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Are green firms more financially constrained? The sensitivity of investment to cash flow

Tommaso Oliviero[*], Sandro Rondinella[†], and Alberto Zazzaro[‡]

Abstract
Green investment by private companies is essential to sustainable growth paths in the advanced economies. Whether, and to what extent, investments by green firms are hampered by lack of external finance is an open question. Here we estimate the sensitivity of investment to internal finance in firms engaging in green innovation, finding that the elasticity of investment to cash flow is four times less for green than for non-green firms. This result is stronger among smaller firms and robust to alternative definitions of "green firms." Our findings indicate that green firms are less financially constrained, consistent with the growing perception of the importance of the green transition, which potentially affects financial investors outside the company.

JEL Classification: E22; G30; Q55.

Keywords: Green investment; cash flow; external finance; financial constraints.

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1. Introduction

The UN Climate Change Conference in 2015 and the European Green Deal in 2019 introduced the first legally binding global climate accords to slow global warming and eventually achieve climate neutrality. This highly ambitious objective requires structural economic change and enormous financial resources for green investment in research and in products and processes directed to eco-innovation and decarbonization. In this respect, a crucial role in moving towards a greener economy naturally goes to corporate investment. Insofar as the corporate sector is typically subject to financial constraints that prevent the realization of the optimal level of investment (Almeida et al., 2014), it is of first-order importance to understand how far the investment of green firms is subject to this type of impediment.

The role of finance in promoting green investments and innovations is an open, empirical question. This paper contributes to the debate on how financial constraints affect the green transition by estimating and comparing the elasticity of investment to cash for green than for non-green firms. The literature offers diverging insights on whether investments by green firms could be hampered by lack of external finance.

On the one hand, green investments are comparable to innovation projects to create something new, and like all innovative projects they are characterized by significant information asymmetries between insiders and outside investors, intangible assets that cannot be collateralized, and potential negative externalities for incumbent firms (Clemenz, 1991; Hall and Lerner, 2010; Minetti, 2011; Degryse et al., 2023). These factors may exacerbate adverse selection and moral hazard for lenders, induce losses on their legacy investment in the brown technologies, and ultimately create stricter financial constraints for green firms. Accordingly, the investments of green firms may be expected to be more sensitive to the availability of internal financial resources than those of non-green firms (Kapoor et al., 2011). Consistent with this hypothesis, recent empirical studies find that lack of access to finance impedes the adoption of eco-innovations (Cuerva et al., 2014; Ghisetti et al., 2015; De Haas et al., 2023, Aghion et al., 2023) and limits the number of firms' green patents (Yuan et al. 2021;

Zhang and Jin, 2021; Noailly and Smeets, 2022). In the context of bank-firm relations, there is evidence that the investment of green firms responds significantly to variations in the availability of bank credit (Accetturo et al., 2022). Moreover, loans to sectors more exposed to the green transition are significantly greater when banks' legacy positions in these sectors are less evenly distributed (Degryse et al., 2023); and carbon-intensive industries reduce emissions more slowly in countries where the financial sector is dominated by banks (De Haas and Popov, 2023).

However, there is also good reason to argue that green investments face less severe financial constraints than brown investments and are thus less sensitive to firms' internal cash flow. The empirical evidence on this point, in fact, is far from conclusive. First, a good part of the returns to clean technologies and products extends beyond the single company to create positive externalities for the entire society. For this reason, green investment is more sensitive to public incentives, such as carbon taxes, research subsidies, and other forms of environmental regulation and subsidy, than it is to the availability of internal and external financial resources (Rennings, 2000; Acemoglu et al., 2012, 2016; Aghion et al., 2023). Second, investors have the incentive to price the environmental risks associated with business activity and climate regulatory policy, thus tightening the financing constraints on polluting companies that use dirty technologies.[1] Third, the growing environmental awareness and green preferences of private savers and financial institutions in recent years could produce greater availability of external financing for green firms, hence less need for internal finance to fund green investments and innovations (Zhang and Jin, 2021). In this sense, several studies document that public funding and environmental regulation are key drivers of green innovation (Horbach, 2008; Cecere, 2020); that banks and investors evaluate environmental risk and the sustainability of companies (Hartzmark and Sussman, 2019; Krueger et al., 2020; Newton et al., 2022;

[1] Overall climate change risk could be broken down into: i) physical risk, directly imposed by costs and damage associated with extreme weather events and natural disasters (Ghisetti et al., 2015; Hong et al., 2019); ii) regulatory risk, originating from government policies and regulations to curb carbon emission and combat climate change (Fard et al., 2020; Seltzer et al., 2022); iii) transition risk emanating from climate-related innovations that could be disruptive to certain industries (Delis et al., 2019; Bolton and Kacperczyk, 2020).

Altavilla et al., 2023); that the cost of debt is lower for green than for environmentally dirty or risky firms (Chava, 2014; Bolton and Kacperczyk, 2021; Fatica et al., 2021); that banks' lending policies respond to changes in public climate policy (Delis et al., 2019; Ehlers et al., 2022; Reghezza et al., 2022; Degryse et al., 2023; Martini et al., 2023);[2] and that green innovators are more likely to receive external funding from venture capitalists (Bellucci et al., 2023) and nonbank investors in the syndicated loan market (Gallo and Park, 2023) and mutual funds (Cornelli et al., 2024).

Our contribution is to examine the role of financial constraint for the green transition with an empirical analysis of the sensitivity of green firm investment and green innovation to the availability of internal finance. The hypothesis underlying this established approach to identifying financial constraints on private investment is that there is a wedge between the cost of internal and external funds; and the larger this cost-wedge, the greater the sensitivity of investment to cash flow (Fazzari et al., 1988; Kaplan and Zingales, 1997). Therefore, we expect that if financial constraints are more binding for green investment, the cash-flow sensitivity of green firms' investment and green innovations will be greater than that of their non-green counterparts.

We consider a large sample of manufacturing firms in Italy from 2014 to 2019, classifying firms as "green" on the basis of patenting in green technologies in the fifteen years before the sample period. The results indicate that the investment of green firms is statistically and economically less sensitive to their cash flow than that of non-green firms. In addition, we find that the number of a firm's green patents is not sensitive to the availability of internal finance, while "brown" patents are positively associated with higher firms' cash flows. The results are robust to restricting the comparison group to non-green innovative firms, that is with at least one non-green patent between 2000 and 2013. The moderating effect of a firm's greenness on investment sensitivity to cash flow is stronger for smaller companies, which are more likely to face financing constraints. Finally, since green investments may well be unrelated to green innovations, we repeat our analysis by classifying firms by the greenness

[2] Even if banks' words are not always followed by deeds (Giannetti et al., 2023).

of their industry rather than their patents. Once again, the results confirm the significantly lower sensitivity of investment to internal finance for firms operating in sectors more exposed to green technologies.

The paper also relates closely to the literature on investment-cash flow sensitivity,[3] and in particular to the numerous studies on the sensitivity of R&D investment and innovation to the availability of internal finance (Hall, 1992; Himmelberg and Petersen, 1994; Harhoff, 2000; Bond et al. 2003; Ughetto, 2008; Brown et al. 2009, 2012). To the best of our knowledge, this is the first paper to analyze the sensitivity of green investment and green innovation to internal cash flow, with the partial exception of Cohn and Derugyna (2018), who document a negative relationship in the U.S. between firms' cash flow and the number of environmental spills for which they are responsible, suggesting that firms that invest in projects to mitigate environmental risk are more financially constrained.

The rest of the paper is organized as follows. Section 2 describes how green firms are identified in the data. Section 3 presents the sample and the econometric model, Section 4 shows the estimation results and robustness checks, Section 5 sets out additional results, and Section 6 concludes.

2. "Green" investment and "green" firms

A common issue in empirical studies on financial constraints to green investment is properly identifying and measuring investment in green activities at firm level, especially for unlisted private companies. Balance sheets often fail to distinguish between green and non-green fixed assets, so in order to identify investments in green assets and the financial resources allocated to them, empirical studies resort to self-reported survey data (Cuerva et al., 2014; Ghisetti et al., 2017; Cecere et al., 2020; De Haas et al., 2023) or else pick out green investments through textual analysis of the firms'

[3] With reference to Italy, a good number of studies have documented that the fixed investment of firms that, for various reasons, face stricter constraints on external finance is more sensitive to their internal cash-flow dynamics (Rondi et al. 1994; Becchetti et al. 2000; Ughetto, 2008; Alessandrini et al. 2009; La Rocca et al. 2015; Peruzzi, 2017).

own description of the investment (Gallo and Park, 2023); or, again, they classify as "green" the assets, expenditures and borrowing of firms that are classed as "green" based on some predetermined features such as greenhouse gas emissions, adoption of green technologies, release of an ESG report or the firm's ESG rating, disclosure of environmental data, and participation in environmental organizations or sustainability programs (Ehlers et al., 2022; Reghezza et al., 2022; Accetturo et al. 2022; Degryse, 2023).

Taking this latter approach, we distinguish firms that invest in green technology based on patenting. Patent data are publicly available, cover long periods and large numbers of firms, and should not suffer from problems of sample selection (Marin and Lotti, 2017). Moreover, thanks to patent statement, the content of the abstract and the resulting classification class, patents offer a wealth of information about the technological field of innovation; this allows us to identify firms that have registered green patents. We can therefore reasonably assume that obtaining green patents requires making (and financing) investment in green technologies and eco-innovations and that firms continue to invest in green activities even after patent registration.

