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Abstract

Using data on 10,769 firms across 22 emerging markets, we show that both credit constraints and weak green management hold back corporate investment in green technologies embodied in new machinery, equipment and vehicles. In contrast, investment in measures to explicitly reduce emissions and other pollution, is mainly determined by the quality of a firm's green management and less so by binding credit constraints. In addition, data from the European Pollutant Release and Transfer Register reveal the climate impact of these organizational constraints. In areas where more firms are credit constrained and weakly managed, industrial facilities systematically emit more CO2 and other greenhouse gases. A counterfactual analysis shows that credit constraints and weak management have respectively kept CO2 emissions 4.8% and 2.2% above the levels that would have prevailed without such constraints. This is further corroborated by our finding that in localities where banks had to deleverage more due to the Global Financial Crisis, carbon emissions by industrial facilities remained 5.8% higher a decade later.

JEL Classification: D22, L23, G32, L20, Q52, Q53

Keywords: Green management, Credit constraints, CO2 emissions, Energy efficiency

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Managerial and Financial Barriers to the Green Transition

Ralph De Haas,[*] Ralf Martin,[†] Mirabelle Muûls,[‡] and Helena Schweiger[¶]

March 27, 2023

Abstract

Using data on 10,769 firms across 22 emerging markets, we show that both credit constraints and weak green management hold back corporate investment in green technologies embodied in new machinery, equipment and vehicles. In contrast, investment in measures to explicitly reduce emissions and other pollution, is mainly determined by the quality of a firm's green management and less so by binding credit constraints. In addition, data from the European Pollutant Release and Transfer Register reveal the climate impact of these organizational constraints. In areas where more firms are credit constrained and weakly managed, industrial facilities systematically emit more CO_2 and other greenhouse gases. A counterfactual analysis shows that credit constraints and weak management have respectively kept CO_2 emissions 4.8% and 2.2% above the levels that would have prevailed without such constraints. This is further corroborated by our finding that in localities where banks had to deleverage more due to the Global Financial Crisis, carbon emissions by industrial facilities remained 5.8% higher a decade later.

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1 Introduction

The severe impact that climate change will have on future generations is becoming increasingly clear. Droughts, floods, storms and extreme temperatures are already causing substantial human and economic losses (Cavallo, Galiani, Noy and Pantano, 2013; Felbermayr and Gröschl, 2014). There now exists incontrovertible evidence that CO_2 (carbon dioxide) and other greenhouse gases are the main cause of climate change (Nordhaus, 2019; Eyring et al., 2021). In the absence of technologies to remove CO_2 from the biosphere, mitigating climate change requires a drastic reduction of new carbon emissions (Pacala and Socolow, 2004). In line with commitments under the Paris Climate Agreement, many countries therefore aim to emit zero net greenhouse gases by 2050 or earlier. Achieving this goal requires large-scale corporate investment in cleaner technologies and energy-efficiency measures to reduce firms' carbon footprint: the green transition.

The adoption of greener technologies by firms is progressing only slowly (Allcott and Greenstone, 2012). This reflects that while such technologies can be optimal from a societal point of view, they may not be cost-effective from the perspective of individual firms. Carbon pricing via taxes or carbon trading can correct this externality, but remains politically contentious. Moreover, even with carbon pricing in place, organizational constraints—of either a financial or managerial nature—can prevent firms from investing in green technologies. Firms not only vary in their ability to access external funding, they also differ in terms of their management quality in general (Bloom and Van Reenen, 2007) and their green management practices in particular (Martin, Muûls, de Preux and Wagner, 2012). Those with better access to funding and with stronger green management may invest more in energy-efficient production methods and cut greenhouse gas emissions more drastically as a result.

This paper sheds light on the qualitative and quantitative importance of these constraints by leveraging a rich new data set on 10,769 firms across 22 emerging markets. We use these data to analyze how financial and green managerial constraints hold back corporate investment in green technologies and the abatement of greenhouse gas emissions. Such organizational constraints can hamper green investments in poor countries in particular. A lack of external finance (Aghion, Howitt and Mayer-Foulkes, 2005; Bircan and De Haas, 2020), deficient management practices (Bloom, Eifert, Mahajan, McKenzie and Roberts, 2013), and misaligned incentives within the firm (Atkin, Chaudhry, Chaudry, Khandelwal and Verhoogen, 2017) have all been shown to impede technological adoption and investment in the developing world. This is especially concerning because nearly all growth in greenhouse gas emissions over the next three decades will come from emerging markets and developing countries (Wolfram, Shelef and Gertler, 2012).

Our data come from unique face-to-face surveys with firm managers. The surveys give us access to information on firms' credit constraints, green management practices, and green investments. In terms of green management, we collect standardized data on firms' strategic objectives concerning the environment and climate change; whether there is a manager with an explicit mandate to deal with environmental issues; and how the firm sets and monitors targets (if any) related to energy and water usage, CO_2 emissions, and other pollutants. Using these novel data, we document that green management practices vary significantly between and within countries. In terms of green investments, we collect comprehensive data on investments in machinery and equipment upgrades; vehicle upgrades; heating, cooling and lighting improvements; the on-site generation of green energy;[1] waste minimization, recycling and waste management; improvements in energy and water management; and measures to control air or other pollution. We combine these survey data with pollution data from the European Pollutant Release and Transfer Register (E-PRTR). This register provides us with information on the emission of greenhouse gases and other air pollutants by 3,386 industrial facilities in 12 countries.

We pursue three distinct though related empirical approaches. First, we assess the impact of credit and green managerial constraints on firms' investment in green technologies. Causality may run in both directions here. For example, rapidly growing (and investing) firms may be more likely to be credit constrained or to adopt state-of-the-art management techniques, thus biasing OLS estimates upwards. Alternatively, green management could be little more than 'greenwashing' for firms that do not care to invest in green measures. Green management improvements can then be used to appease and prevent potential regulatory moves or to superficially address concerns by customers or other stakeholders (Lyon and Maxwell, 2011). This would bias OLS estimates downwards.

To deal with such issues, we develop several instruments. First, to obtain exogenous variation in credit constraints, we create instruments capturing the characteristics of bank branches close

[1] Green energy refers to more climate-friendly energy—that is, renewable energy.

to each firm. Firms tend to predominantly obtain loans from banks that have branches in their vicinity (Guiso, Sapienza and Zingales, 2004; Granja, Leuz and Rajan, 2022). Hence we argue that the financial strength of banks with branches close to a firm becomes an exogenous driver of the firm's credit constraints after conditioning out a variety of local characteristics. Our first instrument captures the branch-weighted change in nearby banks' Tier 1 ratio between 2007 (just before the Global Financial Crisis) and 2014 (after this crisis and the subsequent Eurozone crisis). The intuition is that firms located near branches of banks that had to recapitalize more during these crisis periods, including through shedding risk-weighted assets, were more credit constrained. A second instrument exploits the 2014 regulatory stress tests of the European Banking Authority (EBA). It builds on the idea that firms surrounded by branches of banks that did well in the EBA stress test (as indicated by a large difference between their predicted Tier 1 ratio in the 2016 baseline scenario and the 8% hurdle rate) found it easier to access bank credit.

For green management practices, we construct a leave-out, jackknife-style instrument where we use the green management quality of nearby firms that are larger as an instrument for a firm's green management quality. This is motivated by the idea that variation in green management quality is driven by information asymmetries about good green management practices; that such information about good green management can flow from one firm to the other; and that these information flows are typically from larger to smaller firms (for example, from a multinational to a small local firm). Hence, and again subject to local area controls, the green management quality of local larger firms becomes a plausibly exogenous driver of firm-level green management quality.

Using this instrumentation strategy, we find that credit constraints significantly reduce green investment by firms. Credit constrained firms are about 30 percentage points less likely to make a green investment. Importantly, the effect is stronger and indeed only statistically significant for green technologies embodied in regular investments, such as the purchase of more energy-efficient machinery or cleaner vehicles. This shows how credit constraints can slow down the diffusion of green innovations across firms. In contrast, we find no clear impact of credit constraints on investments with an explicit focus on energy efficiency or pollution abatement, such as the on-site generation of green energy or recycling. The quality of a firm's green management, on the other hand, has a positive effect on *all* types of green investment that we distinguish in our survey data. We also find that better green management leads to a lower energy intensity of overall firm production.

The second part of our analysis considers the cross-sectional relationship between credit or managerial constraints and pollution outcomes. Due to limited overlap between the E-PRTR facilities with pollution data and firms with survey data, we develop a reduced-form version of our instrumental variable approach. Similar to before, we rely on the characteristics of banks and firms in the vicinity of each facility for which we have pollution data. Because we do not directly observe the credit constraints or green management practices of facility i, we construct these by averaging the predicted credit constraint and green management quality of all firms j in the vicinity of facility i but that are not in the same industry as i.

We find that the presence of credit constraints leads to higher CO_2 emissions, whereas better green management reduces them. A counterfactual analysis shows that in the absence of local credit constraints, carbon emissions would have been 4.8 percent higher. Likewise, a significant upgrade in firms' green management practices, to the 75^{th} percentile of the distribution, would have reduced carbon emissions by about 2.2 percent.

Lastly, we apply a difference-in-differences design to examine the impact of the biggest shock to financial constraints in recent history: the Global Financial Crisis. More specifically, we argue that local banks' pre-crisis exposure to short-term wholesale funding provides exogenous variation in financial constraints in the wake of the crisis. This again allows us to assess whether credit constraints matter for environmental outcomes and, if so, whether they increase or decrease emissions. In this third part of our analysis, we find—consistent with the previous results—positive impacts of financing constraints (that is, more emissions) due to the global financial crisis. We estimate the medium-term effect of the crisis to be, on average across the countries we study, a 5.7 percent increase in CO_2 emissions by 2017.

Our study contributes to and connects three strands of the literature. First, we provide new insights into the determinants of firms' investment in carbon abatement and energy efficiency.[2] Because low-carbon technologies generate large environmental (and hence social) returns, while private profitability is often unclear, managerial adoption decisions may differ from those of regular technologies. Empirical evidence on the diffusion of low-carbon technologies is scarce (Burke

[2]Hottenrott, Rexhauser and Veugelers (2016) provide an overview of the literature on the determinants of firm investment in green technologies while Cagno, Worrell, Trianni and Pugliese (2013) propose a taxonomy of barriers to industrial energy efficiency improvement.

et al., 2016) and we shed light on the comparative role of management and access to finance in this regard. Bloom, Genakos, Martin and Sadun (2010) measure management practices in over 300 manufacturing firms in the UK. They find that better managed firms are more productive and less energy and carbon intensive. Martin, Muûls, de Preux and Wagner (2012) find similar results using a measure of green rather than general management practices. One interpretation of these results is that well-managed firms adopt modern manufacturing practices, which allows them to increase productivity by using energy more efficiently.[3] Their managers may be better informed about the costs and benefits of energy efficiency improvements and suffer less from present-biased preferences in which they focus too much on upfront costs and too little on future recurring energy savings (Allcott, Mullainathan and Taubinsky, 2014). Our contribution is to provide direct evidence, based on a large international firm-level data set, for a key mechanism through which green managerial constraints limit energy efficiency improvements in production: the reduced incidence of investments in green technologies and carbon abatement.

Second, we provide micro evidence on how credit constraints deter investments in carbon abatement. Credit constrained firms cannot finance all economically viable projects available to them, but instead need to allocate scarce funding to the projects with the highest expected net present value. Earlier evidence shows that credit constraints are responsible for reduced investment even in advanced economies with well-developed capital markets (Almeida and Campello, 2007; Campello, Graham and Harvey, 2010; Duchin, Ozbas and Sensoy, 2010). Because environmental investments often entail large upfront expenditures (Fowlie, Greenstone and Wolfram, 2018) and have an uncertain cost-savings potential, financially constrained firms may prioritize investments in core activities.[4] This may especially be the case if the financial payoff of green investments is small relative to the positive environmental externalities that can be reaped and firms internalize these externalities insufficiently.[5]

[3]Bai, Jin and Serfling (2022) show how U.S. firms with more structured (i.e., formal and explicit) management practices improve the management (and subsequent performance) of establishments they acquire.

[4]When the cost of external capital is high, and investments in emissions reductions therefore expensive, firms that are forced by environmental regulation to reduce carbon emissions may move polluting activities elsewhere instead of investing in cleaner production. Bartram, Hou and Kim (2022) show how financially constrained firms in California responded to the introduction of a state-level cap-and-trade program by shifting emissions to other states.

