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

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Abstract

Green investment by private companies is essential to sustainable growth paths in advanced economies. Whether, and to what extent, investments by green firms are hampered by lack of external finance is an open question. 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 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 firms' 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 and non-green firms.

The literature offers diverging insights (and mixed evidence) on whether investments by green firms may be hampered by a lack of external finance. On the one hand, green firms are comparable to innovative firms. They are endowed with projects to create or introduce something new, and as with all innovating firms, their investments are characterized by significant information asymmetries between insiders and outside investors, tangible and intangible assets that are less collateralizable, and potential negative externalities for incumbent non-green firms (Clemenz, 1991; Hall and Lerner, 2010; Minetti, 2011; Degryse et al., 2023). These factors may exacerbate adverse selection and moral hazard problems for lenders, induce losses on their legacy investment in the brown technologies, and ultimately create stricter financial constraints for green firms. Accordingly, the wedge between opportunity cost of internal finance and its cost of external debts can be expected to be larger for green firms and therefore their investments to be more sensitive to cash flows than those of non-green firms (Kapoor et al., 2011). Consistent with the hypothesis of a finance gap for green firms' investments, numerous 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, 2016). 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 considerably 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 are also good reasons to argue that green firms face less severe constraints in accessing external finance than brown firms and that their investment is thus less sensitive to internal cash flow. 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., 2022). 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, and their wedge between internal and external costs of finance.[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 and, therefore, less need for internal finance to fund green investments and innovations (Zhang and Jin, 2021). In this sense, extensive

[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).

empirical evidence shows 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; 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; Martin et al., 2023; Jia et al., 2025);[2] and that green innovators are more likely to receive external funding from venture capitalists (Bellucci et al., 2023), nonbank investors in the syndicated loan market (Gallo and Park, 2023), mutual funds (Cornelli et al., 2024) and Fintech (Li 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 firms' 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.[3]

We consider a large sample of manufacturing firms in Italy from 2014 to 2019, classifying firms as "green" based on 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, and this especially holds for small firms. In addition, we find that the number of a firm's green patents is not sensitive to the availability of internal finance,

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

3 In Section 3.3 we discuss the Kaplan and Zingales (1997) criticism to the use of sensitivity of investment to cash flows as a measure of the degree of financial constraints to firms' activity and provide a validation of this measure in our empirical context.

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 the firms 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 can be unrelated to green innovations, we repeat our analysis by classifying firms by the greenness 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 contributes to the literature on investment-cash flow sensitivity,[4] 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; Beladi at al., 2021). To the best of our knowledge, this is the first paper to analyze the sensitivity of green firms' investment and green innovation to internal cash flow. The only the partial exception a study 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

[4] 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; Ughetto, 2008; Alessandrini et al. 2009; Becchetti et al. 2010; La Rocca et al. 2015; Peruzzi, 2017).

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 and Quartaro, 2017; Cecere et al., 2020; De Haas et al., 2023) or else pick out green investments through textual analysis of the firms' own description of the investment (Gallo and Park, 2023); or, again, they classify as "green" the assets, expenditures and borrowing of firms that are classified 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 et al., 2023).

Taking this latter approach, we distinguish green firms engaged in green activities 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 patents in green technologies. We can therefore reasonably assume that obtaining green patents requires making (and financing) investment in green technologies and eco-innovations and that investments by green firms are directed towards eco-friendly activities even if if they are not immediately associated with obtaining patentsIn 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.[5] An advantage of using patenting activity measured in the long past with respect to the empirical analysis is that our definition of green innovative firms does not entail concerns of reverse causality between contemporaneous (green) investment opportunities and cash flows. [6]

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 uniform among the firms registering green patents. However, it is plausible 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, 357 of the 75,014 patents registered in the period 2000-2013 are classified as "green" using the above criteria, and 311 firms registered at least one patent with a code associated

[5] 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, 2023; Bellucci et al., 2023).

6 In Table A5, we provide estimates by considering patents registered during the period 2000 – 2013, thus including the years of the analysis.

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 of this variable, we also re-construct the variables *GREENFIRM*, 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).[7] This classification criterion for green firms is broader: it finds 650 firms registering at least one patent with one or more green codes, while on average *GREENPAT* is 2.1 and for 25% of green firms it is greater than 2.[8]

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. These data are linked, exploiting the Orbis firm identifier, to 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

[7] 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 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).

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

patents, in line with the measurement strategy outlined in Section 2, we match this information with the CCMT tagging scheme. In our baseline analysis, we include companies that have at least two years of observations in the period 2000-2013 in order to limit the issue of misclassification of green companies among the younger firms that were not active in the years we use to identify the greenness of the business. The final sample comprises 32,844 manufacturing firms, of which green firms (*GREENFIRM* = 1) make up about 1%.[9] This low percentage is not surprising, given the large incidence in the sample 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. Second, 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 4,224 firms (and 20,843 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. Finally, 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 the matching approach is the

[9] However, when we classify firms on the basis of the greenness of their main sector of activity, we remove this age-sample restriction and consider all the 36,174 manufacturing firms included in the Orbis dataset for the period 2014-2019.

significant reduction of the sample. Notice this approach has been adopted also using the sub-sample of innovative firms only.[10] Table 1 reports the definitions of the variables and their summary statistics; Table A7 in the appendix, reports the correlation matrix among the main variables.

[Insert Table 1 here]

3.2 *Regression model*

To gauge the extent to which investment-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:

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

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 the year $t-1$ to year t divided by

[10] For a detailed description of the coarse matching procedure and the regression results, see Appendix A, section A.1.

the replacement value of the firm's capital stock, i.e. $INVESTMENT_t/CAPITAL_{t-1}$.[11] 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 variable *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. For our sample, primarily consisting of unlisted firms, this serves 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.

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

[11] 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).

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 firm fixed effects, which naturally absorb all time-invariant firm characteristics (including the *GREENFIRM* dummies), and sector-year fixed effects, which, as Bond et al. (2003) suggest, can account for the variation in the cost of capital services.

We apply the first-difference 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 unobserved firm heterogeneity into account by estimating the equation in first-differences and endogeneity problems related to all the financial variables by using the lagged levels of variables as instruments. We treat all explanatory variables in equation (1) as endogenous and firm and sector-year fixed effects as strictly exogenous.[12]

3.3. *Sensitivity of investments to cash flows for (predetermined) financially constrained firms*

As is well known, Kaplan and Zingales (1997) have shown that, under specific conditions on the curvature of firms' output and financial cost functions, the sensitivity of firms' investment to cash flows may not increase with the degree of external financing constraints. Therefore, to validate the use of the sensitivity of investments to cash flows as a measure of the degree of financing constraints of firms in our sample, in this section we provide a test that allows us to confidently assume that KZ's

[12] As a robustness, we estimate a version of the equation (1) using the SYS-GMM methodology, where lagged levels of endogenous variables serve as instruments for the regression in difference, and lagged differences as instruments for the regression in level. Results are displayed in the Appendix, Table A6.

criticism is not relevant in our empirical context. In particular, we test whether the sensitivity is significantly higher for firms that, according to predetermined criteria, can be confidently classified as financially constrained. Specifically, we use three well-received measures of financial constraints for small-medium sized and unlisted companies: the SA index (Hadlock et al., 2010), the ASCL index (Mulier et al., 2016), the FCP index (Schauer et al., 2019).[13] For all three indexes, higher values suggest that firms face more difficulty in accessing external financing and managing liquidity and are more likely to be financially constrained. Following Schauer et al. (2019), for each of the indexes, we classify as financially constrained the firms that fall in the last two deciles of the annual index distribution and as financially unconstrained all remaining firms.[14]

[Insert Table 2 here]

Table 2, column (1), reports the estimation results when the SA index distribution is used to define financially constrained companies. It shows that the cash flow sensitivity to investment is positive and statistically different from zero in our sample of unconstrained firms; at the same time, looking at the coefficient attached to the interaction term between cash flow and the indicator variable for the presence of financing constraints, we find a positive estimate; importantly, it implies a cash flow sensitivity which is about three times larger for the constrained firms. Similar results have been found by looking at the estimates in columns (2) and (3), where the financially constrained firms are

[13] The SA index is calculated as $SA_t = -0.737 \times Size_t + 0.043 \times Size_t^2 - 0.040 \times Age_{it}$, where *Size* is the natural logarithm of total assets and *Age* is the number of years since incorporation (capped at 37). The ASCL index is calculated as the sum of four indicators, including *Size* (firms' total assets), *Age* (number of years since incorporation), *Cash Flow* and Leverage (long-term debt to total assets) which take value of 1 if they are below (for Size, Age and Cash Flow) or above (for Leverage) the industry median, 0 otherwise. The FCP index is calculated as $FCP_{it} = -0.123 \times Size_{t-1} - 0.024 \times Cash\ Holdings_{it-1} - 0.404 \times Interest\ Coverage_{it-1} - 1.716 \times ROA_{it-1}$, where *Size* is the natural logarithm of total assets, Cash Holdings is the ratio of cash to beginning-of-year total assets. Interest Coverage is the ratio of EBIT to interest expenses and ROA is the ratio of net income to total assets.

