Centre for Economic Performance

Discussion Paper
ISSN 2042-2695

No.1837
March 2022

Managerial and financial barriers during the green transition

Ralph De Haas
Ralf Martin
Mirabelle Muûls
Helena Schweiger

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

Abstract
We use data on 10,852 firms across 22 emerging markets to analyse how credit constraints and deficient firm management inhibit corporate investment in green technologies. For identification, we exploit quasi-exogenous variation in local credit conditions. Our results indicate that both credit constraints and green managerial constraints slow down firm investment in more energy efficient and less polluting technologies. Complementary analysis of data from the European Pollutant Release and Transfer Register (E-PRTR) reveals the pollution impact of these constraints. We show that in areas where more firms are credit constrained and weakly managed, industrial facilities systematically emit more CO2 and other gases. This is corroborated by the finding that in areas where banks needed to deleverage more after the Global Financial Crisis, industrial facilities subsequently reduced their carbon emissions considerably less. On aggregate this kept CO2 emissions 5.6% above the level they would have been in the absence of credit constraints.

Keywords: Credit constraints, green management, CO2 emissions, energy efficiency
JEL classification: D22, L23, G32, L20, Q52, Q53

This paper was produced as part of the Centre's Growth Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We thank Cevat Giray Aksoy, Darwin Choi (discussant), Richard Damania (discussant), Pedro de Lima (discussant), Harry Huizinga (discussant), Vasso Ioannidou (discussant), Valerie Karplus (discussant), Hendrik Schuldt (discussant), Piotr ´Spiewanowski, Marie-Theres von Schickfus (discussant), Trang Tan (discussant), Michael Toffel (Department Editor), three anonymous referees, and seminar participants at the EBRD, Bank of Finland, ESRI (Dublin), World Bank, EIB, University of Z¨urich, the LSE-Imperial Business School "Workshop in Environmental Economics", the 25th Annual Conference of the European Association of Environmental and Resource Economists, the 30th Congress of the European Economic Association, the 2020 International Workshop on Financial System Architecture & Stability (Bayes Business School), the 2021 Swiss Winter Conference on Financial Intermediation (Lenzerheide), the 9th Mannheim Conference on Energy and the Environment, and the 7th IWH-FIN-FIRE Work-shop on "Challenges to Financial Stability" for helpful comments and discussions. The views expressed in this paper are ours and not necessarily those of the EBRD.

Ralph De Haas, EBRD, CEPR and KU Leuven. Ralf Martin, Imperial College Business School, CEPR and Centre for Economic Performance, London School of Economics. Mirabelle Muûls, Imperial College Business School and Centre for Economic Performance, London School of Economics. Helena Schweiger, EBRD.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

1 Introduction

The severe impact that climate change will have on future generations is becoming increasingly clear. Droughts, extreme temperatures, floods, and storms all cause substantial human, economic, and ecological losses (Cavallo, Galiani, Noy and Pantano, 2013; Felbermayr and Gröschl, 2014). There now exists incontrovertible evidence that CO_2 and other greenhouse gas (GHG) emissions are the principal cause of climate change (Nordhaus, 2019; Eyring et al., 2021). In the absence of technologies to remove carbon dioxide from the biosphere, mitigating climate change therefore requires a drastic reduction of carbon emissions (Pacala and Socolow, 2004).

For this reason, and in line with commitments under the Paris Climate Agreement, many countries aim to produce zero net greenhouse gas emissions by 2050 at the latest. This green transition requires large-scale corporate investment in cleaner technologies to reduce firms' carbon footprint. Yet, while such green investments may be optimal from a societal point of view, they may not be cost-effective from the perspective of individual firms. The purpose of carbon pricing (via taxes or carbon trading) is to correct this externality. However, even if carbon pricing is in place, organizational constraints—of either a financial or managerial nature—can prevent firms from investing in green technologies that would benefit them. Firms not only differ in their ability to access external funding, they also differ widely 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 external funding and those with stronger green management may then invest more in energy-efficient manufacturing technologies and, as a result, cut greenhouse gas emissions more drastically as well.

Yet, from an environmental point of view, financial and green managerial constraints might not necessarily lead to higher greenhouse gas emissions: causality could go in different directions. For example, clean-technology investment might be mainly determined by regulation and primarily be financed with internal funds. Green management practices could also be the consequence of clean investments rather than their cause. Alternatively, green management could be little more than 'greenwashing' to appease and prevent potential regulatory moves or to superficially address concerns by customers or other stakeholders (Lyon and Maxwell, 2011). Moreover, green and general investments might complement each other, so that any improvements in energy efficiency due to the former would be dominated by increased activity due to the latter, thus resulting in a net increase in emissions.

The aim of this paper is to shed light on these issues, and the associated causality routes, by leveraging a rich new data set on 10,852 firms across 22 emerging markets. Using these data, we analyze how credit and green managerial constraints hold back corporate investment in the abatement of greenhouse gas emissions. These 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 et al., 2013), and misaligned incentives within the firm (Atkin et al., 2017) have all been shown to impede technological adoption and investment in the developing world. This is especially concerning because nearly all of the growth in energy demand and 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. These surveys give us access to information on firms' credit constraints and on their organizational response to climate change in the form of 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. In terms of green investments, we collect data on investments in machinery 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-based data with official 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 3,388 Emerging European industrial facilities.

We pursue three distinct though related empirical approaches. First, we explore the link between, on the one hand, credit and green managerial constraints and, on the other hand, investment in green technologies. To obtain exogenous variation in credit constraints, we develop an instrumental variable based on the characteristics of bank branches located close to each particular firm.

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

Firms tend to predominantly obtain loans from banks that have branches in their vicinity. 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. More specifically, our instrument reflects that firms surrounded by branches of banks that had to boost their Tier 1 capital ratio more during the Global Financial Crisis, found it subsequently more difficult 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 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.

Second, we look at the cross-sectional relationship between pollution outcomes and credit or managerial constraints. Due to insufficient overlap between the sample of facilities with pollution data and firms with survey data, we develop a reduced-form version of our instrumental variable approach. That is, as in the first approach, we rely on the characteristics of banks and firms in the vicinity of each facility in our pollution data. Because we do not have direct data on the credit constraints or green management practices of facility i, we use predicted values for both these variables from the first stage of our first approach. We then create instruments for facility i by averaging these predicted values for survey firms j in the vicinity of i, excluding those in the same sector as i, and relate those to pollution levels.

Third, 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 allows us to assess whether financial constraints matter at all for environmental outcomes and, if so, whether they increase or decrease emissions.

Our main results are threefold. First, financing constraints significantly reduce 'green' investment activities by firms. Credit constrained firms are about 30 percentage points less likely to engage in green investment. The effect is stronger and indeed only significant for green investments embodied in regular ones, such as the purchase of more energy-efficient machinery or cleaner vehicles. In contrast, we find no or weaker effects for more exclusively clean types of investments such as in the on-site generation of green energy or recycling. Green management, on the other hand, has a positive effect on *all* types of green investment that we can distinguish in our survey data. Second, we find that credit constraints increase CO_2 emissions, whereas better green management reduces them. A one standard deviation increase in our index of local credit constraints is associated with close to 5 percent higher emissions. Likewise, a one standard deviation increase in the localized management score reduces emissions by almost 3 percent. Third, and consistent with the previous results, we find positive impacts of financing constraints (that is, more emissions) due to the global financial crisis. We estimate this medium-term effect of the Global Financial Crisis to be, on average across the countries we study, a 5.4 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 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 not only more productive overall but also 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

[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. The adoption of energy efficient technologies remains low (Allcott and Greenstone, 2012). As a result, as much as 44 percent of all reductions in global emissions by 2040 could come from energy efficiency gains (International Energy Agency, 2017).

[3] More generally, Bai, Jin and Serfling (2021) show how U.S. firms with more structured (that is, formal and explicit) management practices improve the management (and subsequent performance) of the establishments they acquire.

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 cross-country 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 hold back 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 matter and 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 and have an uncertain cost-savings potential, financially constrained firms may instead prioritize investments in core activities.[4] This may occur in particular in firms with weaker green management where managers are more biased against investments outside the main business activities.[5]

Related empirical work on the U.S. has shown a negative relationship between credit availability and firm pollution, without actually 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, for a large sample of emerging markets, for an important underlying mechanism: credit constraints reduce firms' investments in pollution abatement.

