	0.02	1	
18 stockCIT_GT	−0.06	−0.07	−0.02	0.29	−0.03	−0.02	−0.02	0.00	0.02	0.02	0.00	0.02	0.02	0.00	0.04	0.04	0.86	1

Table 3. Results of the MV equation for only R&D reporting firms without any correction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D/Asset	0.0044***	0.0044***	0.0044***	0.0044***	0.1187***	0.1188***	0.1188***	0.1191***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0200)	(0.0200)	(0.0200)	(0.0201)
PAT/R&D	0.0304**				0.0591***			
	(0.0118)				(0.0099)			
SIZE	−0.2470***	−0.2472***	−0.2468***	−0.2458***	−0.1672***	−0.1666***	−0.1667***	−0.1654***
	(0.0085)	(0.0085)	(0.0085)	(0.0085)	(0.0166)	(0.0166)	(0.0166)	(0.0166)
GT/R&D		0.0934**	0.0457	0.0456		0.2233***	0.2341**	0.2342**
		(0.0413)	(0.0708)	(0.0704)		(0.0186)	(0.0978)	(0.0992)
PAT_NOGT/R&D			0.0215	0.0219			−0.0035	−0.0034
			(0.0249)	(0.0249)			(0.0324)	(0.0329)
EPS				0.2842*				0.2809
				(0.1509)				(0.2700)
Constant	−2.0500***	−2.0361***	−2.0496***	−2.1132***	−3.1544***	−3.1678***	−3.1673***	−3.2494***
	(0.2977)	(0.3001)	(0.2977)	(0.2967)	(0.2570)	(0.2570)	(0.2571)	(0.2680)
N	4831	4831	4831	4831	1419	1419	1419	1419
R^2	0.439	0.439	0.439	0.439	0.447	0.448	0.448	0.449
Adj. R^2	0.4350	0.4350	0.4351	0.4354	0.4419	0.4437	0.4433	0.4433
Predict R&D	No	No	No	No	No	No	No	No
Sample	Full	Full	Full	Full	Filter	Filter	Filter	Filter
Sector fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y	Y	Y

Standard errors in parentheses.

*$P < 0.10$,   **$P < 0.05$,   ***$P < 0.01$.

Table 4. Results of the MV equation for R&D predicted through the Heckman and Wooldridge procedures

	(1)	(2)	(3)	(4)	(5)	(6)
R&D/Asset	0.0124*	0.0124*	0.0125*	0.0207*	0.0207*	0.0208*
	(0.0072)	(0.0072)	(0.0072)	(0.0120)	(0.0120)	(0.0120)
GT/R&D	0.5086***	0.5460**	0.5547**	0.4203***	0.4454**	0.4545**
	(0.1458)	(0.2272)	(0.2288)	(0.1386)	(0.2041)	(0.2052)
SIZE	−0.2105***	−0.2105***	−0.2095***	−0.2075***	−0.2075***	−0.2065***
	(0.0152)	(0.0152)	(0.0153)	(0.0166)	(0.0166)	(0.0167)
PAT_NOGT/R&D		−0.0102	−0.0107		−0.0066	−0.0071
		(0.0431)	(0.0436)		(0.0371)	(0.0374)
EPS			0.5446**			0.4111*
			(0.2344)			(0.2360)
Constant	−2.7808***	−2.7807***	−2.9122***	−3.0724***	−3.0725***	−3.1670***
	(0.2381)	(0.2382)	(0.2466)	(0.2559)	(0.2560)	(0.2647)
N	2250	2250	2250	2165	2165	2165
R^2	0.277	0.277	0.278	0.292	0.293	0.293
Adj. R^2	0.2729	0.2726	0.2739	0.2885	0.2882	0.2888
Predict R&D	Heckman	Heckman	Heckman	Wooldridge	Wooldridge	Wooldridge
Sample	Filter	Filter	Filter	Filter	Filter	Filter
Sector fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y

Standard errors in parentheses.

*$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.

markets. This also holds true when green knowledge is included in the MV equation in the alternative model described in equation (5). However, when we included green and nongreen patent stocks together in the regression, neither significantly affected the MV of firms.

