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CREDIT SUPPLY AND GREEN INVESTMENTS

by Antonio Accetturo[*], Giorgia Barboni[♣], Michele Cascarano[♦],
Emilia Garcia-Appendini[♥] and Marco Tomasi[♠]

Abstract

Does an increase in credit supply affect firms' likelihood to invest in green technologies? Using text algorithms to extract information on the green investments of Italian firms between 2015 and 2019 and a firm-level instrument for credit availability, we find a large positive elasticity of green investments to credit supply. Consistent with a large capital intensity of green investments, this effect is concentrated among firms with ample internal resources. We find also that private credit supply must be supplemented by public subsidies to accelerate green transition.

JEL Classification: G32, Q54, Q55.

Keywords: credit supply, CO_2 emissions, green investments, climate finance, bank credit.

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1 Introduction[1]

Does an increase in bank credit supply make firms more likely to invest in green technologies? Answering this question helps us understand whether credit fluctuations – which can be influenced by supervision authorities and central banks – speed up or slow down the transition to a green economy. It can also inform whether improving firms' access to credit will help achieve the goal of decarbonizing our economy, following the Paris Agreement.

In this paper, we address this key question by analyzing loans to a sample of privately held Italian firms, including a large number small and medium enterprises (SMEs), which typically rely on bank credit for their capital expenditures. A distinctive aspect of our approach involves using natural language processing techniques (NLP) to extract information about the *actual* green investments undertaken by the companies. We classify firms investing in green technologies by searching for specific words such as 'photovoltaic', 'recycling', etc. in the written comments within the financial statements of these firms. Our findings indicate that the likelihood to undertake green investments responds strongly to credit supply.

To achieve causality, we use an exogenous firm-specific time-varying instrument for bank credit supply following a methodology similar to Berton et al. (2018) – itself in the spirit of Greenstone et al. (2020). Our preferred instrumental variable specifications include several time-varying firm-level controls, and a rich set of fixed effects that allow us to control for idiosyncratic shocks and demand shifters at the province-sector-year level. Our results are robust to alternative instrumentation strategies that allow us to control for demand shifters

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at more granular levels, including the firm-year level as in Amiti and Weinstein (2018).

From a theoretical perspective, it is not clear whether an increase in credit supply should lead to an increase in *green* investments. A large literature shows that capital expenditures and labor respond to credit shocks (e.g., Peek and Rosengren, 2000; Cingano et al., 2016; Amiti and Weinstein, 2018, among many others). However, green investments are special investments. First, their purpose is to reduce or eliminate the negative environmental externalities caused by firms, and not necessarily to increase profitability. Thus, whether firms would undertake such investments, even in the absence of financial frictions, remains an open question. In fact, Acemoglu et al. (2012) and Acemoglu et al. (2016) have argued that firms would not invest in clean technologies without some form of government intervention such as carbon taxes or research subsidies. This conclusion has been challenged by recent evidence showing that entrepreneurs and investors are increasingly internalizing externalities and incorporating environmental and social preferences in their investment decisions, suggesting that firms may deviate from pure value maximization (Bénabou and Tirole, 2006; Hart and Zingales, 2017; Krueger et al., 2020; Pástor et al., 2021; Ceccarelli et al., 2021).

Second, green investments require greater financial resources than regular investments (Allcott and Greenstone, 2012; Fowlie et al., 2018). Therefore, they could be subject to financial frictions in the spirit of Holmstrom and Tirole (1997). Moreover, clean technologies are more costly; hence, financially constrained firms might optimally choose to invest in dirty rather than clean technologies in the presence of financial frictions (Lanteri and Rampini, 2023).

Our baseline results indicate that a one standard deviation increase in the amount of credit supply raises the likelihood to undertake a green investment by 2.7 to 4.7 percentage points, which is roughly equivalent to 19% of its standard deviation. To benchmark our results to other investments, we look at the elasticity of the extensive margin of any capital investment (including non-green investments) to credit supply. In contrast to the results for green investments, the coefficients in this case are not statistically distinguishable from zero. This finding is consistent with empirical evidence (e.g., from the Survey of Italian Manufacturing Firms) showing that the effects of external credit availability on firms' decision to undertake capital investments may have little to no average effects outside of a downturn as there are alternative sources of liquidity available to firms – for example in the form of internal funds or trade credit (Gaiotti, 2013).

A central finding of our paper is that, contrary to normal investments, the elasticity of green investments to credit supply is concentrated among larger, older, more liquid, and more profitable firms, which are *less likely* to be financially constrained. This evidence suggests that green investments require larger financial resources, making them more reliant on external financing than traditional investments (Holmstrom and Tirole, 1997). In line with this interpretation, we find that green investments coincide with large investment peaks (Bachmann and Bayer, 2014). Our results align with existing empirical and theoretical evidence of the larger capital requirements of green investments (Allcott and Greenstone, 2012; Fowlie et al., 2018; Kuik et al., 2022), and with the observed positive link between financial constraints and pollution levels (Bartram et al., 2022; De Haas et al., 2021; Goetz, 2019; Levine et al., 2018; Kim and Xu, 2022).

We also investigate the role of government incentives and subsidies. In line with the predictions of Acemoglu et al. (2012) and Acemoglu et al. (2016), we find that green investments respond to credit supply in the presence of government subsidies for such investments in the region where firms are headquartered. This finding suggests that private credit supply must be complemented with green subsidies to accelerate the green transition. The higher elasticity of green investments to credit supply in high-subsidy regions is also consistent with our interpretation that green investments are capital intensive.

Using measures from Google Search and the European Values Study, we find that the elasticity of green investments to credit supply is stronger in the most environmentally aware regions in Italy. The elasticity is even more pronounced for regions with high industry competition. This finding highlights the central role of environmental preferences in our results, and aligns with Aghion et al. (2023)'s work showing that the probability of investing in clean technologies increases with environmental awareness, especially in competitive industries.

Finally, we analyze the role of regulatory risk in our results (Dechezleprêtre and Sato, 2017; Ramadorai and Zeni, 2021; Seltzer et al., 2022). Regulatory risk should be larger for firms with high carbon emissions, where regulations are more likely to be implemented. Our analysis is however inconclusive in this regard, as we do not find a differential elasticity of green investments to credit supply across sectors with high and low emissions.

Our paper offers four main contributions to the literature. First, it adds to the extensive empirical literature on the real effects of credit supply (see e.g. Cingano et al., 2016 and Amiti and Weinstein, 2018) by showing that these effects can extend to investment in green technologies, and as such, that credit can be a key tool to facilitate the green transition.

Second, our paper contributes to the literature that studies the increasingly relevant role of environmental awareness in financial markets. Theoretical and empirical work in this area indicate that investors' preferences and awareness about climate risks can affect stock prices (Heinkel et al., 2001; Pástor et al., 2021; Choi et al., 2020; Ramelli and Brière, 2021; Krueger et al., 2020). Our results showing that local environmental preferences strengthen the effect of credit supply on firms' green investment decisions suggest that some agents internalize externalities and incorporate environmental preferences in their decisions (Bénabou and Tirole, 2006; Hart and Zingales, 2017; Oehmke and Opp, 2020; Pástor et al., 2021).

Our paper is also related to the growing literature on the relevance of debt financing for the green transition. This literature has mostly focused on banks' credit allocation to green vs. brown firms in terms of quantities and prices (Kacperczyk and Peydró, 2021; Reghezza et al., 2021; Mueller and Sfrappini, 2021; Degryse et al., 2020a), on green bonds (Flammer, 2021), and on carbon leakage across markets (Beyene et al., 2021; Benincasa et al., 2021; Laeven and Popov, 2021). Our approach differs significantly from these studies, as we focus on the effects of bank credit supply on firms' investment decisions. Our study is closer to De Haas et al. (2021), who also analyze the demand side of firms' investment in green technologies while focusing on managerial and financial barriers to the adoption of green technologies. Our study differs in several aspects. First, we improve upon their measurement of green technologies, by using text-based measures obtained directly from the investments section of firms' financial statements rather than through survey responses. Second, we have a direct measurement of credit supply based on firm-bank matched data rather than on shocks to banks situated in the vicinity of the firms; this allows us to estimate the increase in firms' likelihood of investing in green technology per euro of credit supplied. Third, we uncover a significant amount of heterogeneity in firms' propensity to use bank credit to invest in green technologies. Fourth, we study the respective roles of bank credit supply and firm internal resources on firms' decision to invest in green technologies and show that the capital intensity of green investments is one key impediment to their more widespread adoption.

Finally, our paper contributes to the literature that uses NLP techniques to identify patterns from firms' financial statements. Text algorithms have been first employed in the finance literature to identify distinct sets of words conveying the sentiment of financial texts (Loughran and McDonald, 2011). More recently, they have been used to uncover firm characteristics that cannot be easily obtained from financial statements, such as financial constraints (Hoberg and Maksimovic, 2015; Bodnaruk et al., 2015; Buehlmaier and Whited, 2018); political risk (Hassan et al., 2019); attention to macroeconomic dynamics (Song and Stern, 2020); exposure to climate risks (Sautner et al., 2023). As in these papers, our approach consists of searching for a set of pre-determined keywords in the financial statements. We differ in that our goal is to identify a specific type of technologies linked to green investments employed by the firms. We follow a similar strategy as in Bodnaruk et al. (2015) and Song and Stern (2020), and classify firms according to the prevalence of specific keywords in the text without qualifying their tone. This approach is well suited for our purposes, as the presence of terms that refer to green technologies (e.g., 'photovoltaic panel' or 'renewable energy sources') allows us to unambiguously identify firms' use of these technologies. We differ from all these papers in that the information we process is contained in financial statements of a large sample of privately held enterprises, rather than stemming from publicly traded firms. In addition, we extract the information from the specific section of firms' disclosures that focuses on tangible and intangible investments, further reducing the possibility of obtaining false positives or capturing greenwashing efforts by the firms' management. Using text algorithms to uncover the type of investment technologies chosen by firms is unique to the literature on green finance. Papers in this literature have relied on self-reported measures of firm greenness, such as their adherence to climate initiatives like the Carbon Disclosure Project or the Science Based Target Initiative, or answers to surveys (e.g., Degryse et al., 2020a; De Haas et al., 2021), or estimations of their CO_2 emissions (e.g., Kacperczyk and Peydró, 2021).

2 Data and methodology

2.1 Identifying green firms using text algorithms

We obtain text information on firms' financial statements for years 2015-2019 from the Infocamere dataset, which is managed by the Italian Chamber of Commerce. According to Italian law, all companies must present yearly balance sheet statements to the Italian Chamber of Commerce, and except for the smallest and youngest firms, these statements should be commented in a set of accompanying notes ("note integrative"). From these notes, we extract all comments referring to firms' tangible and intangible assets.[2] After cleaning the text (i.e., removing any html code, as well as symbols, punctuation, and numbers) we iden-

[2] More precisely, we extract the following from the notes accompanying the balance sheet: introduction to tangible assets, comments to tangible assets, introduction to intangible assets, and comments to intangible assets.

tify all instances containing words related to green technologies, following a dictionary-based approach. We create this "green" dictionary by combining three different sources: the European Union's taxonomy for sustainable activities; the list of words associated with climate change as identified by Sautner et al. (2023) from firms' conference calls; and the sustainability reports required for Italian publicly listed large firms. Our final dictionary, which we denote as the set D, consists of a set of almost 80 terms or "tags". This list includes words such as 'photovoltaic', 'energy efficiency', 'electric vehicle', 'cogeneration', etc.[3]

We denote a firm as "green" in a given year with a dummy that equals one if at least one word of the dictionary is contained in the accompanying notes of the firm for that year, and the firm has positive capital expenditures during the year. More formally, let W_{it} be the set of words in the comments to the balance sheet of firm i in year t; the green firm dummy is defined as $\text{Green}_{it} = \mathbb{1}_{D \cap W_{it} \neq \emptyset} \cdot \mathbb{1}_{\text{Capital Expenditure}_{it} > 0}$. We introduce the second term, a dummy variable equal to one when the firm has positive capital expenditures in year t, to reduce the possibility that firms are commenting on investments occurring in a different year (for example, if they are referring in year t to the amortization of a green investment occurring prior to t). Appendix Table A3 contains all variable definitions. About 39.8% of Italian companies are exempt from presenting detailed financial statements, and hence are automatically excluded from our sample as there is no text information available to us about their green or other investments. In Appendix Table A4 we show that firms with this exemption tend to be younger and smaller than firms reporting detailed financial statements, but are otherwise very similar in terms of other observable characteristics.

One concern of text-based approaches like the one we follow is that firms could self-promote as environmentally friendly in the attempt to increase their market shares by attracting environmentally-conscious clients ("greenwashing"). This is unlikely to be the case

[3] Appendix Table A1 contains the full list of stemmed words in our "green" dictionary D (in Italian). Table A2 presents examples of the original phrases where the dictionary words were found in the accompanying notes (also in Italian).

in our context, for two reasons. First, the vast majority of the firms under analysis are privately held, small or medium-sized firms, and the comments to the financial statements filed by these firms are intended for their private shareholders and are not easily accessible to the wider public.[4] Second, we limit the search of green terms to the investments section of the financial statement and do not search for green terms in the introductory remarks, which due to their salience are more susceptible to greenwashing. In general, the types of green investments captured with our measure are references to actual investments in green technologies realized by the firm.

We perform several analyses to assess and validate our measure of green investments. First, we make sure that our measure correlates with sector-level measures of green technology adoption obtained through surveys. Second, we verify that our measure of green investments predicts improvements in environmental performance, using a subsample of firms for which we have information about their emissions. Third, we ensure through a visual analysis of the most frequent words appearing in the texts that our measure is not capturing other types of special technologies such as high-tech, artificial intelligence (AI) or biotechnology. Fourth, we check that "green" firms are more similar to other green firms than to non-green firms, while sharing a common support with the latter. Appendix B details these tests.

Identifying green investments through text-based analysis rather than through answers to survey questions has some advantages and disadvantages. On the one hand, survey-based measures can identify green investments with more precision since they answer specific questions of interest to the researchers. However, data based on surveys are generally cross-sectional or have limited time variation stemming from answers to retrospective questions. Thus, studies relying on survey answers cannot use panel-data techniques to control for time-invariant unobserved heterogeneity. Text-based approaches can be applied in countries and periods of time for which surveys are not available. Moreover, being administrative

[4]To access these files, final consumers would need to solicit them to the Italian Chamber of Commerce, as these are not easily downloadable from a public repository.

documents, they are also less subject to some of the typical problems associated with the reliability of surveys, like selection of respondents or the "social desirability" bias highlighted by Bertrand and Mullainathan (2001).[5]

2.2 Credit and balance sheet data

We merge information about green investments with firm-level balance sheet information sourced from the Cerved dataset using unique firm-level identification codes (the value-added tax (VAT) identification code, or "codice fiscale"). We also use the VAT identification code to uniquely match this information with loan data from the Italian Central Credit Register (CR), owned and administered by the Bank of Italy. This database contains information about all performing, non-performing, and bad loans extended by all banks and financial companies operating in Italy. On a monthly basis, banks have to report to the CR the amount of each loan granted to each firm above a minimum reporting threshold of 30,000 euros, and what fraction of this loan has been drawn by the borrowers. Given the low threshold, these data can be taken as census. From this database we draw the borrower's outstanding loans from each bank and the bank market share for each borrower at the beginning of the period, which we use to construct our instrumental variable (explained in detail in the following subsection).