[5]Howell (2017) shows that firms that receive grants from the U.S. Small Business Innovation Research Program generate more revenue and patent more (compared with similar but unsuccessful applicants). These effects are largest for financially constrained firms and those in sectors related to clean energy and energy efficiency. Recent work by Berkouwer and Dean (2022) finds that credit constraints prevent *households* in Kenya from adopting durable goods (charcoal cookstoves) that are more energy efficient and have large private benefits.

Related empirical work on the U.S. has shown a negative relationship between credit availability and firm pollution, without observing firms' green investments as an intermediary step in the hypothesized causal chain. In particular, Levine, Lin, Wang and Xie (2018) show how positive credit supply shocks in U.S. counties—due to fracking of shale oil in other counties—reduce local air pollution. In a similar vein, Goetz (2019) finds that financially constrained firms reduced toxic emissions when their capital cost decreased as a result of the U.S. Maturity Extension Program. Lastly, Cohn and Deryugina (2018) document a negative relationship between U.S. firms' contemporaneous and lagged cash flow and the occurrence of environmental spills. Our contribution is to provide direct evidence, based on a large sample of emerging markets, for an important mechanism: credit constraints reduce firms' investments in specific types of green technologies.[6]

Third, we offer fresh evidence on the environmental consequences of financial crises. On the one hand, episodes of dysfunction in the financial system can lead to reductions in pollution in the short term simply because economic activity and energy usage decline (Sheldon, 2017; De Haas and Popov, 2023). Moreover, if crises force inferior-technology and energy-inefficient firms to exit the market, then the energy efficiency of the average surviving firm may improve.[7] On the other hand, longer-term impacts will be less benign if firms deprioritize adhering to environmental standards and postpone or cancel investments in cleaner technologies (Peters, Marland, Quéré, Boden, Canadell and Raupach, 2012).[8] Indeed, Pacca, Antonarakis, Schroder and Antoniades (2020) argue that financial crises may be "one step forward, two steps back for air quality". Our findings are clearly at odds with an environmentally cleansing effect of financial crises. Instead, our analysis of rich cross-country micro-data shows how even temporary disruptions in the supply of external finance have long-lasting negative implications for the carbon intensity of manufacturing.

We organize the rest of this paper as follows. Section 2 introduces our data and main variables, after which we discuss our empirical approach in Section 3. Section 4 then provides the empirical results and Section 5 concludes.

[6] Accetturo, Barboni, Cascarano, Garcia-Appendini and Tomasi (2022) show for a sample of Italian firms that positive credit supply shocks lead to a higher propensity to invest in green technologies.

[7] This cleansing effect (Caballero and Hammour, 1994) will be smaller if some high-productivity firms are also credit constrained (Osotimehin and Pappada, 2015).

[8] Prior work shows how financial crises, and the associated reduction in bank lending, tighten corporate credit constraints and reduce investment in R&D and fixed assets (Campello, Graham and Harvey, 2010; Duchin, Ozbas and Sensoy, 2010; Nanda and Nicholas, 2014; Beck, Degryse, De Haas and Van Horen, 2018).

2 Data

Our analysis relies on matching three data sets: (i) information from the EBRD-EIB-WB Enterprise Surveys on firms' credit constraints, green management and green investments; (ii) the exact location of bank branches from the EBRD Banking Environment and Performance Survey (BEPS) II and data on bank funding from ORBIS; and (iii) data on pollution and emissions from the European Pollutant Release and Transfer Register (E-PRTR).

2.1 Firm-Level Data

We use the Enterprise Surveys to measure the incidence of credit constraints as well as firms' management practices and green investments. The surveys took place between October 2018 and August 2020 and cover 22 countries in Emerging Europe, where 13,353 firms were interviewed.[9] The Enterprise Surveys involve face-to-face interviews with the owner or main manager of registered firms with at least five employees. Eligible firms are selected using stratified random sampling. The strata are sector (manufacturing, retail and other services), size (5-19, 20-99 and 100+ employees) and regions within a country. The main purpose of the survey is to measure the quality of the local business environment in terms of, for example, infrastructure, labor, and business-government relations. The survey also collects various important firm characteristics and their geographic coordinates.[10]

Importantly, the most recent Enterprise Surveys include a new Green Economy module. This unique module gathers detailed information on key aspects of firm behavior related to the environment and climate change, including green management practices and green investments. The response rate for the Green Economy module was over 95 percent. We thus have a representative snapshot—stratified by sector, firm size, and region—of firms' green credentials in each of these countries.

[9] Our final sample contains 10,769 firms with non-missing values for all the required variables. Appendix Table A2 presents a breakdown by country while Table A3 contains summary statistics for all our variables. Online Appendix A describes the Enterprise Surveys methodology and discusses survey response rates.

[10] In robustness tests, we use firm-level controls such as age and dummy variables for whether the firm is publicly listed, a sole proprietorship, an exporter, and whether an auditor reviews its financial statements.

2.1.1 Credit Constraints

By combining answers to several survey questions, we distinguish between firms with and without a demand for credit. Among the former, we then identify those that were *Credit Constrained* as those that were either discouraged from applying for a loan or were rejected when they applied. Non-credit constrained firms are those that either had no need for credit or whose demand for credit was satisfied.[11] As shown in Appendix Table A3, almost a quarter of all firms are credit constrained (22.3 percent).

2.1.2 Green Management Practices

The Green Economy module asks firms in detail about their green management practices in four areas. The first one covers strategic objectives related to the environment and climate change. The second area looks at whether firms employ a manager with an explicit mandate to deal with green issues. Conditional on the presence of such an environmental manager, additional information is collected on whom they report to and whether they are evaluated against how well the firm performs on energy consumption, CO_2 emissions or other pollution or environmental targets.[12] The third area asks whether firms have clear and attainable environmental targets. Lastly, the fourth area looks at whether firms actively and frequently monitor their energy and water usage, as well as CO_2 emissions and other pollutants, in order to reduce their environmental footprint.

We assign a score between 0 and 1 to each question (see Online Appendix A.1.1 for details) and aggregate them to averages for each of the four areas. Lastly, we create an overall green management score as an unweighted average of the four areas. Appendix Table A3 confirms that this *Green management* variable is by construction between 0 and 1 (the maximum in the sample is below 1). Using these novel data, we document that green management practices vary significantly between

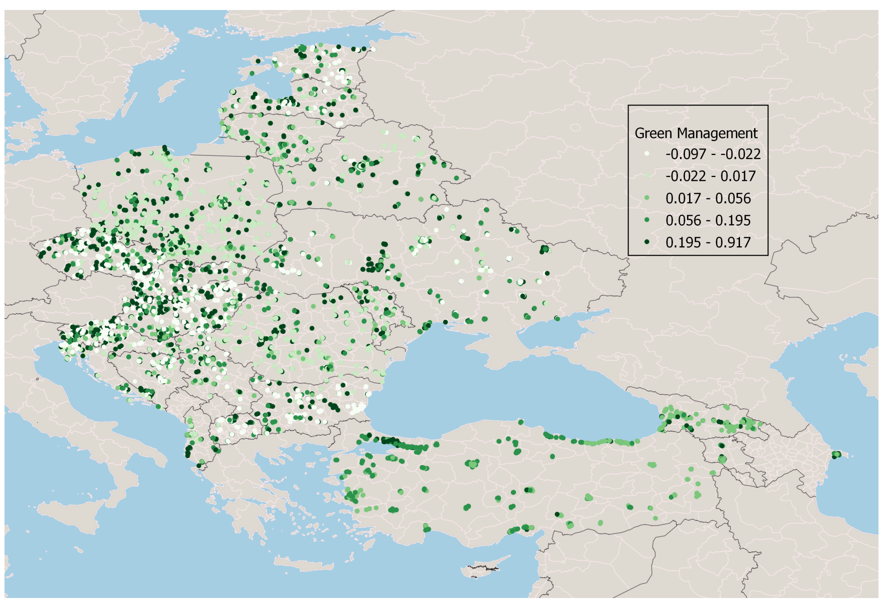
[11] We start by using the question: "Did the establishment apply for any loans or lines of credit in the last fiscal year?" Firms that answered "No", were then asked: "What was the main reason the establishment did not apply for any line of credit or loan in the last fiscal year?" Firms that answered "Yes", were asked: "In the last fiscal year, did this establishment apply for any new loans or new credit lines that were rejected?" We classify firms that applied for credit and received a loan as unconstrained while we classify firms as credit constrained if they were either rejected or discouraged from applying due to "Interest rates are not favorable"; "Collateral requirements are too high"; "Size of loan and maturity are insufficient"; or "Did not think it would be approved".

[12] Earlier research shows that the link between a firm's strategic environmental objectives and its day-to-day actions depends on its organizational structure. The closer the person with environmental responsibilities is to the firm's most senior manager, the more they are able to solve problems and overcome ill-defined incentives (Martin, Muûls, de Preux and Wagner, 2012).

and within countries (Table OD.1 in the Online Appendix). For example, while almost 60 percent of firms monitor their energy consumption, fewer monitor carbon emissions: Almost 1 in 6 firms emit CO_2 but less than half of them monitor these emissions. In terms of cross-country differences, we find for example that while only 7.4 percent of Turkish firms have strategic objectives related to the environment or climate change, this is the case for over 30 percent of Slovak firms.

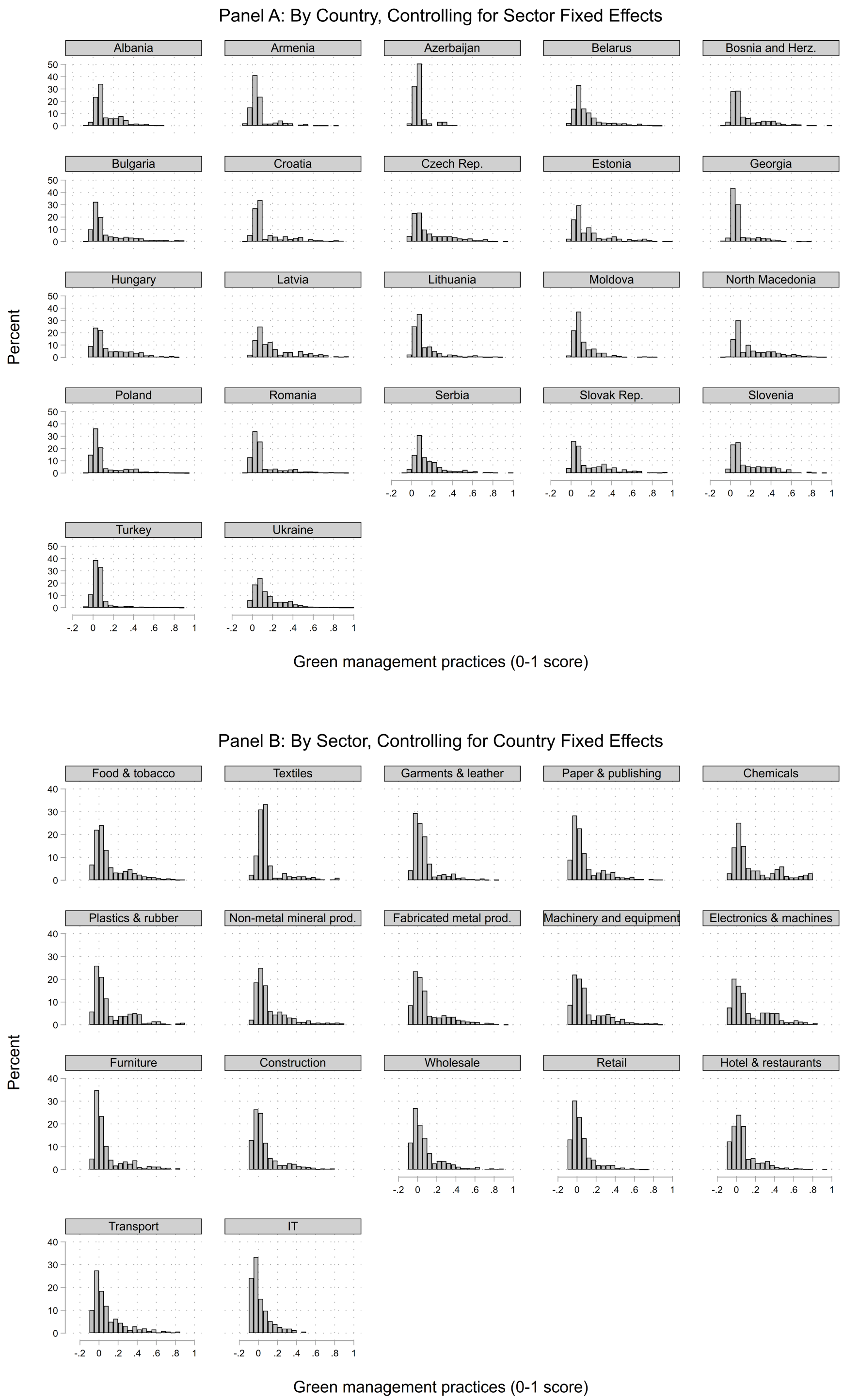
Yet, most variation in green management practices (91 percent) occurs *within* countries, even when accounting for international differences in sectoral composition. Figure 1 depicts firms with low and high green management scores in every country: this is the granular variation that we will use in our empirical analysis. Figure 2 further illustrates the substantial variation in green management quality within countries (Panel A) and sectors (Panel B). These distributions are left-skewed, indicating that within countries and sectors there exist a relatively small number of 'green leaders' and a large group of 'green laggards' with less-developed green management.