Our previous results could be biased by the fact that not all R&D-active firms are able to generate GTs. This is because knowledge is cumulative, and the capacity to respond to regulation-driven market opportunities, by means of green knowledge generation, may be unevenly distributed across sectors. To reduce this bias, we selected a subsample of firms operating in sectors featured by a high propensity to patent, that is the three sectors in which there is the highest concentration of green patents: Manufacture of chemical and chemical products; Manufacture of computer, electronic, and optical products; and Manufacture of motor vehicles, trailers and semitrailers, and other transport equipment (Nace Revision 2: CE, CI, and CL). We then replicated our analyses and the results are reported in columns (5)–(8). The positive relationship between MV and innovation was also confirmed for this "filtered" sample. When we turned to the evaluation of the green knowledge stock, we found that the GT/R&D coefficient was positive and significant across all the specifications, while PAT_NOGT/R&D never yielded a statistically significant impact. Surprisingly, the EPS coefficient did not seem to be significant.

These results support the idea that GTs represent a valuable asset for firms listed on stock markets.

It is worth noting that, since the choice of reporting R&D information from balance sheets is voluntary in the countries under examination, the sample of R&D firms may not be fully representative of the entire population, and this could lead to a selection bias. To correct for this potential bias, we ran several alternative specifications, as described in Section 3.

Table 4 reports the estimation results on the basis of a model strategy in which we predicted R&D expenditures for nonreporting firms using a two-stage Heckman model (columns [1]–[3]), and a strategy in which we used the Wooldridge approach (columns [4]–[6]) for panel data to predict R&D expenditures for nonreporting firms (see Section 3.1).

Results of both corrections are coherent. The GT/R&D coefficient is positive and significant, and this result is robust to different model specifications. The effect of EPS is positive and significant, thus suggesting that environmental regulation stringency growth plays a role in influencing the stock markets' evaluation of firms operating in sectors with a high propensity to green patenting. The combination of the two main results about GT/R&D and EPS

Table 5. Results of the MV equation for R&D predicted including overall citations and interactions with regulation variables

	(1)	(2)	(3)	(4)	(5)	(6)
R&D/Asset	0.0122*	0.0203*	0.0123*	0.0204*	0.0122*	0.0202*
	(0.0071)	(0.0118)	(0.0071)	(0.0118)	(0.0071)	(0.0118)
stockCIT	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SIZE	−0.2288***	−0.2257***	−0.2276***	−0.2244***	−0.2282***	−0.2252***
	(0.0161)	(0.0177)	(0.0161)	(0.0176)	(0.0161)	(0.0176)
PAT_NOGT/R&D	−0.0136	−0.0095	−0.0244	−0.0171	−0.0219	−0.0154
	(0.0410)	(0.0356)	(0.0362)	(0.0333)	(0.0388)	(0.0350)
GT/R&D	0.5356**	0.4351**	0.0018	−0.0286		
	(0.2198)	(0.1988)	(0.1991)	(0.1882)		
EPS			0.5785**	0.4419*		
			(0.2357)	(0.2373)		
EPS*GT/R&D			2.6375***	2.3738***		
			(0.8079)	(0.7185)		
GT/R&D*EPS_above					0.7445***	0.6321***
					(0.2182)	(0.2081)
GT/R&D*EPS_below					0.1140	0.0789
					(0.1734)	(0.1705)
Constant	−2.6002***	−2.8458***	−3.1940***	−3.1736***	−2.6120***	−2.8542***
	(0.2434)	(0.2676)	(0.2538)	(0.2826)	(0.2433)	(0.2674)
N	2250	2165	2250	2165	2250	2165
R^2	0.283	0.298	0.287	0.302	0.284	0.300
Adj. R^2	0.2783	0.2939	0.2820	0.2966	0.2795	0.2948
Predict R&D	Heckman	Wooldridge	Heckman	Wooldridge	Heckman	Wooldridge
Sample	Filter	Filter	Filter	Filter	Filter	Filter
Sector fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
EPS	Continuous	Continuous	Continuous	Continuous	Dummy	Dummy
Citations	All PAT	All PAT	All PAT	All PAT	All PAT	All PAT

Standard errors in parentheses. EPS is taken in continuous terms in columns (1–4) and (7–10), while it transformed into a dummy variable taking value 1 if the EPS in the country is above the overall EPS median value (EPS_above), while it takes 0 otherwise and a symmetrical dummy taking value 1 if the EPS is below the median value. The continuous GT/R&D is then interacted with both variables in columns (5) and (6). *stockCIT* takes the stock of citations of all the patents of the firm since 1985 deflated using the PIM divided by the count of patent applications of the firm in that year.