[4] 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.

[5] 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 respond by moving their polluting activities elsewhere instead of by investing in cleaner production. Bartram, Hou and Kim (2019) show how financially constrained firms in California responded to the introduction of a state-level cap-and-trade program by shifting emissions to their plants in other states.

Third, we offer fresh evidence on the real-economic 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, 2019). Moreover, if crises mainly force inferior-technology and energy-inefficient firms to exit the market, then the energy efficiency of the average surviving firm may improve.[6] 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 et al., 2012).[7] 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.

2 Data

Our analysis requires us to match 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 II as well as data on bank funding from the ORBIS database, and (iii) data on pollution and greenhouse gas 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 we use took place between October 2018

[6] This cleansing effect (Caballero and Hammour, 1994) will be smaller if some high-productivity firms also fall victim to credit constraints (Osotimehin and Pappada, 2015).

[7] An extensive literature 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).

and August 2020 and cover 22 countries in Emerging Europe, where 13,353 firms were interviewed.[8] 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 examine the quality of the local business environment in terms of, for example, infrastructure, labor, and business-government relations. It also collects basic firm characteristics such as its age and its geographic coordinates.[9]

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. In most countries, the response rate for the Green Economy module for our sample 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.

2.1.1 Credit Constraints

By combining answers to various 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.[10] As shown in Appendix Table A3, almost a quarter of all firms are credit constrained (22.5 percent).

[8] Our final sample contains 10,852 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.

[9] In some robustness specifications, we use firm-level control variables. These include firm age and dummy variables for whether the firm is publicly listed, a sole proprietorship, an exporter, and whether an external auditor reviews its financial statements.

[10] 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".

2.1.2 Green Management Practices

The Green Economy module asks firms in considerable 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, as well as whether their performance is evaluated against how well the firm performs on energy consumption, CO_2 emissions or other pollution or environmental targets.[11] The third area covered by the Green Economy module 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.[12]

We normalize the scores for each question so that they have a sample mean of 0 and a standard deviation of 1. We then aggregate them to average z-scores for each of the four areas of green management. Lastly, we create an overall green management z-score as a normalized unweighted average of the four areas. A z-score above zero indicates that a firm's management practices exceed the sample average. Appendix Table A3 confirms that this standardized *Green management* variable is by construction close to zero on average but varies between -1.91 and 6.98.

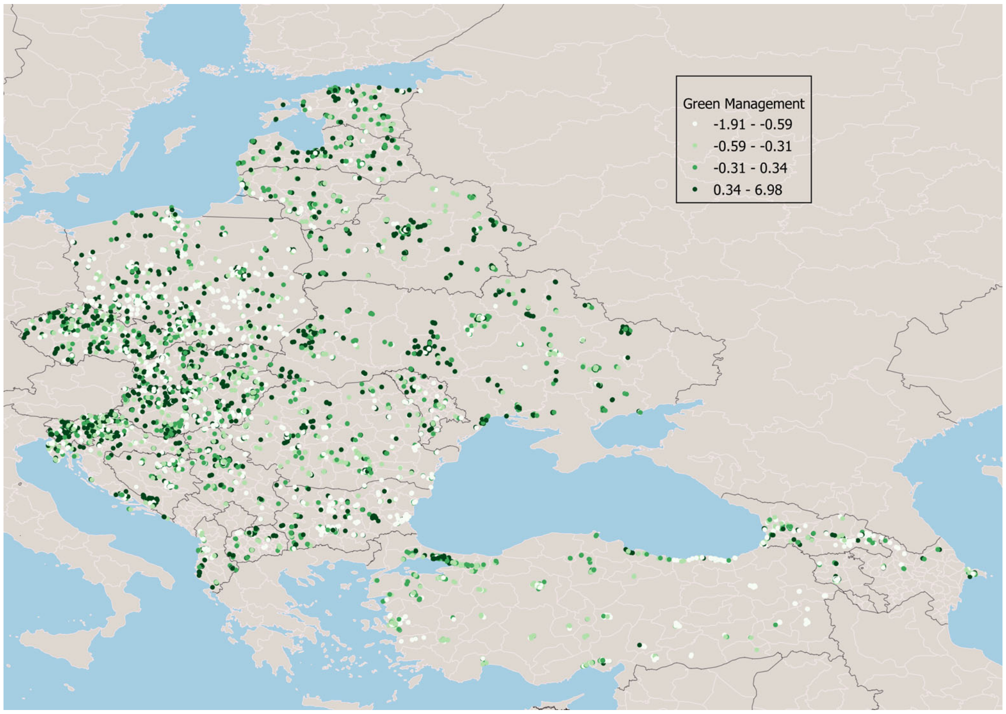
We find that green management practices vary significantly between and within countries, as reported in Table OD.1 in the Online Appendix. In terms of cross-country differences, the data show for example that while only 7.4 percent of all Turkish firms have strategic objectives related to the environment or climate change, this is the case for over 30 percent of all Slovak firms. Likewise, the percentage of firms with a dedicated green manager varies between 2.6 percent in Azerbaijan and 22.6 percent in the Czech Republic. While almost 55 percent of firms in our sample monitor their energy consumption, fewer monitor carbon emissions: About 1 in 7 firms emit CO_2 but less than half of them also monitor these emissions.

Yet, most of the variation in green management practices (91 percent) is found *within* economies,

[11] Earlier research suggests that the link between a firm's strategic environmental objectives and its day-to-day actions depends crucially 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 et al., 2012).

[12] Energy use is a key source of greenhouse gas emissions. Others include physical and chemical processing and the transportation of materials, products, waste, and employees.

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



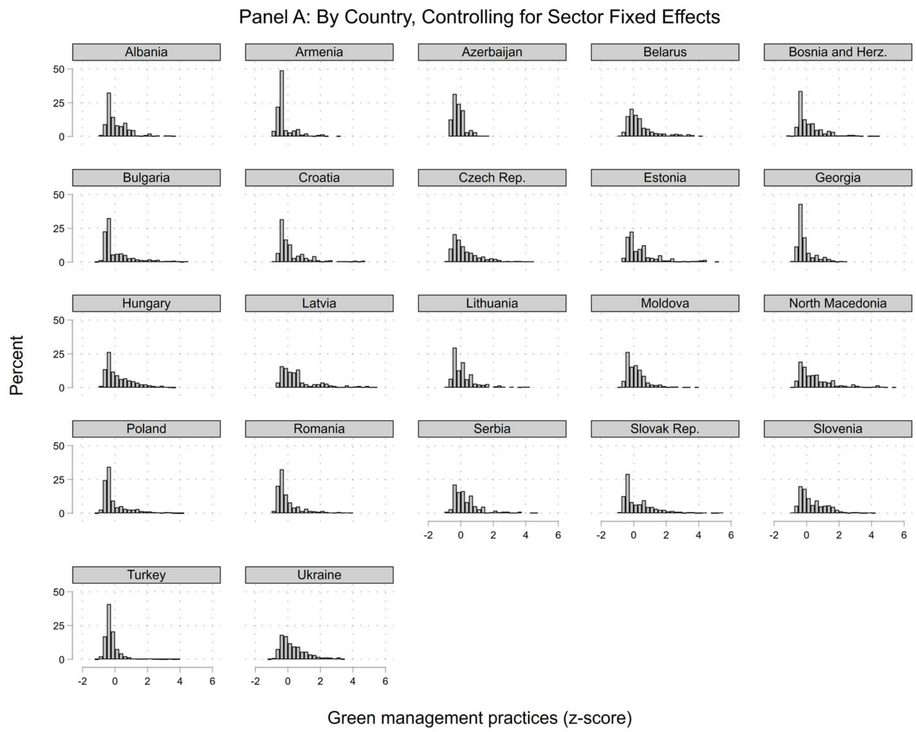
Notes: This map shows the geographical distribution of the 10,852 firms that make up the sample used in Tables 1 and 2. Each dot represents one or several firms in a locality. Darker green colors indicate higher-quality green management. Green management is measured as a z-score based on four areas of 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. *Source*: EBRD-EIB-WBG Enterprise Surveys.