Figure 1: Geographical Distribution of Firms and the Quality of their Green Management



Notes: This map shows the geographical distribution of the 10,769 firms that make up the sample used in Tables 1 and 2. Each dot represents one or several firms in a locality. Darker green colors indicate higher-quality green management. Green management is measured as a score between 0 and 1 based on four areas of green management practices: strategic objectives related to the environment and climate change; whether the firm has a manager with an explicit mandate to deal with green issues, who this manager reports to and whether their performance is evaluated against the establishment's environmental performance; environmental targets; and monitoring of energy and water usage, CO_2 and other pollutant emissions. The map shows green management scores after netting out country fixed effects (so that negative values are possible). *Source*: EBRD-EIB-WBG Enterprise Surveys.

Figure 2: Distribution of the Quality of Green Management by Country and Sector



Notes: These figures show the distribution of the quality of green management practices of the 10,769 firms that make up the sample used in Tables 1 and 2 by country, controlling for sector fixed effects (Panel A) and by sector, controlling for country fixed effects (Panel B). Sector groupings can be found in Table OB.2 in Online Appendix B.

2.1.3 Green Investments

The Enterprise Surveys ask managers whether they made several types of green investments in the last three years. A first set of questions deals with green investments to upgrade machinery, equipment, or vehicles. These investments involve the purchase of fixed assets that have a greener technology embedded in them. For instance, as innovation proceeds, new vintages of machinery and vehicles tend to be more energy efficient than the outdated models they replace. Such green investments mainly have an environmental impact as a by-product of achieving other objectives.

A second set of questions deals with investments that explicitly target an increase in the firm's energy efficiency and/or a reduction in pollution or other negative environmental impacts. These include improvements to heating, cooling and lighting systems; on-site green energy generation; waste minimization, recycling and waste management; energy and water management; and measures to control air and other pollution.

Overall, 74.6 percent of firms made at least one type of green investment in the past three years. Table A3 in the Appendix reports that more than half of all firms made improvements to heating, cooling or lighting systems—making this the most common type of green investment. In contrast, only 12.4 percent invested in green energy generation on site, possibly because such projects typically require very sizable investments.

Lastly, the Enterprise Surveys also allow us to create a measure of the energy intensity of each firm's production, defined as the total cost of electricity and fuel normalized by sales (*Energy cost per sales)*. This variable helps to gauge whether the absence of credit constraints and the presence of effective green management, not only translates into more green investment but ultimately also in a lower energy intensity of firm-level production.

2.2 Bank-Level Data

To implement our IV strategy (which we describe in more detail in Section 3.1) and to control for local credit market conditions in both the OLS and IV estimations, we use detailed data about the banking sectors in our sample countries. First of all, we access the geographical coordinates of 67,559 branches operated by 609 banks in these countries. These coordinates were collected by specialized consultants as part of the second round of the EBRD Banking Environment and

Performance Survey (BEPS II). The 609 banks represent 97 percent of all bank assets in these 22 countries in 2013, so that we have a near complete bank branch footprint. As described in Section 3.1.1, we connect the firm and branch data by drawing circles with a radius of 15 km around the coordinates of each firm and then linking the firm to all branches inside that circle. This allows us to control for the number and size of the banks that make up the local credit market around each firm.

For each branch we know the bank it belongs to. We merge this information with bank balance sheet information from Bureau Van Dijk's ORBIS database. We download information about each bank's balance sheet in 2007, just prior to the Global Financial Crisis, in 2014 (after this crisis and the subsequent Eurozone crisis) and in 2016. We also collect information on each bank's performance during the 2014 EBA regulatory stress tests.

2.3 Pollution Data

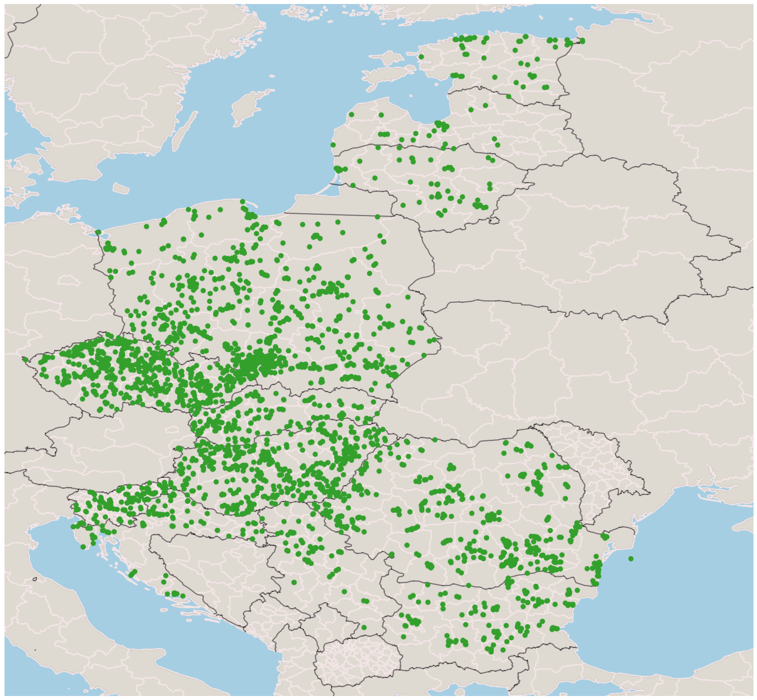
We use the European Pollutant Release and Transfer Register (E-PRTR, version 18), which contains annual data on some 30,000 industrial facilities covering 65 economic activities across Europe. For each facility, E-PRTR reports the amounts released to air, water, and land from a list of 91 key pollutants including heavy metals, pesticides, greenhouse gases and dioxins.[13] Data are available from 2007 onward. For industrial facilities with missing information on specific releases, we assume that they were equal to threshold reporting values for that pollutant (Table OC.1 lists the pollutants and reporting thresholds).

We focus on the 3,386 industrial facilities in 12 Emerging European countries in the E-PRTR that overlap with the Enterprise Surveys country sample (Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Serbia, the Slovak Republic and Slovenia).[14] The green dots in Figure 3 show the locations of these facilities. We combine the E-PRTR data with information from ORBIS on the firms that own the industrial facilities (including their date of registration, listed status, and location) and our data on bank branch networks. Appendix Table A3 shows substantial variation in the types of emissions across industrial facilities. All of the

[13]We provide more details in Online Appendix C.

[14]Table A2 provides the number of facilities by country. These are all facilities for which data are available for the years 2015, 2016, and 2017 (and in most cases also for all earlier years dating back to 2007). We focus on the facilities with data coverage in 2015-17 as this period is closest to the roll-out of the Enterprise Surveys, on which we base our vicinity measures of green management practices.

Figure 3: Geographical Distribution of E-PRTR Industrial Facilities in Emerging Europe



Notes: This map shows the geographical distribution of the 3,388 industrial facilities across Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Romania, Poland, Serbia, Slovak Republic, and Slovenia that are observed in every year during 2015-17. *Source*: European Pollutant Release and Transfer Register (E-PRTR, version 18).

companies owning these facilities have at least one bank branch within a 15 km radius, allowing us to adopt a similar empirical strategy as in the first part of our analysis.

3 Empirical Methodology

3.1 The Organizational Constraints to Green Investment

We are interested in the link between credit constraints, green management practices, and green investment. We start with the following empirical model:

$$Y_i = \beta_0 + \beta_1 CreditConstrained_i + \beta_2 GreenManagement_i + \gamma^{'}\mathbf{X_i} + \epsilon_i \quad (1)$$

where Y_i is an indicator equal to 1 if firm i made a particular type of green investment in the past three years and 0 otherwise. The independent variables of interest are *Credit Constrained*, an indicator for whether the firm is credit constrained or not (see Section 2.1.1) and *Green Management*, our summary measure of a firm's green management quality (see Section 2.1.2). The vector $\mathbf{X}_i$ represents a set of control variables: the population size bracket of a firm's locality, region fixed effects, and controls about the banks located in a firm's vicinity (that is, within a 15km radius). We also control for the number of branches in a firm's vicinity and the amount of assets held by the banks owning these branches.[15]

We start by fitting Equation (1) via OLS although this may bias our estimates of the causal impact of credit constraints and of green management on green investments. For example, it may be the case that only rapidly growing firms that want to invest, find themselves credit constrained. This could introduce an upward bias in our OLS estimates. Likewise, successful firms may be more inclined to adopt advanced management practices—including green ones. This could again bias the OLS estimates upwards. An alternative concern is that firms engage in greenwashing. That is, firms that have decided not to invest in green technologies might be using aspects of green management (for example, appointing a manager in charge of climate change) as a token measure to appease regulators, investors, or concerned customers. This would introduce a downward bias in our OLS regressions. To deal with these potential issues, we develop several instruments that we now discuss.

3.1.1 Instruments for Credit Constraints

International evidence shows that due to agency costs, most small and medium-sized enterprises can only borrow from nearby banks.[16] The local banking landscape near firms then imposes an exogenous geographical limitation on the banks that firms have access to (Berger et al., 2005). We build on this idea by using variation in local banks' capital availability as a plausibly exogenous driver of the credit constraints of firms.

More specifically, we consider the change in nearby banks' Tier 1 capital ratio. The Tier 1 capital ratio relates a bank's core equity capital to its risk-weighted assets. During and after the Global Financial Crisis, many banks had to improve this capital ratio within a short period of time. Since raising additional equity was costly due to the difficult situation in the global capital markets,

[15] Locality is the city, town or village where the firm is located. Regions are defined at the NUTS 1 or equivalent level and sectors at the 2-digit ISIC level (Rev 3.1). Online Appendix B provides region and sector definitions.

[16] For example, the median Belgian SME borrower in Degryse and Ongena (2005) was located 2.5 km from the lending bank branch. In the U.S. data of Petersen and Rajan (1994) and Agarwal and Hauswald (2010), the corresponding median distances were 3.7 km and 4.2 km, respectively.

most banks deleveraged by shrinking their risk-weighted assets, including through cuts in lending (Gropp, Mosk, Ongena and Wix, 2019).[17] The intensity of deleveraging varied significantly across banks—even within the same country. Our instrument captures the idea that firms that were surrounded by branches of banks that had to boost their Tier 1 capital ratio more during the crisis found it more difficult to access bank credit.[18] We therefore expect a positive relationship between the average local increase in banks' Tier 1 capital ratio and the likelihood that nearby firms were credit constrained.

To create the instrument $\Delta\,Tier1$, we combine information on the geographic coordinates of both firms and the bank branches that surround them. $\Delta\,Tier1$ then captures the change in the average regulatory capital (Tier 1) ratio over the period 2007 (just before the Global Financial Crisis) to 2014 (after both the Global Financial Crisis and the subsequent Eurozone crisis) for all banks in a firm's vicinity (defined as a circle with a 15 km radius).[19]

$$\Delta Tier1_i = \frac{1}{\#} \sum_{b \text{ s.t. } v(b)=v(i)} Tier1_{b,2014} - \frac{1}{\#} \sum_{b \text{ s.t. } v(b)=v(i)} Tier1_{b,2007} \tag{2}$$

where b indexes bank branches.