*$P < 0.10$,   **$P < 0.05$,   ***$P < 0.01$.

provides support to our hypothesis about the relevance of the regulatory push–pull effects in shaping the MV of firms generating green patents. In fact, stringent regulation is likely to boost the demand for GTs, and lead to the creation of new market niches or to the expansion of existing markets for GTs. This implies that the firms that supply GTs are likely to experience important demand increases and positive profit expectations. The positive evaluation of the stock markets reflects this high probability of appropriating increasing streams of profits in the future.

Overall, in view of our estimates, we cannot reject our core working hypothesis about the relevance of green patenting and of the stringency of the regulatory framework in shaping the positive stock market evaluation of firms operating in green sectors.

We then accounted for the quality of the knowledge stocks a firm possesses by means of the forward citations of its patents. Specifically, we first control for citations to patents pertaining to any field by the variable *stockCIT* (Table 5), then for those citations targeting GTs solely (Table 6). Our results show that, in both cases, citations matter in explaining the MV returns, as both stocks of citations (*stockCIT*) are positively and significantly associated to firms' Tobin's *q*.

Table 6. Results of the MV equation for R&D predicted including citations to green patents and interactions with regulation variables

	(1)	(2)	(3)	(4)	(5)	(6)
R&D/Asset	0.0123*	0.0204*	0.0124*	0.0205*	0.0123*	0.0204*
	(0.0071)	(0.0119)	(0.0071)	(0.0119)	(0.0071)	(0.0119)
stockCIT	0.0010***	0.0010***	0.0011***	0.0011***	0.0010***	0.0010***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
SIZE	−0.2209***	−0.2179***	−0.2199***	−0.2167***	−0.2204***	−0.2174***
	(0.0162)	(0.0178)	(0.0162)	(0.0177)	(0.0162)	(0.0177)
PAT_NOGT/R&D	−0.0090	−0.0056	−0.0194	−0.0129	−0.0172	−0.0114
	(0.0436)	(0.0374)	(0.0388)	(0.0351)	(0.0412)	(0.0366)
GT/R&D	0.5212**	0.4222**	−0.0154	−0.0444		
	(0.2272)	(0.2040)	(0.2046)	(0.1926)		
EPS			0.5458**	0.4091*		
			(0.2362)	(0.2377)		
EPS*GT/R&D			2.6388***	2.3776***		
			(0.8149)	(0.7245)		
GT/R&D*EPS_above					0.7280***	0.6171***
					(0.2258)	(0.2136)
GT/R&D*EPS_below					0.1037	0.0697
					(0.1783)	(0.1741)
Constant	−2.6740***	−2.9533***	−3.3016***	−3.2809***	−2.6860***	−2.9620***
	(0.2453)	(0.2672)	(0.2542)	(0.2821)	(0.2452)	(0.2671)
N	2250	2165	2250	2165	2250	2165
R^2	0.279	0.295	0.283	0.298	0.280	0.296
Adj. R^2	0.2745	0.2901	0.2780	0.2926	0.2756	0.2910
Predict R&D	Heckman	Wooldridge	Heckman	Wooldridge	Heckman	Wooldridge
Sample	Filter	Filter	Filter	Filter	Filter	Filter
Sector fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
EPS	Continuous	Continuous	Continuous	Continuous	Dummy	Dummy
Citations	Only to GT	Only to GT	Only to GT	Only to GT	Only to GT	Only to GT

Standard errors in parentheses. EPS is taken in continuous terms in columns (1–4) and (7–10), while it transformed into a dummy variable taking value 1 if the EPS in the country is above the overall EPS median value (EPS_above), while it takes 0 otherwise and a symmetrical dummy taking value 1 if the EPS is below the median value. The continuous GT/R&D is then interacted with both variables in columns (5) and (6). *stockCIT* takes the stock of citations of all the green patents of the firm since 1985 deflated using the PIM divided by the count of patent applications of the firm in GTs that year.

*$P < 0.10$,   **$P < 0.05$,   ***$P < 0.01$.