2.3 Sample description

Table 1 contains a description of our estimation dataset. Our final sample consists of 110,044 firm-year observations, 6.4% of which correspond to firms that undertook green investments ($\text{Green}_{it} = 1$). The last row in the Table shows that our estimation sample consists of 28,308 unique firms, 9.9% of which invested in green technologies at least once during the sample period. In Table 2 we focus on these unique firms. Panel A shows that firm size is positively

[5] To the extent that respondents want to appear more environmentally responsible and exaggerate their investments in green technologies, the social desirability bias could be a reason why De Haas et al. (2021) do not find significant effects of financial constraints on specific green investments (such as 'green energy generation', 'air/other pollution control' or 'energy/water management'), while they do find significance for less specific investments such as vehicle or machinery upgrades.

associated with investments in green technology. Panel B indicates that there is a larger fraction of firms investing in cleaner technologies in the electricity, gas, and steam supply sector, followed by water supply and waste management.

Table 3 contains summary statistics for the main variables in our analysis. In Appendix Table A5 we compare these variables across observations with different values of Green_{it}. Firms investing in green technologies are larger and have a larger share of tangible assets than those not investing in green technologies. However, firms are similar across other characteristics such as age, riskiness, cash holdings, leverage, and profitability, as shown by the low values of the normalized differences (Imbens and Wooldridge, 2009). The table also shows that firms investing in green technologies have similar loan growth rates (ΔLoan) and similar amounts of credit supply (variable CSI, explained in the following section) as those that do not invest in green technologies.

2.4 Methodology

Our objective is to analyze the effect of credit supply on green investments by estimating the following model:

$$\text{Green}_{it} = \beta \Delta \text{Loan}_{it} + \delta X_{it} + \mu_i + \tau_t + \gamma_{s(i)\times\tau_t} + \eta_{c(i)\times\tau_t} + \theta_{p(i)\times\tau_t} + \epsilon_{it}, \tag{1}$$

where ΔLoan_{it} is the symmetric growth rate of loans obtained by firm i from the banking system between periods $t-1$ and t, defined as $\frac{\text{Loan}_t - \text{Loan}_{t-1}}{0.5\times(\text{Loan}_t + \text{Loan}_{t-1})}$.

Estimation of the effect of bank lending on green investments, measured by β, is challenging for two main reasons. First, the observed amount of bank credit is the demand and supply equilibrium. We control for demand and productivity shocks by adding firm fixed effects μ_i and time-varying controls X_{it}. In addition, we saturate the model with location (province) $\times$ time fixed effects ($\theta_{p(i)\times\tau_t}$), industrial sector (2-digit) $\times$ time fixed effects ($\gamma_{s(i)\times\tau_t}$), and size-class $\times$ time fixed effects ($\eta_{c(i)\times\tau_t}$, for $c(i) \in$ {micro, small, medium, large}). Our fixed effects and controls absorb any firm-specific time-invariant demand shifters, time-varying changes in firm conditions, and common shocks occurring in the economy at time t. Our most saturated specification controls for the interaction of location, industry, size, and time fixed effects (Degryse et al., 2019).

Second, bank lending is endogenous to firms' economic conditions and investment choices, so standard ordinary least squares (OLS) estimates are likely to be biased. The sign of the bias is unknown ex-ante. The entrepreneurs' (unobserved) willingness to invest in green technologies can be positively correlated with their ability to receive credit from the banking sector. If this were true, OLS would be upward biased. However, their desire to adopt cleaner technologies can also be correlated to the possibility to access to other external funds or public subsidies, or to generate internal resources (by restricting, for example, the distribution of dividends). In this case, OLS estimates would be downward biased. Moreover, OLS estimates are plagued by simultaneity bias, since green investments and loan growth are measured in equilibrium. As underlined by Roberts and Whited (2013), simultaneity bias cannot be signed ex-ante, since it depends on the relative importance of supply and demand channels in the regression.

To isolate a credit supply shock from a lower demand for credit we follow the identification strategy in Berton et al. (2018), itself in the spirit of Greenstone et al. (2020), and construct a time-varying, firm-specific credit supply index (CSI_{it}) that we use as an instrument for ΔLoan_{it}. This index is constructed by first estimating bank-time specific lending policies, and then aggregating these at the firm level using the bank shares at the firm in the beginning of the period.

More precisely, we first estimate bank lending practices in a given year by fitting the following regression equation using the complete CR information aggregated at the bank-province-sector-time level:

$$\Delta\text{Loan}_{bpst} = \delta_{bt} + \gamma_{pst} + \epsilon_{bpst}. \tag{2}$$

The dependent variable ΔLoan_{bpst} is the change in aggregate outstanding loans by bank b

in province p for sector s at time t; γ_{pst} are province-sector-time fixed effects –a measure of local demand– and δ_{bt} are bank-fixed effects –a measure of bank lending practices, our main parameters of interest. Using the estimated bank-supply shocks $\hat{\delta}_{bt}$, we compute the supply of credit at the firm level as the weighted average of the estimated credit supply of banks lending to firm i at the beginning of our sample period (end of 2014):

$$\text{CSI}_{i,t} = \sum_b w_{b,i,t_0} \times \hat{\delta}_{bt},$$

where

$$w_{b,i,t_0} = \frac{\text{Loan}_{i,b,2014}}{\sum_b \text{Loan}_{i,b,2014}}.$$

CSI is a Bartik-type instrument; section C in the Appendix provides an extended discussion of the identification assumptions for this instrument. Figure 1 depicts the evolution of average credit supply $\overline{\text{CSI}}_t$ over years 2010-2019. Panel A shows the average amount of credit supply, averaged across banks using market weights. During our sample period (2015-2019) credit supply was moderate, fluctuating around zero, with the highest values occurring in year 2017. In spite of the moderate credit supply over our sample period, there is considerable heterogeneity across banks, as shown by the box-and-whisker plots in Panel B. As a validation of our measure of credit supply, Figure 2 shows the results of the survey of bank lending standards (BLS). The credit supply index calculated using our methodology shows similar trends, peaks and troughs as in the BLS, especially in the period of analysis.

Given the granularity of the fixed effects introduced in Equation 1, our identification hinges on the assumptions that (i) all firms operating in the same 2-digit sector, in the same province, and in the same class size face the same demand or productivity shock in each time period (Degryse et al., 2019), and (ii) firms' unobserved characteristics that determine their propensity to invest in green technologies (such as awareness of firms about their impact on climate change, the managerial ability to seize green investment opportunities, etc) are orthogonal to credit supply shocks. In particular, assumption (ii) requires there is no bank lending specialization or preference for green projects or firms. These assumptions are standard in the related literature, and are especially likely to hold in our sample consisting primarily of privately held SMEs which typically have very stable management and ownership structures. In Section 5 we discuss these assumptions in more detail and show that different estimation strategies that rely on less restrictive assumptions yield similar results.

3 Credit supply and green investments

Table 4 reports different coefficients for variable ΔLoan in Equation 1. Estimates in Panel A correspond to OLS; Panel B contains 2SLS coefficients. The following fixed effects are included in each regression: only province-year fixed effects (columns 1 and 5); province-year and sector-year fixed effects (columns 2 and 6); province-year, sector-year and size-year fixed effects (columns 3 and 7); and the interaction of year with province, industry, and class size fixed effects (columns 4 and 8). All models include firm fixed effects and one-year lags of the following time-varying firm-level controls: size (log of assets), log of age, debt ratio, cash to assets ratio, tangible assets to total assets ratio, profitability, and rating dummies. Standard errors are clustered at the firm level.

Results in Panel A of Table 4 show that the OLS estimates are statistically equal to zero. However, these coefficients are biased, as discussed in the previous section. The main coefficients of interest, estimated via 2SLS and contained in Panel B, show a positive effect of credit supply on green investments.

The bottom part of Panel B of Table 4 reports the first-stage estimates. We find that the credit supply index CSI is positively associated with our main endogenous variable of interest, ΔLoan. This coefficient is estimated with precision: it is statistically different from zero at the 1% level. These results suggest that CSI is a relevant instrument for variable ΔLoan. The appropriateness of our instrument is also confirmed by the first-stage F-statistic, which ranges between 79 and 127, and is well above the critical values identified by Olea and

Pflueger (2013) for the weak instrument bias. Thus, the credit supply index is a strong and valid instrument for our main variable of interest.

The elasticity of green investments to credit supply, estimated through our instrumental variables approach, ranges from 0.039 in the least saturated models (columns 5 and 6) to 0.067 in the most saturated one (column 8). Economically, these coefficients indicate that a one-standard deviation increase in ΔLoan (0.695, as indicated in Table 3) increases the likelihood that firms invest in green technologies by 2.7 to 4.7 percentage points, which amounts to up to 19% of the standard deviation of variable $\text{Green}_{i,t}$ (0.240, see Table 3). Overall, the estimates in Table 4 show that the elasticity of green investments to credit availability is economically important and indicate that the decision to invest in green technologies (extensive margin) depends crucially on credit availability.

In Table 5, we benchmark our results to other investments; we present OLS (Panel A) and 2SLS (Panel B) coefficients for ΔLoan in a model similar to Equation 1. The dependent variable in columns 1 through 4 and 6 through 9 is $\mathbf{1}_{\text{Capital Expenditures}>0}$ (i.e., the propensity to undertake any capital expenditures). In column 5 and 10, we focus on the intensive margin of investment (i.e., the ratio of total investment to total assets). In contrast with results shown in Table 4, the 2SLS coefficients in the first four columns are precisely estimated but not statistically distinguishable from zero. These results show that the extensive margin of investment does not crucially depend on external credit availability during the non-recessionary period of our analysis. This finding is consistent with previous work showing that the effects of external credit availability on firms' decision to undertake a capital investment may have little to no average effects outside of a downturn, as during these times there are alternative sources of liquidity available for firms – for example in the form of internal funds or trade credit (Gaiotti, 2013). In contrast, the estimates shown in the last column indicate that investment is responsive to credit supply in the *intensive* margin. These results are in line with the literature that finds positive effects of credit supply shocks on investment (Amiti and

Weinstein, 2018; Cingano et al., 2016, among others), and serve as an additional validation for our methodology.[6]

Overall, the results from Table 4 show that the likelihood of firms to invest in clean technologies is largely responsive to credit supply. In the next section, we explore the variables that contribute to the positive elasticity of green investments to credit supply, and provide explanations for why it differs from the elasticity of overall investments to credit supply.

4 Heterogeneity analysis

4.1 Capital intensity and financial constraints

We first investigate the role of upfront capital expenditures and, relatedly, financial constraints in our findings regarding both the positive elasticity of green investments and the zero elasticity of normal investments to credit supply. Previous work has shown that green investments are more capital intensive and require higher upfront costs than other productive investments (Allcott and Greenstone, 2012; Fowlie et al., 2018). In line with this evidence, in a recent firm survey conducted by the European Central Bank managers list high investment costs as the second most important challenge to the green transition, preceded only by technology availability (Kuik et al., 2022). Theories of financial intermediation under asymmetric information suggest that investments with higher upfront costs require larger amounts of external financing, and in some cases cannot be undertaken by firms with low availability of internal resources (see e.g. Holmstrom and Tirole, 1997). More recently, Lanteri and Rampini (2023) endogenize the higher upfront costs of green technologies and show that financially constrained firms will optimally invest in dirty technologies. Thus, if the large upfront costs

[6] From our data we cannot observe the intensive margin of investments in green technologies because firms do not usually provide detailed investment amounts by item, and measures based on the ratio of "green" to total words in the text proved to be uninformative in a validation analysis. Therefore, we cannot compare the elasticity of the intensive margin of investment in green technologies with the overall elasticity of investment. However, based on the fact that the intensive margin of normal investments responds significantly to credit supply vs. the extensive margin, and –as we will show below– that green investments are highly capital intensive, we expect the coefficients in Table 4 to be a lower bound for the elasticity to credit supply of the intensive margin of green investments.

of green investments are contributing to the positive elasticity of green investments to credit supply, we should observe higher elasticities among firms with better ability to bear the large upfront investment costs, and either no response to external funds or no green investments altogether for firms with low availability of internal funds. In contrast, these differences should not hold for normal investments which carry lower average upfront costs.

To test this hypothesis, we consider a set of firm characteristics Z_i that are associated with the availability of internal resources (profitability, liquidity, size and age). We then estimate Equation 1 for two subsets of firms: one for which these characteristics fall above the median of the distribution of Z_i, corresponding to firms with high availability of internal resources, and one for which these characteristics fall below the median (low internal resources). Results are shown in Table 6, Panel A ("Availability of Internal Resources").[7] Columns 1 – 3 (4 – 6) contain estimations of Equation 1, over subsamples with values of variable Z_i larger (smaller) than the median. Variable Z_i is labeled on the left-hand side. In each pair of rows, columns 1 and 4 contain the estimated coefficient for ΔLoan (top) and its t-statistic (bottom, in parentheses); columns 2 and 5 contain the R^2 of the second-stage estimation (top) and the F-statistic of the first-stage estimated equation (bottom); and columns 3 and 6 contain the number of observations of each subsample. All estimations include firm fixed effects, sector-size-province-year fixed effects, and the same time-varying controls as in Table 4.

Consistent with the idea that green investments are capital intensive and require high upfront costs, we find that the elasticity to credit supply is stronger for more profitable, more liquid, as well as larger and older firms – that is, firms with more internal financial resources (Panel A). In a similar spirit, we repeat this exercise using several measures of financial constraints commonly used in the literature (see Mulier et al., 2016). Results are shown in Table A6 in the Appendix. They align with the previous ones and they demonstrate

[7] Figure B5 in the Appendix shows to what extent the characteristics of firms outlined in Table 6 correlate with each other. Overall, these characteristics are weakly correlated, suggesting a low overlap across these categories.

that only unconstrained firms have a positive and significant elasticity of credit supply to green investments. The results suggest that external financing can be combined with internal resources to fund green investments. All in all, these results support our hypothesis that green investments require larger external financial resources.

In Panel B, we repeat this exercise using the *sector* dependence on external finance (following the approach introduced by Rajan and Zingales, 1998). We find that the elasticity of green investment to credit supply is positive and significant for firms in sectors with *both* high and low dependence on external finance. This result shows that, even in sectors with a lower need for external financing, green investments respond positively to credit shocks. Once more, this finding is consistent with a high capital intensity of green investments.

To complement the above results, we look at normal investments and perform a similar exercise as in Table 6 but for firms' propensity to carry out any investment, green or not green. Results are shown in Table A7 in the Appendix, and are strikingly different. In this case, we do not find different elasticities across subsets of financially constrained and unconstrained firms (Panel A). However, we do find a positive elasticity for firms in high-EFD sectors (Panel B). These results line up well with the hypothesis that –similar to the investments of high-EFD sectors– green investments are more capital intensive than normal investments, and hence rely more crucially on external financing to be undertaken.

As an additional test for the role of upfront capital in our results, we study whether investments in green technologies have bigger surges (or are more "spikey", as defined by Gourio and Kashyap, 2007) than ordinary investments. Capital intensive investments should be associated with larger increases in capital expenditures, and hence, with higher growth rates of investment and investment spikes. We identify firms' investment spikes using the definition in Bachmann and Bayer (2014) (investment growth higher than 20%). We then look at the differences between non-green and green investments in terms of investment growth and investment spikes. Table A8 in the Appendix shows that investments in green technologies display higher growth rates and larger spikes than other investments, confirming the hypothesis that investments in green technologies are more capital intensive.