In this paper, we use both the Cooperative Patent Classification (CPC) and the International Patent Classification (IPC). The CPC is developed and maintained jointly by the European Patent Office (EPO) and the US Patent and Trademark Office. Based on the CPC classification, in 2013 the EPO introduced the Y02 tagging scheme for patents related to climate change mitigation technologies (CCMT), distinguishing technological inventions that reduce greenhouse gas emissions in relation to buildings (Y02B), gas capture and storage (Y02C), energy generation, storage and distribution (Y02E), production (Y02P), transport (Y02T), waste treatment (Y02W), and smart grids (Y04S). Our main independent variable is the indicator *GREENFIRM,* which takes the value of 1 if the firm registered at least one patent with at least one CCMT code in the period 2000-2013, and zero otherwise.[4]

[4] The CPC classification scheme for identifying green patents is widely used in studies on green innovation and green finance (Popp, 2019, De Haas and Popov, 2021; Bellucci et al., 2023).

Clearly, *GREENFIRM* is only a rough indicator of firms' green investment activity; it may well overestimate or underestimate their actual commitment to green technology. First, by using a dummy we implicitly assume that the share of green investment in a firm's total investment is constant and uniformly greater for all the firms registering green patents. However, it is a plausible hypothesis that firms with more green patents also have a higher share of investment in green activities. Second, since each patent can be associated with several CPC codes, the "greenness" of a patent may cover aspects of the technology to different degrees. Therefore, following Wurlod and Noailly (2018), as an alternative indicator of green investment we consider the number of green patents of the company in the period 2000-2013, weighted by the share of green codes in total codes reported in the patent. Specifically, we define a variable $GREENPAT_i = \sum_{p=1}^{P_i} \frac{c_{g,p}}{c_p}$, where P_i denotes the total number of patents of firm i, c_p the number codes indicated by patent *p*, and $c_{g,p}$ the number of patent *p*'s green codes. As a further alternative definition, we consider an indicator of green intensity of firms' patented technologies, measured as *GREENPAT* over total patents; that is, $GREENNESS_i = GREENPAT_i/P_i$.

In our sample, 360 of the 77,020 patents registered in the period 2000-2013 are classified as "green" by these criteria; and 316 firms registered at least one patent with a code associated with a green technology. Conditional on *GREENFIRM* = 1, the average number of green patents, weighted by degree of greenness, is 1.1; 10% of these firms have a value of *GREENPAT* greater than 2.4.

As a final robustness check on the measurement, we also re-construct the variables *GREENFIRM*, *GREENPAT* and *GREENNESS* replacing IPC with the patent classification of the World Intellectual Property Organization (WIPO). Following Gagliardi et al. (2016) and Ghisetti and Quartaro (2017), we classify an IPC code as green if it is included in the WIPO IPC Green Inventory (IPC-GI) or the OECD Environmental Policy and Technological Innovation indicators (ENV-TECH).[5] This

[5] In 2010, the WIPO released the IPC-GI to highlight environmentally sound technologies within the IPC classification. It covers some 200 topics relevant to environmentally sound technologies, each linked to the most relevant IPC classes chosen by experts (for a detailed description of the IPC-GI see Marin and Lotti, 2017). Similarly, in 2015 the OECD set

classification criterion for green firms is broader: it finds 657 firms registering at least one patent with one or more green codes, while on average *GREENPAT* is 3.5 and for 25% of green firms it is greater than 2.[6]

3. Empirical analysis

3.1 *Data and sampling*

We use a large sample of Italian private manufacturing firms during the period 2014-2019 (NACE codes from 10 to 33). The initial source of data is Bureau van Dijk's Orbis dataset. It contains yearly information on firms' balance sheets and income statements from official business registers and other information. This data is linked, exploiting the Orbis firm identifier, with information on patents from Orbis Intellectual Properties (Orbis IP). It contains company accounting and patent information worldwide, reporting 115 million patents, with their ownership and date. In addition, to identify green patents, in line with the measurement strategy outlined in Section 2, we match this information with the CCMT tagging scheme. The final sample comprises 36,174 manufacturing firms, of which green firms (*GREENFIRM* = 1) make up about 1%. This low percentage is not surprising, given the large incidence of small, non-innovative companies in Italy. Since comparing a large group of non-green firms with a small group of green firms may produce unwarranted inferences, owing to differences in observable characteristics, we follow three empirical strategies. First, all baseline regressions include regressors for the relevant observable determinants of financial constraint, such as the firm's age, leverage, average cost of debt, and working capital; all specifications also include year and sector fixed effects. Next, as an alternative way of adding controls to the baseline specification, we restrict the sample by coarse matching firms by using age, leverage, working capital, and cost of debt as matching observable variables. The drawback to this approach is the significant reduction of the

out patent search strategies for the identification of selected environment-related technologies, offering a comprehensive methodology for capturing innovation in environmental-related technologies (Haščič and Migotto, 2015).

[6] In detail, we replicate baseline results using this alternative measurement strategy. The results are displayed in Table A1 of the Appendix.

sample, which shrinks to 1,008 non-green and 316 green firms.[7] As a third approach, we account for the fact that green firms constitute a selected sample, consisting by construction of successful innovative enterprises. This means that our "greenness" indicators could be capturing some unobservable characteristics related to the quality of these firms that affect both their access to external financing and the sensitivity of their investment to internal finance. To control for this, we replicate all our analyses with a control group consisting of successful innovative firms in non-green technologies, i.e. firms that registered at least one patent in the period 2000-2013. This selection criterion produces a sample of 4,865 firms (and 21,414 year-firm observations) and allows us to compare the response of investment to internal finance in green and non-green firms that are equally innovative and engaged in patenting.

3.2 *Regression model*

To gauge the extent to which cash flow sensitivity differs between green and non-green firms, we use a workhorse reduced-form investment model based on the error correction model employed by Bond et al. (2003), Mizen and Vermeulen (2005), Bloom et al. (2007), Guariglia (2008) and Mulier et al. (2016). These studies typically assume that the desired stock of capital is a log-linear function of firms' output and the price of capital services and that, given adjustment costs, capital stock dynamics can be approximated by a second-order autoregressive-distributed lag model. Hence, taking sales as a proxy for output, we estimate a standard error-correction investment model augmented by a variable identifying the firm's involvement in green technologies and an interaction term between cash flow and the measure of greenness:

[7] For a detailed description of the coarse matching procedure and the regression results, see Appendix A.

$$\frac{INVESTMENT_{it}}{CAPITAL_{it-1}} = \alpha + \beta_1 \frac{CASHFLOW_{it}}{CAPITAL_{it-1}} + \beta_2 GREEN_i + \beta_3 \frac{CASHFLOW_{it}}{CAPITAL_{it-1}} \times GREEN_i + \beta_4 \frac{INVESTMENT_{it-1}}{CAPITAL_{it-2}} + \beta_5 (LNCAPITAL_{it-2} - LNSALES_{it-2}) + \beta_6 \Delta LNSALES_{it} + \beta_7 \Delta LNSALES_{it-1} + +\beta_8 \Delta EMP_{it-1} + \phi X_{it} + \zeta_s + \varphi_t + \epsilon_{it}\,, \quad (1)$$

where the dependent variable is the investment of firm i at time $t-1$, calculated as the sum of depreciation in year t and the change in tangible fixed assets from year $t-1$ to year t divided by the replacement value of the firm's capital stock, i.e. $INVESTMENT_t/CAPITAL_{t-1}$.[8] On the right-hand side, *CASHFLOW* is cash flow in year *t* scaled by start-of-period capital. *GREEN* is measured in the baseline specification by the dummy variable *GREENFIRM* and, alternatively, by the variables *GREENPAT* and *GREENNESS* as defined in Section 2. $\Delta LNSALES$ is the difference between the log of real total sales and its last log value; this captures the short-run capital dynamics due to output variations, while the error-correction term $(LNCAPITAL_{it-2} - LNSALES_{it-2})$ captures the long-run equilibrium between capital and its target value. The term *ΔEMP* is the rate of growth in the firm's workforce, which serves, as the bulk of our sample firms are not listed, as a substitute for Tobin's q to control for changes in investment demand. Based on the assumption that companies with greater investment opportunities hire more (Mulier et al., 2016) the inclusion of *ΔEMP* helps to distinguish the actual financial-relief effect of cash-flow for current investment from the signalling effect for future business prospects.

[8] The replacement value of the capital stock is calculated by the perpetual inventory formula (Blundell et al., 1992). Taking tangible fixed assets as the historic value of the capital stock and assuming that in the first period, the historic value equals the replacement cost, we calculate the capital stock as $K_{it+1} = K_{it}(1-\delta)(p_{t+1}/p_t) + I_t$. δ is the depreciation rate, defined as depreciation over the real capital stock in the previous year (Gal, 2013); and p_t is the price of investment goods, proxied by the price deflator at the 2-digit industry level (specifically, the intermediate inputs price indices, retrieved from the EU KLEMS database).

Finally, the vector *X* includes observables that are commonly used in these models to control for important confounding factors possibly correlated with cash flow, financial constraint, and investment decisions. First, we consider the age of firms (*AGE*) to control for the typical decline in investment opportunities over firms' life cycle (Hovakimian, 2009). Second, we consider the ratio of total liabilities to total assets (*LEVERAGE*) and the ratio of interest expense to total assets (*DEBTSUST*) as gauges of debt sustainability. High leverage has an ambiguous impact on investment, in that it captures both the weight of debt and the firms' borrowing capacity (Lang et al. 1996; Hovakimian, 2009). By contrast, high debt and interest burden should be expected to undercut the ability to raise external financing and to use internal finance for investment. Third, we include working capital (*WORKCAP*, defined as the surplus of current assets over current liabilities) as a ratio to total assets to control for a firm's liquidity position. Short-term liquidity buffers enable firms to hedge against cash-flow shocks and smooth the investment flow (Holmström and Tirole 2011; Almeida et. al. 2014). On the other hand, as Fazzari and Petersen (1993, p. 329) argue, "if firms face financing constraints, working-capital investment competes with fixed investment for the available pool of finance" and can be negatively associated with the latter. Whichever effect prevails, controlling for working capital allows us to estimate the impact of cash flow shocks more precisely (Fazzari and Petersen, 1993).