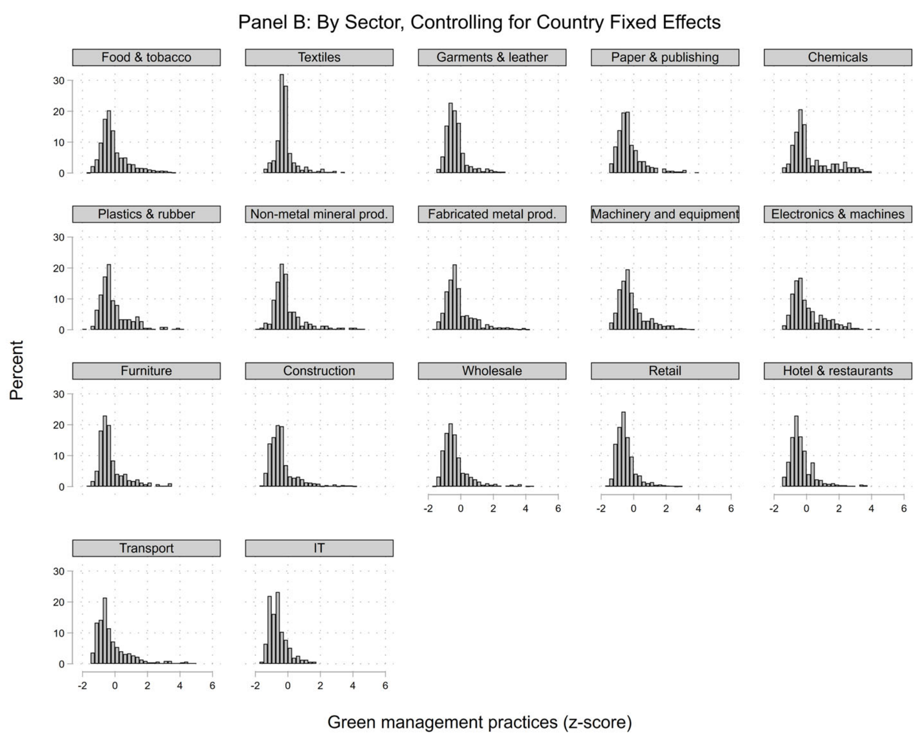
even after accounting for cross-country differences in sectoral composition. Figure 1 depicts firms with low and high green management scores in every economy and this is exactly the granular variation that we use in the rest of the paper. Figure 2 further illustrates the substantial variation in management quality within countries (Panel A) and sectors (Panel B). These distributions are also left-skewed, indicating that within almost all countries and sectors there are a relatively small number of 'green leaders' and a larger group of firms with less-developed green management.

2.1.3 Green Investments

The Enterprise Surveys also ask firm managers whether they made any of the following green investments in the last three years: machinery and equipment upgrades; vehicle upgrades; 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

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 10,852 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.

other pollution.

Most of these investments explicitly target an increase in the firm's energy efficiency and/or a reduction in pollution or other negative environmental impacts. However, some investment types—in particular machinery and vehicle upgrades—mainly have an environmental impact as a by-product of achieving other objectives. For instance, as innovation proceeds, new vintages of machinery and vehicles tend to be more energy efficient than the outdated models they replace. We consider both these direct and indirect types of investments as green ones. Table A3 in the Appendix reports that 74.6 percent of firms made at least one type of green investment in the past three years. 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.

2.2 Bank-Level Data

To implement our IV strategy (which we will 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 the countries in our sample. 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 represented 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.

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, and in 2014, after this crisis and the subsequent Eurozone crisis. For each firm, we first identify the bank branches within a 15 km radius. Second, we calculate the average asset size in 2007 of the banks that operate these branches (weighted by the number of bank branches). This allows us to control for the number and the size of the banks that make up the local credit market around each firm.

The collected bank balance sheets also allow us to construct the Tier 1 capital ratio described in Section 3.1.1 as the ratio of a bank's core equity capital to its total risk-weighted assets. It is calculated in 2007 and 2014 so as to measure, for each firm, the change between those two years in the average Tier 1 capital ratio of banks with branches within a 15 km radius (again weighted by the number of bank branches). The change in local branch-weighted average Tier 1 capital ratio between 2007 and 2014, one of the variables that we will use as an instrument, was on average 2.04 percentage points. Variation between firms is again substantial.

2.3 Pollution Data

We use data from the European Pollutant Release and Transfer Register (E-PRTR, version 18). This register contains annual data on some 30,000 industrial facilities covering 65 economic activities across Europe. For each facility, the data set 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 pollutant releases, we assume that they were equal to threshold reporting values for that pollutant (Table OC.1 lists the pollutants and their reporting thresholds). The actual amount of the pollutant is unknown in these cases as facilities are not required to report them, but they are somewhere below the reporting threshold value.

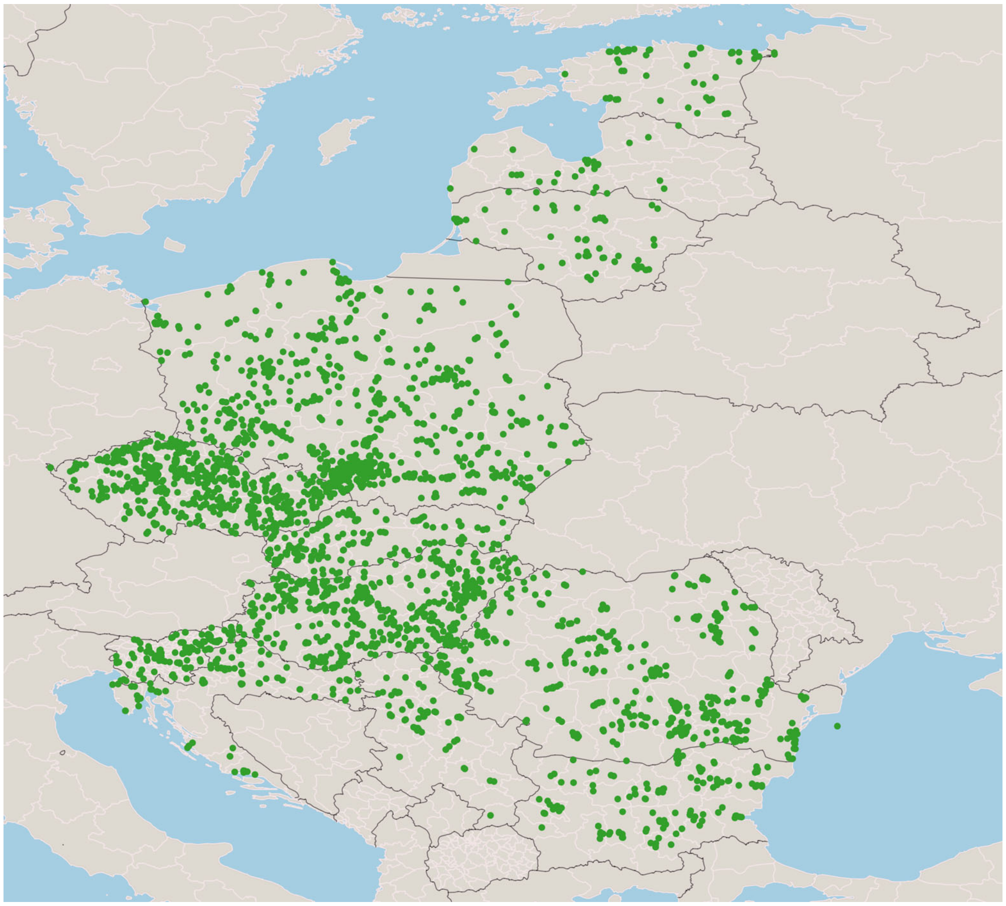
We focus on the 3,388 industrial facilities in 12 Emerging European countries in the E-PRTR that overlap with the Enterprise Surveys data set (Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Serbia, the Slovak Republic and Slovenia).[14] The green dots in 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 different types of emissions across the industrial facilities in our sample. All of the 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 other parts of our analysis.

[13]More details are provided 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).