[14] As a robustness check, we also use a classification in which the firms in the top tercile are considered financially constrained and those in the bottom tercile are financially unconstrained. This strategy assumes that for the firms in the second tercile, it is difficult to determine whether they are financially constrained, and we exclude them from the analysis. However, in this way, the financially constrained status is invariant over time in our sample, and we cannot include the indicator for financially constrained firms in the regression model.

identified using the ASCL and FCP annual distributions, respectively. Taken together, these estimates confirm the appropriateness of using the cash flow sensitivity analysis to gauge the effects of external financing constraints on green firms in our setting.

4. THE RESULTS

4.1 Baseline estimates

Table 3 shows the estimation results from our baseline model, for the two 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.[15]

Moving on to our key coefficient of interest, we find that the coefficient of cash flow in column (1) is positive (0.491) and statistically significant, while the interaction term between cash flow and green firms is negative (-0.488) and statistically significant at the 1% level. In line with the results in column (1), this suggests that the firms in our sample are financially constrained on average, but the investment of green firms is significantly less sensitive to the availability of internal finance than that of non-green firms, statistically and economically. Indeed, with reference to estimates in column (2), which includes control variables, we find that the elasticity of investment to cash flow, evaluated at sample means, is 0.598 for non-green firms, and 0.093 for green firms. That is, a 10% increase in cash flow would lead to a 5.98% increase in investment in physical capital for non-green firms and just 0.93%, almost six times smaller, for firms engaged in green activities.[16] It is worth noting that

[15] All these tests are also passed in all subsequent specifications that use GMM methodology

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

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, 2005; Guariglia, 2008, Mulier et al., 2016).

[Insert Table 3 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 almost always statistically significant and has the expected negative sign: when capital is below the desired level, investment increases to regain the equilibrium level.

The coefficients for *ΔEM*P, *LEVERAGE,* and *DEBTSUST* are not especially precise. Likewise, consistent with the financial constraint hypothesis, *WORKCAP* has a negative and statistically significant impact on current fixed investment. The coefficient of *AGE* is positive and statistically different from zero, suggesting that more established firms display larger investments, on average, *ceteris paribus*.[17]

A potential concern with estimates in columns (1) and (2) of Table 3 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 between the two groups. To address this issue, we limit the non-green 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. Results are displayed in columns (3) and (4).

[17] As mentioned above, we also check the robustness of the baseline results after coarse matching based on these control variables. See Appendix A, section A.1, for a description of the methodology and implementation. The balancing tests in the matched samples are reported in Table A2, while the regression results in Table A3.

Considering the subsample of innovative non-green firms as a benchmark, the coefficient of *CASHFLOW* is still positive and statistically significant, suggesting that, on average, the investment of innovative firms is sensitive to the availability of internal financial resources. Looking at estimates in column (4), the coefficient of cash is 0.577 and the interaction term between cash flow and green firms is -0.342 (both coefficients statistically different from zero). The implied elasticity of investment to internal financial resources, evaluated at sample means, is 1.078 for non-green and 0.439 for green firms. So, in this case, green firms display an elasticity that is about 2.5 smaller than other innovative firms.

4.2 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.[18] The estimates in columns (1) and (2) are for the entire baseline sample used in columns (1) and (2) of Table 3, while estimates in columns (3) and (4). On average, small firms show greater investment sensitivity of investment to cash flow than medium-large firms. In line with the literature, this indicates more binding financial constraints for smaller companies. This difference tends to disappear when analysis is restricted to innovative firms alone; in this subsample, medium-large firms appear even slightly more sensitive to cash flow, although with a negligible difference.

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

More to the point, small green firms show much less sensitivity of investment to cash flow than their non-green counterparts, while among larger 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 no sensitivity. In the subgroup of larger firms (column 2), by contrast, the sensitivity of investment does not differ significantly between non-green and green firms. Similar results are obtained if the control group is limited to innovative non-green firms (columns 3 and 4).

Overall, our findings indicate that greenness reduces the dependence of investment on internal finance 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]

4.3 Alternative measures of green firms

The results in Table 3 are robust to the alternative measure of green firms, that is by using the variable GRENNESS in place of GREENFIRM in the regression analysis. Estimation results are reported in Table 5 and confirm our previous findings, for both the entire sample and the subsample of innovative firms.

[Insert Table 5 here]

Differently from before, the estimates can be better interpreted quantitatively by calculating the marginal impact of cash flow on investment for different levels of *GREENNESS*. Figure 1 reports a graphical representation of the marginal effects with reference to estimates in column (2) of Table 5.[19] The *y*-axis measures the marginal effect of *CASHFLOW* for the values of *GREENNESS* ranging,

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

for the sake of visualization, from 0 to 0.4. The dashed lines define 95% confidence intervals. The marginal effect of cash flow on investment is statistically significant and decreases as the value of the dependent variable increases, up to a threshold of 1.7, above which the effect turns statistically insignificant. In any case, most of the green firms in our sample (more than 70%) fall within the region of significance, corroborating the average results. Computed at the average of *GREENNESS* (0.001), the elasticity of investment to cash flow is about 0.67, and an increase of one standard deviation in *GREENNESS* (0.018) implies a decline of about 7% in the estimated elasticity.

[Insert Figure 1]

Furthermore, in the Appendix, Table A1, we report baseline estimation results using the alternative measure of green patenting activity, namely the IPC codes. Estimates are, again, qualitatively in line with the baseline.

Lastly, as a further robustness check, in Table A5 we re-estimate the model by extending the temporal span for classifying green firms to include patents also registered between 2014 and 2019. The reason we do not use this classification in the baseline analysis is to avoid the reverse contemporaneous effect of registering a green patent on investments, which may bias our estimates. Keeping this limitation, using this broader classification of the GREENFIRM variable the estimates confirm the presence of a lower sensitivity of green firms' investments to internal finance.

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.[20] 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 2 shows the 20 greenest sectors, so identified, in OECD countries since 1977.

[Insert Figure 2 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

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

each sector using that technology.[21] 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 code and $\pi_{GP,s}$ the probability of the patented technology's being used in sector s.[22] Figure 3 shows the 20 greenest sectors, so measured, at 4-digit NACE in OECD countries since 1977.

[Insert Figure 3 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 6, demonstrate the robustness of our results to this alternative classification. Columns (1) and (2) give the results for the entire baseline sample, while columns (3) and (4) are for the sub-sample of innovative firms only. The estimates of our main coefficients of interest, 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.

[Insert Table 6 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 investments, we cannot address

[21] 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.

[22] 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).

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:

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

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

We estimate equation (2) taking as a 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 7, 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.[23]

[23] In Table A4 we replicate the estimation results of Table 7 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.

[Insert Table 7 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 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.

REFERENCES

Accetturo, A., Barboni, G., Cascarano, M., Garcia-Appendini, E. and Tomasi, M., 2022. Credit supply and green investments. *SSRN Working paper 4217890*.