To control for outliers, we drop the tail observations – 1% – of both the level and the first difference of the variables. All specifications include sector and year fixed effects, which, as Bond et al. (2003) suggest, can account for the variation in the cost of capital services. Table 1 reports the definitions of the variables and their summary statistics; Table A8 in the appendix, the correlation matrix among the main variables.

[Insert Table 1 here]

We apply the two-step SYS GMM estimator to equation (1), which is tailored for dynamic panel models, as developed by Arellano and Bover (1995) and Blundell and Bond (1998). This methodology is designed to handle endogeneity problems related to all the financial variables. We take a joint estimation approach where equation (1) is estimated simultaneously in difference and level. Lagged levels serve as instruments for the regression in difference, lagged differences as instruments for the regression in level.[9] Specifically, we employ the two-step GMM system, treating all explanatory variables as endogenous and year and sector fixed effects as strictly exogenous.

4. THE RESULTS

4.1 Baseline estimates

Table 2 shows the estimation results from our baseline model, for the three measures of firm greenness. Note that all specifications pass the standard diagnostic tests for GMM. Negative first-order serial correlation is correctly detected in the differenced residuals AR(1), while the AR(2) statistics indicate that the null hypothesis of no second-order serial correlation cannot be rejected and, hence, that the instruments are not correlated with the error term. Finally, the Hansen test of overidentifying restrictions shows that the moment conditions assumed for GMM estimation are valid, justifying the use of this estimator.[10]

The coefficient of *GREENFIRM* is positive and significant, suggesting that firms engaged in green activities invest more than non-green firms (columns 1). This result is confirmed for alternative gauges of green firms (*GREENPAT* or *GREENNESS*): the coefficients remain positive and statistically significant (columns 2 and 3).

Moving on to our key variables, we find that the coefficient of cash flow in column (1) is positive (0.32) and statistically significant, while the interaction term between cash flow and green firms is negative (-0.23) and statistically significant at the 1% level. This suggests that the firms in our sample are financially constrained in general, but the investment of green firms is significantly less sensitive than that of non-green firms, statistically and economically, to the availability of internal finance. The

[9] As is well known, estimating the regression in first differences and levels addresses the weak instrument problem caused by using lagged levels of persistent explanatory variables as instruments for the regression in differences (Blundell and Bond, 1998) and overcomes much of the efficiency problem in the first version of difference GMM estimators proposed by Arellano and Bond (1991).

[10] All these tests are also passed in the specifications reported in Tables 3, 4 and 6.

elasticity of investment with respect to cash flow, evaluated at sample means for the specification in column (1), is 0.585 for non-green and 0.168 for green firms. That is, a 10% increase in cash flow would lead to a 5.85% increase in investment in physical capital for non-green firms and just 1.68%, more than three times smaller, for firms engaged in green activities.[11] It is worth noting that the magnitude of our estimated elasticities is broadly consistent with those found in previous studies on investment-cash flow sensitivity (e.g., Mizen and Vermulen, 2006; Guariglia, 2008, Mulier et al., 2016).

[Insert Table 2 here]

As to the other covariates, the estimates confirm the validity of the investment model with adjustment costs. The coefficient of lagged investment is negative, while the sales dynamic has a positive and significant impact on current investment. Further, the coefficient of the error correction term is always statistically significant and has the expected negative sign: when capital is below the desired level, investment increases to regain the equilibrium level.

The coefficient for *ΔEM*P has the expected positive sign, although the estimates are not especially precise. That is, firms' investment responds positively to growth opportunities, in support of the thesis that the cash-flow coefficient captures the impediments to accessing external finance. Likewise, consistent with the financial constraint hypothesis, *WORKCAP* has a negative and statistically significant impact on current fixed investment. By contrast, the coefficients of *AGE*, *LEVERAGE* and *DEBTSUST* are imprecisely estimated, although they jointly contribute to our estimates. Indeed, replicating Table 2 excluding these controls (Table A2 in the Appendix), our coefficients of interest are qualitatively unchanged in sign and significance, while the point estimates indicate a larger

[11] The difference in the elasticity of investment to cash flow is confirmed also using the alternative definitions (columns 2 and 3).

difference in the elasticities of investment to cash flow between non-green and green firms (0.969 and 0.212 respectively).[12]

The results in column (2) of Table 2 allow calculation of the marginal impact of cash flow on investment for different levels of *GREENPAT* (graphed in Figure 1).[13] The *y*-axis measures the marginal effect of *CASHFLOW* for the values of *GREENPAT* ranging, for the sake of visualization, from 0 to 10, corresponding to the 99th percentile of the distribution. The dashed lines define 95% confidence intervals. The marginal effect of cash flow on investment is statistically significant and decreases as the number of green patents registered (*GREENPAT*) increases, up to a threshold of 2.6, above which the effect turns statistically insignificant. In any case, a full 92% of the green firms in our sample fall within the region of significance, corroborating the average results. Computed at the average of *GREENPAT* (1.13), the elasticity of investment to cash flow is 0.393, and an increase of one standard deviation in *GREENPAT* (0.18) implies a decline of about 5% in the estimated elasticity.

If the marginal effect is gauged from the results presented in column (3), where the variable used is *GREENNESS* (graphed in Figure 3), the results are similar. In this case, 72% of green firms are within the significance range.

[Insert Figures 1 and 2 here]

4.2 Sample selection based on innovative firms

A possible weakness in the baseline analysis in Table 2 is that the sample of non-green manufacturing firms is much larger and more heterogeneous than the sample of green innovative firms. Therefore, the estimated difference in the elasticity of investment to cash flow may be driven by unobserved factors related to the different propensity to innovate. To address this issue, we limit the non-green

[12] As mentioned above, we also check the robustness of the baseline results after coarse matching based on these control variables. See Appendix A for a description of the methodology and implementation; the results are reported in Tables A3 to A6.

[13] The graphical illustration is helpful, as the effect of *CASHFLOW* could change sign or lose statistical significance for different levels of *GREENPAT*.

sample to innovative firms, i.e. those companies that obtained at least one non-green patent (but no green patents) in the period 2000-2013.

As is shown by Table 3 (on innovative firms), the coefficient of *GREENFIRM* is positive and statistically significant, suggesting that on average the innovative firms that invest in green activities invest more than non-green innovative firms (column 1). This is confirmed also using our alternative definitions of green firms (*GREENPAT* or *GREENNESS*) – the estimated coefficients for both remain positive. The coefficient of cash flow in column (1) is 0.246 and the interaction term between cash flow and green firms is -0.161 (both coefficients statistically different from zero).[14] The implied elasticity of investment to internal financial resources, evaluated at sample means, is 0.453 for non-green and 0.157 for green firms. These estimates, quantitatively consistent with the baseline results in Table 2, confirm that the subgroup of innovative firms as such are financially constrained, but that green firms' investment is about three times less sensitive to cash flow.

[Insert Table 3 here]

4.3 Heterogeneity analysis

Empirical studies confirm that small firms are more likely to be subject to binding financial constraints and that their investment and R&D spending are more dependent on internal finance than those of large firms (Fazzari et al. 1988; Ughetto, 2008; Brown et al. 2012). Accordingly, we first test whether small firms' investment is more sensitive to cash flow, and then whether the lesser sensitivity of green firms' investment to internal finance is more pronounced among small than larger firms.

Table 4 replicates the baseline analysis splitting the sample between small and medium-large firms, according to the European Commission's classification criterion of €10 million in total assets.[15] The estimates in columns (1) and (2) are for the entire baseline sample used in Table 2. On average, small firms show greater investment sensitivity of investment to cash flow than medium-large firms,

[14] Using the alternative measure of green patenting activity, namely the IPC codes, the results are qualitatively similar, as reported in Table A1.

[15] We take average total assets over the period analysed.

although the difference tends to disappear when analysis is restricted to innovative firms alone (columns 3 and 4). In line with the literature, this indicates more binding financial constraints for smaller companies.

More to the point, small green firms show much less sensitivity of investment to cash flow than their non-green counterparts, while among large firms the difference between green and non-green firms is significantly less marked. With reference to the estimates in column (1), small green firms display a sensitivity about 3.5 times lower than that of small non-green firms (0.1034 vs. 0.3094). In the subgroup of larger firms (column 2), by contrast, the sensitivity of investment does not differ significantly between non-green and green firms. But if the control group is limited to innovative non-green firms (columns 3 and 4), we find that green firms' investment is less sensitive to internal cash flow in both subsamples, but again the difference vis-à-vis non-green firms is more pronounced among the small innovative firms (among small firms the estimated coefficient of green firms is 3.8 times lower than that of non-green firms, compared with 2.2 times among the large firms).

Overall, our findings indicate that greenness reduces the dependence of investment on internal finance for all firms, regardless of size, but that this reduction is economically and statistically more significant for small firms. This suggests that small firms, which generally have less access to external finance, benefit relatively more from an easing of financing constraints when they innovate in green activities.

[Insert Table 4 here]

5. Additional Results

5.1 Firms in green sectors

In identifying green as against non-green firms, two distinct types of error may be made: 1) mistakenly classifying non-green firms as green; or 2) excluding firms from the green group even though they actually make environmentally related investments. So far, we have identified green firms by patenting activity, a restrictive definition that minimizes type-1 problems but remains vulnerable to type-2, especially for smaller non-innovative firms. To overcome this issue, we propose an alternative classification, adopting a broader definition based on the greenness of the firm's economic sector rather than its individual involvement in green activities. In other words, we test the investment cash-flow sensitivity of firms in green as against other sectors.