4.2 Environmental preferences

We next explore the role of environmental preferences of the population on the elasticity of credit supply on green technology investments. There is growing evidence that the salience of weather events and preferences for the environment play an increasingly important role in financial markets (e.g. Krueger et al., 2020; Choi et al., 2020; Ramelli and Brière, 2021) as well as in firms' investment decisions (Aghion et al., 2023). Local preferences for a clean environment should increase the demand for clean technologies. Thus, the responsiveness of green investments to credit supply should be higher in areas where the population ascribes higher value to the environment.

In Table 7, we test this hypothesis using two measures that capture local environmental preferences. In the first two columns, firms' headquarter locations (regions) are classified according to whether the population places high weight on environmental protection (i.e., larger shares of individuals state that they prefer environment protection to economic growth according to the 2017 European Value Study). In the last two columns, the locations of firms' headquarters are divided according to a measure of climate change awareness (i.e., Italian regions with highest rates of Google search for "climate change", according to Google Trends). This measure reflects the view that environmental preferences are more central in places where climate change is a more salient issue. In both cases, we find that the elasticity of green investment to credit supply is higher where there is higher environmental awareness. These results demonstrate that local environmental preferences play an important role in our results.[8]

4.3 Green subsidies

Several researchers argue that government action in the form of subsidies and grants are crucial to stimulate firms to invest in green assets (Acemoglu et al., 2012, 2016). Additionally, investments in green technologies can be thought of as a public good, and the literature suggests that private investments in public goods should be incentivized through tax benefits or similar subsidies (Roberts, 1987).

In Table 8 we study the role of government subsidies in influencing the elasticity between green investments and credit supply shocks. Subsidies could increase the amount of funds available to firms to cover upfront investment costs, reducing financial constraints and hence affecting the responsiveness to credit supply. To test this hypothesis, we create a regional measure of green subsidies by identifying all green subsidies granted in each Italian region, and counting these within each region. We classify subsidies using the 2018 Italian census of regional subsidies, and looking for words in our green dictionary in the description of the subsidies. We then classify regions into those granting a higher or lower than median number of green subsidies, and estimate Equation 1 on the resulting subsamples. Results of this analysis are shown in the first two columns of Table 8. We find that the coefficient for ΔLoan is only statistically significant in the subsample of high green subsidy regions

[8] One concern of these results is that environmental awareness is correlated with some unobserved variable driving the propensity to carry out *any* type of investment. In order to discard this possibility, we perform a placebo test where we analyze whether the extensive margin of general capital investments is affected by environmental preferences. The results reported in Table A9 suggest that this is not the case.
A related question is whether the entrepreneurs' environmental preferences matter for green investments. To answer this question, we perform a heterogeneity analysis where we estimate Equation 1 over subsamples of firms based on their distance to the final consumers. We use the industry-level measures of firm "upstreamness" estimated for Italy by Antràs et al. (2012) and split the sample at the median according to this measure. Results are shown in the first two columns of Table A10. We find that the positive elasticity of green investments to credit supply is only statistically significant for the most upstream firms, albeit it cannot be statistically distinguished from the coefficient in downstream sectors. In columns 3 through 6, we further add to this result by estimating the elasticity separately for high and low environmentally aware regions, and for high and low firm upstreamness. While the point estimates are higher for subsamples with higher environmental awareness, they are not statistically different across upstream vs. downstream firms. Therefore this test is inconclusive about the role of the entrepreneurs' environmental preferences.

(column 2). This result suggests that private credit supply must be complemented with green subsidies to speed up the transition to a green economy. In addition, this result is also consistent with the idea that green investments are highly capital intensive.

We expand our analysis and explore the joint role of green subsidies and environmental preferences. We create four subsamples through the cross-tabulation of green subsidies and environmental preferences, and estimate Equation 1 over all resulting subsamples. Results are contained in columns 3 through 6 of Table 8. The coefficient for ΔLoan is only statistically significant in the subsample of high green subsidy regions *and* high environmental protection, indicating that green investment will react to credit provision only in regions where there are subsidies and that have a strong preference for environmental protection. The number of observations within each of the four groups suggests that the two regions' classifications do not perfectly overlap; therefore, there is no perfect correlation between local environmental preferences and local presence of green subsidies. Our results qualify previous findings in the literature by showing a large complementarity among bank credit, public funds, and environmental preferences. In particular, public subsidies are a necessary condition for green investments, highlighting the role of policy coordination for green transition.

4.4 Market competition

Aghion et al. (2023) show theoretically that market competition can influence the investment in green technologies, and that this relationship can be particularly strong in regions with high environmental awareness. We test this hypothesis by computing a measure of industry competition (at 2-digit Nace rev. 2 level) through the Herfindahl Index of all firms in the Cerved dataset. We first estimate Equation 1 separately for firms at or above the median market competition measure and for those below it. Results are shown in the first two columns of Table 9. We find that the coefficient for ΔLoan is statistically different from zero only in industries with high levels of competition. However, coefficients are not statistically different across the two subsamples.

We then analyze whether environmental preferences interact with market competition through a double-crossing procedure that allows us to classify firms based on the degree of competition they face in their industry and the environmental preferences in the location they operate. Results are shown in columns 3 through 6 of Table 9. Firms' elasticity of green investments to credit supply is more pronounced in markets with higher competition and high levels of environmental awareness. This finding is fully consistent with Aghion et al. (2023)'s model, and once more confirms the prominent role of environmental preferences as a catalyst of firms' green innovation in the face of positive credit supply shocks.

4.5 Regulatory risk

We also explore the role of regulatory risk in our main findings. The Paris Agreement led to an increase in regulatory risk, both in realized and in expected terms (see e.g. Seltzer et al., 2022). One consequence of increased regulatory risk is an increase in the probability of brown assets becoming stranded, which in turn lowers the collateral value of these firms' assets. Sectors with higher vs. lower climate transition risk could therefore respond differently to credit supply when investing in green technologies (Ramadorai and Zeni, 2021). Using the 2015 Paris Agreement as a shock to regulatory risk, some authors have found evidence that banks and financial markets have incorporated this risk in their credit decisions, albeit the literature is not conclusive (Delis et al., 2018; Beyene et al., 2021; Mueller and Sfrappini, 2021; Degryse et al., 2020b; Seltzer et al., 2022).

To explore this issue, we exploit the heterogeneity in our results according to firms' exposure to regulatory risk. Given that our sample period corresponds largely to the post-Paris Agreement era, we measure the firms' exposure to regulatory risk using the average level of greenhouse gas air emissions in the firm's main industrial sector (sourced from the World Input Output Data, for Italian firms). The underlying assumption is that sectors with higher carbon emissions are more susceptible to climate transition risk. Table 10 presents estimates of Equation 1 across subsamples of sectors with high and low greenhouse gas emissions, split at the median. We find that the elasticity of green investments to credit supply is only statistically significant for firms in industries with low emissions. However, the point estimate for high-emission industries is larger, and the coefficients are not statistically distinguishable across the two groups. Hence, we cannot conclude whether regulatory risk contributes to the positive response of green investment to credit supply.

5 Threats to identification and robustness tests

5.1 Bank specialization

As mentioned earlier, one potential threat to our identification strategy is that credit supply for green investments is not similar across the banks in our sample. This could occur if for example some banks specialize in lending to green firms (Degryse et al., 2020a; Paravisini et al., 2023). We verify if this is indeed the case in our sample by comparing the market share of total non-green lending by bank to the share of total green lending. If there is no specialization to lending to green firms by some banks, we should observe that for each of the banks in our sample, their market share of lending to non-green firms is proportional to their market share of lending to green firms. We test for the presence of bank specialization by regressing banks' market share to non-green firms on their market share to green firms. The fitted line of this regression is graphically shown in Figure 3. While we cannot plot the individual bank shares for confidentiality reasons, we find that these are almost perfectly aligned with a 45 degree line: the fitted slope is 1.03, and the R^2 in the regression is 0.96. In addition, the distribution of the residuals of this regression is tightly centered around zero. These results show that all banks lend to green firms proportionally to their market shares to non-green firms, and hence the results rule out the existence of banks specialized into lending to green firms. These results support the validity of our identification approach.

A related concern is that there might be a preferential supply of credit to firms that are investing in green technologies. This is a concern particularly given that our sample period begins after the signing of the Paris Agreement in 2015, a period that raised environmental awareness around the world and triggered some of the first private and public initiatives to act on climate change. The concern is therefore that these initiatives could have tilted the supply of credit into a greater lending to green firms. This is however not likely to affect our results. In fact, the earliest Italian banks to signal their involvement in climate action by signing the Principles for Responsible Banking (PRB) program of the United Nations' Environment Program Finance Initiative (UNEP FI) (Delis et al., 2018; Degryse et al., 2020a) did so only in September and October of 2019, i.e., at the very end of our sample period. Thus, it is unlikely that a significantly larger amount of credit was provided for green investments relative to normal ones.

We nevertheless analyze more closely whether there might indeed be a differential supply of credit by certain "green-oriented" banks. We first classify all banks operating in Italy that joined the PRB initiative as of December 2021 as green banks. The assumption is that a future endorsement of these initiative is a proxy of the green awareness or green preferences of these banks, which might indicate a larger supply of credit for green investments during our sample period. We consequently classify the firms in our sample as borrowers from green banks if they are obtaining at least 50% of their total credit from a PRB signatory bank (PRB signatory).

As a second measure for green banks, we take each bank's share of lending to industries with high greenhouse gas emissions. We define a green bank in this case as a bank whose share to high greenhouse gas emissions industries is lower than the (weighted) average share to these industries across all banks. Arguably, banks that have a legacy portfolio of lending to low-emissions firms can more easily provide higher amounts of credit for green technologies than banks with a legacy portfolio more tilted towards brown assets (Degryse et al., 2020b).

An analysis by subsamples of green and not-green banks as defined by these two measures is contained in Table A11 in the Appendix. Results show a positive coefficient in all subsamples, which is statistically insignificant for green-oriented banks. We conclude that a larger supply of credit for green investments is unlikely to drive our results, in line with our identification assumption.

5.2 Robustness on the instrument

Another concern regarding our identification strategy is that Equation 2 should be correctly specified to purge local loan demand shocks from bank credit supply shifters. To control for the robustness of our instrument, we re-estimate the credit supply index using a modified version of Equation 2 that relies on data aggregated at a more granular level, and controlling for demand factors using fixed effects for smaller clusters of firms.

Specifically, in Table 11 we instrument ΔLoan using the bank-time estimates of the following equation: $\Delta \text{Loan}_{bw(i)t} = \delta_{bt} + \gamma_{w(i)t} + \epsilon_{bw(i)t}$, where b and t are as in Equation 2 and $w(i)$ corresponds to different levels of aggregation of the data along firm i's characteristics. In column 1, $w(i)$ stands for the cross-product of firm i's province, industrial sector, and an institutional size category defined by Bank of Italy which considers firm size and type of incorporation.[9] In column 2, $w(i)$ corresponds to the cross-tabulation of firm i's province, sector, institutional size category, and four loan size categories. In columns 3 and 4, $w(i)$ corresponds to firm i itself; the estimation equation used to compute the instrument in column 4 additionally includes firm-bank fixed effects. The specifications in columns 3 and 4 are in line with the identification strategies proposed by Khwaja and Mian (2008) and Amiti and Weinstein (2018), and necessarily rely on firms borrowing from multiple banks during the same period, which correspond to one fourth of the original database. Details on the data construction and estimation procedure for these estimates are provided in Appendix D.

The results of these estimations are contained in Table 11. The estimates are similar both

[9]See Circolare 140, Bank of Italy.

in significance and in magnitude to our baseline model shown in Table 4. The similarity of these coefficients to our baseline estimates in Table 4 confirms the validity of the identifying assumption of our baseline methodology, which requires that firms of similar size operating in the same sector, province, and class size face very similar demand shocks in each time period.

6 Conclusions

In this paper, we study the role of a key source of financing for the transition to greener economy: bank credit. Specifically, we analyze whether credit supply affects firms' investment in green technologies.

We use text algorithms to extract information on green investments from the comments to the financial statements of Italian firms between 2015 and 2019, and match this information with loan-level data from the Italian Credit Registry. To identify the effect of credit supply on green investments, we follow Berton et al. (2018) and construct an exogenous firm-specific time-varying measure of bank credit supply, based on the estimation of time-varying nation-wide bank lending policies that are purged of local loan demand and idiosyncratic shocks at the province-sector-year level. Our firm-level measure of credit supply is the weighted average of these bank credit supply indices, using the lagged shares of loans from each lending bank as weights.

We find that green investments display a strong, positive response to credit supply. We rule out that our results are driven by a more advantageous credit supply for green investments, or by larger credit allocation for green projects. Our results largely support the idea that green investments are more capital intensive; we also show that local environmental preferences and regional subsidies play an important role in explaining our results.

Our results have far-reaching policy implications. First, by showing that green investments are particularly sensitive to banking supply shocks, we provide additional evidence of the economic and social costs of credit crunches: the slow-down in the adoption of more environmentally-friendly technologies and, therefore, a possible delay in the green transition. Second, we provide evidence that public subsidies represent a necessary condition for private credit to be used for sustainable investments; a relevant result that underlines the importance of policy coordination in accelerating the green transition. Third, we show that environmental preferences are fundamental drivers of the positive response of green investments to larger credit supply: the green transition will only be possible if firms embrace environmental norms and attitudes. Targeted policies promoting pro-social behavior among managers and local regulators (e.g., through education and awareness campaigns) can therefore have a positive effect on firms' investment decisions.

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Tables

Table 1: Sample observations by year

	Green_{it}			%
Year	0	1	Total	Green
2015	20,791	1,444	22,235	6.5
2016	23,221	1,544	24,765	6.2
2017	22,550	1,590	24,140	6.6
2018	21,047	1,442	22,489	6.4
2019	15,345	1,070	16,415	6.5
Total obs.	102,954	7,090	110,044	6.4
Unique firms	25,503	2,805	28,308	9.9

This table contains the number of observations by year in the source firm-year level sample. Columns labelled "0" and "1" contain the number of firms with values of variable Green_{it} respectively equal to zero (did not invest in green technologies in year t) and one (invested in a green technology). Green_{it} is defined according to our text classification (see Section 2 and Table A3 for details). "% Green" is the fraction of firms that are investing in a green technology in each year. In the last row we classify each unique firm in our sample according to variable $\text{Green}_i = \max_t\{\text{Green}_{it}\}$, i.e. whether they have or have not made at least one green investment during our entire sample period.