3 Empirical Methodology

3.1 Regressions of 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 green investment in the past three years and 0 otherwise. Our data allow us to distinguish between various types of green investments (see Section 2.1.3). 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 $Green\ Management$, a z-score measuring the quality of green management (see Section 2.1.2). The vector $\mathbf{X}_i$ represents a set of control variables. These include the population size bracket of a firm's locality, region fixed effects, and controls about the banks located in the firm's vicinity, i.e. within a 15km radius around a firm. These include the number of branches in the vicinity and the amount of assets held by banks owning those branches. We also include sector fixed effects.[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 to be 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 management. This could again bias the OLS estimates upwards. An alternative concern could be 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 in turn.

3.1.1 Instruments for Credit Constraints

We assume that the local banking environment creates meaningful exogenous variation in how credit constrained individual firms are. We observe that many firms—in particular small and medium-sized ones —rely on banks in their vicinity. That is, the banking landscape near firms imposes an exogenous geographical limitation on the banks that firms have access to (Berger et al., 2005).[16]

We can then use variation in those banks' capital availability as a plausibly exogenous driver of credit constraints of firms. More specifically, we look at 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

[15] Locality is the city, town or village where the firm is located. Regions are defined at NUTS 1 or equivalent level, while sectors are defined based on 2-digit ISIC Rev 3.1. More details on region and sector definitions can be found in Online Appendix B.

[16] International evidence shows that due to agency costs, small and medium-sized firms can only access nearby banks. 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.

and after the Global Financial Crisis, and in particular after the 2011 regulatory stress tests by the European Banking Authority, 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, 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. These firms were more exposed to credit rationing in which banks decline to fund some investment projects that are indistinguishable from other projects they *do* finance (Stiglitz and Weiss, 1981).[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. 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 $s(i) \neq s(j)$:

$$CreditConstrainedLO_i = \frac{1}{\#} \sum_{j \text{ s.t. } s(j)\neq s(i) \text{ \& } v(j)=v(i)} CreditConstrained_j \tag{3}$$

Hence, we assume that any shocks ϵ_i to credit constraints affect at most firms within the same 2-digit

[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 would have had a lower regulatory capital ratio prior to 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.

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).[20]

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 suggest that one meaningful reason for exogenous variation in green management is information asymmetry: some firms do not adopt certain green management practices even though it would be in their interest to do so.[21] We therefore build an instrument based 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). In particular, firms close to well-managed firms are likely to be more aware of good green management. For firm i we could 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 none of the firms j are influenced by i in turn. We hence assume that knowledge about green management practices tends to flow from larger to smaller firms.[22] 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.[23] 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.

$$GreenManagementsLO_i = \frac{1}{\#} \sum_{j \text{ s.t. } decile(j)>decile(i) \text{ \& } v(j)=v(i)} GreenManagement_j \qquad (4)$$

For firms in the top size decile or firms that do not have any firms in higher size deciles located

[20]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".

[21]Bloom et al. (2013)'s evidence suggests that informational barriers are a primary reason why firms do not adopt better management practices that would increase their profitability.

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

[23]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.

in their vicinity, we set $GreenManagementsLO_i$ equal to 0 and include an indicator identifying such cases in the regression as a control variable.

3.1.3 Two Stage Least Squares Approach

Consequently, our 2SLS framework comprises of the first-stage equations

$$\Xi_i = \delta_0 + \delta_1 CreditConstrainedLO_i + \delta_2 \Delta Tier1_i + \delta_3 GreenManagementLO_i + \gamma^{'}\mathbf{X_i} + \epsilon_i \quad (5)$$

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

$$Y_i = \delta_0 + \delta_1 Credit\widehat{Constrained}_i + \delta_2 Green\widehat{Management}_i + \gamma^{'}\mathbf{X_i} + \varepsilon_i \quad (6)$$

where the instrumental variables are as detailed above, and 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 limited overlap between the facilities in the E-PRTR 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 our approach there. Specifically, we create credit constraint and green management quality indicators for a facility i in E-PRTR by averaging the predicted credit constraint and green management quality for firms j in the vicinity of i that are not in the same sector as i:[24]

$$Credit\overline{Constraints}_i = \frac{1}{\#} \sum_{j \text{ s.t. } s(j) \neq s(i) \ \& \ v(j)=v(i)} Credit\widehat{Constraints}_i \quad (7)$$

and

$$Green\overline{Management}_i = \frac{1}{\#} \sum_{j \text{ s.t. } s(j) \neq s(i) \ \& \ v(j)=v(i)} Green\widehat{Management}_i \quad (8)$$

[24]We do not have size information for facilities in E-PRTR so we cannot implement the equivalent of the size restriction in Equation (4).

This is measured for 84 percent of all the E-PRTR facilities in our country sample. We can then estimate the following equation:

$$log(Emissions_i) = \beta_0 + \beta_1 Credit\overline{Constraints}_i + \beta_2 Green\overline{Management}_i + \gamma^{'} \mathbf{X_i} + \epsilon_i \qquad (9)$$

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).[25] Bootstrapped standard errors are clustered by facility. $Credit\overline{Constraints}_i$ and $Green\overline{Management}_i$ rely on information from one round of the Enterprise Surveys, so we estimate Equation (9) using data on emissions for the years 2015-17.

3.3 The Global Financial Crisis and Industrial Emissions

Annual E-PRTR data are available from 2007 onward.[26] This allows us to develop a difference-in-differences design where we examine the impact of what is arguably the biggest shock to credit constraints in recent memory: the 2007-08 Global Financial Crisis. In particular, our data allow us to examine the longer-term impact of this crisis on industrial emissions across Emerging Europe. 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. We could envisage three different scenarios: firstly, emissions might simply have reverted back to pre-crisis levels. Secondly, emissions could be lower if the crisis had a cleansing effect as it allowed firms to replace inefficient equipment more swiftly than would have happened without any recession. Thirdly, it could have increased emissions 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 stable deposit base were more stable lenders (Iyer, Peydró, da Rocha-Lopes and Schoar, 2013; De Haas and Van Lelyveld, 2014). As argued before, banks' branch networks were predetermined before the crisis and overlap only partially. This creates a

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

[26] For a sub-sample of firms these data go back to 2004. We use these in robustness tests in Online Appendix D.5.

spatially varied pattern of changes in funding conditions, with facilities in some localities having access to banks with stable funding whereas other facilities had to rely on branches of banks on a steep deleveraging path (Popov and Udell, 2012; Beck et al., 2018). Hence, with one year of pollution data from right before the crisis (2007), we can relate 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.[27] We then create a variable that measures the average reliance on wholesale funding in 2007, just before the outbreak of the Global Financial Crisis, of these surrounding bank branches.

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

$$\begin{aligned} log(Emissions_{it}) = {} & \beta_0 + \beta_1 WSFReliance_{15km,i} \\ & + \beta_2 WSFReliance_{15km,i} \times Post2007_t + \beta_3 Post2007_t \\ & + \zeta_t + \zeta_i + \epsilon_{it}, \end{aligned} \tag{10}$$

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.[28] $WSFReliance$ 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. $\mathbf{X}$ 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 (10) where we split the post 2007 period into further 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).

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

[28] 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 Credit Constraints, Green Management, and Green Investments

Table 1 reports our results on the effects of credit constraints and green management on various types of investment. The table shows OLS estimates (based on Equation 1) in Panel A and the equivalent IV results in Panel B (based on Equation 5). Each column refers to indicators of different kinds of investments. In column 1, we first look at an indicator that is equal to 1 if the firm purchased any fixed assets in the previous fiscal year (general investment). Column 2 refers to any green investment, whereas the remaining columns examine specific types of green investment. Generally we find that credit constraints hamper investment. For example, our IV results in column 1 of Panel B suggest that credit-constrained firms are 35.9 percentage points less likely to engage in any fixed investment. This is in line with expectations.

A priori it is not clear that this extends to green investments. Green investments might not be affected by credit constraints if firms do not rely on external funding for them. This could be the case because green investments might be smaller projects for which no external funding is necessary. It could also be that firms engage in green investments for other reasons than a financial return, for example to superficially demonstrate their green credentials (such as through visible solar panels on their roof). Finally, certain green investments may simply be mandated by strict regulation and firms therefore have to engage in them, finding the necessary funds irrespective of credit constraints (and perhaps foregoing other investments instead).