To gauge a sector's greenness we first identify green patents, exploiting the IPC codes of the groups selected by the OECD and/or the WIPO project, extending the analysis to all patents registered in OECD countries since 1977.[16] Second, we link the patent to the owner or applicant firm in order to determine the sector (four-digit NACE-rev2) in which the technology is used. Third, following Ghisetti and Quartaro (2017), if a patent is used by a firm operating in a sector, that patent counts for the degree of greenness of that sector. Hence, the greenness of sector *s* is given by the share of green patents in total patents of firms in *s*, $SECT\_GREENNESS_s = \frac{\sum GPat_s}{\sum Pat_s}$, where $GPat_s$ (or Pat_s) is equal to 1 if the green patent (or the patent) is held by a firm operating in sector *s* and 0 otherwise. Figure 3 shows the 20 greenest sectors, so identified, in OECD countries since 1977.

[Insert Figure 3 here]

We also apply a second measure of sectoral greenness, based on the industry-technology approach suggested by Wurlod and Noailly (2018). After identifying the green patents as above, we relate patents (coded in IPC) to their sectors relying on the Algorithmic Links with Probabilities (ALP) concordance table developed by Lybbert and Zolas (2014) together with the World Intellectual Property Organization (WIPO). The ALP table reports the likelihood of a given technology's use in production by firms in each sector. Specifically, for each IPC code the table lists the sectors and the probability of firms in each sector using that technology.[17] Then, following Wurlod and Noailly (2018), we count the number of patents allocated to each sector weighted by the corresponding probabilities, $WN\_SECT\_GREENNESS_s = \sum_{GP=1}^{N} GP\pi_{GP,s}$, where GP denotes patents with at the least one green

[16] As above, for patents that have more than one IPC code we use the fractional count.

[17] The authors use text analysis software and keyword extraction programs to develop a probability distribution of possible industries with which a patent in each technology field may be associated. See Lybbert and Zolas (2014) for a detailed description of their algorithm.

code and $\pi_{GP,s}$ the probability of the patented technology's being used in sector s.[18] Figure 4 shows the 20 greenest sectors, so measured, at 4-digit NACE in OECD countries since 1977.

[Insert Figure 4 here]

We replicate the baseline analysis in equation (1) with these two sectoral identifiers of greenness in lieu of the firm-level classification. The regressions, reported in Table 5, demonstrate the robustness of our results to this alternative classification. Columns (1) and (2) give the results for the entire baseline sample, columns (3) and (4) for the sub-sample of innovative firms only. The estimates of our main coefficients of interest in columns (1) and (2), namely cash flow and its interaction with the green identifier, indicate that the sensitivity of investment to cash flow is positive for both non-green and green firms, but significantly lower for firms in greener sectors. These results are confirmed for the sub-group of innovative firms.

[Insert Table 5 here]

5.2 Patenting and internal finance

In interpreting our results, a natural question is whether the lesser stringency of financial constraints on green firms relates to all types of physical capital or only to green-type capital. Unfortunately, since balance sheets do not distinguish between green and non-green investment, we cannot address this issue directly. However, we can use patenting activity, distinguishing between "green" patents (those with at least one green CCMT code) and others. Then, on the assumption that a green or non-green patent will require a corresponding green or non-green fixed investment, we test the relative sensitivity of green and non-green patenting activity to cash flow.

Specifically, following Lööf and Nabavi (2016) and Zhang and Jin (2021), we estimate the subsequent regression model:

[18] For instance, if there are 10 patents in this IPC classification (with one single IPC code) and the probability of belonging to a certain sector is 0.5, five patents will be allocated to this industrial sector. For a detailed description, the reader may refer to Wurlod and Noailly (2018).

$$ZPAT_{it} = \alpha + \beta_1 \frac{CASHFLOW_{it}}{CAPITAL_{it-1}} + \beta_2 ZPAT_{it-1} + \beta_3 \Delta LNSALES_{it-1} + \beta_4 \Delta EMP_{it-1}$$

$$+\phi X_{it-1} + \zeta_s + \varphi_t + \epsilon_{it}, \qquad (2)$$

We estimate equation (2) taking as dependent variable either the number of non-green patents (NOGREENPAT) or the number of green patents (GREENPAT). The explanatory variables are cash flow over lagged capital, the lagged number of non-green/green patents, and the lagged annual change in sales and employment; the controls are the same as in equation (1) and specifications include sector and year fixed effects. As the dependent variables are left-censored at zero, we use a Tobit regression model.

The results in Table 6, columns (1) and (2), are for the entire sample; in columns (3) and (4) the sample is restricted to innovative firms only. Columns (1) and (3) show that cash flow is positively and significantly related to the number of non-green patents, consistent with earlier studies (Ughetto, 2008; Brown et al., 2009; Lööf and Nabavi, 2016; Zhang and Jin, 2021). By contrast, there is no significant effect of cash flow on the number of green patents (columns 2 and 4). These results strongly suggest that investment in green technology is less subject to external financial constraints than that in non-green technology, which confirms our results as regards total investment.[19]

[Insert Table 6 here]

6. Concluding Remarks

This paper seeks to determine how much the sensitivity of investment to cash flow differs between firms investing in green patents and other firms. We find robust evidence that green and innovative firms have significantly lower elasticity, in keeping with the hypothesis that these firms are less financially constrained. Our analysis of patenting suggests that this reduced sensitivity is driven at least

[19] In Table A7 we replicate the estimation results of Table 5 using OLS. In this case the dependent variable is either the log of the number of non-green patents (LNNOGREENPAT) or the log of the number of green patents (LNGREENPAT). The coefficients are consistent with the marginal effects from Tobit estimation in both sign and statistical significance.

in part by investment in green intangible capital, offering support for the thesis that the recent public awareness of the importance of carbon transition may have induced outside investors to favor green firms, easing the financial constraints on their capital investments. Our results are consistent with recent findings on the role of stepped-up government commitment to stricter enforcement of climate policies (e.g. the Paris Agreement of 2015) in influencing the lending behavior of banks and other financial institutions to favor green firms.

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APPENDIX A

A.1 Coarse matching

We control for the observable determinants of financial constraint on firms by checking the main variables identified in the literature, such as age, leverage, average cost of debt, and working capital. Another feasible, if more restrictive, strategy is to match non-green and green firms according to specific observables to generate balanced summary statistics. Here we adopt this strategy via coarse matching before replicating our baseline regression. Specifically, we utilize a 1:3 matching without replacement, linking case observations to control observations. The procedure comprises four variables: age, leverage, working capital, and cost of debt. Different calipers are specified for each matching variable, namely 3, 0.1, 0.05, and 0.1 respectively. The final matched sample consists of 1,324 firms, 1,008 of them classified as non-green. Table A3 shows that the two groups in the matched sample display no significant differences in any of the matching covariates except DEBTSUST, where the test is statistically significant at 7.2%. We then use this sample to estimate equation (1) without the vector of controls. This enables us to assess robustness using a more parsimonious specification and aligning with a reduced-form investment model based on the error correction approach taken by Bond et al. (2003), Mizen and Vermeulen (2005), Bloom et al. (2007), Guariglia (2008), and Mulier et al. (2016). The estimates in Table A4 confirm our main findings: all firms experience financial constraints, but the investment of green firms is significantly less sensitive to the availability of internal finance than that of non-green firms. Lastly, we replicate the coarse matching for the subsample of innovative firms (Table A5 reports the balance of the covariates after this matching). Again, the results confirm the robustness of our findings after this further sample restriction (Table A6).

Table 1 - Description and summary statistics

		Mean	Std. Dev.	Min	Max	Obs
Main variables						
INVESTMENT	Sum of depreciation in year t and the change in tangible fixed assets from year t −1 to year t diveded by replacement value of the firm's capital stock.	0.575	1.237	-0.847	14.283	146,537
CASHFLOW	Cash flow scaled by its beginning of period capital.	1.054	2.680	-23.743	30.574	146,537
GREENFIRM	Dummy = 1 if the firm has at least one green patent (CPC code) during the period 2000 - 2013.	0.007	0.085	0	1	146,537
GREENPAT	Number of firm green patent identified by CPC code during the period 2000 -2013. See section 2 for a detailed description.	0.008	0.182	0	17.944	146,537
GREENNESS	Number of firm green patent identified by CPC code over total patent during the period 2000 -2013. See section 2 for a detailed description.	0.001	0.018	0	1	146,537
ΔSALES	Change in the log of real total sales.	0.050	0.242	-3.752	3.906	146,537
DIFFKAPSALES	Difference between the log of capital and the log of real total sales.	2.240	1.462	-4.306	8.475	146,528
ΔEMP	Change in the log of real total costs of employees	0.055	0.151	-2.763	2.219	146,537
AGE	Current year minus firm's year of establishment	20.513	13.202	3	61	146,537
LEVERAGE	(Current plus non-current liabilities) to total assets	0.711	0.212	0.054	1.250	146,537
DEBTSUST	Interest paid to total sales	0.011	0.017	0	0.397	146,537
WORKCAP	(Currents assets minus current liabilities) to total assets	0.227	0.248	-0.981	0.962	146,537
Other variables						
SECT_GREENNESS	Log of the number of green patent at sectoral level (4-digit). See section 5.1 for a detailed description.	7.621	2.026	0	11.432	146,537
WN_SECT_GREENNESS	Log of the number of green patent at sectoral level (4-digit), following Wurload and Noailly methodology. See section 5.1 for a detailed description.	4.794	4.056	0	12.779	146,537
GREENFIRM2	Dummy = 1 if the firm has at least one green patent (IPC code) during the period 2000 - 2013.	0.016	0.124	0	1	146,537
GREENPAT2	Number of firm green patent identified by IPC code during the period 2000 -2013. See section 2 for a detailed description.	0.034	0.489	0	19.102	146,537
GREENNESS2	Number of firm green patent identified by IPC code over total patent during the period 2000 -2013. See section 2 for a detailed description.	0.004	0.046	0	1	146,537

Notes: to control for outliers, we drop observations in the 1% tails of the distribution of these variables.