Table 2: Sample composition by size and sector (unique firms)

	Green_i			%
	0	1	Total	Green
Panel A: Composition by size category				
Large	2,878	488	3,366	14.5
Medium	13,512	1,637	15,149	10.8
Small	7,421	562	7,983	7.0
Micro	1,692	118	1,810	6.5
Panel B: Composition by sector				
A - Agriculture, forestry and fishing	345	64	409	15.6
B - Mining and quarrying	40	2	42	4.8
C - Manufacturing	10,745	1,452	12,197	11.9
D - Electricity, gas, steam supply	203	173	376	46.0
E - Water supply; sewerage, waste management	428	88	516	17.0
F - Construction	1,561	126	1,687	7.5
G - Wholesale and retail trade	7,802	668	8,470	7.9
H - Transportation and storage	1,279	107	1,386	7.7
I - Accommodation and food service activities	431	20	451	4.4
J - Information and communication	600	9	609	1.5
L - Real estate activities	35	4	39	10.3
M - Professional, scientific and tech. act.	546	26	572	4.5
N - Admin. and support activities	648	20	668	3.0
P - Education	49	1	50	2.0
Q - Human health and social work	640	35	675	5.2
R - Arts, entertainment and recreation	94	6	100	6.0
S - Other service activities	57	4	61	6.6

This table contains the number of unique firms in our sample that are investing in a green technology at least once during our sample period (i.e. $\text{Green}_i = \max_t\{\text{Green}_{i,t}\} = 1$) or not ($\text{Green}_i = 0$). In Panel A, firms are classified by size category according to the definitions of the European Commission (EU recommendation 2003/361): large firms are defined as those with more than 250 employees, medium firms as those with 50 to 250 employees, while small and micro firms as those with respectively less than 50 and 10 employees. In Panel B, firms are classified according to their broad industrial sector following the NACE Rev. 2 classification.

Table 3: Summary statistics

Variable	Mean	Median	S. Dev.
	(N = 110,044)		
Green	0.062	0.000	0.240
ΔLoan[1]	0.006	-0.012	0.695
CSI[1]	-0.007	-0.018	0.203
Assets	9.524	9.473	1.172
Age	3.239	3.367	0.612
Debt ratio[1]	0.267	0.254	0.191
Cash to assets ratio[1]	0.092	0.046	0.116
Tangible to fixed assets ratio[1]	0.208	0.149	0.200
Rating: 1	0.000	0.000	0.020
Rating: 2	0.004	0.000	0.066
Rating: 3	0.024	0.000	0.154
Rating: 4	0.051	0.000	0.220
Rating: 5	0.077	0.000	0.266
Rating: 6	0.117	0.000	0.322
Rating: 7	0.245	0.000	0.430
Rating: 8	0.169	0.000	0.375
Rating: 9	0.233	0.000	0.423
Rating: 10	0.078	0.000	0.269

[1] Winsorized between 1 and 99%

This table contains descriptive statistics (mean, median, and standard deviation) of the dependent and control variables used to estimate Equation 1. The sample corresponds to all Italian firms filing detailed financial statements and with text available in the accompanying notes. Assets and age are measured in logs. Rating 1 and Rating 10 are respectively the lowest and highest risk ratings. Section 2 and Table A3 contain variable definitions.

Table 4: Main results: Credit supply and green investments

	Panel A - OLS			
	(1)	(2)	(3)	(4)
ΔLoan	0.0005	0.0004	0.0005	0.0004
	(0.702)	(0.665)	(0.690)	(0.496)
Observations	110,044	110,044	110,044	110,044
R-squared	0.745	0.745	0.745	0.796
	Panel B - IV			
	(5)	(6)	(7)	(8)
ΔLoan	0.0390**	0.0387**	0.0405**	0.0670**
	(2.032)	(2.007)	(2.070)	(2.497)
Observations	110,044	110,044	110,044	110,044
R-squared	0.735	0.736	0.736	0.774
Firm controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	.
Sector-Year FE	.	Y	Y	.
Size-Year FE	.	.	Y	.
Province-Sector-Size-Year FE	.	.	.	Y
First-stage:				
CSI	0.245***	0.244***	0.242***	0.212***
	(6.971)	(6.934)	(6.877)	(5.486)
F-statistic weak instruments	126.9	125.7	123.9	78.86

This table contains the estimated coefficient for ΔLoan for different specifications of Equation 1. The dependent variable is Green_{it}, a dummy taking the value one if the firm invests in a green technology. The sample consists of firm-year observations in the Italian Credit Registry between 2015 and 2019 for which information about green investments is available. Estimations include the set of fixed effects indicated with the label "Y", and the following firm-level controls (lagged): log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies. Panel A contains OLS estimates. In Panel B, ΔLoan is instrumented using the credit supply index, variable CSI, as described in Section 2. T-statistics in parentheses. Standard errors are clustered at the firm level.
*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table 5: Credit supply and the propensity to invest in capital expenditures

	Panel A - OLS				
	Extensive margin				Intensive margin
	(1)	(2)	(3)	(4)	(5)
ΔLoan	0.0035***	0.0034***	0.0027***	0.0018	0.0059***
	(3.307)	(3.251)	(2.609)	(1.576)	(23.62)
Observations	110,044	110,044	110,044	110,044	110,044
R-squared	0.442	0.444	0.446	0.556	0.657
	Panel B - IV				
	(6)	(7)	(8)	(9)	(10)
ΔLoan	0.0103	0.00874	0.0102	0.0338	0.0164*
	(0.316)	(0.266)	(0.311)	(0.830)	(1.949)
Observations	110,044	110,044	110,044	110,044	110,044
R-squared	0.442	0.444	0.445	0.551	0.646
Firm controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	.	.
Sector-Year FE	.	Y	Y	.	.
Size-Year FE	.	.	Y	.	.
Province-Sector-Size-Year FE	.	.	.	Y	Y
First-stage:					
CSI	0.245***	0.244***	0.242***	0.212***	0.212***
	(6.971)	(6.934)	(6.877)	(5.486)	(5.486)
F-statistic weak instruments	126.9	125.7	123.9	78.86	78.86

This table contains the estimated coefficient for ΔLoan in several specifications of Equation 1, modified by substituting the dependent variable with either $\mathbb{1}_{\text{Inv}>0}$ (a dummy taking the value one if the firm has positive investments during the year, columns 1-4 and 6-9) or the investment to capital ratio (columns 5 and 10). The sample consists of firm-year observations in the Italian Credit Registry between 2015 and 2019 for which information about green investments is available. Estimations include the set of fixed effects indicated with the label "Y", and the following firm-level controls (lagged): log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies. Panel A contains OLS estimates. In Panel B, ΔLoan is instrumented using the credit supply index, variable CSI, as described in Section 2. T-statistics in parentheses. Standard errors are clustered at the firm level.
*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table 6: Firm characteristics, credit supply and green investments

	Z_i above median			Z_i below median		
	β	R^2	Obs.	β	R^2	Obs.
	(t-stat)	F		(t-stat)	F	
$\beta(\Delta\text{Loan})$	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Availability of Internal Resources						
Z_i : Profitability	0.129**	0.703	49,532	0.0376	0.813	49,362
	(2.336)	25.52		(0.901)	34.26	
Z_i : Liquidity	0.107**	0.728	49,464	0.012	0.815	49,570
	(2.226)	25.57		(0.259)	31.67	
Z_i : Size	0.0794**	0.772	51,681	0.0306	0.811	51,518
	(1.987)	46.40		(0.901)	30.38	
Z_i : Age	0.0903**	0.769	49,178	0.0344	0.808	50,717
	(2.066)	38.29		(0.886)	29.13	
Panel B - Dependence on External Finance						
Z_i : Rajan-Zingales	0.0697**	0.797	47,168	0.0662*	0.753	61,337
	(2.027)	48.67		(1.657)	34.88	

Columns 1-3 consider 2SLS estimations of the coefficient for ΔLoan in Equation 1 in a subsample of firms with characteristic Z_i above the median. Columns 4-6 consider 2SLS estimations of the coefficient for ΔLoan in Equation 1 in a subsample of firms with characteristic Z_i below the median. In each pair of rows, characteristic Z_i refers respectively to profitability, liquidity, solvency, size and age of firm i as averages on the sample period (see Table A3 for variable definitions). In each pair of rows, columns 1 and 4 contain the estimated coefficient (above) and the t-statistic (below, in parentheses); columns 2 and 5 contain the R^2 (above) and the F-statistic of the first-stage estimated equation (below); and columns 3 and 6 contain the number of observations of each subsample. All estimations include the same set of fixed effects and firm-level controls as in columns 4 and 8 of Table 4. Figure B5 in the Appendix provides a correlation matrix for firm characteristics Z_i.

*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table 7: Environmental preferences and green investments

	Env. Protection		Climate Change	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
ΔLoan	0.0236	0.117**	0.0492*	0.136*
	(0.765)	(2.422)	(1.742)	(1.738)
Observations	55,750	54,045	88,496	21,405
R-squared	0.795	0.730	0.782	0.712
Firm Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Province-Sector-Size-Year FE	Y	Y	Y	Y
F-statistic weak instruments	41.80	37.93	61.89	16.54

This table contains 2SLS estimated coefficients for variable ΔLoan in Equation 1. In columns 1 and 2, the sample is split according to variable High Environmental Protection, a dummy variable taking the value one for Italian regions where a higher than average fraction of individuals answered "yes" to the question of whether they prefer protecting the environment to economic growth (Basilicata, Trentino-Alto Adige, Umbria, Lazio, Friuli-Venezia Giulia, Veneto, Emilia-Romagna, Toscana, Campania. Data Source: 2017 European Value Study). In columns 3 and 4, the sample is split according to variable High Climate Change, a dummy taking the value one for Italian regions where the Google searches for "climate change" are higher than the average (Valle D'Aosta, Trentino-Alto Adige, Molise, Friuli-Venezia Giulia, Basilicata, Umbria, Lazio, Sardegna, Toscana. Data source: Google Trends 2004–2014). The dependent variable is a dummy variable taking the value of one when the firm invests in a green technology. Estimations include firm fixed effects, interacted province-sector-size-year fixed effects, and the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies. T-statistics in parentheses. Standard errors are clustered at the firm level.
*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table 8: Green subsidies, environmental protection and green investments

			Green subsidies			
			Low		High	
	Green subsidies		Environmental Protection			
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLoan	0.0518	0.0723**	0.0451	0.0500	0.0217	0.167**
	(0.996)	(2.301)	(0.459)	(0.861)	(0.671)	(2.211)
Observations	31,587	78,316	8,652	22,843	47,081	31,162
R-squared	0.780	0.770	0.809	0.767	0.791	0.685
Firm Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Province-Sector-Size-Year FE	Y	Y	Y	Y	Y	Y
F-statistic weak instruments	20.41	58.53	7.924	14.72	34.72	23.74

This table contains 2SLS estimated coefficients for variable ΔLoan in Equation 1. In columns 1 and 2, the sample is split according to variable High Green Subsidies, a dummy that takes the value one if the total number of regional green subsidies in the region of the firm headquarter locations are higher than the median (Piemonte, Sicily, Toscana, Emilia-Romagna, Liguria, Friuli Venezia Giulia, Umbria, Lombardia, Trentino-Alto Adige, Campania. Source: Italian permanent census of enterprises, 2019, ISTAT). In columns 3-6, the sample is split into groups according to the cross-tabulation of variables High Green Subsidies and High Environmental Protection. The latter is a dummy variable taking the value one for Italian regions where a higher fraction of individuals answered "yes" to the question of whether they prefer protecting the environment to economic growth (Basilicata, Trentino-Alto Adige, Umbria, Lazio, Friuli-Venezia Giulia, Veneto, Emilia-Romagna, Toscana, Campania. Data Source: 2017 European Value Study). The dependent variable is a dummy variable taking the value one when the firm invests in a green technology. Estimations include firm fixed effects, interacted province-sector-size-year fixed effects, and the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies.
T-statistics in parentheses. *,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table 9: Market competition and green investments

	Competition		Competition Low		Competition High	
			Environmental Protection			
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLoan	0.0487	0.0846*	0.0181	0.139	0.0329	0.110**
	(1.487)	(1.922)	(0.580)	(1.279)	(0.479)	(2.024)
Observations	42,322	67,281	22,296	19,894	33,266	33,901
R-squared	0.791	0.755	0.793	0.730	0.794	0.723
Firm Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Province-Sector-Size-Year FE	Y	Y	Y	Y	Y	Y
F-statistic weak instruments	51.45	31.97	45.91	8.624	7.794	28.46

This table contains 2SLS estimated coefficients for variable ΔLoan in Equation 1. In columns 1 and 2, the sample is split according to values of variable High Competition, a dummy which takes the value one if the Herfindahl Index (HHI) of concentration in the location and industry of the firm is lower than the median, and zero otherwise. In columns 3-6, we subdivide the sample into four groups according to the cross-tabulation of variables High Competition and High Environmental Protection. The latter is a dummy variable taking the value one for Italian regions where a higher than average fraction of individuals answered "yes" to the question of whether they prefer protecting the environment to economic growth (Basilicata, Trentino-Alto Adige, Umbria, Lazio, Friuli-Venezia Giulia, Veneto, Emilia-Romagna, Toscana, Campania. Data Source: 2017 European Value Study). The dependent variable is a dummy variable taking the value one when the firm invests in a green technology. Estimations include firm fixed effects, interacted province-sector-size-year fixed effects, and the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies. T-statistics in parentheses. Standard errors are clustered at the firm level.
*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table 10: Greenhouse gas emissions and green investments

	CO_2-e Emissions	
	Low	High
	(1)	(2)
ΔLoan	0.0566**	0.104
	(2.069)	(1.339)
Observations	82,759	27,229
R-squared	0.770	0.772
Firm Controls	Y	Y
Firm FE	Y	Y
Province-Sector-Size-Year FE	Y	Y
F-statistic weak instruments	64.80	14.96

This table contains 2SLS estimated coefficients for variable ΔLoan in Equation 1. The sample is split according to variable High CO_2-e, a dummy which takes the value one for the sectors with largest fraction of CO_2-equivalent emissions (Electricity supply, agriculture, metallurgy, transportation, manufacturing of chemicals), and zero otherwise (Source: Greenhouse Gas Air Emissions by Sectors, Italy, World Input Output Data, 2013). The dependent variable is a dummy variable taking the value one when the firm invests in a green technology. Estimations include firm fixed effects, interacted province-sector-size-year fixed effects, and the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies. T-statistics in parentheses. Standard errors are clustered at the firm level. *,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table 11: Credit supply and green investments. Instrument validation

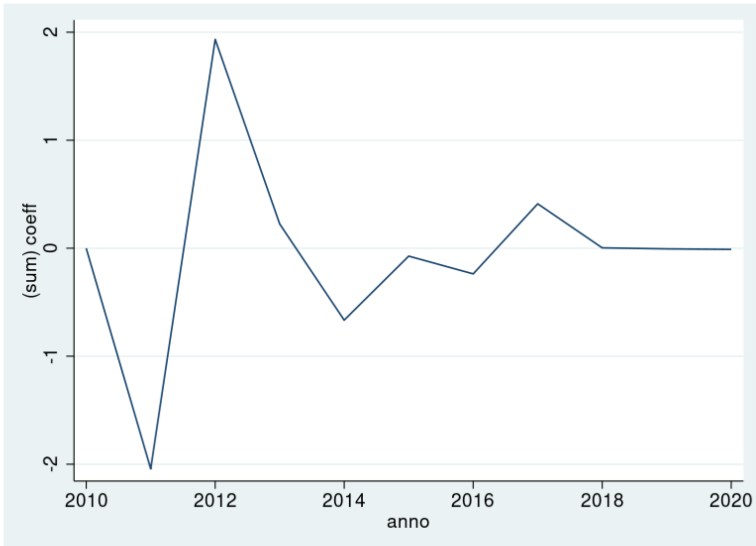
	(1)	(2)	(3)	(4)
ΔLoan	0.062*	0.065*	0.067**	0.069**
	(1.74)	(1.85)	(2.18)	(2.15)
Observations	110,044	110,044	110,044	110,044
R-squared	0.777	0.775	0.773	0.773
Firm controls	Y	Y	Y	Y
Province-Sector-Size-Year FE	Y	Y	Y	Y
First-stage:				
CSI	0.288***	0.302***	0.460***	0.445***
	(5.44)	(5.56)	(6.02)	(5.82)
CSI regressors:				
Bank-Year FE	Y	Y	Y	Y
Province-Sector-Size Category-Year FE	Y	N	N	N
Province-Sector-Size Category-Loan Size-Year FE	N	Y	N	N
Firm-Year FE	N	N	Y	Y
Firm-Bank FE	N	N	N	Y
F-statistic weak instruments	52.7	55.0	67.6	62.7
Observations	110,044	110,044	110,044	110,044
R-squared	0.400	0.400	0.400	0.400