Importantly, however, in column 2 we find that credit constraints also matter for green investments overall. The IV results indicate that credit-constrained firms are 28 percentage points less likely to engage in green investment overall. Columns 3 to 9 reveal considerable heterogeneity in this result across different types of green investment. The IV results indicate that it is particularly green investments embodied in more general investments—that is, machinery and vehicle upgrades in columns 3 and 4—that is affected. Point estimates are smaller and not statistically significant for purely green investments such as green energy generation or waste and recycling.

Table 1: Firm-Level Credit Constraints, Green Management, and Green Investments

Dependent variable →	Fixed asset investment (indicator)	Green investment (indicator)	Machinery, equipment upgrades	Vehicle upgrades	Improved heating / cooling / lighting	Green energy generation	Waste and recycling	Energy / water management	Air / other pollution control
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Panel A: OLS									
Credit constrained	-0.101***	-0.029***	-0.046***	-0.055***	-0.043***	-0.016*	-0.035***	-0.031***	-0.002
	(0.013)	(0.011)	(0.012)	(0.011)	(0.013)	(0.009)	(0.011)	(0.011)	(0.011)
	[0.000 / 0.000]	[0.021 / 0.003]	[0.001 / 0.000]	[0.000 / 0.000]	[0.004 / 0.000]	[0.170 / 0.066]	[0.008 / 0.003]	[0.008 / 0.007]	[0.848 / 0.775]
Green management	0.075***	0.087***	0.116***	0.106***	0.119***	0.095***	0.126***	0.180***	0.154***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
	[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 / 0.000]	[0.000 / 0.000]
Panel B: IV									
Credit constrained	-0.359**	-0.280*	-0.440***	-0.446***	-0.218	-0.012	-0.254	-0.224	-0.113
	(0.163)	(0.145)	(0.160)	(0.147)	(0.160)	(0.104)	(0.162)	(0.144)	(0.112)
	[0.069 /0.007]	[0.045 / 0.010]	[0.023 / 0.003]	[0.007 / 0.002]	[0.175 / 0.206]	[0.932 / 0.888]	[0.105 / 0.145]	[0.160 / 0.186]	[0.382 / 0.425]
Green management	0.229***	0.242***	0.270***	0.283***	0.281***	0.207***	0.269***	0.345***	0.232***
	(0.056)	(0.041)	(0.040)	(0.036)	(0.055)	(0.029)	(0.040)	(0.040)	(0.030)
	[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 / 0.000]	[0.000 / 0.000]
Observations	10,852	10,852	10,852	10,852	10,852	10,852	10,852	10,852	10,852
Clusters (localities)	2,529	2,529	2,529	2,529	2,529	2,529	2,529	2,529	2,529

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 green investments. 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; 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, the p-values taking into account spatial correlation following Colella et al. (2019) and, second, the p-values under Bonferroni-Holm multiple hypothesis testing. Table 2 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.

Also note that the OLS results suggest a smaller impact for credit constraints across all asset types. This is consistent with an upward bias, for example because only firms that have plans to invest have a chance to know they are facing credit constraints, as discussed in Section 3. Hence those firms are more likely to report being credit constrained.

Turning to the impact of green management practices, we find for all investment types a significant negative impact. A one standard deviation increase in the green management score increases the likelihood of green investment by between 20 and 30 percentage points. Unlike for credit constraints, the size of the impact 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 4 summarizes the IV coefficients of Table 1 (Panel B).

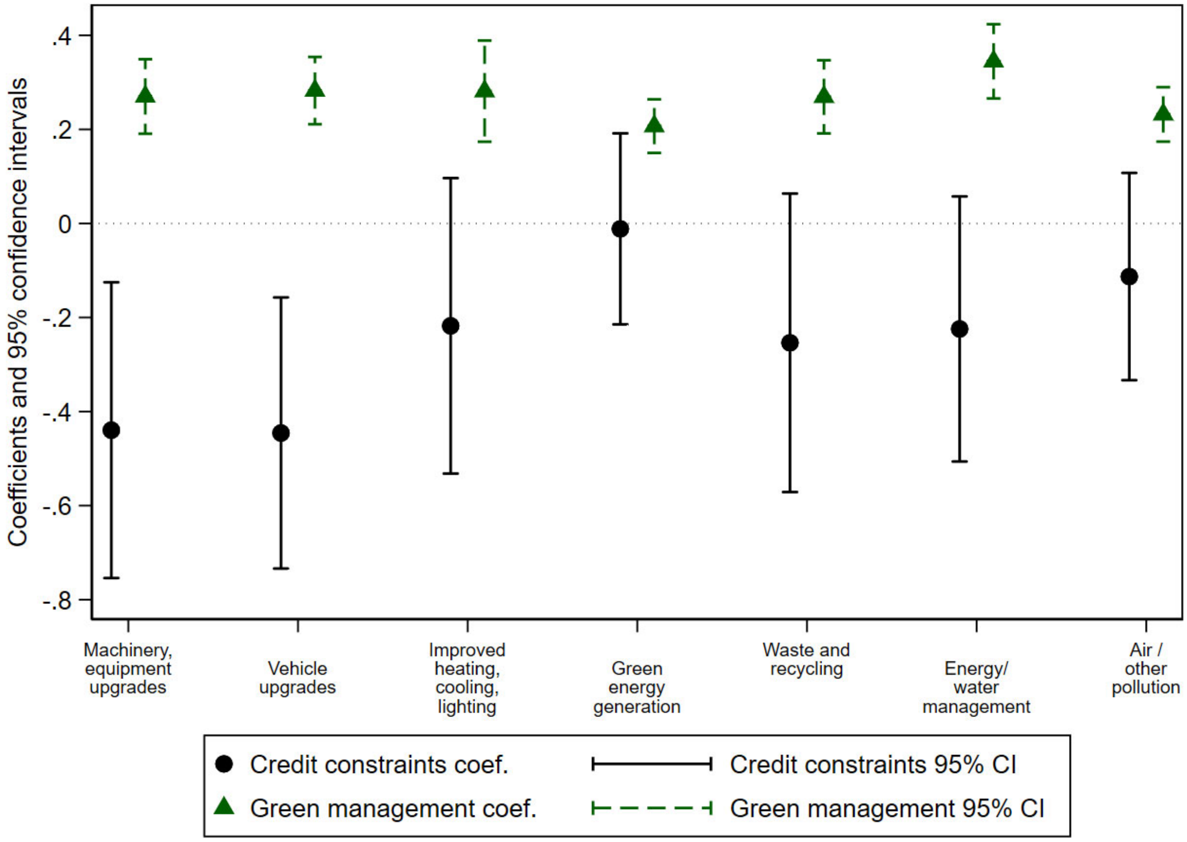
Several additional points are worth discussing in relation to these results. First, it is remarkable that both credit constraints and green management have a distinct impact on green investment. This implies that measures to make finance for green investments more accessible—such as green credit lines—may be an important element of efforts to increase firm-level green investments. The same holds for efforts to improve management practices, such as green consultancy programs.

Second, investment in green technology does not necessarily equate with desirable environmental outcomes. Given the results above we might have a number of distinct concerns. Given that credit constraints seem only relevant for green investments embodied in general investments it might be the case that such investments on net are associated with an increase in emissions. 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 investment, we might be concerned that the impact of these investments on actual pollution outcomes is rather minimal. Hence, we explore in the following sections the impact on actual emission outcomes.

Third, we might ask whether there is something specific about green management that differs from general good management. For a sub-sample of our firms we have data on general management practices based on questions from the US Census Bureau's Management and Organizational Practices Survey (MOPS).[29] We discuss these results in Online Appendix D.3. They indicate that it is specifically green management that drives green investment. In contrast, it is general manage-

[29] These are larger firms with at least 20 employees. Note that this implies a 40 percent drop in sample size.

Figure 4: Firm-Level Credit Constraints, Green Management, and Green Investments



Notes: This figure summarizes the IV coefficients of Table 1, Panel B, 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 - confidence interval.

ment that drives the results for general investment in column 1. This indicates that although green and general management are correlated (p=0.21), they are distinct management 'technologies' that each effect firms' investment activity in different ways.