Acemoglu, D., Aghion, P., Bursztyn, L. and Hemous, D., 2012. The environment and directed technical change. *American Economic Review*, *102*(1), pp.131-166.

Acemoglu, D., Akcigit, U., Hanley, D. and Kerr, W., 2016. Transition to clean technology. *Journal of Political Economy*, *124*(1), 52-104.

Aghion, P., Boneva, L., Breckenfelder, J., Laeven, L.A., Olovsson, C., Popov, A.A. and Rancoita, E., 2022. Financial markets and green innovation. *ECB Working Paper* No. 19.

Aghion, P., Bergeaud, A., De Ridder, M. and Van Reenen J. 2023. Lost in transition: Financial barriers to green growth. *Working Paper*.

Alessandrini, P., Presbitero, A.F. and Zazzaro, A., 2009. Banks, distances and firms' financing constraints. *Review of Finance*, *13*(2), pp.261-307.

Almeida, H., Campello, M., Cunha, I. and Weisbach, M.S. 2014. Corporate liquidity management: A conceptual framework and survey. *Annual Review of Financial Economics*, *6*, 135-162.

Altavilla, C., Boucinha, M., Pagano, M. and Polo, A. 2023. Climate risk, bank lending and monetary. *Working paper*.

Arellano, M. and Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29-51.

Becchetti, L., Castelli, A. and Hasan, I., 2010. Investment–cash flow sensitivities, credit rationing and financing constraints in small and medium-sized firms. *Small Business Economics*, *35*, pp.467-497.

Beladi, H., Deng, J. and Hu, M., 2021. Cash flow uncertainty, financial constraints and R&D investment. International Review of Financial Analysis, 76, p.101785.

Bellucci, A., Fatica, S., Georgakaki, A., Gucciardi, G., Letout, S. and Pasimeni, F., 2023. Venture capital financing and green patenting. *Industry and Innovation*, *7*(30), 947-983.

Bloom, N., Bond, S. and Van Reenen, J., 2007. Uncertainty and investment dynamics. *Review of Economic Studies*, *74*(2), 9-415.

Blundell, R. and Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), pp.115-143.

Blundell, R., Bond, S., Devereux, M. and Schiantarelli, F., 1992. Investment and Tobin's Q: Evidence from company panel data. *Journal of Econometrics*, *51*(1-2), pp.233-257.

Bolton, P. and Kacperczyk, M., 2021. Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), pp.517-549.

Bolton, P. and Kacperczyk, M., 2020. Global pricing of carbon-transition risk. *NBER Working Papers*, No. 28510.

Bond, S., Elston, J.A., Mairesse, J. and Mulkay, B., 2003. Financial factors and investment in Belgium, France, Germany, and the United Kingdom: A comparison using company panel data. *Review of Economics and Statistics*, *85*(1), 153-165.

Brown, J.R., Fazzari, S.M. and Petersen, B.C., 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *Journal of Finance*, *64*(1), 151-185.

Brown, J.R., Martinsson, G. and Petersen, B.C., 2012. Do financing constraints matter for R&D?. *European Economic Review*, *56*(8), 1512-1529.

Cecere, G., Corrocher, N. and Mancusi, M.L., 2020. Financial constraints and public funding of eco-innovation: Empirical evidence from European SMEs. *Small Business Economics*, *54*(1), 285-302.

Chava, S., 2014. Environmental externalities and cost of capital. *Management science*, *60*(9), 2223-2247.

Clemenz, G., 1991. Loans for projects with interdependent returns. *Journal of Institutional and Theoretical Economics (JITE)/Zeitschrift für die gesamte Staatswissenschaft*, *147*(2), 337-353.

Cornelli G., Gambacorta L., Takahashi K., and Oliviero T. 2024. Mutual funds and climate news. *In progress*

Cohn, J. and Deryugina, T., 2018. Firm-level financial resources and environmental spills. *NBER Working Paper*,s No. 24516.

Cuerva, M.C., Triguero-Cano, Á. and Córcoles, D., 2014. Drivers of green and non-green innovation: empirical evidence in Low-Tech SMEs. *Journal of Cleaner Production*, *68*(1), pp.104-113.

De Haas, R. and Popov, A.A., 2023. Finance and green growth. *Economic Journal*, 133(650), 637-668

Degryse, H., Goncharenko, R., Theunisz, C. and Vadasz, T., 2023. When green meets green. *Journal of Corporate Finance*, 78, article No. 102355

Delis, M.D., De Greiff, K. and Ongena, S., 2019. Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans. *EBRD Working Papers* No. 231.
Ehlers, T., Packer, F. and de Greiff, K., 2022. The pricing of carbon risk in syndicated loans: which risks are priced and why?. *Journal of Banking & Finance*, *136*, article No. 106180.
Fard, A., Javadi, S. and Kim, I., 2020. Environmental regulation and the cost of bank loans: International evidence. *Journal of Financial Stability*, *51*, article No. 100797.
Fatica, S., Panzica, R. and Rancan, M., 2021. The pricing of green bonds: are financial institutions special? *Journal of Financial Stability*, *54*, article No. 100873.
Fazzari, S., Hubbard, R.G. and Petersen, B.C., 1988. Financing constraints and corporate investment. *Brookings Papers on Economic Activity*, No 1, 141-206
Gagliardi, L., Marin, G. and Miriello, C., 2016. The greener the better? Job creation effects of environmentally-friendly technological change. *Industrial and Corporate Change*, *25*(5), pp.779-807.
Gal, P.N., 2013. Measuring total factor productivity at the firm level using OECD-ORBIS. *OECD Economic Department Working Papers*, No. 24516
Gallo A. and Park M. 2023. Financing green transition. *SSRN Working Paper* 4585722
Ghisetti, C. and Quatraro, F., 2017. Green technologies and environmental productivity: A cross-sectoral analysis of direct and indirect effects in Italian regions. *Ecological Economics*, *132*, pp.1-13.
Ghisetti, C., Mazzanti, M., Mancinelli, S. and Zoli, M., 2015. Do financial constraints make the environment worse off? Understanding the effects of financial barriers on environmental innovations. *SEEDS Working Paper Series, No 115*.
Giannetti, M., Jasova, M., Loumioti, M. and Mendicino, C., 2023. “Glossy green” banks: The disconnect between environmental disclosures and lending activities. *Swedish House of Finance* No. 23/07.
Guariglia, A., 2008. Internal financial constraints, external financial constraints, and investment choice: Evidence from a panel of UK firms. *Journal of Banking & Finance*, *32*(9), 1795-1809.
Hadlock, C.J., Pierce, J.R., 2010. New evidence on measuring financial constraints: moving beyond the KZ index. *Review of Financial Studies*, 23 (5), 1909–1940.
Hall, B.H. and Lerner, J., 2010. The financing of R&D and innovation. In *Handbook of the Economics of Innovation* (Vol. 1, 609-639). Amsterdam: North-Holland.
Hall, B.H., 1992. Investment and research and development at the firm level: does the source of financing matter? *NBER Working Papers* No. 4096
Harhoff, D., 2000. Are there financing constraints for R&D and investment in German manufacturing firms? In *The economics and econometrics of innovation* (pp. 399-434). Springer, Boston, MA.
Hartzmark, S.M. and Sussman, A.B., 2019. Do investors value sustainability? A natural experiment examining ranking and fund flows. *The Journal of Finance*, *74*(6), pp.2789-2837.
Haščič, I. and Migotto, M. 2015. Measuring environmental innovation using patent data. *OECD Environment Working Papers* No. 89.
Himmelberg, C.P. and Petersen, B.C., 1994. R&D and internal finance: A panel study of small firms in high-tech industries. *Review of Economics and Statistics*, *76*(1), 38-51.
Holmstrom, B. and Tirole, J., 2011. *Inside and outside liquidity*. MIT press.
Horbach, J. (2008). Determinants of environmental innovation – new evidence from German panel data sources. Research Policy, 37, 163–173.
Hovakimian, G., 2009. Determinants of investment cash flow sensitivity. *Financial management*, *38*(1), pp.161-183.
Hong, H., Li, F.W. and Xu, J., 2019. Climate risks and market efficiency. *Journal of Econometrics*, *208*(1), 265-281.
Jia, H., Li, R., Guo, Y. and Zhao, Z., 2024. Research on corporate environmental investment behaviour driven by green credit policies. International Review of Financial Analysis, p.103800
Kaplan, S.N. and Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics*, *112*(1), 169-215.
Kapoor, S., Oksnes, L. and Hogarth, R., 2011. Funding the green new deal: building a green financial system. *Green European Foundation. Green New Deal Series*, *6*.
Krueger, P., Sautner, Z. and Starks, L.T., 2020. The importance of climate risks for institutional investors. *Review of Financial Studies*, *33*(3), 1067-1111.
Lang, L., Ofek, E. and Stulz, R., 1996. Leverage, investment, and firm growth. *Journal of financial Economics*, *40*(1), pp.3-29.