Table 2 - Investment-cash flow sensitivity: green vs no-green firms. Baseline estimation results

	1	2	3
CASHFLOW	0.3176***	0.2698***	0.3368***
	0.0654	*0.0677*	*0.0903*
GREENFIRM	0.4098**		
	0.1604		
CASHFLOW*GREENFIRM	-0.2265***		
	0.0762		
GREENPAT		0.1670**	
		0.0732	
CASHFLOW*GREENPAT		-0.0497*	
		0.0279	
GREENNESS			1.8096*
			0.9394
CASHFLOW*GREENNESS			-1.3013**
			0.6507
INVESTMENT_1	-0.0867	0.0327	0.1386
	0.1021	*0.1111*	*0.1156*
ΔSALES	-0.1623	-0.2885	-0.4830
	0.2075	*0.2716*	*0.3039*
ΔSALES_1	0.3689***	0.2521*	0.1778
	0.1130	*0.1471*	*0.1728*
DIFFKAPSALES_2	-0.2920***	-0.2446**	-0.0887
	0.0906	*0.1142*	*0.1287*
ΔEMP	0.3632	0.4497	0.6763**
	0.2297	*0.2899*	*0.3283*
AGE	-0.0016	0.0049	0.0060
	0.0032	*0.0042*	*0.0044*
LEVERAGE	0.6261	0.3117	0.4057
	0.5121	*0.5691*	*0.6478*
DEBTSUST	-3.3828*	0.1022	-1.9824
	2.0289	*2.3877*	*2.9703*
WORKCAP	-0.9922**	-1.2227**	-1.1806**
	0.4238	*0.5017*	*0.5621*
Year dummies	*Yes*	*Yes*	*Yes*
Sector dummies	*Yes*	*Yes*	*Yes*
Observations	146,537	146,537	146,537
AR(1) z-statistic	-4.7099	-5.1214	-5.5173
AR(1) z-statistic (p)	0.0000	0.0000	0.0000
AR(2) z-statistic	-0.1596	1.0021	1.4707
AR(2) z-statistic (p)	0.8730	0.3160	0.1410
Hansen test	72.4681	72.5551	54.8882
Hansen test (p)	0.1300	0.1280	0.3660
Joint significance test(CASHF, GREENFIRM)	24.7508		
P(CASHF, GREENFIRM)	0.0000		
Joint significance test(CASHF, GREENPAT)		17.3498	
P(CASHF, GREENPAT)		0.0002	
Joint significance test(CASHF, GREENNESS)			13.9996
P(CASHF, GREENNESS)			0.0009

Notes: table 2 shows estimates of equation (1). Estimations are carried out by using the two-step SYS GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics. Tests for the first and second order autocorrelation (AR(1) and AR(2)), and the Hansen test of overidentifying restrictions are reported.

Table 3 - Investment-cash flow sensitivity: green vs no-green firms. Focussing on innovative sample

	1	2	3
CASHFLOW	0.2460***	0.2662***	0.3069***
	0.0350	0.0425	0.0445
GREENFIRM	0.3771**		
	0.1701		
CASHFLOW*GREENFIRM	-0.1606**		
	0.0751		
GREENPAT		0.1583**	
		0.0712	
CASHFLOW*GREENPAT		-0.0380*	
		0.0214	
GREENNESS			0.8310*
			0.4434
CASHFLOW*GREENNESS			-0.8695**
			0.3558
INVESTMENT_1	-0.1944**	-0.2503**	-0.1905**
	0.0825	0.1094	0.0774
ΔSALES	0.2061	0.1439	0.1484
	0.2332	0.2393	0.2309
ΔSALES_1	0.4268***	0.4198**	0.4413***
	0.1517	0.1691	0.1407
DIFFKAPSALES_2	-0.3540***	-0.4909***	-0.3906***
	0.1326	0.1557	0.1134
ΔEMP	-0.1287	-0.0659	-0.0417
	0.2649	0.2523	0.2583
AGE	-0.0081	0.0030	-0.0027
	0.0094	0.0072	0.0062
LEVERAGE	1.8221***	1.8780***	1.6078***
	0.6162	0.4862	0.4140
DEBTSUST	2.3513	2.8142	4.6210*
	2.9007	3.0285	2.6266
WORKCAP	-0.4427	-0.7654	-0.6873*
	0.5343	0.5370	0.3728
Year dummies	*Yes*	*Yes*	*Yes*
Sector dummies	*Yes*	*Yes*	*Yes*
Observations	21,414	21,414	21,414
AR(1) z-statistic	-4.8346	-3.7077	-5.2967
AR(1) z-statistic (p)	0.0000	0.0000	0.0000
AR(2) z-statistic	-1.5940	-1.4571	-1.3987
AR(2) z-statistic (p)	0.1110	0.1450	0.1620
Hansen test	93.4858	86.6657	90.7502
Hansen test (p)	0.2720	0.2350	0.2880
Joint significance test(CASHF, GREENFIRM)	50.6030		
P(CASHF, GREENFIRM)	0.0000		
Joint significance test(CASHF, GREENPAT)		47.0343	
P(CASHF, GREENPAT)		0.0000	
Joint significance test(CASHF, GREENNESS)			47.8453
P(CASHF, GREENNESS)			0.0000

Notes: table 3 shows estimates of equation (1). Estimations are carried out by using the two-step SYS GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics. Tests for the first and second order autocorrelation (AR(1) and AR(2)), and the Hansen test of overidentifying restrictions are reported.

Table 4 - Estimation results comparing small and medium/large firms

	1	2	3	4
CASHFLOW	0.3094***	0.1289*	0.2137***	0.2112***
	0.0703	0.0739	0.0395	0.0526
GREENFIRM	0.3870***	0.2985*	0.2449**	0.2790**
	0.1253	0.1720	0.1114	0.1247
CASHFLOW*GREENFIRM	-0.2060*	-0.0670	-0.1575*	-0.1158*
	0.1058	0.0756	0.0923	0.0696
INVESTMENT_1	0.0238	-0.2022	-0.0948	-0.2069**
	0.1138	0.1811	0.0838	0.0911
ΔSALES	-0.3283	0.2791	0.0934	0.0625
	0.2387	0.2264	0.2633	0.2818
ΔSALES_1	0.2409**	0.4954***	0.4421***	0.4742***
	0.1192	0.1589	0.1633	0.1613
DIFFKAPSALES_2	-0.2149***	-0.4696***	-0.4765***	-0.3501***
	0.0789	0.1476	0.1240	0.1077
ΔEMP	0.5233*	-0.1497	-0.0141	0.1759
	0.2745	0.2225	0.3193	0.2930
AGE	0.0019	-0.0019	-0.0005	0.0033
	0.0023	0.0068	0.0071	0.0074
LEVERAGE	0.4361	0.9528	0.8623*	0.7333
	0.5206	0.7565	0.4888	0.6890
DEBTSUST	-3.7756**	9.1442*	2.4010	9.6392
	1.7088	5.1294	2.9735	9.1417
WORKCAP	-0.9893**	0.0785	-1.0894***	-0.5637
	0.4171	0.5707	0.4012	0.4791
Year dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Observations	131,634	14,903	14,532	6,882
AR(1) z-statistic	-4.7556	-1.7597	-5.3696	-2.8627
AR(1) z-statistic (p)	*0.0000*	*0.0780*	*0.0000*	*0.0040*
AR(2) z-statistic	0.7177	-0.2080	0.6340	-1.4914
AR(2) z-statistic (p)	*0.4730*	*0.8350*	*0.5260*	*0.1360*
Hansen test	74.1182	61.0202	98.6171	85.3341
Hansen test (p)	*0.1820*	*0.4750*	*0.2280*	*0.3790*
Joint significance test(CASHF, GREENFIRM)	20.3721	3.9768	30.2724	16.1382
P(CASHF, GREENFIRM)	*0.0000*	*0.1369*	*0.0000*	*0.0003*
Firm size	Small	Medium-Large	Small	Medium-Large
Sample	All	All	Innovative	Innovative

Notes: table 4 shows estimates of equation (1). Estimations are carried out by using the two-step SYS GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics. Tests for the first and second order autocorrelation (AR(1) and AR(2)), and the Hansen test of overidentifying restrictions are reported.