To conclude this section we also examine the first stage regression in Table 2. We regress each firm's credit constraint indicator and green management score on all three instruments in columns 1 and 2, respectively. Column 1 displays positive and significant coefficients for the first two variables. This confirms that firms are more likely to be credit constrained if companies from other sectors in their vicinity are also constrained. This is also true if the banks in the firms' vicinity had to increase their Tier 1 ratio between 2007 and 2014 substantially.[30] In column 2, the green management

[30]The green management instrument negatively (though statistically weakly) affects the firm's credit constraints.

score is positively affected by the related instrument: the average green management score of nearby larger firms. 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. The first-stage F-statistics on the excluded instruments are comfortably above the rule-of-thumb of 10.[31]

Table 2: Firm-Level IV regressions: First Stage

Dependent variable →	Credit constrained (indicator)	Green management (z-score)
	[1]	[2]
Leave-out mean credit constraints	0.233***	0.074
	(0.036)	(0.096)
Change in average local Tier 1 capital ratio	0.003**	-0.001
	(0.001)	(0.004)
Leave-out mean green management	-0.012*	0.216***
	(0.007)	(0.044)
Observations	10,852	10,852
Clusters	2,529	2,529
R^2	0.145	0.189
F test of excluded instruments	19.588	13.355
SW multivariate F-test of excluded instruments	27.445	13.625
Angrist-Pischke χ^2 test	55.509	28.438
Angrist-Pischke χ^2 test p-value	0.000	0.000
Angrist-Pischke F-test	27.547	14.113
Angrist-Pischke F-test p-value	0.000	0.000
Angrist-Pischke R^2	0.009	0.020

Notes: This table presents the first-stage regressions corresponding to Panel B of Table 1. 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 15km 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.

This could be because better managed larger firms surrounding the firm transfer knowledge on how to obtain financing. Alternatively, good management practices with well defined business plans, good governance etc. will directly lead to less reservations by external funders.

[31] Sanderson-Windmeijer multivariate F-tests yield a p-value of 0.00, indicating that in both cases the null hypothesis of an underidentified endogenous variable can be rejected. Table OD.3 in Online Appendix D provides a battery of additional diagnostic tests in support of our instrumentation strategy.

4.2 Credit constraints, Green Management, and Facility-Level Emissions

While green investments are a necessary condition to de-pollute economic output, there is no guarantee that more investment does necessarily translate into reduced emissions as discussed in the previous section. Unfortunately, there is no comprehensive pollution data available for the firms used in the analysis above to explore this. As discussed in section 3, we therefore make use of the E-PRTR facility-level data that we introduced in Section 2.3.

Table 3 presents estimates of Equation (9) to explain facility emissions through local variation in credit constraints and green management quality.[32] 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 pollutant 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 provide support for 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 one 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 during 2007-14. This suggests that the reduction in the supply of bank lending during and immediately after the Global Financial Crisis resulted in lower green investments in the subsequent

[32]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.

years and led as a result to a worse performance in terms of facilities' carbon emissions and other air pollutants. Moreover, the quality of green management in firms surrounding a facility tends to reduce the emission of CO_2 and NO_x (with the coefficient for SO_x imprecisely estimated). This suggests that firms' green management practices can indeed spillover to other firms and facilities in the vicinity, even when from other sectors.

There is a small but insignificant impact, in the expected direction, of local credit constraints and green management practices on the local emissions of hazardous air pollutants (column 4). This may reflect that in our sample of EU countries, the emissions of hazardous pollutants are subject to strict regulations. Recent evidence from the U.S. shows that financial constraints will 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).

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	0.377**	0.386**	0.298*	0.048
	(0.152)	(0.183)	(0.158)	(0.045)
Local mean green management	-0.090**	-0.094**	-0.055	-0.000
	(0.039)	(0.044)	(0.038)	(0.011)
Observations	10,164	10,164	10,164	10,164
Number of facilities	3,388	3,388	3,388	3,388

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 2 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.

How quantitatively important are the effects found above? And how do the credit constraint effects compare to the green management ones? We explore this by looking at two counterfactual scenarios. First, we examine by 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 badly (green) managed firms to the green management quality of well-managed firms. We implement this by taking 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 suggests a reduction in 2017 of aggregate CO_2 emissions by 5.6 percent when removing credit constraints and by 2.3 percent when improving green management practices. The equivalent numbers for NO_x, SO_x, and hazardous air pollutant emissions are 5.5, 4.2, and 0.7 percent reductions, respectively, for the impact of credit constraints and 2.3, 1.4 and 0.002 percent reduction, respectively, for the impact of green management improvement.

4.3 The Global Financial Crisis, Local Credit Shocks, and Industrial Emissions

As an alternative way of exploring the relevance of credit constraints we examine the effects of the credit constraints, we explore the Great Recession which was responsible for one of the biggest shocks to finance in living memory. Table 4 reports results from our difference-in-differences specification as described in Equation (10). 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 all four types of emissions by industrial facilities during and after the global financial crisis. Yet, the interaction term of interest—between the *Post 2007* dummy and local banks' reliance on wholesale funding—also shows that this decline was significantly lower for those industrial facilities that were surrounded by branches of banks that had to deleverage more in the wake of the global financial crisis. The estimated coefficients are positive, large and statistically significant, at least at the 10 percent level. The estimates indicate that, all else kept constant, 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 in the absence of credit constraints. Moreover, in this setup we now also find statistically significant but economically small impacts on hazardous air pollutants (2.3 percent higher than in the absence of 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 most of the emission differences between facilities surrounded by affected versus less affected banks only emerge during the 2014-17 years. This lag reflects that it takes several years before variation in local credit conditions translates into differences in green investments and, ultimately, in carbon and other emissions.

Figure 5 visualizes the impact of local credit shocks on various facility-level emissions for the individual years in our sample.[33] In line with the second part of Table 4, this figure clearly 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. As mentioned before, for a sub-sample of facilities we have data for the year 2004 as well (but not for 2005-06). While this does not allow us to assess the presence of pre-trends, Figure OD.2 in Online Appendix D.5 does show the absence of significant effects in the pre-treatment year 2004 for most pollutants we examine.

Lastly, Figure 6 provides a quantification of the cumulative impact of local credit constraints on one of our main outcomes, CO_2 emissions. The solid line shows the actual secular 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 5.6 percent above the level they would have been in the absence of financial frictions. The equivalent numbers for NO_x, SO_x, and hazardous air pollutants are 6.7, 9.5, and 3.7 percent, respectively. Note that these figures are remarkably similar to the counterfactual figures reported for credit constraints in the previous section despite the very different econometric design.

[33] That is, we interact year dummies with the $WSFReliance$ variable.

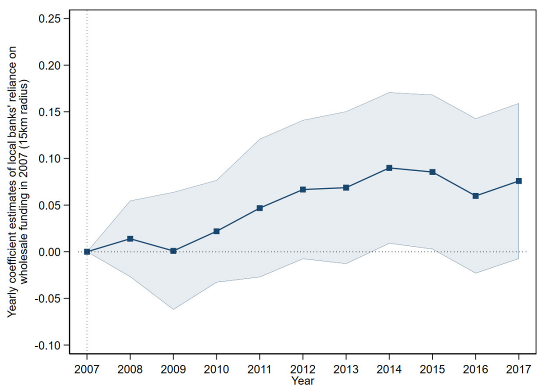
Table 4: Local Credit Shocks and Industrial Emissions

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	0.176	-0.306	-1.750*	-0.497	0.126	-0.073	-1.256	-0.031
wholesale funding	(0.262)	(0.336)	(1.059)	(0.423)	(0.246)	(0.288)	(0.826)	(0.239)
Post 2007 × Local banks'	0.053*	0.057*	0.081**	0.030**				
reliance on wholesale funding	(0.031)	(0.032)	(0.037)	(0.014)				
Post 2007	-0.055**	-0.090***	-0.126***	-0.026**				
	(0.023)	(0.024)	(0.028)	(0.013)				
2008-2013 × Local banks'					0.037	0.035	0.063*	0.028**
reliance on wholesale funding					(0.027)	(0.026)	(0.033)	(0.014)
2014-2017 × Local banks'					0.081**	0.093**	0.111**	0.041**
reliance on wholesale funding					(0.040)	(0.043)	(0.047)	(0.018)
2008-2013					-0.040**	-0.062***	-0.092***	-0.024**
					(0.020)	(0.019)	(0.024)	(0.012)
2014-2017					-0.082***	-0.140***	-0.183***	-0.034**
					(0.029)	(0.032)	(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