La Rocca, M., Staglianò, R., La Rocca, T. and Cariola, A., 2015. Investment cash flow sensitivity and financial constraint: a cluster analysis approach. *Applied Economics*, *47*(41), pp.4442-4457.
Li, Y., Chu, E., Nie, S., Peng, X. and Yi, Y., 2024. Fintech, financing constraints and corporate green innovation. International Review of Financial Analysis, 96, p.103650
Lööf, H. and Nabavi, P., 2016. Innovation and credit constraints: evidence from Swedish exporting firms. *Economics of Innovation and New Technology*, *25*(3), 269-282.
Lybbert, T.J. and Zolas, N.J., 2014. Getting patents and economic data to speak to each other: An 'algorithmic links with probabilities' approach for joint analyses of patenting and economic activity. *Research Policy*, *43*(3), 530-542.
Marin, G. and Lotti, F., 2017. Productivity effects of eco-innovations using data on eco-patents. *Industrial and Corporate Change*, *26*(1), 125-148.
Martin, F., Sautner, Z., Steffen, S. and Theunisz, C., 2023. Climate transition risks of banks. *Swiss Finance Institute*, *Research Paper Series*, No. 23-66.
Minetti, R., 2011. Informed finance and technological conservatism. *Review of Finance*, *15*(3), 633-692.
Mizen, P. and Vermeulen, P., 2005. Corporate investment and cash flow sensitivity: What drives the Relationship? *SSRN Working Paper* 711165.
Mulier, K., Schoors, K. and Merlevede, B., 2016. Investment-cash flow sensitivity and financial constraints: Evidence from unquoted European SMEs. *Journal of Banking & Finance*, *73*(1), 182-197.
Newton, D., Ongena S., Xie, R. and Zhao, B. 2022. Banks vs. markets: Are banks more effective in facilitating sustainability? Swiss Finance Institute, Research Paper Series 22-22.
Noailly, J. and Smeets, R., 2016. Financing energy innovation: The role of financing constraints for directed technical change from fossil-fuel to renewable innovation. *EIB Working Papers* No. 2016/06.
Peruzzi, V., 2017. Does family ownership structure affect investment-cash flow sensitivity? Evidence from Italian SMEs. *Applied Economics*, *49*(43), pp.4378-4393.
Popp, D., 2019. Environmental policy and innovation: a decade of research. *NBER Working Papers* No. 25631
Reghezza, A., Altunbas, Y., Marques-Ibanez, D., d'Acri, C.R. and Spaggiari, M., 2022. Do banks fuel climate change? *Journal of Financial Stability*, *62*, article No. 101049.
Rennings, K., 2000. Redefining innovation—eco-innovation research and the contribution from ecological economics. *Ecological Economics*, *32*(2), 319-332.
Rondi, L., Sembenelli, A. and Zanetti, G., 1994. Is excess sensitivity of investment to financial factors constant across firms? Evidence from panel data on Italian companies. *Journal of Empirical Finance*, *1*(3-4), pp.365-383.
Schauer, K., Elsas, R. and Breitkopf, N. 2019. A new measure of financial constraints applicable to private and public firms. *Journal of Banking & Finance*, 101, 270-295
Seltzer, L.H., Starks, L. and Zhu, Q., 2022. *Climate regulatory risk and corporate bonds*. *NBER Working Papers* No. 29994.
Ughetto, E., 2008. Does internal finance matter for R&D? New evidence from a panel of Italian firms. *Cambridge Journal of Economics*, *32*(6), 907-925.
Wurlod, J.D. and Noailly, J., 2018. The impact of green innovation on energy intensity: An empirical analysis for 14 industrial sectors in OECD countries. *Energy Economics*, *71*(1), 47-61.
Yuan, G., Ye, Q. and Sun, Y., 2021. Financial innovation, information screening and industries' green innovation—Industry-level evidence from the OECD. *Technological Forecasting and Social Change*, *171*, article No. 120998.
Zhang, D. and Jin, Y., 2021. R&D and environmentally induced innovation: Does financial constraint play a facilitating role? *International Review of Financial Analysis*, *78*, article No. 101918.

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.	0.557	1.208	-0.847	14.283	136,834
CASHFLOW	Cash flow scaled by its beginning of period capital.	1.041	2.668	-23.743	30.574	136,834
GREENFIRM	Dummy = 1 if the firm has at least one green patent (CPC code) during the period 2000 - 2013.	0.008	0.087	0	1	136,834
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	136,834
ΔSALES	Change in the log of real total sales.	0.048	0.239	-3.752	3.272	136,834
DIFFKAPSALES	Difference between the log of capital and the log of real total sales.	2.273	1.470	-4.306	8.475	136,826
ΔEMP	Change in the log of real total costs of employees	0.053	0.147	-2.763	2.219	136,834
AGE	Current year minus firm's year of establishment	21.654	12.920	3	61	136,834
LEVERAGE	(Current plus non-current liabilities) to total assets	0.704	0.212	0.054	1.250	136,834
DEBTSUST	Interest paid to total sales	0.011	0.017	0	0.397	136,834
WORKCAP	(Currents assets minus current liabilities) to total assets	0.233	0.248	-0.981	0.962	136,834
Other variables						
SECT_GREENNESS	Log of the number of green patent at sectoral level (4-digit). See section 5.1 for a detailed description.	7.627	2.040	0	11.432	136,834
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.	4.785	4.070	0	12.779	136,834
GREENFIRM2	Dummy = 1 if the firm has at least one green patent (IPC code) during the period 2000 - 2013.	0.017	0.128	0	1	136,834
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	0.048	0	1	136,834

Notes: to exclude outliers, we drop observations in the 1% tails of the distribution of continous variables.

Table 2 - Estimation results comparing constrained and unconstrained firms based on SA, ASCL and FCP Indexes

	1	2	3
CASHFLOW	0.2656***	0.1726***	0.4233***
	0.0791	0.0417	0.0553
CONSTRFIRM	-1.9561**	-0.5930***	0.4554
	0.8051	0.2203	0.3741
CASHFLOW * CONSTRFIRM	0.4413**	0.6997***	0.3997*
	0.1835	0.1473	0.2218
INVESTMENT_1	-0.1139***	0.0027	-0.0385*
	0.0321	0.0249	0.0214
ΔSALES	0.2986	-0.1672	0.0351
	0.2347	0.2059	0.2011
ΔSALES_1	0.4540***	0.1264	0.3355***
	0.1248	0.1473	0.1032
DIFFKAPSALES_2	-0.4800***	-0.0373	-0.1721***
	0.1186	0.0803	0.0642
ΔEMP	-0.1511	0.2568	0.0889
	0.2536	0.2110	0.2161
AGE	0.0151	0.0256**	0.0217*
	0.0094	0.0117	0.0129
LEVERAGE	0.8961	2.6105**	1.6449
	0.5888	1.0612	1.0672
DEBTSUST	-4.7454	-8.5113***	-9.1669***
	4.0051	*2.4018*	3.2493
WORKCAP	-0.3904	1.1018**	0.0295
	0.3488	0.4354	0.8371
Year * Sector dummies	Yes	Yes	Yes
Observations	93,868	93,868	82,513
AR(1) z-statistic	-16.9635	-15.2827	-12.3960
AR(1) z-statistic (p)	*0.0000*	*0.0000*	*0.0000*
AR(2) z-statistic	-1.0894	-1.1565	-1.1771
AR(2) z-statistic (p)	*0.2760*	*0.2470*	*0.2390*
Hansen test	64.8179	82.3633	63.5190
Hansen test (p)	*0.1490*	*0.1130*	*0.1120*
FC Index	SA	ASCL	FCP