This table contains the estimated coefficient for ΔLoan for different specifications of Equation 1. The dependent variable is Green_{it}, a dummy taking the value one if the firm invests in a green technology. The sample consists of firm-year observations in the Italian Credit Registry between 2015 and 2019 for which information about green investments is available. Estimations include the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies. ΔLoan is instrumented using a credit supply index that is estimated by running the following regression: $\Delta\text{Loan}_{bw(i)t} = \delta_{bt} + \gamma_{w(i)t} + \epsilon_{bw(i)t}$, where b and t are as in Equation 2 and $w(i)$ corresponds to different levels of aggregation of the data. In column 1, $w(i)$ corresponds to the cross-product of firm i's province, sector, and an institutional size category defined by Bank of Italy (Circolare 140, Bank of Italy), which considers firm size and type of incorporation (and hence is a more granular measure of firm size than in Table 4). In column 2, $w(i)$ corresponds to the the cross-tabulation of firm i's province, sector, institutional size category, and four loan size categories. In columns 3 and 4, $w(i)$ corresponds to firm i itself. The credit supply index used as an instrument in column 4 is additionally purged of firm-bank fixed effects. T-statistics in parentheses. Standard errors are clustered at the firm level.
*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels

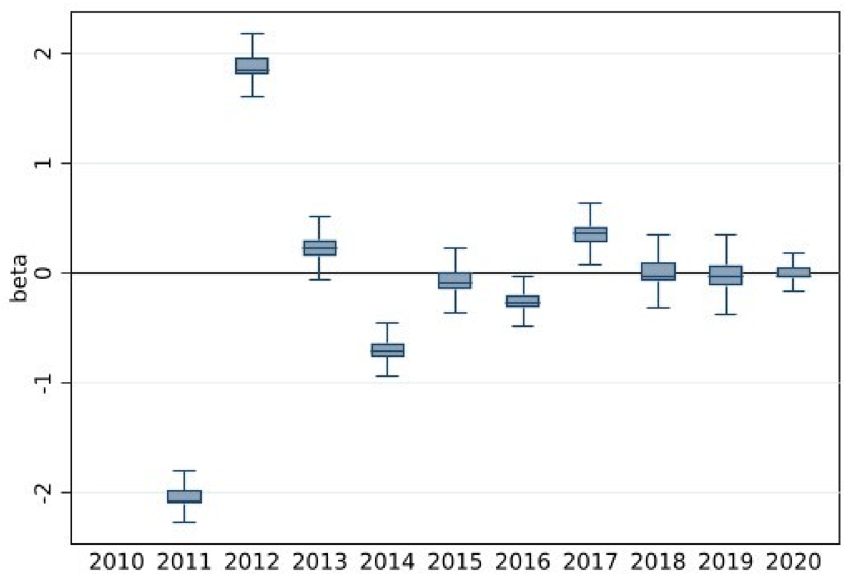
Figures

Figure 1: Credit supply over time

Panel A

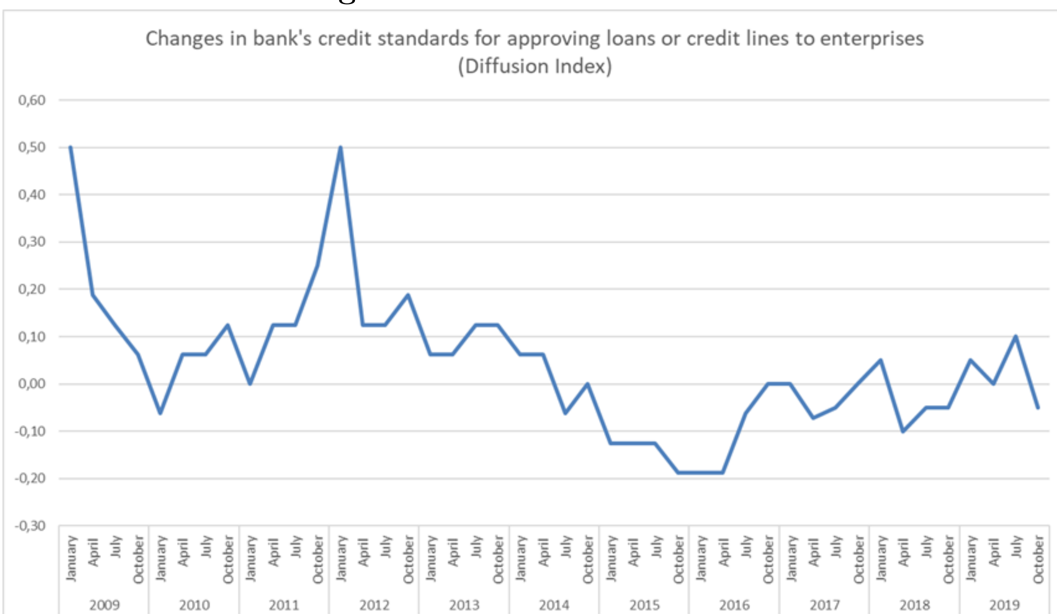


Panel B



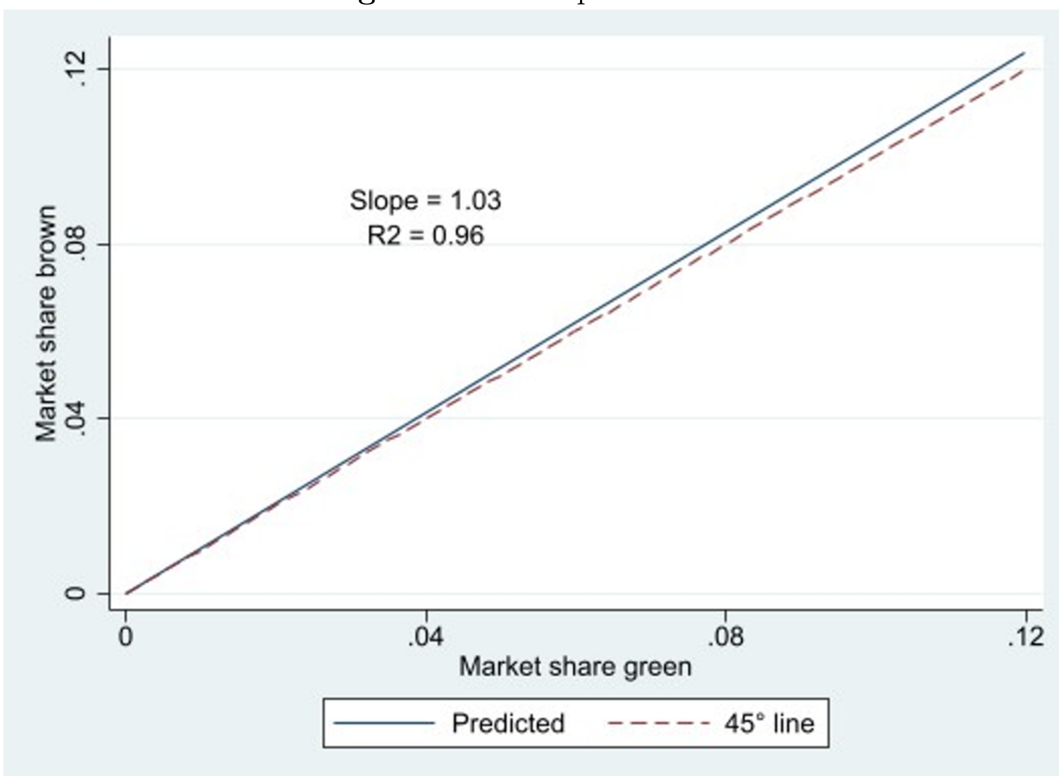
This figure shows the evolution of average bank credit supply over time. Bank-specific credit supply indices are estimated using Equation 2. The line in Panel A depicts the average of the estimated bank-supply indices $\hat{\delta}_{bt}$, weighted by market share. Panel B shows the variation in credit supply across banks within each year. The limits of each box represent the interquartile range Q1-Q3 of the distribution of the credit supply indices for each year, while the upper and lower whiskers depict Q3+1.5·(Q3−Q1) and Q1−1.5·(Q3−Q1), respectively.

Figure 2: Bank credit standards



This figure depicts the changes in banks' credit standards for approving loans or credit lines to enterprises. The line is the so-called *diffusion index*, namely is the (weighted) difference between the share of banks reporting that credit standards have been tightened and the share of banks reporting that they have been eased (Source: Regional bank lending survey, Bank of Italy).

Figure 3: Bank specialization



	mean	sd	p1	p10	p25	p50	p75	p90	p99
residuals	0.00000	0.00177	-0.00317	-0.00019	0.00004	0.00006	0.00012	0.00030	0.00281

This figure shows that there is no bank specialization to green firms. The continuous line corresponds to the fitted regression line for each bank's market share to firms not investing in green technologies (y-axis) on its market share to firms investing in green technologies (x-axis). The estimated slope coefficient of this regression is 1.03, and the R^2 is 0.96. For comparison, the broken line shows the 45° line. The bottom part of the figure contains the distribution of the residuals.

Appendix

A Additional tables

Table A1: Dictionary of green terms

Rank	Keyword	Rank	Keyword
1	fotovoltaic	39	aspett. ambiental
2	eolic	40	fin. ambiental
3	cogenera	41	font. energetic.
4	idrolettric	42	protezione ambiental
5	risparmi(o)* energetic	43	macchinari(o)* ambiental
6	investiment. ambiental	44	font. solar
7	impatt. ambiental	45	impatt. energetic
8	efficienz. energetic	46	energi. alternativ
9	efficientament. energetic	47	energia pulita
10	qualificazion. energetic	48	material._(di\s)*ricicl
11	riqualificazion. energetic	49	basse emissioni
12	font. rinnovabil.	50	impronta\b \bdi\b carbonio
13	consum. energetic	51	\bgas\b \bdi\b scarico
14	certificazion. ambiental	52	colonnin(a—e)\b \bdi\b \bricarica
15	energi. rinnovabil.	53	class. energetic
16	pannell. solar	54	standard ambiental
17	trigenera	55	\bnox\b
18	veicol. elettric	56	font. energetic(a|he) rinnovabil
19	um.\b nociv	57	climalterant
20	impiant. solar	58	eco energetic
21	tutela ambiental	59	energi. verd
22	recuper. energ	60	impatto zero
23	isolament termic	61	emissioni zero
24	gestione ambiental	62	adeguament. energetic.
25	\bauto\b \belettric	63	us. energetic
26	diagnosi energetic	64	configurazion. energetic
27	certificazion. energetic	65	impiant. tecnic. ambiental
28	rinnovabil. solar	66	sfruttament. energetic
29	ecosostenibil	67	ottimizzazion. energetic
30	anidride carbonica	68	zero emissioni
31	geotermic	69	stazion.\b (di\s)*ricarica
32	sicurezza ambiental	70	recupero \bdi\b energi
33	\bstazion.\b \bdi\b \bricarica\b	71	sprec(o|hi) \bdi\b energia
34	impiant. ambiental	72	energia sostenibile
35	energi. solar	73	riscaldamento globale
36	sostenibilit. ambiental	74	emissioni fuggitive
37	audit energetic	75	\bgas\b nociv
38	monitoraggi(o)* energetic	76	colonn(a—e)\b \bdi\b \bricarica

Table A2: Examples of green keywords in firms' comments to their financial statements

#	Text
1	Spese di progettazione per l'ampliamento delle celle frigo e l'installazione di un **impianto fotovoltaico** (€ 5.148) e interventi generici di manutenzione straordinaria (€ 24.800), presso il settore del Mattatoio.
2	Attività di sviluppo precompetitivo finalizzate all'individuazione di nuove soluzioni tecniche e tecnologiche per la messa a punto di soluzioni innovative di packaging totalmente riciclabile e provenienti da **fonti ecosostenibili**.
3	Tali investimenti hanno valenza a **fini ambientali** in quanto lo scopo dell'investimento è di produrre energia elettrica mediante impianto alimentato da **fonte rinnovabile solare** e nel contempo di ridurre la domanda di energia da altre fonti tradizionali.
4	I modesti incrementi dell'esercizio sono riferiti all'aggiornamento della certificazione SOA e ad oneri connessi con la ricerca nel campo delle **fonti rinnovabili**.
5	Si ricorda che all'interno della categoria Impianti e macchinariâ sono compresi gli **investimenti ambientali** realizzati dalla società negli esercizi precedenti, costituiti da **impianti fotovoltaici** destinati alla produzione di energia elettrica da **fonti rinnovabili** da impiegare nel ciclo produttivo.
6	Le aliquote di ammortamento mediamente applicate sono le seguenti: FABBRICATI 3% MOBILI E ATTREZZATURE 10% MACCHINE D'UFFICIO 12% ATTREZZATURA GENERICA 12,5% ATTREZZATURA SPECIFICA 12,5% BIANCHERIA E LANERIA 20% **IMPIANTO FOTOVOLTAICO** 15% IMPIANTO ANTINCENDIO 10% IMPIANTO DI RISCALDAMENTO 12%