The second instrument reflects the 2014 regulatory stress tests by the European Banking Authority (2014). The EBA stress tests banks in the European Union to assess their resilience to various economic scenarios. The baseline scenario assumes a continuation of current economic and financial trends and policies over a three-year period. For each bank, the EBA then estimates the Tier 1 capital ratio under this baseline scenario and compares it to an 8 percent minimum hurdle rate. Our instrument captures the idea that firms surrounded by branches of banks whose 2016 baseline scenario Tier 1 ratio was more comfortably above the hurdle rate, found it easier to access bank credit than firms surrounded by branches of banks whose predicted Tier 1 ratio was closer to or even below the 8 percent hurdle. We therefore expect a negative relationship between the local average difference in the 2016 baseline scenario Tier 1 ratio and the hurdle rate, and the likelihood

[17]One could argue that the change in Tier 1 capital ratio might correlate with geographical remoteness because for some reason, banks with branches in more remote locations had a lower regulatory capital ratio before the financial crisis. We therefore control for locality size in all regressions.

[18]In line with this idea, Popov and Udell (2012) show how firms in localities in Emerging Europe with financially weaker foreign banks had greater difficulty in accessing credit during the crisis.

[19]In robustness tests we vary the size of the circle.

that nearby firms were credit constrained.[20] To create the instrument $\Delta\,Tier1H$, we again combine information on the geographic coordinates of both firms and the branches around them:

$$\Delta Tier1H_i = \frac{1}{\#} \sum_{b \text{ s.t. } v(b)=v(i)} (Tier1_{b,2016} - 8\%) \tag{3}$$

where b indexes bank branches.

Additionally, we construct a "leave-out" (LO) instrument: for firm i we include the average credit constraint indicator of all firms j in the vicinity (v) (15 km radius) of i such that the sector $s(i) \neq s(j)$:

$$CreditConstrainedLO_i = \frac{1}{\#} \sum_{j \text{ s.t. } s(j)\neq s(i) \text{ \& } v(j)=v(i)} CreditConstrained_j \tag{4}$$

Hence, we assume that any shocks ϵ_i to credit constraints affect at most firms within the same 2-digit sector $s(i)$, but have no impact on other firms in the vicinity of i. Consequently, $CreditConstrainedLO_i$ becomes an indicator of local financing conditions while being quasi random. This is similar to the "leave-one-out" strategy pursued in jackknife approaches (Angrist, Imbens and Krueger, 1999).[21] For firms without any nearby firms in other sectors, we set $CreditConstrainedLO_i$ equal to 0. In the regressions, we include an indicator variable identifying such cases.

Leave (one) out instruments have recently received some criticism (Betz, Cook and Hollenbach, 2018; McKenzie, 2021). We highlight three issues. First, we require an exclusion restriction such that $x_i = CreditConstrained_i$ is affected by x_j while x_j is not affected by x_i. Second, there must be no direct causal effect of x_j on Y_i other than via x_i (exclusivity). Third, Betz et al. (2018) suggest that there is an inherent simultaneity bias in the first stage of any such IV strategy. However, in our case, we rely on the setting described by Sundquist (2021) and which avoids these issues. That is, what our leave out instrument captures is not a causal effect that operates between firm j and i. Rather, both x_i and x_j are affected by some exogenous variable z— in our case, the credit constraints of banks that happen to be present locally. The leave out instrument for firm i then becomes a proxy of this underlying variable that is free from any effect ϵ_i might have on x_i.

[20] For banks not included in the 2014 EBA stress test, we use the actual 2016 Tier 1 ratio.

[21] Similar approaches have been used in a number of other studies including Fisman and Svensson (2007), Aterido, Hallward-Driemeier and Pagés (2011), and Commander and Svejnar (2011). Because we leave out more than one firm in constructing the instrument, we label it "leave-out" rather than "leave-one-out".

3.1.2 Instrument for Green Management

We construct a similar "leave-out" (LO) instrument for green management. Our motivation in this case, and the details of its construction, are slightly different. We build on the idea that depending on their (conditionally exogenous) local environment, some firms have better access to information about good green management than others (Fu, 2012).[22] In particular, firms close to well-managed other firms are likely to be more aware of good green management. For firm i, we can therefore compute the average green management quality of firms j in its vicinity. This will only then be exogenous with respect to ϵ_i if these firms j are not influenced by i in turn. We hence assume that knowledge about green management flows from larger to smaller firms.[23] For example, a multinational enterprise is unlikely to look for good green management practices in a small local firm. However, if a small local company happens to be near a multinational, it might pick up some frontier green management practices that it would not have adopted otherwise.

To operationalize this, we divide firms into deciles based on their employee numbers.[24] For firm i, we then use the average green management scores of firms j that are within a 15 km radius and in all size deciles above i's own decile.

$$GreenManagementLO_i = \frac{1}{\#} \sum_{j \text{ s.t. } decile(j)>decile(i) \text{ \& } v(j)=v(i)} GreenManagement_j \tag{5}$$

For firms in the top size decile, or firms without any nearby firms in higher size deciles, we set $GreenManagementLO_i$ equal to 0 and include an indicator variable identifying such cases in the regressions. In addition, we introduce a further control variable $\bar{Y}_{-i}$, which is defined similarly to $GreenManagementLO_i$. However, rather than providing averages of nearby larger firms' management score, it captures their investment outcomes Y_j:

$$\bar{Y}_{-i} = \frac{1}{\#} \sum_{j \text{ s.t. } decile(j)>decile(i) \text{ \& } v(j)=v(i)} Y_j \tag{6}$$

[22]Bloom, Eifert, Mahajan, McKenzie and Roberts (2013)'s evidence suggests that informational barriers are a primary reason why firms do not adopt better management practices that would increase their profitability.

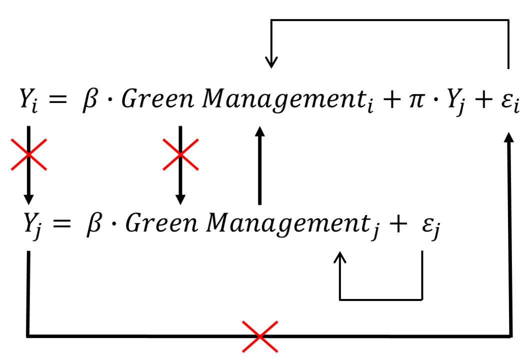
[23]This would be in line with localized productivity spillovers from larger to smaller manufacturing firms as documented by Greenstone, Hornbeck and Moretti (2010). Inter-firm information flows regarding managerial practices are one channel through which such spillovers may materialize.

[24]We measure employment as the number of permanent, full-time employees reported in the Enterprise Survey. Deciles are defined at the country level, using all firms with data on the number of permanent, full-time employees.

This accounts for the possibility that a firm i could respond to aspects of a (larger) firm j other than management practices. Most notably, suppose a larger firm j in the neighborhood of i adopts a new environmental technology—solar panels, say. Then this adoption could directly affect firm i's knowledge set, irrespective of firm j's management quality. Of course, the latter might be causally affected by such an adoption decision as well. However, by including $\bar{Y}_{-i}$ as a control variable, we close this causal channel, thereby isolating the effect of better management quality. For firms in the top size decile, or firms without any nearby firms in higher size deciles, we set $\bar{Y}_{-i}$ equal to 0. In the regressions, we include an indicator variable identifying such cases.

Figure 4 summarizes this identification strategy. Note that this approach addresses the potential issues about leave out instruments discussed in the previous section in a somewhat different way. First, we address the exclusion restriction and the concern about simultaneity bias by our assumption that information about management practices only flows from larger to smaller firms (but not in reverse).[25] Second, we ensure conditional exclusivity by including Y_j as a control variable.

Figure 4: Illustration of identification strategy for green management



Notes: This figure illustrates our identification strategy for green management effects. Firm i may learn about green management from firm j. Yet, if firm j equally learns from i, $GreenManagement_j$ will also be endogenous. We therefore assume that a large firm ignores the activities of smaller firms. Moreover, rather than learning from j's management practices, i might simply copy j's (green) investment decision (which may or may not be driven by green management). To rule out that factors other than management drive the effect, we include $\bar{Y}_{-i} = f(Y_J)$ as an additional control.

[25]This implies that we can write the weight matrix W introduced by Betz, Cook and Hollenbach (2018) in a lower triangular form if firms are sorted by size in descending order, which avoids the simultaneity basis. This would be equivalent to an autoregressive regression when working with time series data.

3.1.3 Two Stage Least Squares Approach

Using the above instruments, our 2SLS framework comprises the first-stage equations:

$$\begin{aligned}\Xi_i = \delta_0 + \delta_1 CreditConstrainedLO_i + \delta_2 \Delta Tier1_i + \delta_3 \Delta Tier1H_i \\ + \delta_4 GreenManagementLO_i + \gamma^{'}\mathbf{X_i} + \delta_5 \bar{Y}_{-i} + \epsilon_i\end{aligned} \tag{7}$$

for $\Xi \in \{CreditConstrained, GreenManagment\}$; and the second-stage equation:

$$Y_i = \beta_0 + \beta_1 Credit\widehat{Constrained}_i + \beta_2 Green\widehat{Management}_i + \gamma^{'}\mathbf{X_i} + \beta_3 \bar{Y}_{-i} + \varepsilon_i \tag{8}$$

where all other variables are as described for the OLS estimation of Equation (1).

3.2 Regressions of Industrial Emissions

To examine the impact of credit and managerial constraints on industrial emissions, we use data from the E-PRTR. Unfortunately, there is only limited overlap between the E-PRTR facilities and the firms in the Enterprise Surveys, so we cannot directly extend the approach outlined in the previous section. However, we can adopt a reduced form version of that approach. Specifically, we create credit constraint and green management indicators for an E-PRTR facility i by averaging the predicted credit constraint and green management quality for all firms j in the vicinity of i and that are not in the same sector as i:[26]

$$Credit\overline{Constraints}_i = \frac{1}{\#} \sum_{j \text{ s.t. } s(j) \neq s(i) \ \& \ v(j)=v(i)} Credit\widehat{Constraints}_i \tag{9}$$

and

$$Green\overline{Management}_i = \frac{1}{\#} \sum_{j \text{ s.t. } s(j) \neq s(i) \ \& \ v(j)=v(i)} Green\widehat{Management}_i \tag{10}$$

This is measured for 98.6 percent of all the E-PRTR facilities in our country sample. For

[26] We do not have size information for facilities in E-PRTR so we cannot implement the equivalent of the size restriction in Equation (5).

E-PRTR facilities without any nearby firms in other sectors, we set $Credit\overline{Cons}traints_i$ and $Green\overline{Mana}gement_i$ equal to 0. In the regressions, we include an indicator variable identifying such cases. We can then estimate the following equation:

$$log(Emissions_i) = \beta_0 + \beta_1 Credit\overline{Cons}traints_i + \beta_2 Green\overline{Mana}gement_i + \gamma^{'}\mathbf{X_i} + \epsilon_i \tag{11}$$

where *Emissions* is either the log of CO_2, NO_x, SO_x, or hazardous air pollutant emissions by industrial facility i and $\mathbf{X}$ is defined analogously to Equation (1).[27] Bootstrapped standard errors are clustered by facility. $Credit\overline{Cons}traints_i$ and $Green\overline{Mana}gement_i$ rely on information from one round of the Enterprise Surveys, so we estimate Equation (11) using data on emissions for the years 2015-17.

3.3 The Global Financial Crisis and Industrial Emissions

The third and final part of our analysis comprises a difference-in-differences design to examine the environmental impact of what is arguably the biggest shock to credit constraints in recent history: the 2007-08 Global Financial Crisis. Annual E-PRTR data are available from 2007 onward so that we can examine the longer-term impact of this crisis on industrial emissions across Emerging Europe.[28] In the short run, it is uncontroversial that the crisis reduced emissions along with economic activity. However, it is not clear what happened after economic activity picked up again. One can envisage three scenarios: first, emissions may simply have reverted back to pre-crisis levels. Second, emissions could be lower if the crisis had a cleansing effect by allowing firms to replace inefficient equipment more swiftly than would have happened otherwise. Third, emissions could have increased if—due to credit constraints—equipment and machinery was replaced more slowly or not at all.

We explore this by exploiting the fact that banks that had funded themselves with short-term and relatively unstable wholesale funding before the crisis had to deleverage more afterwards. In contrast, banks that could count on a steady deposit base were more stable lenders (Iyer, Peydró, da Rocha-Lopes and Schoar, 2013; De Haas and Van Lelyveld, 2014).

[27]Specifically, $\mathbf{X}$ includes credit market characteristics in the vicinity of each facility, the population size bracket of the locality, and region and sector fixed effects.

[28]For some firms these data go back to 2004 and we use these in robustness tests in Online Appendix D.5.