Table 5 - Robustness check using Green sector

	1	2	3	4
CASHFLOW	0.7090**	0.3605**	0.7733**	0.2350***
	0.3167	*0.1488*	*0.3085*	*0.0577*
SECT_GREENNESS	0.2843**		0.1092**	
	0.1262		*0.0487*	
CASHFLOW*SECT_GREENNESS	-0.0703**		-0.0663**	
	0.0352		*0.0335*	
WN_SECT_GREENNESS		0.2139**		0.0162*
		0.0859		*0.0098*
CASHFLOW*WN_SECT_GREENNESS		-0.0326**		-0.0120*
		0.0158		*0.0070*
INVESTMENT_1	0.1966*	0.2199*	-0.1709	-0.1115
	0.1086	*0.1244*	*0.1180*	*0.1002*
ΔSALES	-0.0351	-0.2974	0.0845	0.1330
	0.2504	*0.3382*	*0.2433*	*0.2041*
ΔSALES_1	0.3111**	0.2085	0.5260***	0.5070***
	0.1423	*0.2150*	*0.1841*	*0.1507*
DIFFKAPSALES_2	-0.2615***	-0.2109*	-0.4868***	-0.4279***
	0.0783	*0.1181*	*0.1465*	*0.1128*
ΔEMP	0.1636	0.4411	0.0794	-0.0090
	0.2749	*0.3494*	*0.2563*	*0.2226*
AGE	0.0069	0.0169**	-0.0089	-0.0108**
	0.0042	*0.0083*	*0.0063*	*0.0049*
LEVERAGE	-0.2931	-0.3415	0.6790	0.3986
	0.4168	*0.6356*	*0.7315*	*0.6258*
DEBTSUST	-2.1028	0.5013	2.8771	2.6299
	2.0276	*2.7144*	*2.1224*	*1.9630*
WORKCAP	-0.9917**	-1.3082**	-1.5393*	-1.2926*
	0.4034	*0.5890*	*0.8082*	*0.7108*
Year dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Observations	146,298	146,298	21,414	21,414
AR(1) z-statistic	-6.3370	-7.4652	-3.4792	-4.3344
AR(1) z-statistic (p)	0.0000	0.0000	0.0010	0.0000
AR(2) z-statistic	-1.0725	-0.3481	-0.2602	-0.0142
AR(2) z-statistic (p)	0.2830	0.7280	0.7950	0.9890
Hansen test	70.7499	51.7531	78.1386	99.4583
Hansen test (p)	0.1410	0.1210	0.2900	0.1900
Joint significance test(CASHF, SECT_GREENNESS)	7.0433		6.3503	
P(CASHF,SECT_GREENNESS	0.0296		0.0418	
Joint significance test(CASHF, WN_SECT_GREENNESS)		9.1547		31.5572
P(CASHF, WN_SECT_GREENNESS)		0.0103		0.0000

Notes: table 5 shows estimates of equation (1). Estimations are carried out by using the two-step SYS GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics. Tests for the first and second order autocorrelation (AR(1) and AR(2)), and the Hansen test of overidentifying restrictions are reported.

Table 6 - Estimation results using patenting activity as a dependent variable.

	1	2	3	4
CASHFLOW	0.0015***	0.0001	0.0150***	0.0001
	0.0003	0.0001	0.0029	0.0001
NOGREENPAT_1	0.1902***		0.1369***	
	0.0092		0.0107	
GREENPAT_1		0.0059***		0.0135***
		0.0009		0.0036
ΔSALES	-0.0005	-0.0001	-0.0223	0.0000
	0.0048	0.0001	0.0458	0.0012
ΔEMP	0.0755***	0.0010***	0.4021***	0.0051***
	0.0090	0.0002	0.0830	0.0017
AGE	0.0009***	0.0000***	-0.0044***	-0.0000*
	0.0001	0.0000	0.0008	0.0000
LEVERAGE	-0.0510***	-0.0010***	-0.3004***	-0.0072***
	0.0061	0.0002	0.0568	0.0019
DEBTSUST	-0.2375***	0.0029**	-2.7043***	0.0237*
	0.0861	0.0014	0.7888	0.0123
WORKCAP	-0.0321***	-0.0006***	-0.2565***	-0.0053***
	0.0054	0.0002	0.0520	0.0018
Year dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Observations	148,125	148,125	21,313	21,313
Dep. Variable	NOGREENPAT	GREENPAT	NOGREENPAT	GREENPAT
Sample	All	All	Innovative	Innovative

Notes: table 6 shows the marginal effects of the covariates on the conditional expected value E(y|y>0, x) of the observed outcome of equation (2). Estimations are carried out by using the Tobit estimator. For the description of the variables, see Table 1. The dependent variable is reported at the bottom of the table. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics.

Figure 1. Marginal Effect of CASHFLOW on INVESTMENT as GREENPAT changes.

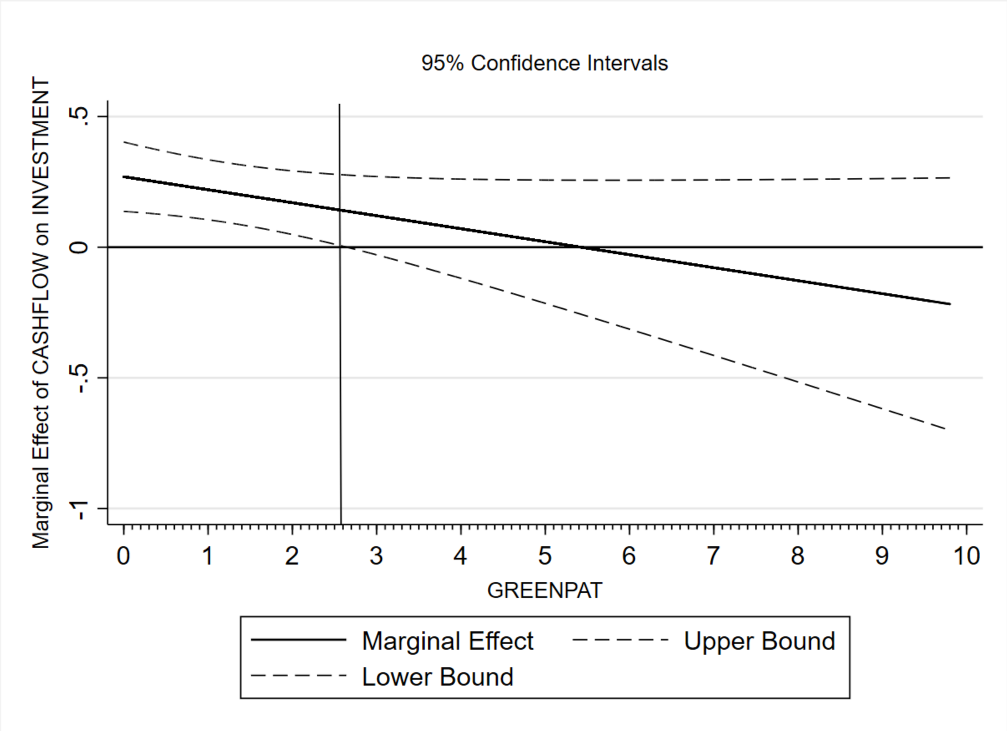

Figure 2. Marginal Effect of CASHFLOW on INVESTMENT as GREENNESS changes.

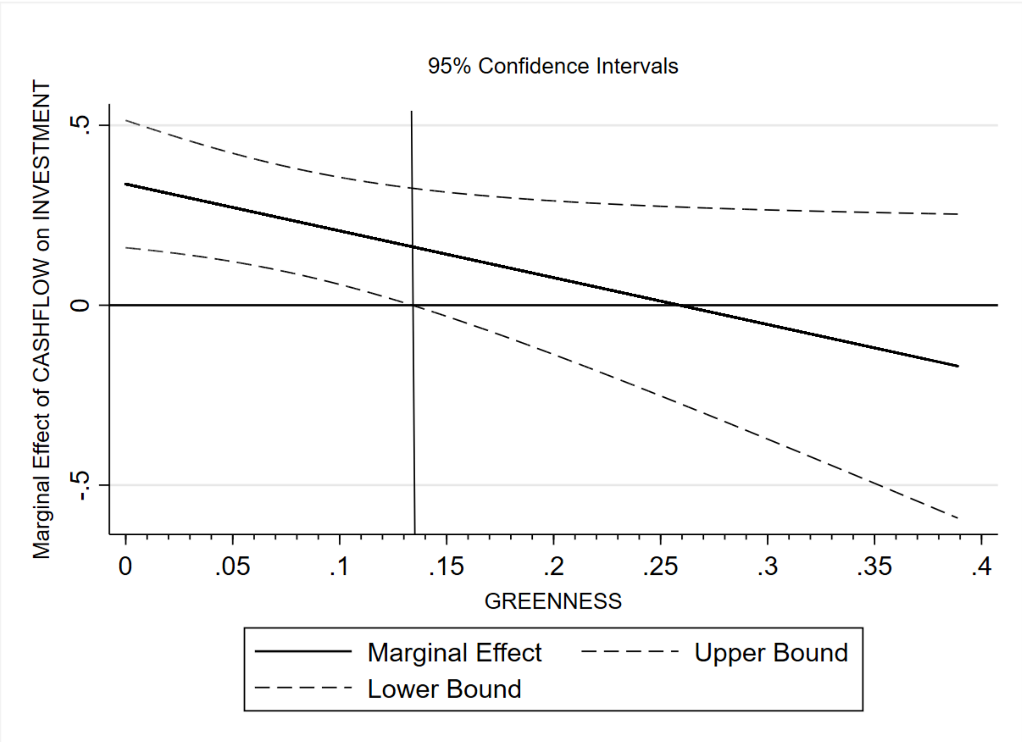

Figure 3. Top 20 Green sector in OECD Countries, by Number of Green Patents.