Lastly, we have tested for the interplay between GTs and environmental regulations, to account for the possible moderating effect environmental policies exert on the MV returns of GTs.

At first, we directly included a moderation effect between environmental technologies and the continuous variable measuring the stringency of environmental policy throughout the different countries. Results, reported into columns (3) and (4) of Tables 5 and 6, show a positive and significant moderating role played by the policy. The growth in environmental regulatory stringency both directly (EPS is positive and significant) and indirectly affects market evaluation of the firms through the effect of the policy on GTs (interaction GT/R&D*EPS is positive and significant). In contrast GT/R&D alone, not mediated by the policy, no longer influences market returns. This evidence strongly supports our arguments according to which (i) the market positively evaluates the capability of the firm to generate "greener" technologies; (ii) this effect is stronger in contexts characterized by growing regulatory stringency; and (iii) more importantly, the more regulatory stringency increases the stronger the MV returns of GTs.

At second, we investigated this moderation by the interaction between GT/R&D and both the EPS_above and EPS_below previously described symmetric variables, to directly read the moderation effect of EPS on firms's MV
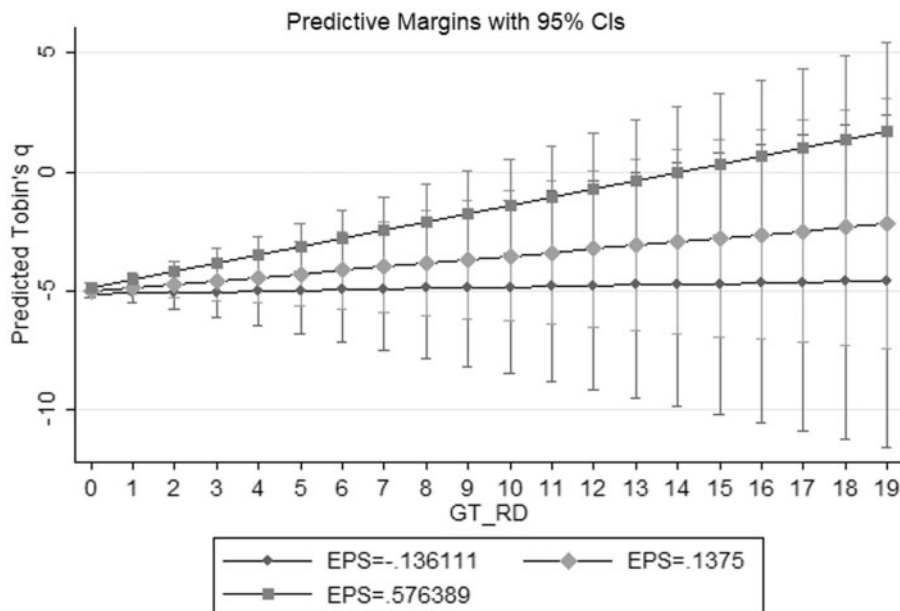
Figure 1. Predicted values of Tobin's *q* at different levels of GT/R&D and EPS at three values: min, mean, and max (of EPS change). Note: The predicted marginal effects of GT/R&D are estimated by means of pooled OLS on the fully specified model, including GT/R&D(heck), EPS the interaction of EPS*GT/R&D, and the stock of citations to patents (as in column [3] of Table 5) at different levels of GT/R&D (from 0 to its maximum, 19) and for three values of the change in EPS: minimum (−0.14), median (0.14), and maximum (0.58).

when the country reports a high versus a low growth in policy stringency. Results, reported into columns (5) and (6) of Tables 5 and 6, provide further support to the moderating role exerted by policy stringency on the impact of GTs on the market evaluation: the interaction between GT/R&D and EPS_above is indeed positive and significant whereas the interaction with EPS_below (the median value) is not significant. In other terms, it is only for firms located in contexts with growing stringent environmental policies that the market would positively value GTs developed by firms.[12]

We provide a visual representation of the moderating effect of EPS on GTs returns on the MV of the firm into Figure 1. We visualize the marginal effects of GT/R&D on the Tobin's *q* at three different levels in the regulatory stringency variable: the minimum, the median, and the maximum. Visually it emerges clearly that the higher the EPS growth, the stronger the market evaluation of GTs.