As argued before, banks' branch networks were predetermined before the crisis and overlap only partially. This creates a spatially varied pattern of changes in funding conditions, with industrial facilities in some localities having access to banks with stable funding whereas other facilities had to rely on banks on a steep deleveraging path (Popov and Udell, 2012; Beck, Degryse, De Haas and Van Horen, 2018). Hence, with one year of pollution data from right before the crisis (2007), we can relate subsequent changes in emissions to changes in the immediate financial environment of firms. To do so, we again match each facility with all bank branches within a 15 km radius.[29] We then create a measure of the average reliance on wholesale funding in 2007, just before the Global Financial Crisis, of these surrounding bank branches.

We estimate the following difference-in-differences, reduced-form model:

$$\begin{aligned} log(Emissions_{it}) = \beta_0 &+ \beta_1 WSFReliance_{15km,i} \\ &+ \beta_2 WSFReliance_{15km,i} \times Post2007_t + \beta_3 Post2007_t \\ &+ \zeta_t + \zeta_i + \epsilon_{it}, \end{aligned} \tag{12}$$

where *Emissions* is either the log of CO_2, NO_x, SO_x, or hazardous air pollutant emissions by an industrial facility i in year t. ζ_t and ζ_i are year and facility fixed effects.[30] $WSFReliance$ is the average reliance of local banks on wholesale funding in 2007. In the case of multi-facility firms, the distance is calculated relative to the parent company. $Post_{2007}$ is a dummy variable that is 1 in 2008 and later years, and 0 in the base year 2007. **X** includes credit market conditions in the vicinity of each facility and the population size bracket of the locality. Standard errors are clustered by facility. Hence, β_2 becomes our measure of the impact of the Global Financial Crisis on industrial emissions. We also explore versions of Equation (12) where we split the post-2007 period into sub periods. Specifically, we split it into the period covering the Global Financial Crisis and the subsequent Eurozone crisis (2008-13), and the period after both crises (2014-17).

[29] As before, we explored robustness to slightly different distances.

[30] In robustness checks we use a hyperbolic sine transformation of emissions. This leads to similar results, see Table OD.9 in Online Appendix D.

4 Empirical Results

4.1 Organizational Constraints and Green Investments

Table 1 examines the first stage of our IV framework. We regress each firm's credit constraint indicator and green management score on all four instruments in columns 1 and 2, respectively. Column 1 displays positive and significant coefficients for the first two instruments and a negative and significant one for the third instrument. This confirms that firms are more likely to be credit constrained if companies from other sectors in their vicinity are also constrained; if nearby banks had to substantially increase their Tier 1 ratio between 2007 and 2014; and if such nearby banks performed worse during the 2014 EBA stress tests. As expected, we find no relationship between the green management instrument and firms' credit constraints in column 1.

In column 2, the green management score is positively affected by the related instrument: the average green management score of nearby larger firms. Importantly, the instruments for credit constraints are not correlated with the green management score. This supports the identifying assumption underlying our instrumentation strategy: the financial health of banks only affects the investment decisions of firms through its impact on local lending conditions. We find very similar results in columns 3 and 4, the first-stage regressions for column 9 of Table 2—which considers firms' energy efficiency as an outcome. The first-stage F-statistics on the excluded instruments are at or above the rule-of-thumb of 10.[31]

Next, Table 2 reports the effects of credit constraints and green management quality on various types of investment. We first show OLS estimates (based on Equation 1) in Panel A and then the equivalent IV results in Panel B (based on Equation 7). Standard errors are clustered by locality.[32] Each column refers to a different investment type. In column 1, we first consider an indicator that is equal to 1 if the firm purchased any fixed assets in the previous fiscal year (general investment).

Our IV results in Panel B indicate that credit-constrained firms are 30.3 percentage points less likely to engage in any fixed investment. A priori it is not clear whether this extends to green

[31] Sanderson-Windmeijer multivariate F-tests yield a p-value of 0.00, indicating that the null hypothesis of an underidentified endogenous variable can be rejected. Table OD.2 in Online Appendix D provides a battery of additional diagnostic tests in support of our instrumentation strategy.

[32] In square brackets, we provide p-values taking into account spatial correlation following Colella, Lalive, Sakalli and Thoenig (2019). In columns 2 to 8, we also present p-values under Bonferroni-Holm multiple hypothesis testing. Online Appendix Table OD.3 shows that the regression results in Table 2 are robust to restricting the sample to clusters with at least three observations.

Table 1: Firm-Level IV regressions: First Stage

	Columns 1-8, Table 2		Column 9, Table 2	
Dependent variable →	Credit constrained (indicator)	Green management (0-1 score)	Credit constrained (indicator)	Green management (0-1 score)
	[1]	[2]	[3]	[4]
Leave-out mean credit constraints	0.226***	0.019	0.200***	0.029
	(0.036)	(0.017)	(0.040)	(0.019)
Change in average local Tier 1 capital ratio (% points)	0.004***	-0.000	0.002	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
EBA 2014 instrument (% points)	-0.014**	0.002	-0.018***	0.001
	(0.006)	(0.002)	(0.006)	(0.002)
Leave-out mean green management	-0.041	0.250***	-0.030	0.266***
	(0.042)	(0.045)	(0.046)	(0.050)
Observations	10,769	10,769	8,637	8,637
Clusters	2,500	2,500	2,119	2,119
R^2	0.146	0.199	0.134	0.215
F-test of excluded instruments	16.439	13.032	10.856	9.987
SW multivariate F-test	21.690	16.321	14.624	14.511
Angrist-Pischke χ^2	65.722	49.389	44.418	44.705
Angrist-Pischke χ^2 p-value	0.000	0.000	0.000	0.000
Angrist-Pischke F-test	21.738	16.336	14.664	14.758
Angrist-Pischke F-test p-value	0.000	0.000	0.000	0.000
Angrist-Pischke R^2	0.010	0.026	0.009	0.030

Notes: This table presents the first-stage regressions corresponding to Panel B of Table 2; columns 1-2 are the first stage regressions for results in columns 1-8 in Panel B of Table 2 and columns 3-4 are the first stage regressions for results in column 9 in Panel B of Table 2. All regressions include locality-level credit market controls (log local banks' average asset size in a 15 km radius and the number of bank branches in a 15 km radius) and population size class; indicators for no firms in other sectors in a 15 km radius with data on credit constraints and green management; and region and sector fixed effects. Table A1 contains all variable definitions, Table A3 provides summary statistics, Table OB.1 provides information on regions and Table OB.2 on sectors. Robust standard errors are clustered by locality and shown in parentheses. ***, ** and * correspond to the 1%, 5%, and 10% level of statistical significance.

investments. Green investments might not be affected by credit constraints if firms do not rely on external funding for them, for example because these are smaller projects. Moreover, certain green investments may simply be mandated by strict regulation. Firms therefore have to implement them, finding the necessary funds irrespective of credit constraints (and perhaps foregoing other investments instead).

The IV results reveal that different types of green investments relate very differently to credit constraints. It is primarily investments in green technologies embodied in general fixed assets that are affected. Credit-constrained firms are 36 and 36.2 percentage points less likely to invest in greener machinery/equipment and vehicle upgrades, as shown in columns 2 and 3, respectively. In sharp contrast, the point estimates are much smaller and not statistically significant for investments that explicitly target lower emissions or pollution (columns 4 to 8), such as green energy generation or improvements in waste and recycling facilities.[33]

Turning to the effect of green management practices, we find for *all* investment types a significant positive impact. A one standard deviation increase in the green management score increases the likelihood of green investment by between 18.1 and 31.8 percentage points. Unlike for credit constraints, the effect size is broadly the same for the different investment types. Again, the impact found with IV is larger than using OLS. This is consistent with at least some firms using green management as a superficial substitute for green investments, as discussed in Section 3. Figure 5 summarizes the IV coefficients of Table 2 (Panel B).

Lastly, we explore in column 9 whether credit constraints and the quality of a firm's green management ultimately affect the energy intensity of production. We run these regressions for a sub-sample of firms that report their energy costs and sales. As expected, credit constraints are positively related to the energy intensity of production, although the estimated coefficient is not statistically significant. We do find a higher energy efficiency for firms with better green management (column 9 of Panel B), which is in line with a higher incidence of investment in greener technologies and energy efficiency by such well-managed firms.

Several additional points are worth discussing in relation to these results. First, it is remarkable that for investments that embody new green technologies, both credit constraints and green management have a distinct impact. This implies that measures to make finance for green investments more accessible—such as green credit lines—may be an important element of efforts to speed up the diffusion of new green technologies across the firm population in emerging markets. This also holds true for efforts to improve green management practices, such as environmental consultancy and training programs. Relatedly, we investigate in unreported regressions whether there are interaction effects between green management quality and credit constraints. For example, it may be the case that a loosening of credit constraints only leads to more green investment if a firm is also well-managed in a green sense. We do not find any evidence for such interaction effects and discuss the implications of this null result in the concluding section.

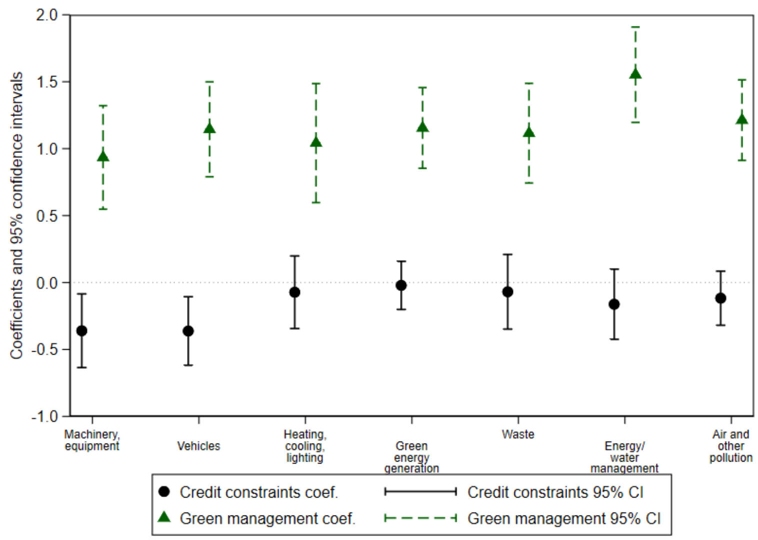
[33]The OLS results suggest a smaller impact for credit constraints across all asset types. This is consistent with an attenuation bias, for example because rapidly growing (and investing) firms are more likely to experience credit constraints.

Table 2: Firm-Level Credit Constraints, Green Management, and Green Investments

Dependent variable →	Fixed asset investment (indicator)	Machinery, equipment upgrades	Vehicle upgrades	Improved heating / cooling / lighting	Green energy generation	Waste and recycling	Energy / water management	Air / other pollution control	Log (energy cost per sales)
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Panel A: OLS									
Credit constrained	-0.100***	-0.046***	-0.054***	-0.045***	-0.015	-0.035***	-0.031***	-0.000	0.013
	(0.013)	(0.012)	(0.012)	(0.013)	(0.010)	(0.011)	(0.011)	(0.010)	(0.041)
	[0.000]	[0.001 / 0.000]	[0.000 / 0.000]	[0.003 / 0.000]	[0.193 / 0.087]	[0.007 / 0.003]	[0.008 / 0.007]	[0.966 / 0.954]	[0.802]
Green management	0.444***	0.677***	0.615***	0.707***	0.580***	0.762***	1.054***	0.926***	-0.043
	(0.032)	(0.032)	(0.034)	(0.030)	(0.037)	(0.031)	(0.031)	(0.028)	(0.105)
	[0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.699]
Panel B: IV									
Credit constrained	-0.303**	-0.360**	-0.362***	-0.073	-0.021	-0.069	-0.162	-0.117	0.518
	(0.142)	(0.140)	(0.130)	(0.138)	(0.092)	(0.142)	(0.134)	(0.103)	(0.590)
	[0.069]	[0.036 / 0.009]	[0.015 / 0.008]	[0.623 / 1.000]	[0.852 / 1.000]	[0.614 / 1.000]	[0.292 / 0.560]	[0.295 / 0.679]	[0.368]
Green management	1.058***	0.935***	1.145***	1.042***	1.155***	1.116***	1.552***	1.213***	-1.774***
	(0.257)	(0.197)	(0.181)	(0.227)	(0.154)	(0.190)	(0.182)	(0.153)	(0.550)
	[0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.000 / 0.000]	[0.001]
Observations	10,796	10,796	10,796	10,796	10,796	10,796	10,796	10,796	8,637
Clusters (localities)	2,500	2,500	2,500	2,500	2,500	2,500	2,500	2,500	2,119

Notes: This table presents OLS (Panel A) and Instrumental Variables (Panel B) regressions to estimate the relation between, on the one hand, firm-level credit constraints and the quality of green management and, on the other hand, firm-level investments in columns 1-8 and firm-level log energy cost per sales in column 9. All regressions include locality-level credit market controls (log local banks' average asset size in a 15 km radius and the number of bank branches in a 15 km radius); population size class; and region and sector fixed effects. Table A1 contains all variable definitions, Table A3 provides summary statistics, Table OB.1 provides information on regions and Table OB.2 on sectors. The square brackets contain, first, p-values taking into account spatial correlation following Colella, Lalive, Sakalli and Thoenig (2019) and, second, p-values under Bonferroni-Holm multiple hypothesis testing. Table 1 provides the first stage of the IV regressions in Panel B. Robust standard errors are clustered by locality and shown in parentheses. ***, ** and * correspond to the 1%, 5%, and 10% level of statistical significance.