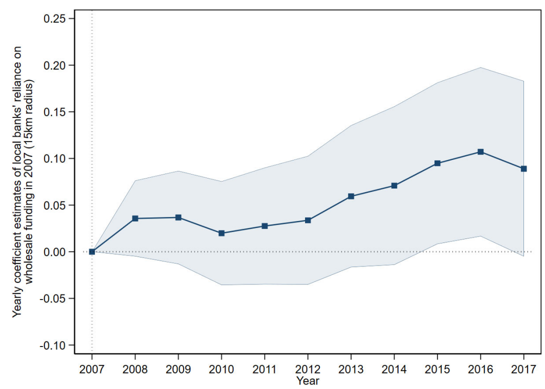
Notes: This table presents OLS regressions to estimate the relation between credit constraints and the log transformation of facility-level emissions of CO_2, NO_x, SO_x, and hazardous air pollutants (using inhalation toxicity weights from EPA's Risk-Screening Environmental Indicators (RSEI) model, see 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.

Figure 5: Local Credit Shocks and Industrial Emissions, 2007-17

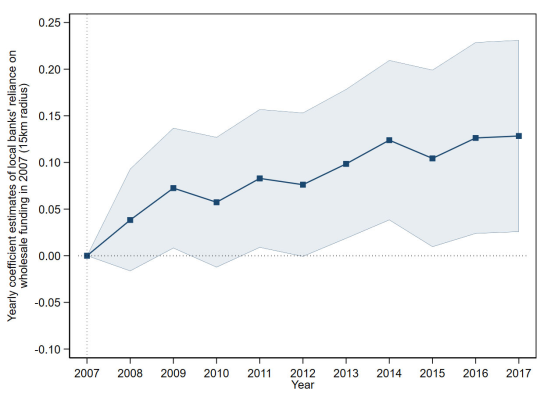
Panel A: CO_2 Emissions



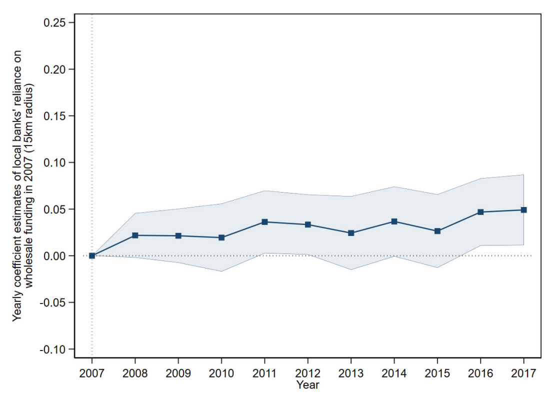
Panel B: NO_x Emissions



Panel C: SO_x Emissions

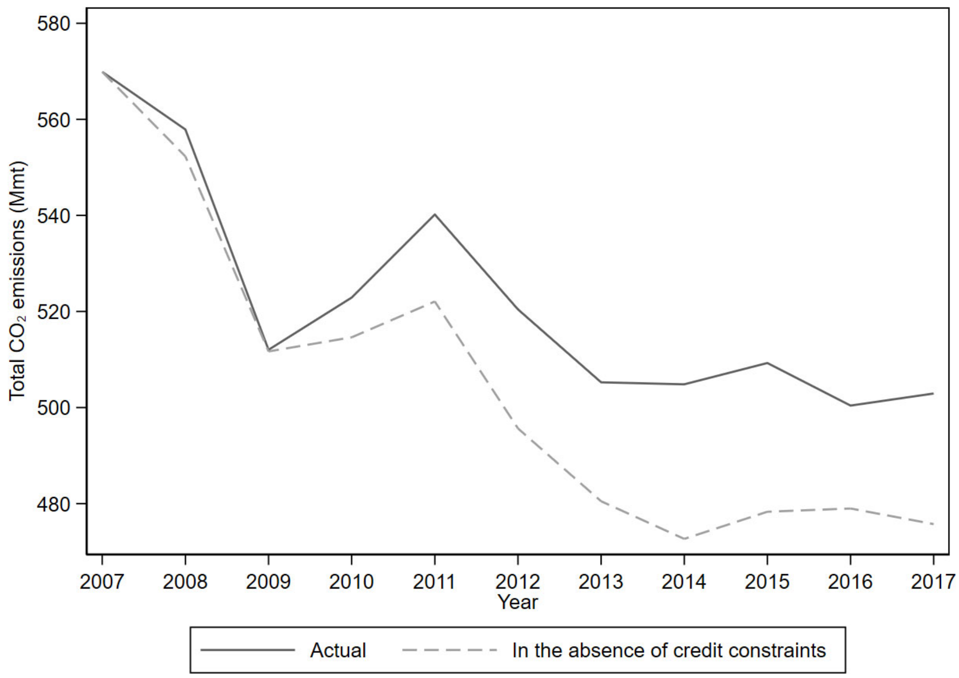


Panel D: Hazardous Air Pollutant Emissions



Notes: These charts summarize the coefficient estimates of difference-in-differences regressions explaining the impact of locality-level credit constraints 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 6: 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 5, Panel A. Mmt - millions of tons.

5 Conclusions

The transition to a low-carbon economy is as challenging as it is urgent. To fulfill the commitments under the Paris Agreement, phasing out the most polluting brown industries and establishing entirely new green industries from scratch will not be enough. Indeed, over the next three decades, substantial investments will also be needed to make industrial production substantially more energy efficient.

The analysis in this paper, based on newly collected data on 10,852 firms across 22 countries, shows how credit constraints continue to hamper firms' implementation of greener technologies and carbon abatement measures. 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 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 (or no) 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 that are contingent on the adoption of better green management practices by firms. Moreover, advisory services, training programs, and other consultancy related interventions can also help firm managers to invest more in energy efficiency and in the abatement of greenhouse gases and other industrial emissions.

References

Agarwal, Sumit and Robert Hauswald (2010) "Distance and private information in lending," *The Review of Financial Studies*, Vol. 23, No. 7, pp. 2757–2788.

Aghion, Philippe, Peter Howitt, and David Mayer-Foulkes (2005) "The Effect of Financial Development on Convergence: Theory and Evidence," *The Quarterly Journal of Economics*, Vol. 120, pp. 73–222.

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky (2014) "Energy Policy with Externalities and Internalities," *Journal of Public Economics*, Vol. 112, pp. 72–88.

Allcott, Hunt and Michael Greenstone (2012) "Is There an Energy Efficiency Gap?," *Journal of Economic Perspectives*, Vol. 26, No. 1, pp. 3–28.

Almeida, Heitor and Murillo Campello (2007) "Financial Constraints, Asset Tangiblity, and Corporate Investment," *Review of Financial Studies*, Vol. 20, No. 5, pp. 1429–1460.

Angrist, Joshua D., Guido W. Imbens, and Alan B. Krueger (1999) "Jackknife Instrumental Variables Estimation," *Journal of Applied Econometrics*, Vol. 14, No. 1, pp. 57–67.

Aterido, Reyes, Mary Hallward-Driemeier, and Carmen Pagés (2011) "Big Constraints to Small Firms' Growth? Business Environment and Employment Growth across Firms," *Economic Development and Cultural Change*, Vol. 59, No. 3, pp. 609–647, April.

Atkin, David, Azam Chaudhry, Shamyla Chaudry, Amit K. Khandelwal, and Eric Verhoogen (2017) "Organizational Barriers to Technology Adoption: Evidence from Soccer-Ball Producers in Pakistan," *The Quarterly Journal of Economics*, Vol. 132, No. 3, pp. 1101–1164.

Bai, John, Wang Jin, and Matthew Serfling (2021) "Management practices and mergers and acquisitions," *Management Science*.

Bartram, Söhnke M., Kewei Hou, and Sehoon Kim (2019) "Real Effects of Climate Policy: Financial Constraints and Spillovers," Working Paper 2019-03-004, Fisher College of Business.