Notes: Estimations are carried out by using the the first-difference GMM estimator (Arellano and Bond, 1991). For the description of the variables, see Table 1. The dependent variable is INVESTMENT. Constrained firms (CONSTRFIRM) are those in the top 20% of the annual distribution of each FC index, while firms in the bottom 80% of the annual distribution of each FC index are considered unconstrained. 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. Baseline estimation results

	1	2	3	4
CASHFLOW	0.4918***	0.3168***	0.3412***	0.5775***
	0.0959	0.0757	0.1024	0.1169
CASHFLOW*GREENFIRM	-0.4882***	-0.2656**	-0.3558***	-0.3418***
	0.1320	*0.1050*	*0.1283*	0.1042
INVESTMENT_1	-0.0413	-0.2166**	-0.1556*	-0.0605
	0.0388	0.1063	0.0885	0.0506
ΔSALES	0.2621	-0.0379	0.8920*	0.2033
	0.3580	0.2938	0.5272	0.2131
ΔSALES_1	0.4958**	0.3936**	0.8453***	0.3672**
	0.2060	0.1591	0.2826	0.1549
DIFFKAPSALES_2	-0.2236	-0.2666*	-0.6753**	-0.3016*
	0.1486	0.1517	0.3024	0.1608
ΔEMP	-0.1110	0.2367	-0.8023	-0.0824
	0.3860	0.3140	0.5947	0.2363
AGE		0.2689***		0.3219
		0.0809		0.3158
LEVERAGE		0.4417		1.9817**
		0.9189		0.9270
DEBTSUST		-2.1598		3.5512
		2.4979		2.9594
WORKCAP		-2.3218***		0.9656
		0.7854		0.9179
Year * Sector dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	93,868	93,868	14,797	14,797
AR(1) z-statistic	-18.4889	-3.6527	-9.1722	-9.7259
AR(1) z-statistic (p)	0.0000	0.0000	0.0000	0.0000
AR(2) z-statistic	-1.0287	-1.5942	0.5578	1.2535
AR(2) z-statistic (p)	0.3040	0.1110	0.5770	0.2100
Hansen test	19.2868	52.4458	30.1652	68.0254
Hansen test (p)	0.6280	0.2080	0.1450	0.4080
Sample	All	All	Innovative	Innovative

Notes: The Table shows estimates of equation (1). Estimations are carried out by using the the first-difference GMM estimator (Arellano and Bond, 1991). 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	0.3192***	0.1553*	0.2217***	0.2458***
	0.0980	0.0815	0.0489	0.0654
CASHFLOW*GREENFIRM	-0.3170*	-0.0650	-0.1564**	0.0068
	0.1850	0.0900	0.0793	0.2045
INVESTMENT_1	-0.0034	-0.3862**	-0.3607***	-0.4005***
	0.0494	0.1722	0.1206	0.1225
ΔSALES	-0.2170	0.1267	1.0060***	0.1362
	0.4183	0.2640	0.3654	0.2922
ΔSALES_1	0.3639	0.5407***	1.1754***	0.8127***
	0.2422	0.2052	0.2546	0.2279
DIFFKAPSALES_2	-0.0841	-0.4003*	-1.0866***	-0.7812***
	0.1887	0.2253	0.2432	0.2568
ΔEMP	0.4729	0.0130	-0.8570**	0.0520
	0.4585	0.2392	0.3934	0.2774
AGE	0.2963**	-0.0175	0.2477	-0.4675*
	0.1158	0.1226	0.3985	0.2411
LEVERAGE	1.1274	1.5902	-0.8482	4.4405***
	1.1420	1.1924	1.1004	1.3375
DEBTSUST	-5.0263	1.4709	7.9625**	11.1830*
	3.4089	6.4057	3.2088	6.0224
WORKCAP	-1.8945*	0.0891	-0.9968	1.3540
	0.9946	1.4024	0.9322	1.3364
Year * Sector dummies	Yes	Yes	Yes	Yes
Observations	83,453	10,415	9,833	4,964
AR(1) z-statistic	-20.6771	-1.1137	-3.6692	-1.9216
AR(1) z-statistic (p)	*0.0000*	*0.2650*	*0.0000*	*0.0550*
AR(2) z-statistic	0.8901	-1.5161	-0.6192	-1.6986
AR(2) z-statistic (p)	*0.3730*	*0.1290*	*0.5360*	*0.0890*
Hansen test	37.0941	53.9027	51.2111	68.4527
Hansen test (p)	*0.4180*	*0.1980*	*0.7830*	*0.3290*
Firm size	Small	Medium-Large	Small	Medium-Large
Sample	All	All	Innovative	Innovative

Notes: The Table shows estimates of equation (1). Estimations are carried out by using the the first-difference GMM estimator (Arellano and Bond, 1991).. 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 - Investment-cash flow sensitivity: green vs no-green firms.
Alternative green measure

	1	2	3	4
CASHFLOW	0.5775***	0.3581***	0.3296***	0.2585***
	0.1169	0.1059	0.0796	0.0619
CASHFLOW*GREENESS	-1.7797***	-1.3735*	-0.7531**	-0.7257**
	0.5180	*0.7261*	*0.3542*	0.3183
INVESTMENT_1	0.0199	-0.0232	-0.0837	-0.3113***
	0.0571	0.1802	0.1406	0.1169
ΔSALES	-0.3385	-0.4032	0.5213*	0.7516**
	0.5542	0.6338	0.3038	0.2975
ΔSALES_1	0.1536	0.1620	0.6728***	0.7658***
	0.3194	0.4396	0.2466	0.2287
DIFFKAPSALES_2	0.0065	0.1997	-0.5056**	-0.5652**
	0.2184	0.3132	0.2556	0.2469
ΔEMP	0.5180	0.6330	-0.4037	-0.6087**
	0.5870	0.6066	0.3348	0.3072
AGE		0.5231***		0.7232**
		0.1390		0.3490
LEVERAGE		1.7003		0.0439
		1.7665		0.9879
DEBTSUST		-4.4864		7.1665***
		5.3579		2.6090
WORKCAP		-2.9498**		-0.8686
		1.1634		0.9339
Year * Sector dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	93,868	93,868	14,797	14,797
AR(1) z-statistic	-13.7583	-2.8488	-4.2240	-3.6478
AR(1) z-statistic (p)	0.0000	0.0040	0.0000	0.0000
AR(2) z-statistic	-1.1640	-0.4388	0.4792	-1.5821
AR(2) z-statistic (p)	0.2440	0.6610	0.6320	0.1140
Hansen test	12.9996	20.9470	31.2676	68.8112
Hansen test (p)	0.8390	0.2820	0.2180	0.2870
Sample	All	All	Innovative	Innovative

Notes: The Table shows estimates of equation (1). Estimations are carried out by using the the first-difference GMM estimator (Arellano and Bond, 1991). 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 - Using Green sector