Table A3: Variable definitions

Variable	Definition
$Green_{it}$	$\mathbb{1}_{D \cap W_{i,t} \neq \emptyset} \cdot \mathbb{1}_{\text{Capital Expenditure}_{i,t} > 0}$, where D is the set of words in our green dictionary; $W_{i,t}$ is the set of words in the text comments to the capital expenditures section of firm i in period t.
ΔLoan_{it}	$(\text{Loan}_{i,t} - \text{Loan}_{i,t-1})/0.5(\text{Loan}_{i,t} + \text{Loan}_{i,t-1})$, where $\text{Loan}_{i,t}$ is the sum of all loans obtained by firm i in year t
Profitability	ROA, defined as the ratio of net income to total assets
Liquidity	Ratio of cash to total assets
High Environmental Protection	Dummy = 1 for regions where a higher than average % of individuals answered "yes" to the question of whether they prefer protecting the environment to economic growth (Basilicata, Trentino-Alto Adige, Umbria, Lazio, Friuli-Venezia Giulia, Veneto, Emilia-Romagna, Toscana, Campania.) Source: 2017 European Value Study
High Climate Change	Dummy = 1 for regions where the Google searches for "climate change" are higher than the average (Valle D'Aosta, Trentino-Alto Adige, Molise, Friuli-Venezia Giulia, Basilicata, Umbria, Lazio, Sardegna, Toscana). Source: Google Trends
High Upstreamness	Dummy = 1 for industries whose distance to the final consumer ("upstreamness" index) is higher than the median. Source: Antràs et al. (2012)
High Green Subsidies	Dummy = 1 if the total number of regional green subsidies in the firm headquarter region is higher than the median (Piemonte, Sicily, Toscana, Emilia-Romagna, Liguria, Friuli Venezia Giulia, Umbria, Lombardia, Trentino-Alto Adige, Campania). Source: Italian permanent census of enterprises, 2019, ISTAT
High Competition	Dummy = 1 if the Herfindahl Index (HHI) of concentration in the location and industry of the firm is lower than the median.
High CO_2-e	Dummy = 1 for the sectors with largest fraction of CO_2-equivalent emissions (Electricity supply, agriculture, metallurgy, transportation, manufacturing of chemicals). Source: GHG Emissions by Sectors, Italy, World Input Output Data, 2013
Whited-Wu index	$= -0.091CF - 0.062DIV_+ + 0.021LTD - 0.044TA + 0.102ISG - 0.035SG$, where CF is the ratio of cash flow to total assets, DIV_+ is an indicator that takes the value of one if the firm pays cash dividends, LTD is the ratio of the long term debt to total assets, TA is the natural log of total assets, ISG is the firm's three-digit industry sales growth, and SG is firm sales growth. (Whited and Wu, 2006)
ASCL index	For each of variables age, size, average cash flow level, and average indebtedness, a score is assigned equal to one if the firm is above or below the industry median in a given year. The index is the sum of the individual scores (Mulier et al., 2016)
FCP index	$= -0.123TA - 0.024IntCov - 4.404ROA - 1.716Cash$, where TA is the natural logarithm of total assets, $IntCov$ is EBIT over interest expenses, ROA is net income over total assets, and $Cash$ is cash holdings over beginning-of-year total assets (all variables are lagged by one period). (Schauer et al., 2019)
Musso-Schiavo index	Each firm is classified into inter-sectorial quintiles of each of the following variables: total assets, ROA, current asset over current liabilities, cash flow, solvency (own funds over total liabilities), trade credit over total assets and financial debt over cash flow. The index then adds the quintiles of each variable and divides the resulting sum into scores ranging from 1 to 5. (Musso and Schiavo, 2008)

Table A4: Average differences in characteristics by presence vs. absence of comments to financial statements

	Text is missing			Text is available				Norm.
Variable	μ_0	σ_0	N_0	μ_1	σ_1	N_1	p-value	Diff.
Age (years)	19.15	14.94	129,705	25.67	17.14	195,556	0.00	0.29
No. of employees	30.27	187.59	125,951	88.79	494.88	193,020	0.00	0.11
Assets	9,554	137,993	129,705	26,260	134,675	195,556	0.00	0.09
Revenues	8,450	66,132	129,705	28,942	159,863	195,556	0.00	0.12
Assets growth[1]	0.04	0.21	100,886	0.04	0.17	136,040	0.00	0.01
Sales growth[1]	0.00	0.34	113,636	0.02	0.25	183,174	0.00	0.04
Leverage[1]	0.75	0.26	122,991	0.70	0.23	189,599	0.00	-0.13
ROA[1]	0.01	2.75	129,705	0.04	0.97	195,556	0.00	0.01
Tangibles/Assets[1]	0.19	0.21	112,476	0.20	0.20	186,164	0.00	0.01
Intangibles/Assets[1]	0.05	0.08	83,046	0.04	0.07	162,430	0.00	-0.11
ΔLoan[1]	-0.06	0.61	83,952	-0.01	0.60	139,460	0.00	0.06
CSI[1]	-0.01	0.16	101,457	-0.01	0.17	161,333	0.00	-0.02

[1] Winsorized between 1 and 99%

This table contains descriptive statistics of several variables (mean μ, standard deviation σ, and number of observations) for firm-year observations classified according to whether text comments to the firm's financial statements, and hence information about whether or not they are investing in green technologies, are available ("Text is available") or not ("Text is missing"). The last two columns contain, respectively, the p-value for a test that the mean is equal across the two subsets ($H_0 : \mu_1 = \mu_0$), and the normalized difference ($\Delta = \frac{\mu_1 - \mu_0}{\sqrt{\sigma_1^2 + \sigma_0^2}}$). Section 2 and Table A3 contain variable definitions.

Table A5: Average differences in firm characteristics of firms with vs. without green investments

	Green$_{it}$ = 0			Green$_{it}$ = 1				Norm.
Variable	μ_0	σ_0	N_0	μ_1	σ_1	N_1	p-value	Diff.
log(Age)	3.264	0.595	106,587	3.349	0.572	7,254	0.000	-0.103
log(Assets)	9.513	1.188	106,587	9.950	1.098	7,254	0.000	-0.270
Risk: Low	0.719	0.449	106,587	0.786	0.410	7,254	0.000	-0.109
Risk: Medium	0.198	0.398	106,587	0.157	0.364	7,254	0.000	0.074
Risk: High	0.083	0.276	106,587	0.057	0.231	7,254	0.000	0.073
Cash/Assets[1]	0.097	0.120	106,587	0.093	0.111	7,254	0.002	0.025
Debt/Assets[1]	0.264	0.192	106,587	0.291	0.204	7,254	0.000	-0.097
Tangibles/Assets[1]	0.202	0.199	106,587	0.285	0.217	7,254	0.000	-0.280
ROA[1]	0.080	0.094	106,587	0.084	0.078	7,254	0.000	-0.031
Δ Loan[1]	0.014	0.712	106,587	0.010	0.622	7,254	0.566	0.005
CSI[1]	-0.007	0.202	106,587	-0.006	0.205	7,254	0.778	-0.002

[1] Winsorized between 1 and 99%

This table contains descriptive statistics (mean μ, standard deviation σ, and number of observations N) of several variables for firm-year observations with values of Green$_{it}$ = 1 vs. those with Green$_{it}$ = 0 . The last two columns contain, respectively, the p-value for a test that the mean is equal across the two subsets ($H_0 : \mu_1 = \mu_0$), and the normalized difference ($\Delta = \frac{\mu_0 - \mu_1}{\sqrt{\sigma_1^2 + \sigma_0^2}}$). Section 2 and Table A3 contain variable definitions.

Table A6: Financial constraints and green investments

	Z_i: Constrained			Z_i: Unconstrained		
	β	R^2	Obs.	β	R^2	Obs.
	(t-stat)	F		(t-stat)	F	
$\beta(\Delta\text{Loan})$	(1)	(2)	(3)	(4)	(5)	(6)
Z_i: Whited-Wu	0.0483	0.797	58,144	0.118**	0.737	44,688
	(1.156)	25.59		(2.359)	35.07	
Z_i: ASCL	-0.868	-1.183	27,238	0.0812***	0.756	73,717
	(-0.207)	0.120		(2.868)	69.36	
Z_i: FCP	0.102	0.777	60,114	0.0613*	0.776	41,275
	(1.419)	15.30		(1.734)	40.48	
Z_i: Musso-Schiavo	0.0823	0.782	44,548	0.0776**	0.775	55,951
	(1.637)	28.49		(2.042)	39.36	

Columns 1-3 consider 2SLS estimations of the coefficient for ΔLoan in Equation 1 in a subsample of constrained firms. Columns 4-6 consider 2SLS estimations of the coefficient for ΔLoan in Equation 1 in a subsample of unconstrained firms. In each pair of rows, financially constrained and unconstrained firms are defined by splitting the sample at the median according to the beginning-of-sample values of the Whited-Wu, ASCL, FCP and Musso-Schiavo indices defined in Table A3. In each pair of rows, columns 1 and 4 contain the estimated coefficient (above) and the t-statistic (below, in parentheses); columns 2 and 5 contain the R^2 (above) and the F-statistic of the first-stage estimated equation (below); and columns 3 and 6 contain the number of observations of each subsample. All estimations include the same set of fixed effects and firm-level controls as in columns 4 and 8 of Table 4.

*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table A7: Firm characteristics, credit supply and normal investments

	Z_i above median			Z_i below median		
	β (t-stat)	R^2 F	Obs.	β (t-stat)	R^2 F	Obs.
$\beta(\Delta\text{Loan})$	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Internal Resources						
Z_i: Profitability	-0.0104	0.549	49,532	0.00843	0.607	49,362
	(-0.183)	25.52		(0.112)	34.26	
Z_i: Liquidity	-0.0972	0.506	49,464	0.142	0.532	49,570
	(-1.504)	25.57		(1.454)	31.67	
Z_{it}: Size	-0.00836	0.516	51,681	0.0931	0.551	51,518
	(-0.197)	46.40		(1.201)	30.38	
Z_i: Age	0.0402	0.534	49,178	-0.0340	0.598	50,717
	(0.804)	38.29		(-0.455)	29.13	
Panel B - Dependence on External Finance						
Z_i: Rajan-Zingales	0.118*	0.552	47,168	-0.0361	0.501	61,337
	(1.917)	48.67		(-0.615)	34.88	

Columns 1-3 refer to 2SLS estimations of the coefficient for ΔLoan in Equation 1 in a subsample of firms with characteristic Z_i above the median. Columns 4-6 refer to 2SLS estimations of the coefficient for ΔLoan in Equation 1 in a subsample of firms with characteristic Z_i below the median. The dependent variable is a dummy taking the value one if the firm has positive investments during the year. In each pair of rows, characteristic Z_i refers respectively to the beginning-of-sample profitability, liquidity, solvency, size and age, as defined in Table A3. In each pair of rows, columns 1 and 4 contain the estimated coefficient (above) and the t-statistic (below, in parentheses); columns 2 and 5 contain the R^2 (above) and the F-statistic of the first-stage estimated equation (below); and columns 3 and 6 contain the number of observations of each subsample. All estimations include the same set of fixed effects and firm-level controls as in columns 4 and 8 of Table 4.
*,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table A8: Green Investments and Investment Peaks

	Growth Rate of Investment (1)	Investment Peaks (2)
Any investment$_{it}$	2.568***	0.590***
	(158.56)	(89.44)
Green word$_{it}$	-0.088	-0.031
	(-1.11)	(-0.94)
Green$_{it}$	0.168**	0.065**
	(2.19)	(2.09)
Observations	107,578	107,578
R-squared	0.465	0.386
Firm Controls	Y	Y
Firm FE	Y	Y
Province-Sector-Size-Year FE	Y	Y

The sample consists of firm-year observations in the Italian Credit Registry between 2015 and 2019 for which information about green investments is available. The dependent variable in column (1) is the symmetric growth rate of investment between year t and $t-1$. The dependent variable in column (2) is a dummy variable taking the value one if the firm experiences an investment peak in a given year using the definition of Bachmann and Bayer (2014). *Any Investment*$_{it}$ is a dummy that equals one if in year t the firm has positive investment. *Green word*$_{it}$ is a dummy that equals one if the firm's accompanying notes contain at least one green word in the dictionary D; *Green*$_{it}$ is the green firm dummy which takes the value of one if the firm has at least one green word in the dictionary D and in the same year it has positive capital expenditures. Estimations include firm fixed effects, interacted province-sector-size-year fixed effects, and the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies.
T-statistics in parentheses. *,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table A9: Placebo test: Environmental preferences and any investments

	Env. Protection		Climate Change	
	Low	High	Low	High
ΔLoan	0.0439	0.0212	0.0031	0.153
	(0.842)	(0.336)	(0.0714)	(1.260)
Observations	55,750	54,045	88,496	21,405
R-squared	0.544	0.554	0.548	0.499
Firm Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Province-Sector-Size-Year FE	Y	Y	Y	Y
F-statistic weak instruments	41.80	37.93	61.89	16.54

This table contains 2SLS estimated coefficients for variable ΔLoan in Equation 1 where the dependent variable is a dummy variable taking the value of one when the firm carries out any investment. In columns 1 and 2, the sample is split according to variable High Environmental Protection, a dummy variable taking the value one for Italian regions where a higher than average fraction of individuals answered "yes" to the question of whether they prefer protecting the environment to economic growth (Basilicata, Trentino-Alto Adige, Umbria, Lazio, Friuli-Venezia Giulia, Veneto, Emilia-Romagna, Toscana, Campania. Data Source: 2017 European Value Study). In columns 3 and 4, the sample is split according to variable High Climate Change, a dummy taking the value one for Italian regions where the Google searches for "climate change" are higher than the average (Valle D'Aosta, Trentino-Alto Adige, Molise, Friuli-Venezia Giulia, Basilicata, Umbria, Lazio, Sardegna, Toscana. Data source: Google Trends). Estimations include firm fixed effects, interacted province-sector-size-year fixed effects, and the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies.
T-statistics in parentheses. *,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table A10: Upstreamness and entrepreneurs' vs. customers' preferences for green investments

			Upstreamness			
			Low		High	
	Upstreamness		Environmental Protection			
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLoan	0.0491	0.0814**	0.0023	0.0649	0.0295	0.239
	(1.199)	(2.261)	(0.0248)	(1.540)	(0.996)	(1.435)
Observations	53,954	55,457	26,527	27,299	28,879	26,461
R-squared	0.785	0.764	0.794	0.780	0.797	0.535
Firm Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Province-Sector-Size-Year FE	Y	Y	Y	Y	Y	Y
F-statistic weak instruments	28.49	51.01	4.164	33.50	48.65	7.393

This table contains 2SLS estimated coefficients for variable ΔLoan in Equation 1 In columns 1 and 2, the sample is split according to values of variable High Upstreamness, a dummy taking the value one for Italian industries whose distance to the final consumer ("upstreamness" index) is higher than the median (Data source: Antràs et al. (2012)). In columns 3 - 6, the sample is split into four groups according to the double crossing of variables High Environmental Protection and High Upstreamness. The dependent variable is a dummy variable taking the value one when the firm invests in a green technology. Estimations include firm fixed effects, interacted province-sector-size-year fixed effects, and the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies.
T-statistics in parentheses. *,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table A11: Green banks and green investments

	PRB Signatory		Share High CO_2-e	
	No	Yes	High	Low
ΔLoan	0.0573*	0.00452	0.0924	0.0383
	(1.941)	(0.123)	(1.413)	(1.311)
Firm Controls	Y	Y	Y	Y
Observations	56,752	32,089	28,537	62,244
R-squared	0.816	0.839	0.806	0.815
Firm FE	Y	Y	Y	Y
Province-Sector-Size-Year FE	Y	Y	Y	Y
F-statistic weak instruments	104.4	28.03	19.36	73.60

This table contains 2SLS estimated coefficients for Equation 1 across mutually exclusive pairs of subsamples, as indicated in the top row. PRB signatory is a dummy variable containing a one if the firms are borrowing at least 50% of their total credit from a signatory of the Principles for Responsible Banking (PRB) program of the United Nations' Environment Program Finance Initiative (UNEP FI). Share High CO_2-e equals "High" if the bank's share of lending to high CO_2-emission industries is larger than the market weighted average. The sample consists of firm-year observations in the Italian Credit Registry between 2015 and 2019 for which information about green investments is available. The dependent variable is a dummy variable taking the value one when the firm invests in a green technology. Estimations include the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies.
T-statistics in parentheses. *,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

B Validation of green investment measure

In this section, we perform several tests to assess the validity of our variable $\text{Green}_{i,t}$. We start by verifying whether our variable correlates well with census measures of green investments carried out by firms in the same industrial sector and region. To assess this issue, we exploit the information contained in the 2019 permanent census of enterprises pertaining period 2016–2018. The permanent census of enterprises is a survey carried out by the Italian statistical office (ISTAT) about Italian firms concerning their organization, competitiveness and, most importantly, their environmental sustainability. For each firm size class and region, we consider the census share of firms carrying out investments in those green technologies that overlap with our dictionary, and we compare this figure to the corresponding share derived from our dummy variable. As shown in Figure B1, the two variables are significantly positively correlated.