Figure 5: Firm-Level Credit Constraints, Green Management, and Green Investments



Notes: This figure summarizes the IV coefficients of Table 1, Panel B, columns 2-8, which represent estimates of the relation between, on the one hand, firm-level credit constraints and the quality of green management and, on the other hand, firm-level green investments. Table A1 contains all variable definitions and Table A3 provides summary statistics. Whiskers represents 95 percent confidence intervals (CI).

Second, one may ask whether there is something special about green management that differs from general good management. For a sub-sample of firms, we have data on general management practices based on questions from the US Census Bureau's Management and Organizational Practices Survey (MOPS).[34] We can therefore perform a 'horse race' between firms' general management practices and their green management quality as drivers of green investment behavior. We present these results in Table OD.7, Online Appendix D.3. Importantly, they indicate that it is specifically green management that drives green investment. In contrast, it is general management that drives the results for general investment in column 1 of Table 2. This indicates that although green and general management are somewhat positively correlated (p=0.36), they are nevertheless distinct management 'technologies' that each effect firms' investment activity in different ways.

Third, investment in greener technologies embodied in new equipment, machinery, and vehicles does not necessarily equate desirable environmental outcomes. Such investments may lead to a net increase in emissions, especially given our finding of a non-significant effect of credit constraints on energy costs per sale. The same could be true for the green management effect on such embodied green investments. Moreover, while we find that green management also affects "pure" green

[34]These are larger firms with at least 20 employees, implying a 40 percent drop in sample size.

investments and energy costs per sale, we might be concerned that the impact of these investments on pollution outcomes is rather minimal. Hence, we explore in the following sections the impact on actual greenhouse gas emissions.

4.2 Organizational Constraints and Facility-Level Emissions

Because there is no comprehensive pollution data available for the firms used in the above analysis, we now move to the E-PRTR facility-level data that we introduced in Section 2.3. Table 3 presents estimates of Equation (11) to explain facility emissions through local variation in credit constraints and green management quality.[35] We concentrate on specific emission types as outcome variables (see Online Appendix C for more details). First, we use CO_2 emissions as this is the primary greenhouse gas emitted by fuel combustion and other human activities. It accounts for almost three quarters of global emissions (Ritchie and Roser, 2020) and 78 percent of all greenhouse gas emissions in our sample during 2007-17. Second, we focus on releases of NO_x and SO_x, two of the five main air pollutants on which EU member states must report. NO_x and SO_x also result from burning fuel but their environmental impact is different (Shelyapina, Rodríguez-Iznaga and Petranovskii, 2021): they cause acid deposition, which deteriorates soil and water quality and damages forests, crops and other vegetation. Third, we investigate hazardous air pollutants that can cause cancer and other diseases. These impacts are often highly localized. We calculate this outcome as the weighted sum of all air releases in E-PRTR for which inhalation toxicity weights are available in the U.S. Environmental Protection Agency's Risk-Screening Environmental Indicators model (see Table OC.1 for availability and inhalation toxicity weights).

The results in Table 3 support the hypothesis that in localities where firms are more credit constrained and less well managed, industrial facilities emit more CO_2, NO_x, and SO_x during 2015-17. We include year, sector and regional fixed effects so that this finding holds when comparing facilities within the same sector or sub-national region. The local credit constraints pick up spatial variation in the earlier tightening of local lending conditions as banks shored up their Tier 1 capital ratios after 2007. This indicates that the reduction in the supply of bank lending during and

[35] The dependent variables are transformed as $log(Emissions)$. Results are robust to using a hyperbolic sine transformation - see Table OD.8 in Online Appendix D. As explained above, we set missing values for releases of specific pollutants to their reporting thresholds. Our results are thus conservative estimates of the effect of credit constraints and green management practices on emissions.

immediately after the Global Financial Crisis led to a worse performance in terms of facilities' carbon emissions and other air pollutants in the subsequent years. Our earlier results provide a mechanism to explain this: the worsening of credit conditions during the crisisresulted in lower green investments in the subsequent years, and as a result more pollution.

Moreover, the quality of green management in firms surrounding a facility tends to reduce a plant's emissions of CO_2 and NO_x (with the coefficient for SO_x imprecisely estimated). Here too, our findings point to a potential explanation: firms' green management practices tend to spill over to other firms and facilities in their vicinity who then reduce their air pollution and CO_2 emissions.

Table 3: Credit Constraints, Green Management, and Facility-level Emissions

Dependent variable →	CO_2	NO_x	SO_x	Hazardous air pollutants
	[1]	[2]	[3]	[4]
Local mean credit constraints	0.338**	0.353**	0.292*	0.022
	(0.141)	(0.171)	(0.153)	(0.042)
Local mean green management	-0.482**	-0.507**	-0.269	0.029
	(0.225)	(0.248)	(0.215)	(0.060)
Observations	10,158	10,158	10,158	10,158
Number of facilities	3,386	3,386	3,386	3,386

Notes: This table presents OLS regressions to estimate the relation between, on the one hand, local credit constraints and the quality of green management and, on the other hand, the log transformation of facility-level CO_2, NO_x, SO_x emissions and emissions of hazardous air pollutants (using toxicity weights from EPA's Risk-Screening Environmental Indicators (RSEI) model, see Online Appendix C, Table OC.1 for details). Missing pollutant emissions are replaced with the pollutant reporting threshold. The sample consists of all facilities that appear in E-PRTR in all years between 2015-17. For each E-PRTR facility, values for the variables *Local mean credit constraints* and *Local mean green management* are calculated as averages of the predicted values from Table 1 across all firms in other sectors within a 15km radius around the industrial facility or, in the case of multi-facility firms the parent company. If there are no such firms within a 15km radius, the value is set to 0. All regressions include indicators for the years 2016 and 2017; locality-level credit market controls (log local banks' average asset size in a 15km radius and the number of bank branches in a 15km radius around the industrial facility or, in the case of multi-facility firms the parent company); an indicator for missing local mean credit constraints/green management value (set to 0 in the variable itself); locality size controls; and region and sector fixed effects. Table A1 contains all variable definitions and Table A3 provides summary statistics. Bootstrapped standard errors are clustered by facility and shown in parentheses. ***, ** and * correspond to the 1%, 5%, and 10% level of significance.

There is only a small and statistically insignificant impact of local credit constraints and green management practices on the local facility emissions of hazardous air pollutants (Table 3, column 4). This may reflect that in our sample of EU countries, the emissions of hazardous pollutants have been subject to strict regulations. Recent evidence from the U.S. shows that financial constraints only impact firms' toxic emissions when local regulation is rather lax and hence provides firms with discretion in terms of trading off investments in pollution abatement versus other investments (Xu and Kim, 2022). A similar argument can be made for the role of green management.

How quantitatively important are the effects we find? And how do the credit constraint effects compare to the green management ones? We explore this by considering two counterfactual scenarios. First, we examine how much emissions would fall in the absence of credit constraints, i.e. if $Credit\overline{Constraints}_i$ was equal to 0 for all firms. Second, we examine the impact of increasing the quality of firms' green management. We implement this by applying the green management score of the firm at the 75^{th} percentile as a benchmark. That is, we counterfactually set the green management score of firms below the 75^{th} percentile equal to the 75^{th} percentile value. This implies a reduction in average 2015-17 aggregate CO_2 emissions by 4.8 percent when removing credit constraints altogether and by 2.2 percent when improving green management practices. The equivalent numbers for NO_x and SO_x are reductions of 5.0 and 4.1 percent, respectively, for the impact of credit constraints; and reductions of 2.3 and 1.2 percent, respectively, for the impact of better green management.

4.3 The Global Financial Crisis and Industrial Emissions

Another way to gauge the empirical relevance of credit constraints is to explore the Global Financial Crisis, one of the biggest financial shocks in living memory. Table 4 reports results from our difference-in-differences specification as described in Equation (12). We focus on the same emission categories as in Table 3. The first four columns provide results from the basic difference-in-differences set up. The negative and significant coefficient estimates for the *Post 2007* dummy indicate a secular decline in industrial emissions during and after the financial crisis. Yet, the interaction term of interest—between the *Post 2007* dummy and local banks' pre-crisis reliance on wholesale funding—shows that this decline was significantly weaker for industrial facilities surrounded by branches of banks that were more vulnerable to funding shortages. The estimated coefficients are positive, large and statistically significant, at least at the 10 percent level.

Table 4: Local Credit Shocks and Industrial Emissions

Dependent variable →	CO_2	NO_x	SO_x	Hazardous air pollutants	CO_2	NO_x	SO_x	Hazardous air pollutants
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Local banks' reliance on	-0.038	-0.589*	-2.659**	-0.790	0.066	-0.242	-1.914*	-0.419
wholesale funding	(0.301)	(0.327)	(1.044)	(0.600)	(0.236)	(0.291)	(1.006)	(0.359)
Post 2007 × Local banks'	0.053*	0.057*	0.082**	0.031**				
reliance on wholesale funding	(0.031)	(0.032)	(0.036)	(0.014)				
Post 2007	-0.056**	-0.092***	-0.128***	-0.027**				
	(0.023)	(0.023)	(0.028)	(0.013)				
2008-2013 × Local banks'					0.036	0.035	0.063**	0.028**
reliance on wholesale funding					(0.027)	(0.026)	(0.032)	(0.014)
2014-2017 × Local banks'					0.078*	0.092**	0.120**	0.043**
reliance on wholesale funding					(0.040)	(0.044)	(0.047)	(0.018)
2008-2013					-0.039**	-0.061***	-0.093***	-0.024**
					(0.019)	(0.019)	(0.024)	(0.012)
2014-2017					-0.080***	-0.140***	-0.190***	-0.036**
					(0.029)	(0.033)	(0.036)	(0.016)
Observations	3,934	3,934	3,934	3,934	5,901	5,901	5,901	5,901
Number of facilities	1,967	1,967	1,967	1,967	1,967	1,967	1,967	1,967

Notes: This table presents OLS regressions to estimate the relation between local bank-funding shocks and the log transformation of facility-level emissions of CO_2, NO_x, SO_x, and hazardous air pollutants (using inhalation toxicity weights from EPA's Risk-Screening Environmental Indicators (RSEI) model, see Online Appendix C, Table OC.1 for details). Missing pollutant emissions are replaced with the pollutant reporting threshold. The sample consists of all facilities present in E-PRTR in all years between 2007-17. Local banks' reliance on wholesale funding (15 km) measures the average reliance (in 2007) on wholesale funding of all bank branches located in a circle with a 15 km radius around the industrial facility or, in the case of multi-facility firms the parent company. All regressions include locality-level credit market controls (log local banks' average asset size in a 15km radius and the number of bank branches in a 15km radius around the industrial facility or, in the case of multi-facility firms the parent company) and facility fixed effects. Table A1 contains all variable definitions and Table A3 provides summary statistics. Standard errors are clustered by facility and shown in parentheses. ***, ** and * correspond to the 1%, 5%, and 10% level of statistical significance.

All else equal, total emissions of CO_2, NO_x, SO_x were on average 4.0, 4.2, and 6.3 percent higher than they would have been without credit constraints.[36] In this setup, we also find statistically significant but economically small impacts on hazardous air pollutants (2.3 percent higher than without credit constraints).

In columns 5 to 8, we replicate the difference-in-differences analysis but split the post period into an early (2008-13) and later (2014-17) time window. We find that the CO_2 and NO_x emission differences between facilities surrounded by affected versus less affected banks only emerge during 2014-17, while the SO_x and hazardous air pollutant emission differences already emerge during 2008-13 but become even stronger during 2014-17. This lag reflects that it takes several years for variation in local credit conditions to translate into differences in green investments and, ultimately, in carbon and other emissions.