All in all, our results do not reject the hypothesis that financial markets positively evaluate the green knowledge assets of firms, and that this evaluation is increased by the stringency of environmental policies and by the quality of the knowledge generated.

6. Conclusions

This paper analyzed the relationship between GTs inventions and the MV of firms. Our main argument is that the generation of GTs is likely to be positively stimulate market evaluation of the firm. The derived demand of GTs is in fact likely to engender positive expectations concerning the profitability of firms that generate GTs, thus leading to better evaluations by prospective stockholders.

By extending the conceptual and empirical framework underlying the MV and innovation literature onto the analysis of the economic effects of eco-innovation and environmental technologies, this paper has articulated and tested

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12   Results are confirmed if the mean in the EPS distribution, instead of the median, is selected to construct EPS_above and EPS_below.

the core research questions about the effects of green inventions and stringent regulatory frameworks on the stock market evaluation of firms.

The empirical analysis has been conducted on a sample of European companies which trade publicly in France, Germany, Italy, the Netherlands, and the UK. To investigate the relationship between the generation of environmental patents and firms' MV, we have estimated MV equations that covered the period from 2002 to 2011 on a restricted sample of sectors that are responsible for the large majority of GTs generation.

Our findings have confirmed previous literature findings that innovation exerts positive effects on MV. More interestingly, when we extended the analysis by adding GT stock variables, our first hypothesis was confirmed: firms that generate GTs have been found to be positively and significantly evaluated by the market. Our second research question on the impact of the regulatory framework found support as well: the stock market evaluation of firms operating in green sectors is positively affected by the degree of stringency. This result is consistent with the argument about the market creation effects of environmental policies. A moderating effect of policy exists EPS growth increases the returns of green patents on firms' MV.

Moreover, we accounted for the quality of the knowledge stock by considering the amount of *citations* (forward citations) to standard and to GTs, which in turn should reflect the technological importance of the patent, and their economic value (Trajtenberg, 1990; Hall *et al.*, 2005). Results confirm that not only the presence of inventions but also their quality positively influences MV returns.

Overall, our results point to relevant policy implications. At first, we position the work in the broader Porter Hypothesis framework and we found support to the hypothesis that stringent environmental policies not only are not necessarily detrimental to firms' competitiveness, but rather may even lead to *win–win* situations in which, by setting the direction of technological change, policies can stimulate firms to innovate and to be positively evaluated in the stock market. At second, we provided a discussion on the channels by which this positive MV evaluation may occur and in particular we have focused on the role of upstream sectors may have in inventing greener technologies later diffused to downstream sectors and on the positive evaluation the market can give to those greener technology providers.

Future research directions emerge from this work and are left to future investigation. On one side, it would be interesting to test for differential returns associated to heterogeneous typologies of GTs. Also, it would be useful to carry out the analysis on a similar sample of US listed firms to obtain a finer-grained understanding of how geographical differences in the approach to environmental policies influence the stock market evaluation of green patents. Lastly, a deeper investigation of the regulation variable may improve the robustness to the above discussed findings: on one side, we were lacking reliable sectoral data on environmental regulation which are also comparable across different countries, on the other side, this can be combined by the intersectoral relatedness of upstream and downstream sector to better shed light on the mechanisms that are behind our main findings.

Acknowledgment

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Appendix

This Appendix provides an additional robustness control to our previous analysis: we adopted nonlinear least squares (NLLS) methods to estimate the MV equation, as in Bloom and Van Reenen (2002) and Hall et al. (2005). For comparison purposes with the previous results, the regressions were run on the filtered sample, alternating the Wooldridge and the Heckman corrections for nonreporting firms (Table A1).

Our results are in line with the extant findings and literature, according to which *R&D/Asset* and Pat/R&D have a positive and significant coefficient. Furthermore, financial markets tend to positively evaluate the green knowledge stock of firms in the selected sectors and this evaluation is positively affected by the stringency of the environmental regulation and the institutional context in which firms operate.

We lastly accounted for both the role of quality of the knowledge stock, through the inclusion of the stock of citations as in Table 5 of the main text and for the moderating role of environmental regulation, as reported in Table A2. Whereas results concerning the moderating role of environmental regulation are mostly confirmed, the stock of citations fails to be found a significant driver for market evaluation when exploiting NLLS estimations. This nonsignificance is found when referring either to citations to any patent or to citations to GTs solely (the latter results are not reported but available upon request).