We next explore the ability of our measure of green investments to predict improvements in environmental performance using emission data obtained from the European Pollutant Release and Transfer Registry (E-PRTR). The E-PRTR is an EU-wide registry containing the quantities of pollutants released to air, water and land by some firms (subject to a reporting threshold). We match the E-PRTR data manually to the firms in our main dataset using the name and the location of the facility appearing in the registry, and we run the following regression:

$$y_{i,t} = \alpha_i + \beta \text{Past Green Investment}_{i,t} + \delta_t + \epsilon_{i,t}. \tag{B.1}$$

$y_{i,t}$ is either the log of a particular pollutant emitted in year t by firm i, or the ratio of emissions to revenues. We consider the three types of air pollutants with the largest number of observations: nitrogen oxides (NO_x), non-methane volatile organic compounds (NMVOC), and carbon dioxide (CO_2). $\text{Past Green Investment}_{i,t}$ is a dummy variable equal to 1 if firm i has carried out a green investment in any year previous to t. α_i and δ_t are respectively firm and time fixed effects. The results of this exercise, contained in Table B1, show that our measure is associated with a statistically significant decrease in the emission of NO_x and CO_2, both in levels (columns 1-3) and in emissions intensity (defined as the level of the pollutant divided by total revenues). These findings suggest that our text-based approach is able to detect investments in cleaner technologies that contribute to abating air pollution.

Another concern is that the firms that are not classified as green according to our measure are not "brown", but are firms that either do not disclose the nature of their investments, or that are investing in other special technologies such as high-tech, AI, biotech or other. To address this issue, we perform a text analysis of the most common words appearing in the comments to the investments section of the financial statements of firms with values of $\text{Green}_{i,t} = 0$ (non-green firms), after removing the words that frequently appear both in green and non-green firms' statements. Table B2 contains the most frequently occurring stemmed words in non-green firms' statements (in Italian). We do not find evidence for alternative investments that are specific to non-green firms: most of these terms are referring to common technologies used in a variety of sectors. This suggests that we are correctly associating the non-green firms with firms that are not investing in clean technologies, and that we are not confounding these with high-tech or other specialized firms.

Finally, we investigate to what extent the financial statements of green and non-green firms are dissimilar. To do so, for each industrial sector we compute the cosine similarity of each financial statement (vector) belonging to a green firm respectively with other green firms and with non-green ones, following the example of Hoberg and Phillips (2016). We calculate the similarity measures between texts after removing stopwords and least common words, as well as keywords in our dictionary, and stemming the resulting documents. Figure B2 shows the distributions of the cosine similarity measures of green firms with other green firms (green distributions) and of green firms with brown firms (brown distributions) for the four sectors with the largest number of green firms. The figure shows that there is common support for both distributions, suggesting that financial statements of the two groups are not completely different. The figure also shows that the texts of green firms have on average higher cosine similarity with the text of other green firms than with the ones of non-green firms. Figure B3 confirms that this remains true for all sectors. In fact, we also find that the difference in mean cosine similarity is statistically always greater than zero (Figure B4). We interpret these results as evidence that, although comments on tangible and intangible assets for the two categories of firms are overall similar, nonetheless our text algorithm allows us to properly discriminate among green and non-green firms.

Table B1: Green investments and emission abatement

	(1)	(2)	(3)	(4)	(5)	(6)
	Emission Level			Emission Intensity		
Dependent variable	NO_x	NMVOC	CO_2	NO_x	NMVOC	CO_2
Past Green Investment	-0.349***	0.595	-0.318***	-2.615***	-0.125	-2.056**
	(-6.356)	(1.534)	(-2.997)	(-2.693)	(-0.486)	(-2.713)
Observations	176	117	96	176	117	96
R-squared	0.922	0.904	0.970	0.902	0.952	0.860
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

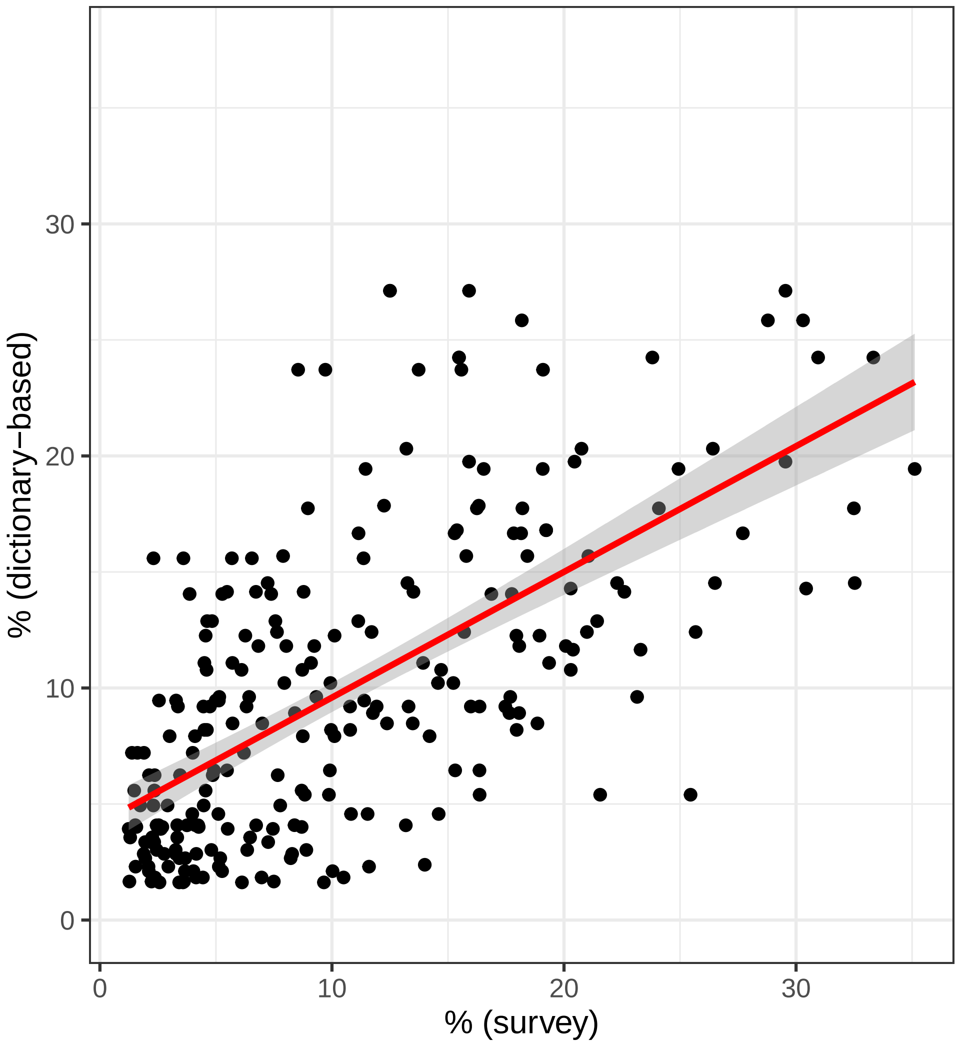
This table contains the estimated coefficients for Equation B.1. The sample consists of firm-year observations in the Italian Credit Registry between 2015 and 2019 for which information about green investments is available and could be matched with pollutant emission data in the European Pollutant Release and Transfer Registry. The dependent variable in columns 1-3 is the natural logarithm of the emitted quantity of a particular air pollutant; in column 4–6 it is emissions intensity (pollutant quantities divided by revenues). T-statistics in parentheses. Standard errors are clustered at the firm level.
*, **, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Table B2: Most frequent words for firms with $G_{i,t} = 0$

1	trasparent	26	ord	51	parol	76	sintet
2	mass	27	pegn	52	notebook	77	snc
3	superammort	28	firenz	53	condominial	78	complementar
4	edizion	29	tant	54	incertezz	79	esposit
5	iperammort	30	sintetizz	55	cod	80	giustif
6	mett	31	proprietàl	56	aud	81	system
7	rich	32	dovess	57	calc	82	rinomin
8	dottrin	33	tribunal	58	esperient	83	tgli
9	inosserv	34	margin	59	contrar	84	patt
10	almen	35	alberg	60	omolog	85	inf
11	evinc	36	produrrann	61	caparr	86	marginal
12	rad	37	esplicit	62	riassum	87	televis
13	revisor	38	alberghier	63	algebr	88	torn
14	transizion	39	altriment	64	pubblicità	89	espong
15	essend	40	vendibil	65	fotograf	90	remot
16	napol	41	descrizionecoefficient	66	evit	91	app
17	catalog	42	perfett	67	raggiunt	92	postul
18	prend	43	sussistent	68	fisiolog	93	denar
19	cndc	44	europ	69	completezz	94	pianif
20	esigu	45	promozion	70	elettrom	95	approfond
21	triennal	46	espression	71	elettrocont	96	attrezzat
22	conduttor	47	repertor	72	promozional	97	sud
23	bilanciol	48	plusvalor	73	estim	98	segn
24	afferm	49	cessazion	74	congruit	99	dinam
25	penetr	50	person	75	introdutt	100	proiezion

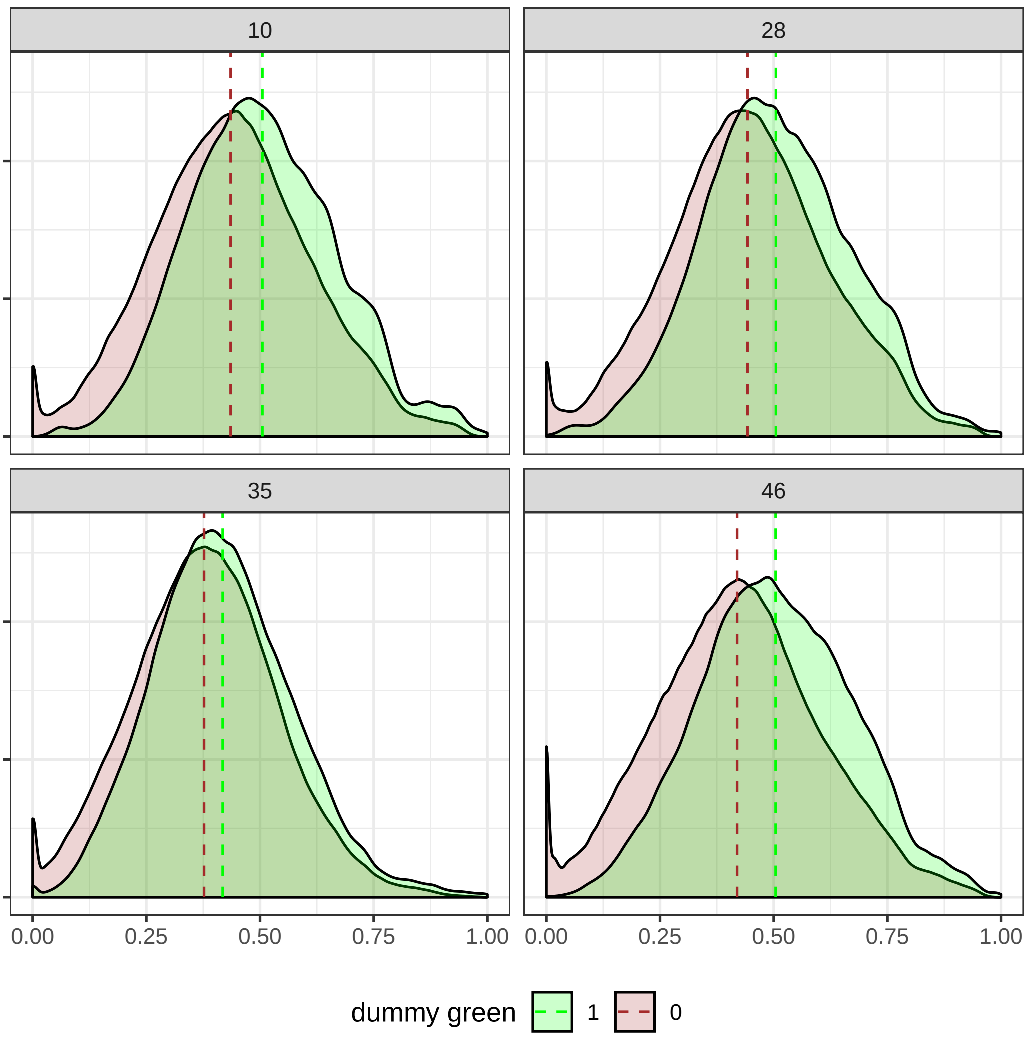
This table contains the most common stemmed words appearing in the comments to the investments section of brown firms' financial statements, after removing the words that frequently occur in green and brown firms' financial statements. Brown firms are those whose comments to their financial statements do not contain any word in our green dictionary, $\text{Brown}_{i,t} = \mathbf{1}_{BS_{i,t} \cap D = \emptyset}$.

Figure B1: Green investment among firms



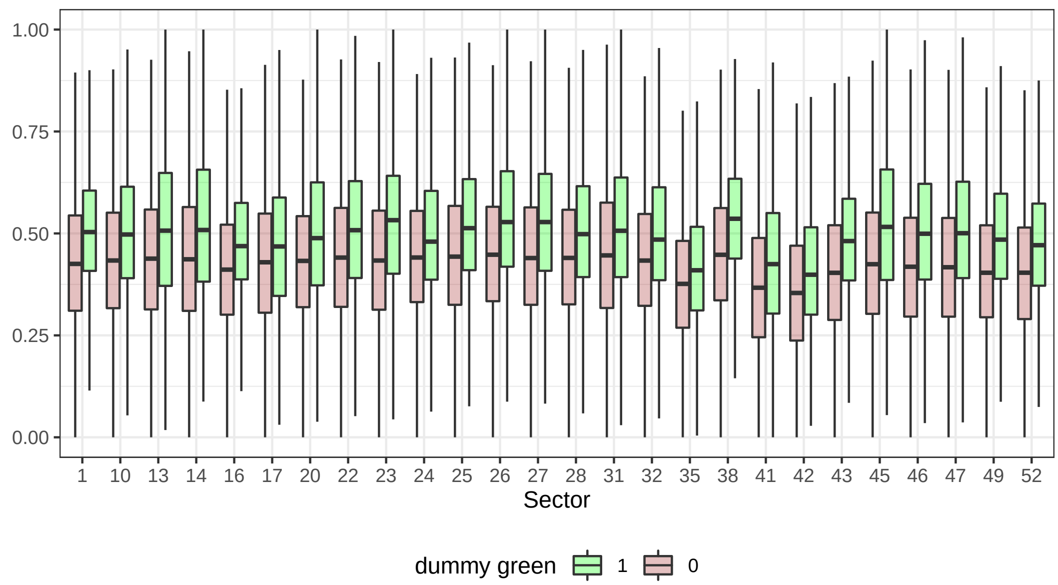
This figure shows the percentage of firms that report green investments in ISTAT's permanent census of enterprises (x-axis), compared with our measure (y-axis). The data are stratified by size class and region. The regression line shows the linear correlation with a 95% confidence interval.