	1	2	3	4
CASHFLOW	0.7869**	0.8532***	0.6991**	0.3432***
	0.3164	0.2195	0.3341	0.1290
CASHFLOW*SECT_GREENNESS	-0.0625*		-0.0666*	
	0.0371		0.0368	
CASHFLOW*WN_SECT_GREENNESS		-0.0718***		-0.0298*
		0.0242		0.0171
INVESTMENT_1	-0.2676***	-0.0321	-0.2488***	-0.2459***
	0.0811	0.0565	0.0842	0.0855
ΔSALES	1.0219***	0.2876	0.9201***	0.8455***
	0.2491	0.3890	0.3235	0.3122
ΔSALES_1	0.7813***	0.1877	1.1070***	1.0422***
	0.1486	0.2853	0.2682	0.2711
DIFFKAPSALES_2	-0.7440***	-0.1595	-0.9598***	-0.9793***
	0.1353	0.2064	0.2804	0.2946
ΔEMP	-0.9595***	-0.2163	-0.6121**	-0.6273**
	0.2586	0.3990	0.3028	0.2950
AGE	0.0272	0.3061**	0.5322*	0.2525
	0.0908	0.1408	0.2723	0.3843
LEVERAGE	-0.8650	-11.8824**	-1.0087	0.0084
	0.8411	5.0309	1.2945	1.3460
DEBTSUST	-0.6618	-21.1268	8.4785***	7.1198***
	3.8099	13.3969	2.4075	2.6794
WORKCAP	-1.4300	-6.7395***	-1.3497	-0.0017
	0.8945	2.2450	1.4572	1.5569
Year * Sector dummies	Yes	Yes	Yes	Yes
Observations	93,868	93,868	14,797	14,797
AR(1) z-statistic	-6.4896	-9.6722	-8.6942	-8.4711
AR(1) z-statistic (p)	0.0000	0.0000	0.0000	0.0000
AR(2) z-statistic	-1.4593	-1.1033	1.5749	0.9776
AR(2) z-statistic (p)	0.1440	0.2700	0.1150	0.3280
Hansen test	56.7775	27.4137	66.5394	55.2139
Hansen test (p)	0.0640	0.4420	0.2070	0.3540
Sample	All	All	Innovative	Innovative

Notes: The Table shows estimates of equation (1).Estimations are carried out by using the the first-difference GMM estimator (Arellano and Bond, 1991). 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 7 - Estimation results using patenting activity as a dependent variable.

	1	2	3	4
CASHFLOW	0.0016***	0.0001	0.0162***	0.0001
	0.0003	*0.0001*	*0.0028*	*0.0001*
NOGREENPAT_1	0.1955***			0.0167***
	0.0098			*0.0032*
GREENPAT_1		0.0060***	-0.0337	-0.0008
		0.0007	*0.0472*	*0.0011*
ΔSALES	-0.0022	-0.0002	0.4465***	0.0059***
	0.0052	*0.0002*	*0.0885*	*0.0016*
ΔEMP	0.0827***	0.0012***	-0.0037***	0.0000
	0.0100	*0.0002*	*0.0008*	*0.0000*
AGE	0.0009***	0.0000***	-0.2996***	-0.0065***
	0.0001	*0.0000*	*0.0572*	*0.0016*
LEVERAGE	-0.0516***	-0.0010***	-3.0671***	0.0151
	0.0064	*0.0002*	*0.8732*	*0.0114*
DEBTSUST	-0.3233***	0.0019	-0.2575***	-0.0052***
	0.0989	*0.0015*	*0.0528*	*0.0015*
WORKCAP	-0.0351***	-0.0006***	-0.2565***	-0.0053***
	0.0058	*0.0002*	*0.0520*	*0.0018*
Year dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Observations	136,834	136,834	20,843	20,843
Dep. Variable	NOGREENPAT	GREENPAT	NOGREENPAT	GREENPAT
Sample	All	All	Innovative	Innovative

Notes: The Table 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.

FIGURES

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

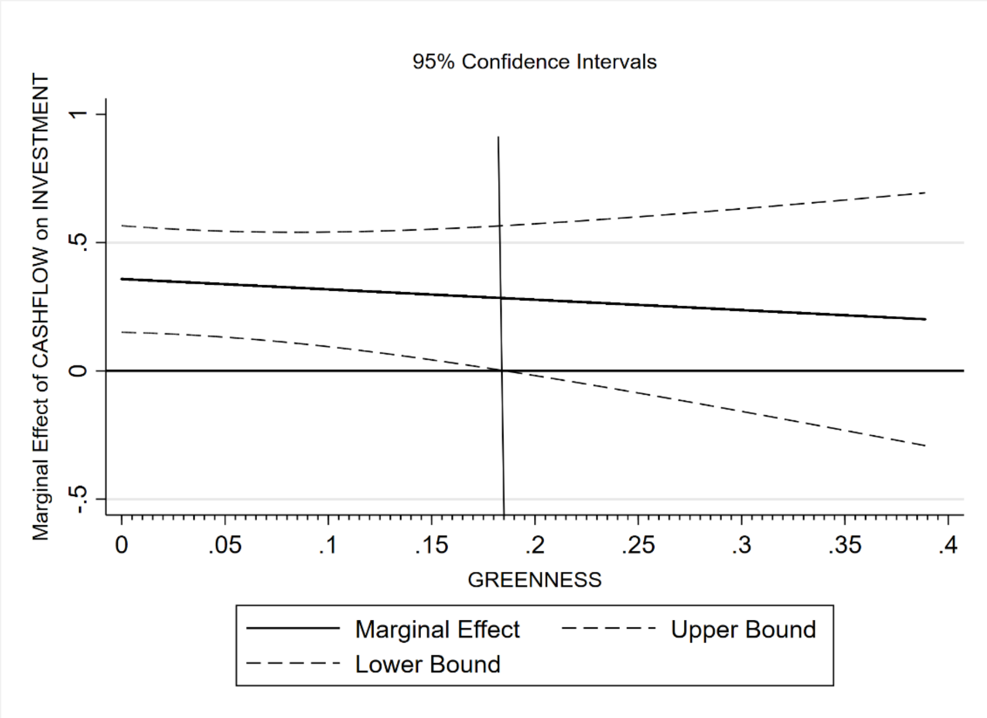


Figure 2. Top 20 Green sector in OECD Countries, by Number of Green Patents.