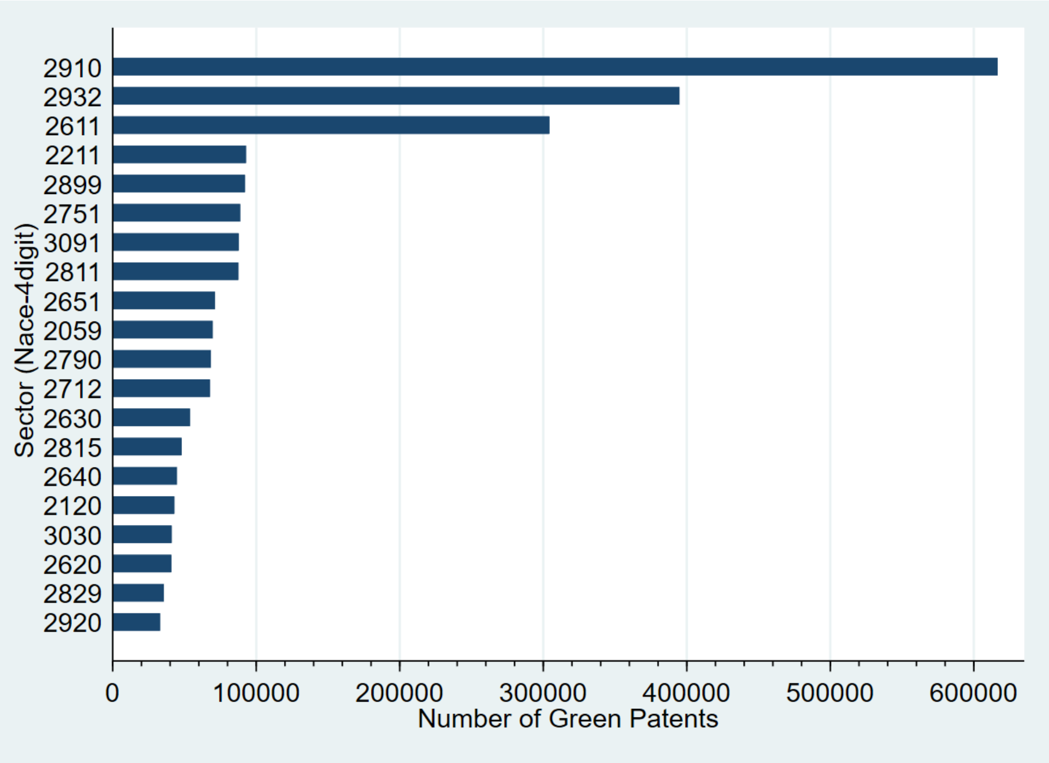

Figure 4. Top 20 Green sector in OECD Countries (Wurlod and Noailly (2018) approach).

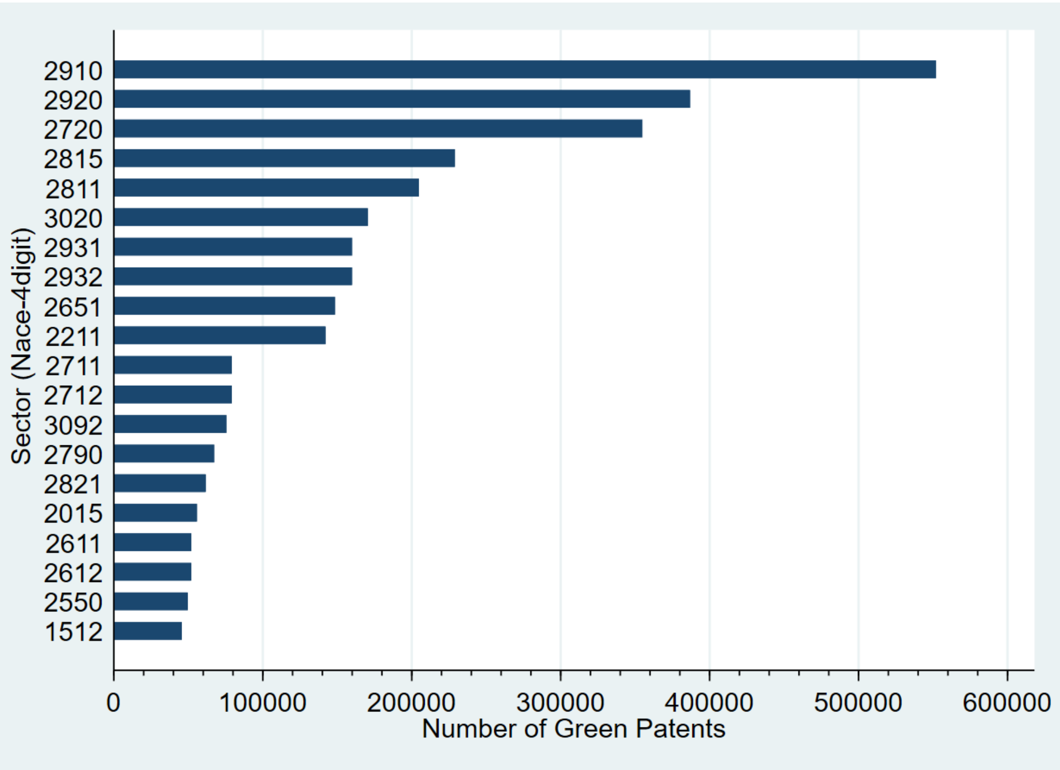

Table A1 - Robustness check: estimation results using alternative measure of green patent

	1	2	3	4	5	6
CASHFLOW	0.1770***	0.2149***	0.1531***	0.2298***	0.1599***	0.3191***
	0.0575	0.0538	0.0413	0.0265	0.0418	0.0428
GREENFIRM2	0.9211**			0.2433***		
	0.4018			0.0606		
CASHFLOW*GREENFIRM2	-0.1346**			-0.1733***		
	0.0629			0.0495		
GREENPAT2		0.0022			0.0047*	
		0.0027			0.0028	
CASHFLOW*GREENPAT2		-0.0013**			-0.0010**	
		0.0005			0.0004	
GREENNESS2			0.6137			0.5687**
			0.5337			0.2442
CASHFLOW*GREENNESS2			-0.0068			-0.4058**
			0.1400			0.1955
INVESTMENT_1	-0.0609	-0.2127*	0.0546	-0.1808***	-0.3988***	-0.0823
	0.1092	0.1265	0.1255	0.0651	0.1406	0.0846
ΔSALES	0.1913	0.4759	-0.0704	0.2031	1.2458***	-0.1433
	0.3054	0.3090	0.3269	0.1981	0.3812	0.2607
ΔSALES_1	0.4444**	0.7590***	0.3413*	0.4319***	1.1156***	0.3230*
	0.1753	0.1878	0.1764	0.1243	0.2526	0.1674
DIFFKAPSALES_2	-0.4078***	-0.6194***	-0.3238**	-0.4006***	-1.0907***	-0.2258*
	0.1450	0.1559	0.1606	0.1001	0.2339	0.1227
ΔEMP	-0.0398	-0.2218	0.2822	-0.1641	-1.0972***	0.2539
	0.3190	0.3276	0.3599	0.2380	0.3832	0.2916
AGE	0.0089	0.0171**	-0.0119	-0.0036	-0.0294**	-0.0063
	0.0061	0.0083	0.0109	0.0053	0.0134	0.0054
LEVERAGE	-0.8285	-0.0576	2.0593*	1.2497***	-0.8338	1.9997***
	0.7273	0.6949	1.2487	0.3247	1.1789	0.4037
DEBTSUST	0.0370	0.0960	-1.5692	2.7380	10.5089*	3.5611
	1.8724	2.5942	6.6961	2.6277	5.8656	3.4343
WORKCAP	-2.0047***	-1.5032***	-0.3894	-0.6197**	-1.3292	-0.2000
	0.6699	0.5787	0.6416	0.3158	0.8466	0.3816
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Sector dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	146,537	146,537	146,537	21,414	21,414	21,414
AR(1) z-statistic	-5.4496	-3.5418	-4.7797	-5.8619	-2.8106	-5.7246
AR(1) z-statistic (p)	0.0000	0.0000	0.0000	0.0000	0.0050	0.0000
AR(2) z-statistic	0.5628	-0.5496	1.4899	-1.3055	-1.1546	-0.4387
AR(2) z-statistic (p)	0.5740	0.5830	0.1360	0.1920	0.2480	0.6610
Hansen test	72.5692	41.1831	58.2004	94.8842	59.0370	70.7747
Hansen test (p)	0.1280	0.5070	0.1270	0.2890	0.6520	0.6170
Joint significance test(CASHF, GREENFIRM2)	15.7056			75.7525		
P(CASHF, GREENFIRM2)	0.0004			0.0000		
Joint significance test(CASHF, GREENPAT2)		16.2660			18.9615	
P(CASHF, GREENPAT2)		0.0003			0.0001	
Joint significance test(CASHF, GREENNESS2)			13.8765			56.4534
P(CASHF, GREENNESS2)			0.0010			0.0000
Sample	*All*	*All*	*All*	*Innovative*	*Innovative*	*Innovative*

Notes: table A1 shows estimates of equation (1). Estimations are carried out by using the two-step SYS GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics. Tests for the first and second order autocorrelation (AR(1) and AR(2)), and the Hansen test of overidentifying restrictions are reported.

Table A2 - Baseline estimation results excluding control variables

	1	2	3
CASHFLOW	0.5259***	0.4209***	0.5447***
	0.0887	0.1048	0.1049
GREENFIRM	0.6013***		
	0.1584		
CASHFLOW*GREENFIRM	-0.4107***		
	0.1086		
GREENPAT		0.3184**	
		0.1449	
CASHFLOW*GREENPAT		-0.1177**	
		0.0469	
GREENNESS			1.5207
			0.9740
CASHFLOW*GREENNESS			-1.4481***
			0.4460
INVESTMENT_1	0.0315	0.0050	0.0398
	0.0261	0.1875	0.0322
ΔSALES	-0.2723	-0.2115	-0.3197
	0.3110	0.3371	0.4693
ΔSALES_1	0.1987	0.1776	0.1233
	0.1909	0.2112	0.3079
DIFFKAPSALES_2	0.0255	-0.1156	0.0532
	0.1046	0.1761	0.1314
ΔEMP	0.4461	0.2611	0.4799
	0.3358	0.3823	0.4744
Year dummies	*Yes*	*Yes*	*Yes*
Sector dummies	*Yes*	*Yes*	*Yes*
Observations	146,537	146,537	146,537
AR(1) z-statistic	-20.6534	-3.4453	-19.1638
AR(1) z-statistic (p)	0.0000	0.0010	0.0000
AR(2) z-statistic	-0.8843	0.0437	-0.8492
AR(2) z-statistic (p)	0.3770	0.9650	0.3960
Hansen test	31.7661	21.6145	33.2538
Hansen test (p)	0.2410	0.3040	0.1550
Joint significance test(CASHF, GREENFIRM)	35.2365		
P(CASHF, GREENFIRM)	0.0000		
Joint significance test(CASHF, GREENPAT)		16.7885	
P(CASHF, GREENPAT)		0.0002	
Joint significance test(CASHF, GREENNESS)			27.8685
P(CASHF, GREENNESS)			0.0000

Notes: table A2 shows estimates of equation (1) excluding the variables of the X vector. Estimations are carried out by using the two-step SYS GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics. Tests for the first and second order autocorrelation (AR(1) and AR(2)), and the Hansen test of overidentifying restrictions are reported.