Figure B2: Cosine similarity of financial statements (selected sectors)



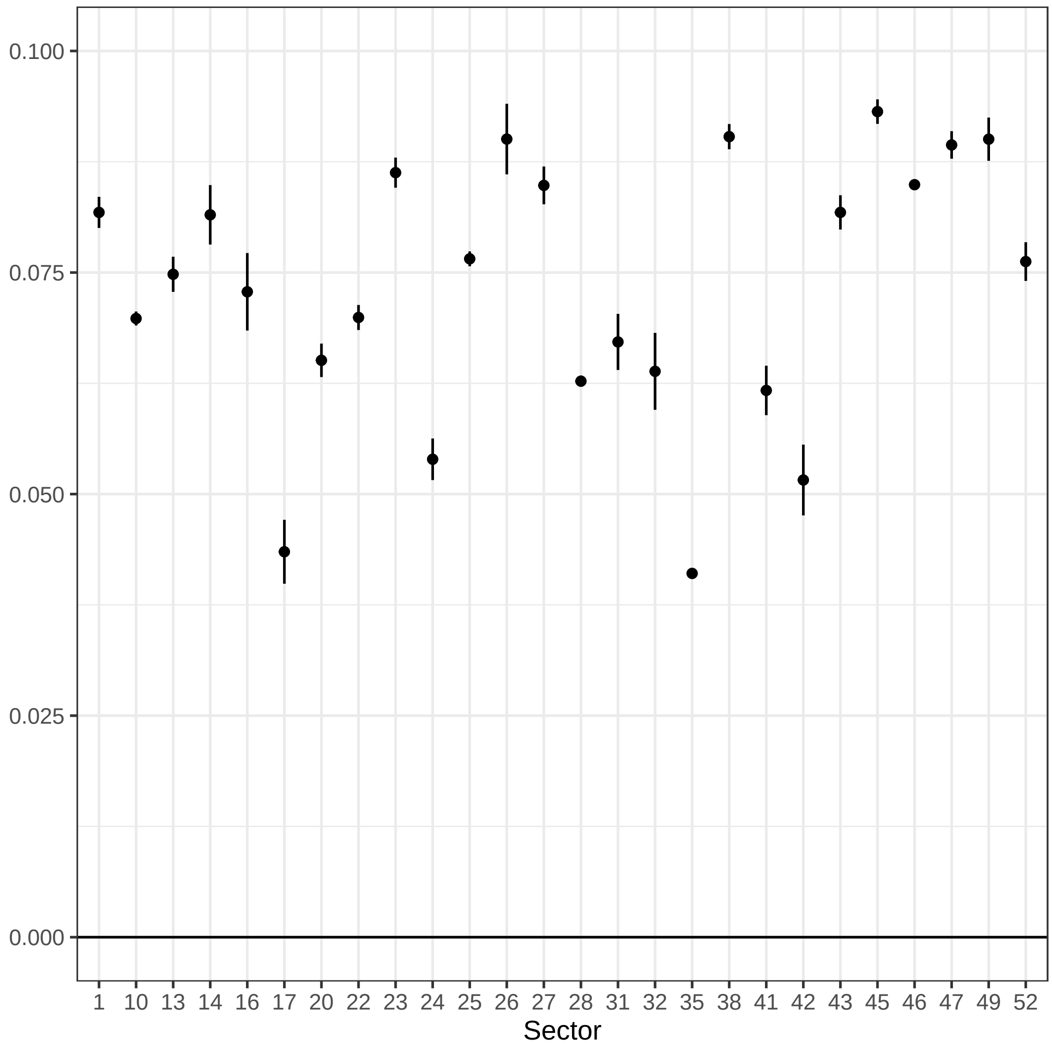
This figure depicts the distribution of the cosine similarity of green firms' financial statements, estimated between each other and the other (non-green) firms. The four sectors with the largest absolute number of green firms have been selected. They are Manufacture of food products (10), Manufacture of machinery and equipment (28), Electricity, gas, steam and air conditioning supply (35) and Wholesale trade, except of motor vehicles and motorcycles (46). The vertical dashed lines indicate the mean values of each distribution.

Figure B3: Cosine similarity of financial statements



This figure depicts the boxplots of the cosine similarity of green firms' financial statements, estimated between each other and the other (non-green) firms. The sectors with at least 100 green firms have been selected.

Figure B4: Difference in mean of cosine similarity of financial statements



This figure depicts the difference in mean of the cosine similarity of green firms' financial statements, estimated between each other and the other (non-green) firms, with a 95% confidence interval. The sectors with at least 100 green firms have been selected.

Figure B5: Correlation matrix

	Rajan-Zingales index	Profitability	Liquidity	Size	Age
Rajan-Zingales index	1.00	−0.11	−0.14	0.01	−0.03
Profitability		1.00	0.28	0.02	−0.05
Liquidity			1.00	0.01	0.10
Size				1.00	0.14
Age					1.00

Correlation

−0.14 1.00

The figure reports a correlation matrix among firms' characteristics used in the heterogeneity analysis of Table 6. Darker shades imply a stronger correlation between the measures.

C Bartik instrument

In this section we provide a discussion on our research design; specifically, on the use of our Bartik-type instrument building on Goldsmith-Pinkham et al. (2020).[10]

From Section 2, we recall the CSI formula:

$$\mathrm{CSI}_{i,t} = \sum_b w_{b,i,t_0} \times \hat{\delta}_{bt},$$

where $\hat{\delta}_{bt}$ are the estimated bank-supply shocks (common to all firms) and w_{b,i,t_0} are the firm i-specific exposure weight, computed at the end of 2014. As argued by Goldsmith-Pinkham et al. (2020), the plausibility of research designs based on Bartik-type instruments hinges upon the exogeneity of weights w_{b,i,t_0}, which should not be correlated with other determinants of the dependent variable.

In our context, the exogeneity of w_{b,i,t_0} implies that firm i's exposure to bank b is not correlated with other factors that might impact on the changes of the propensity to invest in green technologies. This could be the case, for example, when banks specialize in lending to certain industries or type of firms – such as firms in the energy sector or large firms (see Table 2) – that more likely invest in cleaner capital. While this identifying assumption is not directly testable, we present evidence on the fact that it is quite plausible in our setting.

First, following Section 5.1 of Goldsmith-Pinkham et al. (2020), we correlate weights w_{b,i,t_0} with firm characteristics. We estimate the following equation:

$$w_{b,i,t_0} = \delta X_{it_0} + \gamma_{s(i)} + \eta_{c(i)} + \theta_{p(i)} + \epsilon_{b,i,t_0}, \forall b \in \{1, 2, \dots, 20\} \tag{C.1}$$

where $b = 1, 2, \dots, 20$ are the largest 20 banks in Italy in terms of market share.

[10] We refer to Goldsmith-Pinkham et al. (2020) instead of e.g., Borusyak et al. (2022) because, according to the latter, identification in a shift-share IV setting can be achieved when *"shocks are as-good-as-randomly assigned, mutually uncorrelated, large in number, and sufficiently dispersed in terms of their average exposure"*. In our setting, we have several mono-borrowers, and the vast majority of firms borrow from a very limited number of banks; therefore their identifying assumptions cannot be credibly defended.

Equation C.1 is a cross-sectional regression at the firm level that is separately estimated for each bank. The dependent variable is the share of loans that each firm i borrows from b at time t_0 (i.e., 2014).

Explanatory variables include the firm's sector, size, and province dummies. We also control for log of assets, log of age, debt ratio, cash to assets ratio, tangible assets to total assets ratio, and profitability.

The R^2 of these regressions is quite low (Figure C1). For the majority of credit institutions, firm size, location, sector, and profitability (which are potential determinants of green investments) have a low explanatory power for firm's exposure to each bank. This result implies that our assumption of exogeneity of the Bartik-weights (w_{b,i,t_0}) is plausible in our context.

Only for a small number of banks (ranked #20, #11, #8, #18, and #2), which we label *specialized banks*, the R^2 exceeds 0.15. In the second part of the analysis we focus on those five banks, with the aim to show that our baseline results are not driven by firms exposed to those financial institutions.

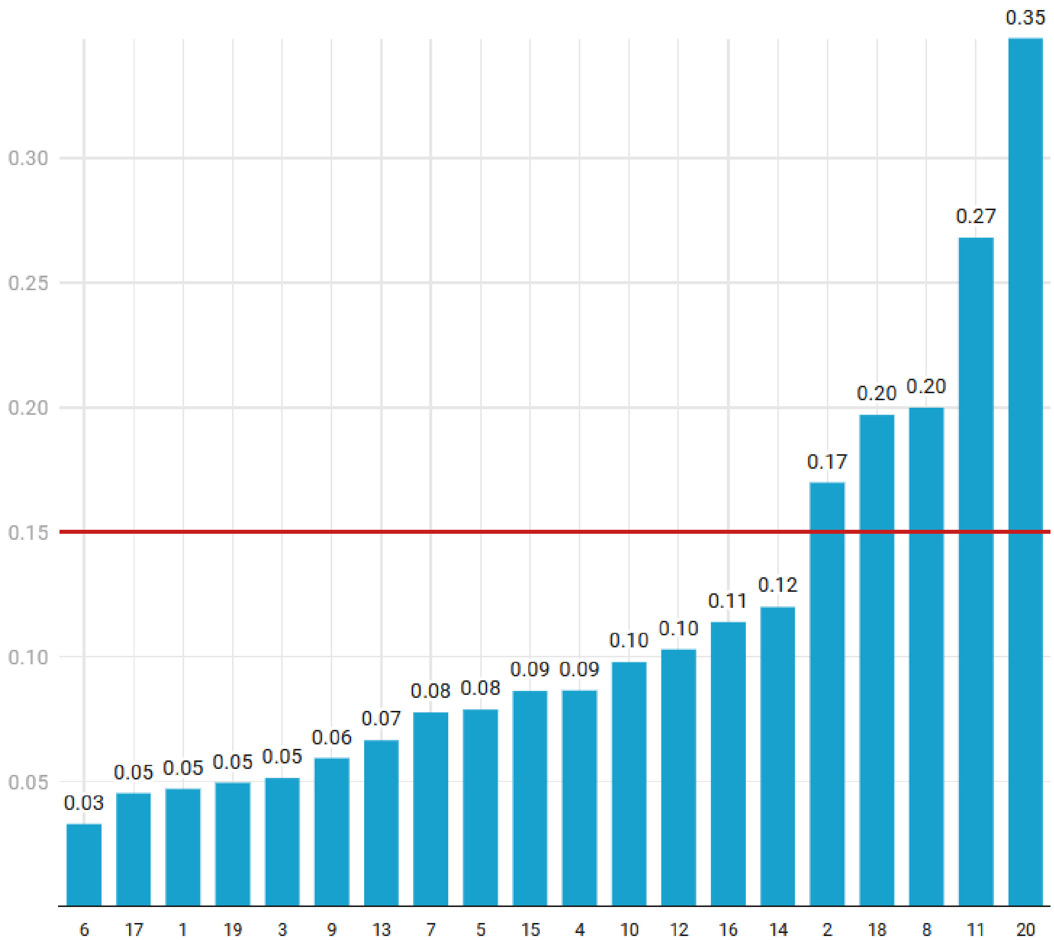
To test this issue, we re-estimate equation 1, by eliminating all firms whose main bank is one of the *specialized bank* (first one by one, and then all together). Results in Table C1 show that our baseline results are entirely confirmed (even in magnitude) when we drop those observation, thus supporting once again the plausibility of our research design.

Table C1: Robustness on Bartik instrument

	(1)	(2)	(3)	(4)	(5)	(6)
ΔLoan	0.0753**	0.0690**	0.0791***	0.0679**	0.0656**	0.0827**
	(2.405)	(2.490)	(2.629)	(2.469)	(2.404)	(2.451)
Observations	97,640	105,484	106,836	107,869	107,596	88,214
R-squared	0.773	0.773	0.766	0.773	0.774	0.771
Firm controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Province-Sector-Size-Year FE	Y	Y	Y	Y	Y	Y
First-stage:						
CSI	0.200***	0.213***	0.202***	0.213***	0.212***	0.196***
	(4.902)	(5.386)	(5.111)	(5.406)	(5.384)	(4.644)
F-statistic weak instruments	61.62	76.02	69.01	76.99	75.89	54.66
Dropped main bank	#2	#8	#11	#18	#20	all

Estimations include the set of fixed effects indicated with the label "Y", and the following firm-level controls: log of total assets, log of age, debt ratio, cash ratio, PPE to assets, profitability, and rating dummies. In each column we drop the firms our our dataset whose main bank has an R^2 greater than 0.15 (see figure C1). In the last column we drop all firms. ΔLoan is instrumented using the credit supply index, variable CSI, as described in Section 2. Standard errors are clustered at the firm level.
T-statistics in parentheses. *,**, and *** respectively refer to statistical significance at the 10, 5, and 1 percent levels.

Figure C1: R^2 of the regression of Bartik-weights on firm characteristics



This figure depicts the R^2 of equation C.1. Each number corresponds to the rank of the bank by size.

D Calculating the CSI with firm fixed effects

In this Appendix, we provide more details on data construction for the estimations of Table 11, columns (3) and (4). These regressions use different versions of CSI which are constructed using firm-time fixed effects to purge for demand factors, in line with the identification strategies proposed by Khwaja and Mian (2008) and Amiti and Weinstein (2018).

In order to take into account the extensive margin of credit links between firms and bank (which is required for the symmetric growth rate), we create a database with all the possible pairs of firms and banks that operated in Italy from 2010 to 2019. To keep this expanded sample computationally tractable, we extracted a random sample of Italian firms equal to 25% of the original credit registry. This amounts to 803,670 individual companies which were matched with 776 banks. Based on this expanded database, we estimate the following equation:

$$\Delta \text{Loan}_{ibt} = \delta_{bt} + \gamma_{it} + \chi_{ib} + \epsilon_{ibt}, \tag{D.1}$$

where i indexes firms. ΔLoan_{ibt} is the symmetric growth rate of loans at bank-firm level.[11] As before, δ_{bt} are bank-time fixed effects which will be used for the calculation of CSI. γ_{it} and χ_{ib} are, respectively, firm-time and bank-time fixed effects. γ_{it} are introduced to capture time-varying demand factors at firm level; while χ_{ib} control for time-invariant characteristics in the firm-bank match, such as the physical distance between the two or bank sectoral or dimensional specialization.

We then follow the procedure described in Section 2, to calculate the CSI.

In particular,

$$\text{CSI}_{i,t} = \sum_b w_{b,i,t_0} \times \hat{\delta}_{bt},$$

[11] The variable is set to zero when loans are nil in both periods.

where

$$w_{b,i,t_0} = \frac{\text{Loan}_{i,b,2014}}{\sum_b \text{Loan}_{i,b,2014}}.$$

We compute two versions of CSI. The first uses $\hat{\delta}_{bt}$ based on a parsimonious version of Equation D.1 without bank-firm fixed effects (χ_{fb}); this corresponds to regression results of table 11, column 3. The second corresponds to the estimation of the full version of Equation D.1 and the estimates are contained in column 4.

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