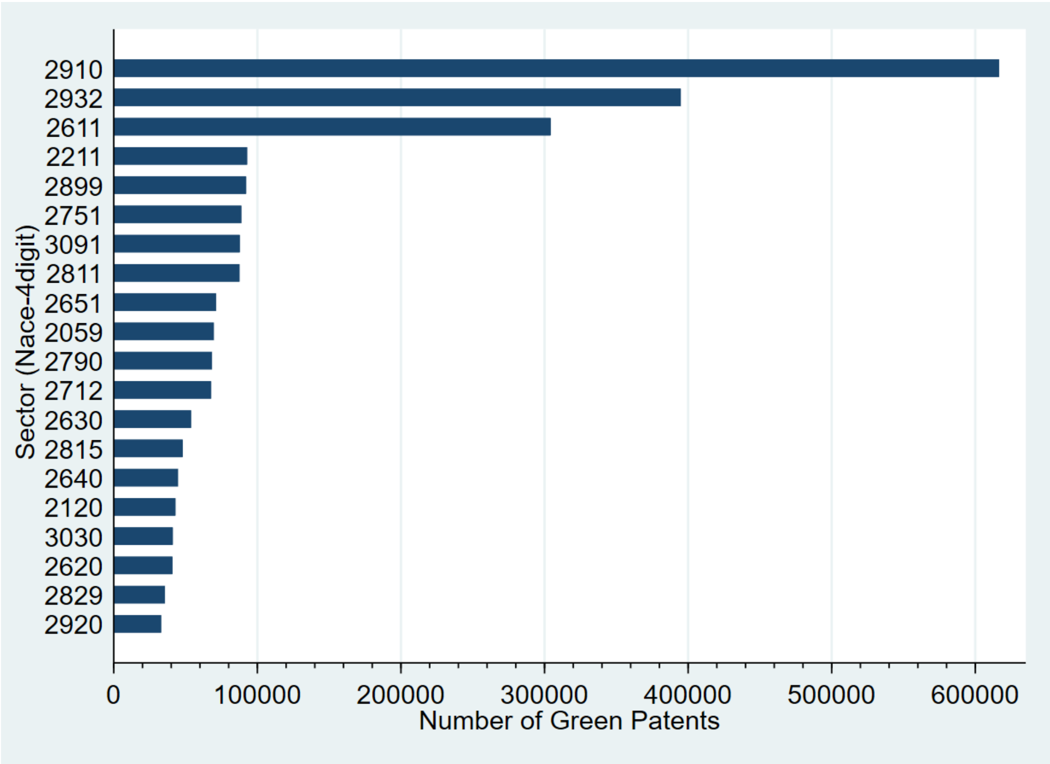
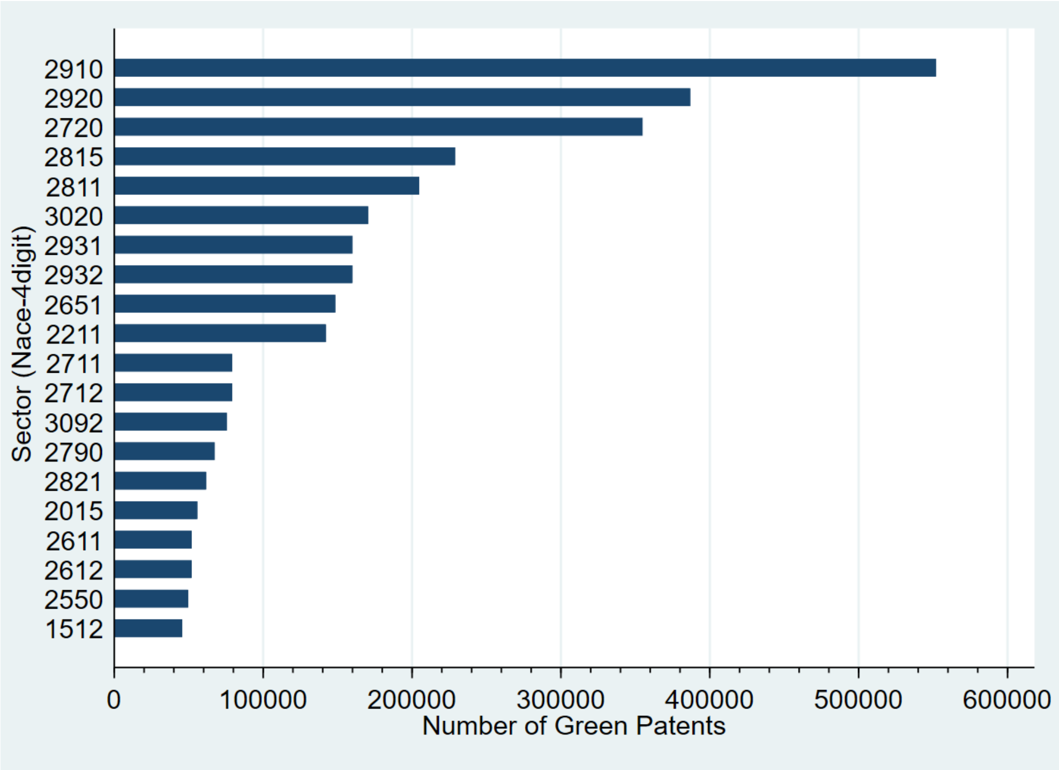


Figure 3. Top 20 Green sector in OECD Countries (Wurlod and Noailly (2018) approach).



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 1,304 firms, 991 of them classified as non-green. Table A2, Panel A, 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 7.1%. 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 A3, columns (1) and (2), 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. Also, we replicate the coarse matching for the subsample of innovative firms (Table A2, Panel B, reports the balance of the covariates after the matching). Again, the results confirm the robustness of our findings after this further sample restriction (Table A6, columns 3 and 4).

Table A1 - Estimation results using alternative classification of green patents

	1	2	3	4
CASHFLOW	0.1692***	0.2823***	0.2130***	0.3762***
	0.0556	0.0543	0.0456	0.0708
CASHFLOW*GREENFIRM2	-0.1484**		-0.1924***	
	0.0626		0.0507	
CASHFLOW*GREENNESS2		-0.7526*		-0.3068*
		0.4062		0.1682
INVESTMENT_1	-0.2315***	-0.2626**	-0.2246***	-0.0551
	0.0806	0.1075	0.0789	0.0531
ΔSALES	0.6453***	0.1268	0.7244***	-0.1046
	0.2487	0.3112	0.2334	0.2754
ΔSALES_1	0.6774***	0.4914***	0.7432***	0.3764**
	0.1531	0.1717	0.1807	0.1706
DIFFKAPSALES_2	-0.6238***	-0.3404**	-0.6057***	-0.3005*
	0.1359	0.1708	0.1879	0.1735
ΔEMP	-0.4821*	0.1227	-0.6195**	0.2854
	0.2577	0.3237	0.2408	0.3034
AGE	0.1825***	0.2666***	0.5846**	-0.0026
	0.0700	0.0860	0.2816	0.0237
LEVERAGE	-1.3926**	0.0095	0.8751	2.1984**
	0.7067	1.3153	0.8210	0.9099
DEBTSUST	2.3578	-1.1047	4.7202*	2.5416
	1.9648	2.7840	2.7655	3.3740
WORKCAP	-3.0476***	-2.6060***	0.4479	1.0735
	0.6406	0.7894	0.7624	0.7787
Year * Sector dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	93,868	93,868	14,797	14,797
AR(1) z-statistic	-6.1257	-3.3774	-6.2458	-9.6309
AR(1) z-statistic (p)	0.0000	0.0010	0.0000	0.0000
AR(2) z-statistic	-1.2484	-1.9696	-0.4811	1.0932
AR(2) z-statistic (p)	0.2120	0.0490	0.6300	0.2740
Hansen test	54.9953	28.3621	88.1160	63.8812
Hansen test (p)	0.2910	0.6970	0.2030	0.3760
Sample	*All*	*All*	*Innovative*	*Innovative*

Notes: The Table shows estimates of equation (1). Estimations are carried out by using the the first-difference GMM estimator (Arellano and Bond, 1991). 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 - Means values of the variables used for the matching

Variable	Green Firms	No-Green Firms	Test of the difference between means *P-Value*
Panel A			
AGE	23.52	23.60	*0.7833*
LEVERAGE	0.668	0.670	*0.6562*
DEBTSUST	0.014	0.015	*0.0713*
WORKCAP	0.23	0.24	*0.7100*
Panel B			
AGE	23.76	24.16	*0.1767*
LEVERAGE	0.662	0.656	*0.2380*
DEBTSUST	0.012	0.010	*0.0000*
WORKCAP	0.25	0.26	*0.0949*

Notes: for the description of the variables, see Table 1. H0: Equal mean among groups. Panel A refers to all sample of firms; while Panel B refers to innovative firms.

Table A3 - Estimation results: robustness on matched sample

	1	3	1	3
CASHFLOW	0.2881**	0.3082***	0.3513**	0.4626***
	0.1226	0.1163	0.1405	0.1500
CASHFLOW*GREENFIRM	-0.3138**		-0.4005**	
	0.1494		0.1648	
CASHFLOW*GREENNESS		-0.8962*		-1.6110**
		0.5253		0.7353
INVESTMENT_1	-0.1438	-0.3867***	-0.1739	0.2171
	0.0933	0.1071	0.1299	0.2040
ΔSALES	0.4296	0.3242	0.7264	-0.1803
	0.5949	0.5410	0.4635	0.7626
ΔSALES_1	0.8519*	0.6527	0.9874***	-0.3521
	0.4531	0.4490	0.3438	0.6612
DIFFKAPSALES_2	-0.4493	-0.8230***	-0.8123**	0.3712
	0.2887	0.2504	0.3772	0.6084
ΔEMP	-0.1051	-0.2049	-0.3751	0.2235
	0.6568	0.5440	0.5315	0.8484
Year * Sector dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3,218	3,218	3,275	3,275
AR(1) z-statistic	-4.2816	-3.1534	-4.3009	-3.9112
AR(1) z-statistic (p)	0.0000	0.0020	0.0000	0.0000
AR(2) z-statistic	0.4611	-0.3468	0.4079	0.7739
AR(2) z-statistic (p)	0.6450	0.7290	0.6830	0.4390
Hansen test	20.5168	18.6225	26.9197	17.0251
Hansen test (p)	0.6670	0.8520	0.3600	0.3170
Sample	All	All	Innovative	Innovative