Figure 6 illustrates the impact of local credit shocks on facility emissions for each sample year. We interact year dummies with the $WSFReliance$ variable and plot these coefficients. In line with the second part of Table 4, this figure shows how the effects on emissions become economically and statistically more pronounced in later years. This increasingly strong effect is consistent with our proposed mechanism: it takes time for green investments to materialize, and thus for differential access to bank credit to result in differing levels of air pollution. The data do not allow us to assess the presence of pre-trends, though for a sub-sample of facilities we have data for the year 2004 (but not for 2005-06). Reassuringly, Figure OD.2 in Online Appendix D.5 demonstrates an absence of significant effects in the pre-treatment year 2004 for CO_2, NO_x and hazardous air pollutants.

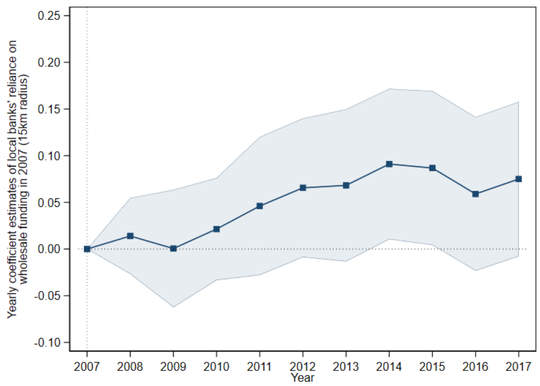
Lastly, Figure 7 provides a quantification of the cumulative impact of local bank-funding shocks on one of our main outcomes, CO_2 emissions. The solid line shows the actual decline in carbon emissions while the dotted line represents the counterfactual that would have emerged in the absence of credit constraints induced by the Global Financial Crisis. In that counterfactual scenario, more industrial facilities would have made green investments. Our estimates imply that this would have kept aggregate carbon emissions in 2017 5.7 percent above the level they would have been in the absence of crisis-related financial frictions. The equivalent numbers for NO_x, SO_x, and hazardous air pollutants are 6.7, 9.5, and 3.7 percent, respectively. These figures are remarkably similar to

[36] This is calculated as $100 * \frac{\sum_{i,t=2008-17} e^{log(Emissions_i)} - \sum_{i,t=2008-17}\left[e^{log(Emissions_i)} - e^{log(Emissions_i - \beta_2 WSFReliance_{15km,i})}\right]}{\sum_{i,t=2008-17}\left[e^{log(Emissions_i)} - e^{log(Emissions_i - \beta_2 WSFReliance_{15km,i})}\right]}$.

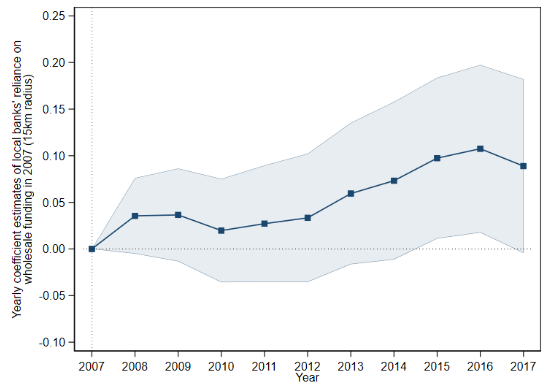
the counterfactual figures reported for credit constraints in the previous section, despite the very different econometric design.

Figure 6: Local Credit Shocks and Industrial Emissions, 2007-17

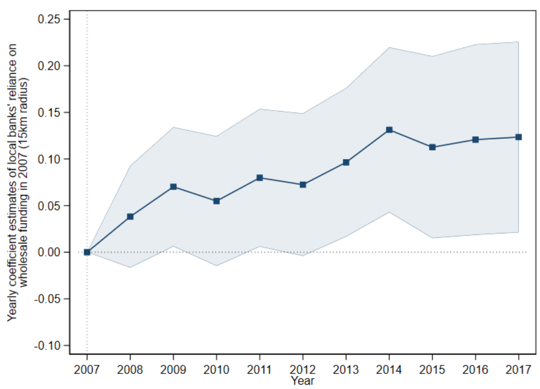
Panel A: CO_2 Emissions



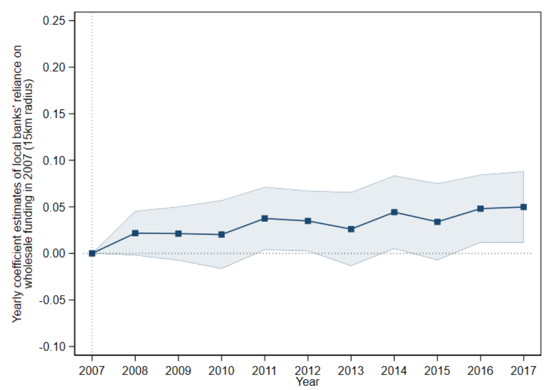
Panel B: NO_x Emissions



Panel C: SO_x Emissions

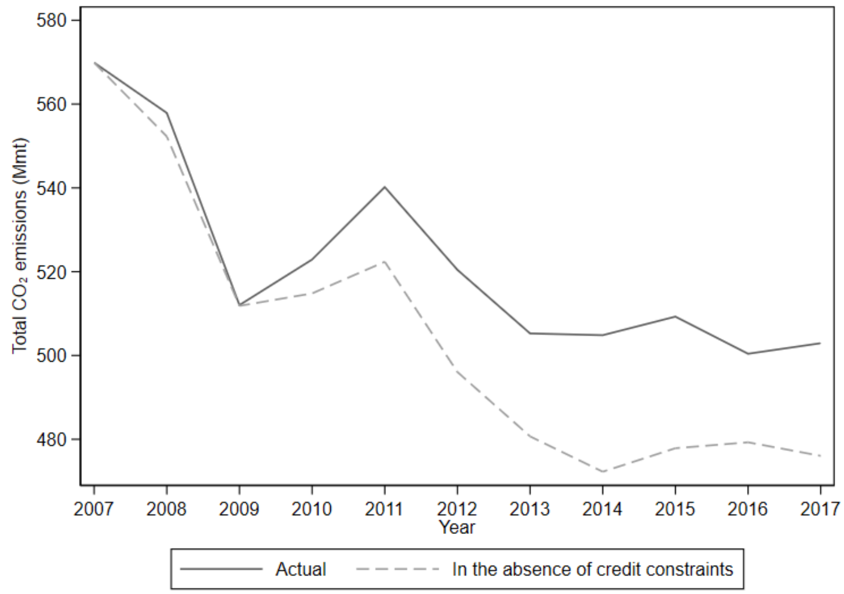


Panel D: Hazardous Air Pollutant Emissions



Notes: These charts summarize the coefficient estimates of difference-in-differences regressions explaining the impact of local bank-funding shocks on CO_2 emissions (log kg, Panel A), NO_x emissions (log kg, Panel B), SO_x emissions (log kg, Panel C), and hazardous air pollutant emissions (log using toxicity weights, Panel D) at the level of industrial facilities. Local banks' reliance on wholesale funding (15 km) measures the average reliance (in 2007) on wholesale funding of all bank branches located in a circle with a 15 km radius around the industrial facility or, in the case of multi-facility firms the parent company. The dots represent coefficient estimates of an interaction term between the variable *Local banks' reliance on wholesale funding in 2007* and individual year dummies during 2007-17 and the shaded area represents the 95% confidence interval. Regressions control for the locality-level credit market controls (log local banks' average asset size in a 15km radius and the number of bank branches in a 15km radius around the industrial facility or, in the case of multi-facility firms the parent company); and facility and year fixed effects.

Figure 7: Actual and Counterfactual CO_2 Emissions, 2007-17



Notes: This chart compares actual CO_2 emissions with counterfactual CO_2 emissions in the absence of credit constraints. The plots are based on Figure 6, Panel A. Mmt - millions of tons.

5 Conclusions

The transition to a low-carbon economy is as challenging as it is urgent. Fulfilling the commitments under the Paris Agreement will entail phasing out the most polluting brown industries and establishing new and greener industries from scratch. But this will not be enough. In addition, substantial investments will be needed over the next three decades to make industrial production substantially more energy efficient. This not only requires the invention of entirely new technologies but also—especially in emerging markets—the large-scale adoption of already existing energy-efficient production technologies and methods.

The analysis in this paper, based on newly collected data on 10,769 firms across 22 countries, shows how credit constraints continue to hamper firms' implementation of greener technologies. This is particularly true for green investments embodied in more general investments such as machinery and vehicle upgrades.

Analysis of data from the European Pollutant Release and Transfer Register (E-PRTR) reveals the environmental consequences of these credit constraints: a substantially slower decline in CO_2

and other industrial emissions. Our results thus reveal how financial crises can slow down the process of decarbonization of economic production. They should also caution against excessive optimism about the potential green benefits of the current economic slowdown which—like any big recession—has led to reductions in emissions. Our results suggest that such short-term reductions might come at the cost of longer-term increases in emissions if they are associated with more severe credit-market frictions that delay or prevent clean investments.

Our analysis also shows that deficient green management tends to hamper green investments across the board, and that they affect more types of investment than credit constraints do. These results suggest that comparatively low-cost measures—such as developing and implementing an environmental strategy; setting and monitoring environmental targets; and putting a manager in charge of climate change and environmental issues—can increase firms' green investments and ultimately decrease their emission of greenhouse gases and pollutants.

It is commonly accepted that a crucial part of the transition to a new greener equilibrium requires strong price signals through carbon taxes or carbon trading. However, our results imply that this may not be enough. Rather, they motivate a broader policy mix to stimulate green investments. This may include requirements to measure and disclose environmental impacts, such as those that will be put forward by the International Sustainability Standards Board, which aims to create a global, comparable set of sustainability standards. In addition, development institutions can scale up green credit lines to help firms that aim to invest in new vintages of machines and equipment that embody new and more energy-efficient technology. Moreover, advisory services, training programs, and other consultancy related interventions can help firm managers to invest more in energy efficiency and in the abatement of greenhouse gases and other industrial emissions. The fact that there appear to be no strong interaction effects between green managerial quality and credit constraints, furthermore suggests that interventions to loosen firms' credit constraints and to improve their green management skills do not necessarily need to be integrated into complex programs but can instead take the form of distinct and targeted policies.

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Appendices

Table A1: Variable Definitions and Data Sources

Variable name	Variable definition	Source
Tables 2-1		
Fixed asset investment	1 if firm purchased any new or used fixed assets, such as machinery, vehicles, equipment, land or buildings, including expansion and renovations of existing structures, in the last complete fiscal year; 0 otherwise	ES
Machinery, equipment upgrades	1 if firm upgraded machinery and equipment over the last three years; 0 otherwise	ES
Vehicle upgrades	1 if firm upgraded vehicles over the last three years; 0 otherwise	ES
Improved heating / cooling / lighting	1 if firm adopted heating and cooling improvements or improvements to lighting systems over the last three years; 0 otherwise	ES
Green energy generation	1 if firm adopted more climate-friendly energy generation on site over the last three years; 0 otherwise	ES
Waste and recycling	1 if firm adopted waste minimistation, recycling and waste management over the last three years; 0 otherwise	ES
Energy / water management	1 if firm adopted energy or water management over the last three years; 0 otherwise	ES
Air / other pollution control	1 if firm adopted air pollution or other pollution control measures over the last three years; 0 otherwise	ES
Green investment	1 if firm adopted at least one of the following measures over the last three years: heating and cooling improvements, more climate-friendly energy generation on site, machinery and equipment upgrades, energy management, waste minimisation, recycling and waste management, air pollution and control measures, water management, upgrade of vehicles, improvements to lighting systems, other pollution control measures; 0 otherwise	ES
Energy cost per sales	Cost of electricity and fuel divided by sales	ES
Credit constrained	1 if firm needed a loan and was discouraged from applying or rejected when it applied; 0 otherwise (including no need for credit or satisfied demand for credit)	ES
Green management	Score between 0 and 1 based on four areas of green management practices: strategic objectives related to the environment and climate change, manager with explicit mandate to deal with green issues, environmental targets, monitoring.	ES
Exporter	1 if firm directly exported at least 10 percent of its sales in the last complete fiscal year; 0 otherwise	ES

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Table A1 – continued from previous page