TABLE A3 - Means values of the variables used for the matching

Variable	Green Firms	No-Green Firms	Test of the difference between means ***P-Value***
AGE	23.17	23.24	*0.8274*
LEVERAGE	0.671	0.666	*0.2641*
DEBTSUST	0.014	0.015	*0.0722*
WORKCAP	0.23	0.24	*0.8105*

Notes: for the description of the variables, see Table 1. H0: Equal mean among groups.

Table A4 - Estimation results: robustness on matched sample

	1	2	3
CASHFLOW	0.2775**	0.3389***	0.4684***
	0.1375	0.1045	0.1624
GREENFIRM	0.3859***		
	0.1490		
CASHFLOW*GREENFIRM	-0.2496*		
	0.1414		
GREENPAT		0.2560*	
		0.1325	
CASHFLOW*GREENPAT		-0.0657*	
		0.0374	
GREENNESS			1.3693*
			0.7558
CASHFLOW*GREENNESS			-1.2620*
			0.7129
INVESTMENT_1	-0.0223	-0.2953	-0.1402
	0.0601	0.2946	0.2409
ΔSALES	-0.7083	-0.8042	-0.4228
	0.5839	0.5829	0.9658
ΔSALES_1	0.1953	0.1737	-0.0154
	0.2572	0.3138	0.6126
DIFFKAPSALES_2	-0.2796	-0.2401	-0.0328
	0.1806	0.1947	0.2492
ΔEMP	1.2398*	1.1537	0.5959
	0.7164	0.7877	1.1346
Year dummies	*Yes*	*Yes*	*Yes*
Sector dummies	*Yes*	*Yes*	*Yes*
Observations	4,576	4,576	4,576
AR(1) z-statistic	-4.7407	-1.7517	-2.5481
AR(1) z-statistic (p)	0.0000	0.0760	0.0110
AR(2) z-statistic	1.0994	-0.4881	0.0696
AR(2) z-statistic (p)	0.2720	0.6250	0.9440
Hansen test	33.2839	24.7708	14.1239
Hansen test (p)	0.7650	0.7780	0.8640
Joint significance test(CASHF, GREENFIRM)	6.9441		
P(CASHF, GREENFIRM)	0.0311		
Joint significance test(CASHF, GREENPAT)		10.5240	
P(CASHF, GREENPAT)		0.0052	
Joint significance test(CASHF, GREENNESS)			9.4353
P(CASHF, GREENNESS)			0.0089

Notes: table A4 shows estimates of equation (1) excluding the variables of the X vector. Estimations are carried out by using the two-step SYS GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics. Tests for the first and second order autocorrelation (AR(1) and AR(2)), and the Hansen test of overidentifying restrictions are reported.

TABLE A5 - Means values of the variables used for the matching (innovative firms)

Variable	Green Firms	No-Green Firms	Test of the difference between means ***P-Value***
AGE	23.44	23.52	*0.7816*
LEVERAGE	0.661	0.660	*0.8861*
DEBTSUST	0.012	0.010	*0.0000*
WORKCAP	0.25	0.26	*0.2347*

Notes: for the description of the variables, see Table 1. H0: Equal mean among groups.

Table A6 - Estimation results: robustness on matched sample of innovative firms

	1	2	3
CASHFLOW	0.4231***	0.2937***	0.5044***
	0.1291	*0.0738*	*0.1655*
GREENFIRM	0.4948***		
	0.1626		
CASHFLOW*GREENFIRM	-0.3868***		
	0.1270		
GREENPAT		0.1894*	
		0.1146	
CASHFLOW*GREENPAT		-0.0503*	
		0.0301	
GREENNESS			4.0266*
			2.0606
CASHFLOW*GREENNESS			-1.4022*
			0.8303
INVESTMENT_1	-0.0442	-0.1804	-0.0451
	0.0750	*0.1371*	*0.2937*
ΔSALES	0.0326	-0.3743	-0.9030
	0.4297	*0.3722*	*0.7844*
ΔSALES_1	0.6144**	0.2883	-0.2664
	0.2514	*0.3720*	*0.4776*
DIFFKAPSALES_2	-0.4184*	-0.2881**	0.2161
	0.2340	*0.1403*	*0.3604*
ΔEMP	0.4700	0.8836**	1.3818*
	0.4989	*0.4204*	*0.7778*
Year dummies	*Yes*	*Yes*	*Yes*
Sector dummies	*Yes*	*Yes*	*Yes*
Observations	4,625	4,625	4,625
AR(1) z-statistic	-4.7293	-2.9497	-2.0797
AR(1) z-statistic (p)	0.0000	0.0030	0.0380
AR(2) z-statistic	0.6545	-0.7607	-0.2380
AR(2) z-statistic (p)	0.5130	0.4470	0.8120
Hansen test	32.1967	14.2547	12.5663
Hansen test (p)	0.8050	0.9690	0.9230
Joint significance test(CASHF, GREENFIRM)	11.0408		
P(CASHF, GREENFIRM)	0.0040		
Joint significance test(CASHF, GREENPAT)		16.3329	
P(CASHF, GREENPAT)		0.0003	
Joint significance test(CASHF, GREENNESS)			9.3072
P(CASHF, GREENNESS)			0.0095

Notes: table A6 shows estimates of equation (1) excluding the variables of the X vector. Estimations are carried out by using the two-step SYS GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics. Tests for the first and second order autocorrelation (AR(1) and AR(2)), and the Hansen test of overidentifying restrictions are reported.

Table A7 - Robustness check: OLS estimation results using patenting activity as a dependent variable

	1	2	3	4
CASHFLOW	0.0008***	0.0001	0.0043***	0.0001
	0.0002	0.0001	0.0011	0.0001
LNNOGREENPAT_1	0.5495***		0.5145***	
	0.0112		0.0125	
LNGREENPAT_1		0.3058***		0.3559***
		0.0558		0.0679
ΔSALES	-0.0014	-0.0001	-0.0108	0.0003
	0.0019	0.0002	0.0144	0.0014
ΔEMP	0.0205***	0.0006**	0.0974***	0.0022
	0.0032	0.0003	0.0281	0.0024
AGE	0.0002***	0.0000	-0.0007***	0.0000
	0.0000	0.0000	0.0002	0.0000
LEVERAGE	-0.0149***	-0.0007***	-0.0756***	-0.0043***
	0.0020	0.0002	0.0162	0.0016
DEBTSUST	-0.0747***	0.0022	-0.6979***	0.0181
	0.0178	0.0015	0.1715	0.0170
WORKCAP	-0.0102***	-0.0004***	-0.0667***	-0.0035**
	0.0015	0.0001	0.0147	0.0015
Year dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Observations	148,125	148,125	21,313	21,313
Dep. Variable	LNNOGREENPAT	LNGREENPAT	LNNOGREENPAT	LNGREENPAT
Sample	All	All	Innovative	Innovative

Notes: table 6 shows shows estimates of equation (1) of equation (2). Estimations are carried out by using the OLS estimator. For the description of the variables, see Table 1. The dependent variable is reported at the bottom of the table. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Robust standard errors are given in italics.

Table A8 - Pearson correlation matrix

	INVESTMENT	CASHFLOW	GREENFIRM	GREENPAT	GREENNESS	ΔSALES	DIFFKAPSALES	ΔEMP	AGE	LEVERAGE	DEBTSUST	WORKCAP
INVESTMENT	1											
CASHFLOW	0.3214	1										
GREENFIRM	0.0071	0.0041	1									
GREENPAT	0.0093	0.0045	0.5299	1								
GREENNESS	0.0037	-0.0006	0.5967	0.4359	1							
ΔSALES	0.0772	0.1392	-0.0037	-0.0018	-0.005	1						
DIFFKAPSALES	-0.1978	-0.3762	0.007	0.0012	0.0027	-0.0892	1					
ΔEMP	0.0914	0.0671	-0.0031	-0.0063	-0.0058	0.4811	-0.0523	1				
AGE	-0.1192	-0.0768	0.0369	0.0181	0.0112	-0.0498	0.237	-0.0737	1			
LEVERAGE	0.08	-0.145	-0.0249	-0.0166	-0.0077	0.0297	-0.1513	0.0242	-0.2507	1		
DEBTSUST	-0.0454	-0.139	0.0039	0.0026	0.0114	-0.1638	0.2849	-0.1264	0.015	0.2539	1	
WORKCAP	0.0184	0.2407	0.0108	0.0071	0.0011	-0.0255	-0.3862	-0.0247	0.1278	-0.5763	-0.2779	1

Notes: For the description of the variables see Table 1. To compute the correlation between the dichotomous variable GREENFIRM and the other continuos variables we perform a point biserial correlation.