Notes: The Table shows estimates of equation (1) excluding the variables of the X vector. Estimations are carried out by using the the first-difference GMM estimator (Arellano and Bond, 1991). 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 A4 - Robustness check: OLS estimation results using patenting activity as a dependent variable

	1	2	3	4
CASHFLOW	0.0008***	0.0001	0.0045***	0.0001
	0.0002	0.0001	0.0011	0.0001
LNNOGREENPAT_1	0.5490***			0.2792***
	0.0114			0.0587
LNGREENPAT_1		0.2417***	-0.0144	0.0000
		0.0457	0.0146	0.0012
ΔSALES	-0.0022	-0.0001	0.1126***	0.0036
	0.0020	0.0002	0.0297	0.0023
ΔEMP	0.0234***	0.0008***	-0.0006**	0.0000
	0.0035	0.0003	0.0002	0.0000
AGE	0.0002***	0.0000	-0.0763***	-0.0041**
	0.0000	0.0000	0.0163	0.0016
LEVERAGE	-0.0150***	-0.0007***	-0.6675***	0.0146
	0.0020	0.0002	0.1759	0.0165
DEBTSUST	-0.0795***	0.0018	-0.0637***	-0.0030**
	0.0184	0.0015	0.0148	0.0014
WORKCAP	-0.0105***	-0.0004**	-0.0667***	-0.0035**
	0.0016	0.0001	0.0147	0.0015
Year dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Observations	136,834	136,834	20,843	20,843
Dep. Variable	LNNOGREENPAT	LNGREENPAT	LNNOGREENPAT	LNGREENPAT
Sample	All	All	Innovative	Innovative

Notes: The Table shows estimates 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 A5 - Robustness check: estimation results using alternative measure of green

	1	2	3	4
CASHFLOW	0.3117***	0.3561***	0.3672***	0.2516***
	0.0756	0.1087	0.0639	0.0625
CASHFLOW*GREENFIRMNEW	-0.2987**		-0.4015***	
	0.1186		0.1036	
CASHFLOW*GREENNESSNEW		-1.6120*		-0.7429**
		0.8289		0.3577
INVESTMENT_1	-0.2174**	-0.0386	-0.0798	-0.3061**
	0.1040	0.1722	0.0513	0.1204
ΔSALES	0.0054	-0.1181	0.2855	0.7213**
	0.2997	0.5683	0.2083	0.3111
ΔSALES_1	0.4084**	0.3794	0.4252***	0.7614***
	0.1604	0.4248	0.1534	0.2333
DIFFKAPSALES_2	-0.2835*	0.1560	-0.3660**	-0.5679**
	0.1534	0.3071	0.1628	0.2464
ΔEMP	0.1879	0.3824	-0.1579	-0.5714*
	0.3204	0.5355	0.2324	0.3199
AGE	0.2643***	0.4845***	0.2396	0.6979**
	0.0803	0.1416	0.3202	0.3357
LEVERAGE	0.3655	2.1750	1.8081**	0.2004
	0.9244	1.9619	0.9203	1.0018
DEBTSUST	-1.8890	-5.3686	3.4843	7.1836***
	2.4961	5.7607	2.9425	2.6280
WORKCAP	-2.3387***	-2.4963*	1.1237	-0.6312
	0.7859	1.3164	0.9187	0.9122
Year * Sector dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	93,868	93,868	14,797	14,797
AR(1) z-statistic	-3.7593	-2.9381	-9.6696	-3.5426
AR(1) z-statistic (p)	0.0000	0.0030	0.0000	0.0000
AR(2) z-statistic	-1.5974	-0.5949	1.3277	-1.4796
AR(2) z-statistic (p)	0.1100	0.5520	0.1840	0.1390
Hansen test	53.0371	22.9181	70.6583	71.8523
Hansen test (p)	0.1920	0.1940	0.3250	0.2080
Sample	*All*	*All*	*Innovative*	*Innovative*

Notes: The Table shows estimates of equation (1). Estimations are carried out by using the the first-difference GMM estimator (Arellano and Bond, 1991). 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 A6 - Investment-cash flow sensitivity: green vs no-green firms.
Baseline estimation results using SYS-GMM

	1	2	3	4
CASHFLOW	0.4904***	0.2800***	0.3741***	0.2200***
	0.0877	0.0710	0.1216	0.0335
GREENFIRM	0.6747***	0.3768***	0.3853*	0.2363**
	0.1880	*0.1395*	*0.2086*	0.1138
CASHFLOW*GREENFIRM	-0.3917***	-0.2104***	-0.2493**	-0.1231**
	0.1091	*0.0725*	*0.1166*	0.0563
INVESTMENT_1	0.0054	-0.0716	-0.1108	-0.2186***
	0.0359	0.1026	0.1899	0.0819
ΔSALES	0.0304	-0.0849	0.0009	0.3709*
	0.3168	0.1995	0.3756	0.2063
ΔSALES_1	0.3258*	0.3895***	0.3876	0.4955***
	0.1947	0.1032	0.2359	0.1427
DIFFKAPSALES_2	-0.0730	-0.2977***	-0.1126	-0.3744***
	0.1253	0.0832	0.2041	0.1223
ΔEMP	0.1120	0.2777	0.0379	-0.3171
	0.3479	0.2279	0.4630	0.2409
AGE		-0.0023		-0.0062
		0.0038		0.0129
LEVERAGE		0.5440		1.2588**
		0.4884		0.4977
DEBTSUST		-4.1166**		4.1273
		1.7773		2.8302
WORKCAP		-0.8210**		-0.6310
		0.3759		0.4884
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*
Sector dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	136,834	136,834	20,843	20,843
AR(1) z-statistic	-19.1505	-4.5597	-2.4233	-4.6465
AR(1) z-statistic (p)	0.0000	0.0000	0.0150	0.0000
AR(2) z-statistic	-0.7627	0.1700	-0.4995	-1.6479
AR(2) z-statistic (p)	0.4460	0.8740	0.6170	0.0990
Hansen test	30.7691	73.7570	35.8616	101.9512
Hansen test (p)	0.2810	0.1090	0.1180	0.1150
Joint significance test(CASHF, GREENFIRM)	31.6068	16.8220	9.5363	44.1517
P(CASHF, GREENFIRM)	0.0000	0.0002	0.0085	0.0000

Notes: The Table 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 A7 - Pearson correlation matrix

	INVESTMEN	CASHFLOW	GREENFIRI	GREENNESS	ΔSALES	DIFFKAPSALE	ΔEMP	AGE	LEVERAGE	DEBTSUST	WORKCAP
INVESTMENT	1										
CASHFLOW	0.3219	1									
GREENFIRM	0.008	0.0045	1								
GREENNESS	0.0047	-0.0004	0.5987	1							
ΔSALES	0.0726	0.1377	-0.0036	-0.0047	1						
DIFFKAPSALES	-0.2084	-0.3792	0.0047	0.0016	-0.0887	1					
ΔEMP	0.0868	0.0663	-0.0029	-0.0056	0.4788	-0.052	1				
AGE	-0.1142	-0.0784	0.0332	0.0075	-0.0402	0.2289	-0.0655	1			
LEVERAGE	0.079	-0.1423	-0.0223	-0.0061	0.0263	-0.1482	0.0211	-0.2329	1		
DEBTSUST	-0.0471	-0.1392	0.0038	0.0115	-0.1648	0.2839	-0.1294	0.0067	0.2624	1	
WORKCAP	0.0286	0.2424	0.0094	-0.0003	-0.0224	-0.3988	-0.0221	0.1077	-0.5721	-0.2873	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.