Table A1. NLLS results of the MV equation for R&D predicted through the Heckman and Wooldridge procedures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D/Asset	7.1604***	7.1984***	7.2264***	7.1240***	6.7271***	6.7550***	6.7775***	6.8940***
	(0.7005)	(0.7028)	(0.7059)	(0.6866)	(0.6219)	(0.6231)	(0.6255)	(0.6278)
PAT/R&D	0.1350***				0.1063***			
	(0.0213)				(0.0200)			
SIZE	0.0364***	0.0379***	0.0382***	0.0387***	0.0053	0.0063	0.0067	0.0095
	(0.0115)	(0.0114)	(0.0114)	(0.0113)	(0.0111)	(0.0111)	(0.0111)	(0.0109)
GT/R&D		0.7435***	0.5924***	0.5987***		0.6452***	0.5239***	0.5319***
		(0.1045)	(0.1592)	(0.1573)		(0.1054)	(0.1529)	(0.1508)
PAT_NOGT/R&D			0.0413	0.0351			0.0322	0.0276
			(0.0328)	(0.0324)			(0.0294)	(0.0290)
EPS				1.1490***				1.2004***
				(0.1513)				(0.1514)
Constant	−7.5814***	−7.6095***	−7.6140***	−7.9004***	−7.0644***	−7.0851***	−7.0896***	−7.4603***
	(0.2004)	(0.2002)	(0.2002)	(0.2013)	(0.1940)	(0.1938)	(0.1938)	(0.1967)
N	2250	2250	2250	2250	2165	2165	2165	2165
R^2	0.545	0.547	0.547	0.559	0.553	0.554	0.555	0.567
Adj. R^2	0.5439	0.5460	0.5461	0.5573	0.5515	0.5534	0.5534	0.5658
Predict R&D	Heckman	Heckman	Heckman	Heckman	Wooldridge	Wooldridge	Wooldridge	Wooldridge
Sample	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter
Sector fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y	Y	Y

Standard errors in parentheses.

*$P < 0.10$,　**$P < 0.05$,　***$P < 0.01$.

Table A2. NLLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)
R&D/Asset	7.3344***	7.1192***	7.2509***	6.8291***	6.8601***	6.7647***
	(0.7247)	(0.6944)	(0.7155)	(0.6369)	(0.6320)	(0.6305)
PAT_NOGT/R&D	0.0420	0.0318	0.0341	0.0325	0.0255	0.0267
	(0.0329)	(0.0326)	(0.0330)	(0.0294)	(0.0291)	(0.0294)
stockCIT	−0.0001	−0.0000	−0.0001	−0.0000	−0.0000	−0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SIZE	0.0420***	0.0402***	0.0419***	0.0088	0.0095	0.0088
	(0.0122)	(0.0120)	(0.0122)	(0.0118)	(0.0116)	(0.0118)
GT/R&D	0.5951***	0.4102*		0.5253***	0.3894*	
	(0.1593)	(0.2281)		(0.1530)	(0.2156)	
EPS		1.1230***			1.1807***	
		(0.1529)			(0.1532)	
EPS*GT/R&D		0.9170			0.7105	
		(0.7995)			(0.7674)	
GT/R&D*EPS_above			0.7836***			0.7087***
			(0.1762)			(0.1722)
GT/R&D*EPS_below			0.2110			0.1890
			(0.2214)			(0.2109)
Constant	−7.6722***	−7.9125***	−7.6618***	−7.1214***	−7.4518***	−7.1130***
	(0.2097)	(0.2099)	(0.2094)	(0.2029)	(0.2049)	(0.2027)
N	2250	2250	2250	2165	2165	2165
R^2	0.547	0.559	0.549	0.555	0.567	0.556
Adj. R^2	0.5461	0.5572	0.5471	0.5532	0.5656	0.5541
Predict R&D	Heckman	Heckman	Heckman	Wooldridge	Wooldridge	Wooldridge
Sample	Filter	Filter	Filter	Filter	Filter	Filter
Sector fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
EPS	Continuous	Continuous	Continuous	Continuous	Dummy	Dummy
Citations	All PAT	All PAT	All PAT	All PAT	All PAT	All PAT

Standard errors in parentheses. *$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.