Variable name	Variable definition	Source
Listed	1 if firm is a shareholding firm with shares traded in the stock market; 0 otherwise	ES
Sole proprietor	1 if firm is a sole proprietorship; 0 otherwise	ES
Audited	1 if firm had its annual financial statements checked and certified by an external auditor; 0 otherwise	ES
Firm age	Log of firm age (from when it was registered)	ES
No. bank branches	Number of bank branches within a 15km radius around the firm	BEPS II and ES
Local banks' average asset size in 2007 (log)	Average asset size of banks with branches within a 15km radius around the firm, weighted by the number of bank branches, logged	BEPS II, Orbis, and ES
Locality size	Variable based on the number of inhabitants in the firm's locality; categories: city with population over 1 million; over 250,000 to 1 million inhabitants; 50,000 to 250,000 inhabitants; fewer than 50,000 inhabitants	ES, verified with official sources
Leave-out mean credit constraints	Credit constraints instrument obtained by averaging the credit constraints of other firms in a 15km radius around the firm, excluding firms in the same sector	ES
Change in average local Tier 1 ratio (% points)	Difference between the average Tier 1 ratio of banks with branches within a 15km radius of the firm in 2014 (weighted by the number of bank branches) and the average Tier 1 ratio of banks with branches within a 15km radius of the firm in 2007 (weighted by the number of bank branches).	BEPS II, Orbis, and ES
EBA 2014 instrument (% points)	Difference between the 2016 baseline scenario Tier 1 ratio and 8% hurdle rate of banks with branches within a 15km radius of the firm (weighted by the number of bank branches). For banks that were not included in the 2014 European Banking Authority stress test, the actual 2016 Tier 1 ratio is used	BEPS II, European Banking Authority (2014), Orbis, and ES
Leave-out mean green management	Green management instrument obtained by averaging the green management of firms in higher size deciles in a 15km radius around the firm	ES
Leave-out mean green investment	Green investment control variable obtained by averaging the green investment of firms in higher size deciles in a 15km radius around the firm	ES
Tables 3-4		
Greenhouse gas emissions	Total quantity of greenhouse gas emissions released by the facility into the air in kg; missing values set to threshold	E-PRTR v18
CO_2 emissions	Total quantity of CO_2 emissions released by the facility into the air in kg; missing values set to threshold	E-PRTR v18
Local mean credit constraints	Averages of the predicted values of credit constraints from Table 1 across all firms in a 15km radius around the industrial facility or, in the case of multi-facility firms the parent company, excluding those in the same sector	ES, BEPS II, Orbis

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Table A1 – continued from previous page

Variable name	Variable definition	Source
Local mean green management	Averages of the predicted values of green management from Table 1 across all firms in a 15km radius around the industrial facility or, in the case of multi-facility firms the parent company, excluding those in the same sector	ES, BEPS II, Orbis
Listed firm (indicator)	1 if firm is listed, 0 otherwise	Orbis
Delisted firm (indicator)	1 if firm was listed in the past but is no longer listed, 0 otherwise	Orbis
Firm age (log)	Age of the industrial facility or, in the case of multi-facility firms the parent company, logged	Orbis
No. bank branches	Number of bank branches within a 15 km radius around the industrial facility or, in the case of multi-facility firms the parent company	E-PRTR v18, BEPS II, Orbis
Local banks' average asset size in 2007 (log)	Average asset size of banks with branches within a 15 km radius around the industrial facility or, in the case of multi-facility firms the parent company, weighted by the number of bank branches, logged	E-PRTR v18, BEPS II, Orbis
Local banks' reliance on wholesale funding in 2007	Average value of net loans over deposits and short-term funding, weighted by the number of bank branches within a 15km radius around the industrial facility or, in the case of multi-facility firms the parent company	E-PRTR v18, BEPS II, Orbis
Locality size	Variable based on the number of inhabitants in the firm's locality; categories: city with population over 1 million; over 250,000 to 1 million inhabitants; 50,000 to 250,000 inhabitants; fewer than 50,000 inhabitants	E-PRTR v18, Orbis and official sources

Notes: Sources in this table are as follows: ES refers to the EBRD-EIB-WBG Enterprise Surveys, BEPS II refers to the second round of the Banking Environment and Performance Survey, and E-PRTR refers to the European Pollutant Release and Transfer Register.

Table A2: Sample Breakdown by Country

Countries	**Number of unique firms and facilities**			
	Table 2 (columns 1-8) & Table 1 (columns 1-2)	Table 2 (column 9) & Table 1 (columns 3-4)	Table 3	Table 4
Albania	281	283	0	0
Armenia	347	327	0	0
Azerbaijan	154	81	0	0
Belarus	540	469	0	0
Bosnia and Herzegovina	270	181	0	0
Bulgaria	625	438	130	72
Croatia	303	293	95	0
Czech Republic	399	399	684	377
Estonia	261	257	71	37
Georgia	406	385	0	0
Hungary	723	627	525	285
Latvia	244	230	29	11
Lithuania	310	279	63	39
Moldova	269	280	0	0
North Macedonia	296	232	0	0
Poland	1,091	255	922	689
Romania	559	585	485	244
Serbia	272	190	60	0
Slovak Republic	369	388	182	113
Slovenia	366	309	140	100
Turkey	1,523	1,399	0	0
Ukraine	1,161	750	0	0
Total	*10,769*	*8,637*	*3,386*	*1,967*

Source: EBRD-EIB-WBG Enterprise Surveys for Tables 2-1 and E-PRTR v.18 for Tables 3 and 4.

Table A3: Summary statistics

	N	Mean	Median	Std. Dev.	Min	Max
	[1]	[2]	[3]	[4]	[5]	[6]
Table 2 (columns 1-8) & Table 1 (columns 1-2)						
Fixed asset investment	10,769	0.451	0.000	0.498	0.000	1.000
Machinery upgrade	10,769	0.470	0.000	0.499	0.000	1.000
Vehicle upgrade	10,769	0.341	0.000	0.474	0.000	1.000
Heat/cool/light	10,769	0.553	1.000	0.497	0.000	1.000
Green energy generation	10,769	0.124	0.000	0.330	0.000	1.000
Waste and recycling	10,769	0.397	0.000	0.489	0.000	1.000
Energy/water management	10,769	0.344	0.000	0.475	0.000	1.000
Air / other pollution control	10,769	0.198	0.000	0.399	0.000	1.000
Credit constrained	10,769	0.223	0.000	0.416	0.000	1.000
Green management (0-1 scale)	10,769	0.119	0.031	0.178	0.000	0.949
Exporter	10,769	0.253	0.000	0.435	0.000	1.000
Publicly listed	10,769	0.064	0.000	0.245	0.000	1.000
Sole proprietorship	10,769	0.161	0.000	0.367	0.000	1.000
Audited	10,769	0.343	0.000	0.475	0.000	1.000
Age (log)	10,769	2.790	2.944	0.690	0.000	5.323
No. bank branches ('000)	10,769	0.201	0.064	0.338	0.001	2.379
Local banks' average asset size in 2007 (log)	10,769	15.220	15.230	1.535	11.320	17.620
Leave-out mean credit constraints	10,769	0.220	0.167	0.213	0.000	1.000
Change in local average Tier 1 ratio (% points)	10,769	2.081	1.464	7.896	-35.880	44.600
EBA 2014 instrument (% points)	10,769	5.713	4.686	3.184	-0.420	22.230
Leave-out mean green management	10,769	0.140	0.102	0.140	0.000	0.932
Leave-out mean green investment	10,769	0.666	0.824	0.365	0.000	1.000
No data on leave-out mean credit constraints	10,769	0.008	0.000	0.089	0.000	1.000
No data on leave-out green management	10,769	0.145	0.000	0.352	0.000	1.000
No data on leave-out green investment	10,769	0.143	0.000	0.350	0.000	1.000
Table 2 (column 9) & Table 1 (columns 3-4)						
Energy cost per sales, log	8,637	-3.813	-3.758	1.399	-10.600	0.405
Credit constrained	8,637	0.220	0.000	0.414	0.000	1.000
Green management (0-1 scale)	8,637	0.120	0.031	0.176	0.000	0.970
Exporter	8,637	0.256	0.000	0.436	0.000	1.000
Publicly listed	8,637	0.067	0.000	0.250	0.000	1.000
Sole proprietorship	8,637	0.143	0.000	0.350	0.000	1.000
Audited	8,637	0.362	0.000	0.481	0.000	1.000
Age (log)	8,637	2.794	2.944	0.684	0.000	5.323
No. bank branches ('000)	8,637	0.168	0.059	0.284	0.001	2.379
Local banks' average asset size in 2007 (log)	8,637	15.180	15.230	1.594	11.320	17.620
Leave-out mean credit constraints	8,637	0.217	0.167	0.208	0.000	1.000
Change in local average Tier 1 ratio (% points)	8,637	2.315	1.895	8.276	-35.880	44.600
EBA 2014 instrument (% points)	8,637	5.966	5.128	3.355	-0.420	22.230
Leave-out mean green management	8,637	0.142	0.105	0.141	0.000	0.932
Leave-out mean green investment	8,637	0.672	0.833	0.363	0.000	1.000
No data on leave-out mean credit constraints	8,637	0.007	0.000	0.085	0.000	1.000
No data on leave-out green management	8,637	0.143	0.000	0.350	0.000	1.000
No data on leave-out green investment	8,637	0.141	0.000	0.348	0.000	1.000

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Table A3 – continued from previous page	N	Mean	Median	Std. Dev.	Min	Max
	[1]	[2]	[3]	[4]	[5]	[6]
Table 3						
Log (CO_2 emissions + 1)	10,158	18.560	18.420	0.547	18.420	23.220
Log (NO_x emissions + 1)	10,158	11.690	11.510	0.614	11.510	16.720
Log (SO_x emissions + 1)	10,158	12.050	11.920	0.573	11.920	18.670
Log (Hazardous air pollutant emissions + 1)	10,158	22.410	22.400	0.140	22.400	25.580
CO_2 emissions (kg, hyperbolic sine)	10,158	36.430	36.150	1.094	36.150	45.740
NO_x emissions (kg, hyperbolic sine)	10,158	22.680	22.330	1.227	22.330	32.740
SO_x emissions (kg, hyperbolic sine)	10,158	23.410	23.140	1.145	23.140	36.640
Hazardous air pollutant emissions (using toxicity weights, hyperbolic sine)	10,158	44.130	44.100	0.281	44.100	50.470
Local mean credit constraints*	10,158	0.146	0.108	0.121	-0.052	0.605
Local mean green management*	10,158	0.131	0.133	0.056	-0.030	0.287
Listed company (indicator)	10,158	0.051	0.000	0.220	0.000	1.000
Delisted company (indicator)	10,158	0.054	0.000	0.226	0.000	1.000
Log (firm age + 1)	10,158	3.011	3.091	0.725	0.000	5.576
No. bank branches ('000)	10,158	0.199	0.065	0.292	0.001	1.223
Local banks' average asset size in 2007 (log)	10,158	16.140	16.310	0.778	12.820	17.340
No data on local credit constraints/green management	10,158	0.014	0.000	0.116	0.000	1.000
Table 4						
Log (CO_2 emissions + 1)	21,637	18.670	18.420	0.743	18.420	24.350
Log (NO_x emissions + 1)	21,637	11.820	11.510	0.838	11.510	17.570
Log (SO_x emissions + 1)	21,637	12.180	11.920	0.822	11.920	19.900
Log (Hazardous air pollutant emissions + 1)	21,637	22.420	22.400	0.182	22.400	25.880
CO_2 emissions (kg, hyperbolic sine)	21,637	36.640	36.150	1.486	36.150	48.010
NO_x emissions (kg, hyperbolic sine)	21,637	22.940	22.330	1.676	22.330	34.460
SO_x emissions (kg, hyperbolic sine)	21,637	23.660	23.140	1.643	23.140	39.100
Hazardous air pollutant emissions (using toxicity weights, hyperbolic sine)	21,637	44.150	44.100	0.365	44.100	51.080
Listed company (indicator)	21,637	0.056	0.000	0.230	0.000	1.000
Delisted company (indicator)	21,637	0.057	0.000	0.232	0.000	1.000
Log (firm age + 1)	21,637	2.918	2.944	0.817	0.000	5.576
No. bank branches ('000)	21,637	0.174	0.056	0.270	0.001	1.223
Local banks' average asset size in 2007 (log)	21,637	16.240	16.370	0.697	14.120	17.340
Local banks' reliance on wholesale funding in 2007 (share)	21,637	0.738	0.705	0.137	0.473	2.004

Notes: Table A1 contains all variable definitions. *Sources*: EBRD-EIB-WBG Enterprise Surveys, Banking Environment and Performance Survey II, Bureau van Dijk's ORBIS database, European Pollutant Release and Transfer Register v18, and authors' calculations.