Beck, Thorsten, Hans Degryse, Ralph De Haas, and Neeltje Van Horen (2018) "When Arm's Length is Too Far: Relationship Banking over the Credit Cycle," *Journal of Financial Economics*, Vol. 127, No. 1, pp. 174–196.

Berger, Allen N., Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan, and Jeremy C. Stein (2005) "Does function follow organizational form? Evidence from the lending practices of large and small banks," *Journal of Financial Economics*, Vol. 76, No. 2, pp. 237–269.

Bircan, Çağatay and Ralph De Haas (2020) "The Limits of Lending? Banks and Technology Adoption across Russia," *The Review of Financial Studies*, Vol. 33, No. 2, pp. 536–609.

Bloom, Nicholas, Christos Genakos, Ralf Martin, and Raffaella Sadun (2010) "Modern Management: Good for the Environment or Just Hot Air?," *The Economic Journal*, Vol. 120, No. 544, pp. 551–572.

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts (2013) "Does management matter? Evidence from India," *The Quarterly Journal of Economics*, Vol. 128, No. 1, pp. 1–51.

Bloom, Nicholas and John Van Reenen (2007) "Measuring and Explaining Management Practices Across Firms and Countries," *The Quarterly Journal of Economics*, Vol. 122, No. 4, pp. 1351–1408, 11.

Bureau van Dijk (2022) "Orbis," `https://orbis.bvdinfo.com/` (accessed 2022-01-20). Subscription required.

Burke, M., C. Craxton, C. Kolstad, C. Onda, H. Allcott, E. Baker, L. Barrage, R. Carson, K. Gillingham, J. Graff-Zivin, M. Greenstone, S.Hallegatte, W. Hanemann, G. Heal, S. Hsiang, B. Jones, D.L. Kelly, R. Kopp, M.Kotchen, R. Mendelsohn, K. Meng, G. Metcalf, J. Moreno-Cruz, R. Pindyck, S.Rose, I. Rudik, J. Stock, and R.S.J. Tol (2016) "Opportunities for Advances in Climate Change Economics," *Science*, Vol. 352, No. 6283, pp. 292–293.

Caballero, Ricardo J. and Mohamad L. Hammour (1994) "The Cleansing Effect of Recessions," *American Economic Review*, Vol. 84, No. 5, pp. 1350–1368.

Cagno, Enrico, Ernst Worrell, Andrea Trianni, and Gina Pugliese (2013) "A Novel Approach for Barriers to Industrial Energy Efficiency," *Renewable and Sustainable Energy Reviews*, Vol. 19, pp. 290–308.

Campello, Murillo, John R. Graham, and Campbell R. Harvey (2010) "The Real Effects of Financial Constraints: Evidence from a Financial Crisis," *Journal of Financial Economics*, Vol. 97, No. 3, pp. 470–487.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano (2013) "Catastrophic Natural Disasters and Economic Growth," *The Review of Economics and Statistics*, Vol. 95, pp. 1549–1561.

Cohn, Jonathan B. and Tatyana Deryugina (2018) "Firm-Level Financial Resources and Environmental Spills," mimeo.

Colella, Fabrizio, Rafael Lalive, Seyhun Orcan Sakalli, and Mathias Thoenig (2019) "Inference with Arbitrary Clustering," Discussion Paper 12584, IZA.

Commander, Simon and Jan Svejnar (2011) "Business environment, exports, ownership, and firm performance," *The Review of Economics and Statistics*, Vol. 93, No. 1, pp. 309–337, February.

De Haas, Ralph and Alexander Popov (2019) "Finance and carbon emissions," CEPR Discussion Paper DP14012, Centre for Economic Policy Research.

De Haas, Ralph and Iman Van Lelyveld (2014) "Multinational banks and the global financial crisis: Weathering the perfect storm?" *Journal of Money, Credit and Banking*, Vol. 46, No. s1, pp. 333–364.

Degryse, Hans and Steven Ongena (2005) "Distance, lending relationships, and competition," *Journal of Finance*, Vol. 60, No. 1, pp. 231–266.

Duchin, Ran, Oguzhan Ozbas, and Berk A. Sensoy (2010) "Costly External Finance, Corporate Investment, and the Subprime Mortgage Credit Crisis," *Journal of Financial Economics*, Vol. 97, pp. 418–435.

European Bank for Reconstruction and Development (2012) "EBRD Banking Environment and Performance Survey II," `https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html`. Not publicly available.

——— (2022) "EBRD-EIB-WBG Enterprise Surveys 2018-20," `https://www.beeps-ebrd.com/data/2018-2020/` (version as of 2022-02-08). Registration required for access; locality and GPS information not publicly available.

European Environment Agency (2020) "European Pollutant Release and Transfer Register (E-PRTR) Database version 18," `https://www.eea.europa.eu/data-and-maps/data/member-states-reporting-art-7-under-the-european-pollutant-release-and-transfer-register-e-prtr-regulation-23` (accessed 2022-01-15).

Eyring, Veronika, Nathan P. Gillett, Krishna M. Achuta Rao, Rondrotiana Barimalala, Marcelo Barreiro Parrillo, Nicolas Bellouin, Christophe Cassou, Paul J. Durack, Yu Kosaka, Shayne McGregor, Seung-Ki Min, Olaf Morgenstern, and Ying Sun (2021) "Human Influence on the Climate System," in Valérie Masson-Delmotte, Panmao Zhai, Anna Pirani, Sarah L. Connors, Clotilde Péan, Sophie Berger, Nada Caud, Yang Chen, Leah Goldfarb, Melissa Ines Gomis, Mengtian Huang, Katherine Leitzell, Elisabeth Lonnoy, J. B. Robin Matthews, Thomas K. Maycock, Tim Waterfield, Özge Yelekçi, Rong Yu, and Baiquan Zhou eds. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group 14 I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*: Cambridge University Press.

Felbermayr, Gabriel and Jasmin Gröschl (2014) "Naturally Negative: The Growth Effects of Natural Disasters," *Journal of Development Economics*, Vol. 111, pp. 92–106.

Fisman, Raymond and Jakob Svensson (2007) "Are corruption and taxation really harmful to growth? Firm level evidence," *Journal of Development Economics*, Vol. 83, No. 1, pp. 63–75.

Fu, Xiaolan (2012) "Foreign Direct Investment and Managerial Knowledge Spillovers through the Diffusion of Management Practices," *Journal of Management Studies*, Vol. 49, No. 5, pp. 970–999.

Goetz, Martin (2019) "Financing Conditions and Toxic Emissions," Working Paper 254, SAFE.

Greenstone, Michael, Richard Hornbeck, and Enrico Moretti (2010) "Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings," *Journal of Political Economy*, Vol. 118, No. 3, pp. 536–598.

Gropp, Reint, Thomas Mosk, Steven Ongena, and Carlo Wix (2019) "Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment," *The Review of Financial Studies*, Vol. 32, No. 1, pp. 266–299.

Hottenrott, Hanna, Sascha Rexhauser, and Reinhilde Veugelers (2016) "Organisational Change and the Productivity Effects of Green Technology Adoption," *Resource and Energy Economics*, Vol. 43, pp. 172–194.

Howell, Sabrina T. (2017) "Financing Innovation: Evidence from R&D Grants," *American Economic Review*, Vol. 107, No. 4, pp. 1136–1164.

International Energy Agency (2017) *Energy Efficiency 2017*, Paris: IEA.

Iyer, Rajkamal, José-Luis Peydró, Samuel da Rocha-Lopes, and Antoinette Schoar (2013) "Interbank Liquidity Crunch and the Firm Credit Crunch: Evidence from the 2007-2009 Crisis," *The Review of Financial Studies*, Vol. 27, No. 1, pp. 347–372, 10.

Levine, Ross, Chen Lin, Zigan Wang, and Wensi Xie (2018) "Bank liquidity, credit supply, and the environment," NBER Working Paper 24375, National Bureau of Economic Research.

Lyon, Thomas P and John W Maxwell (2011) "Greenwash: Corporate Environmental Disclosure under Threat of Audit," *Journal of Economics & Management Strategy*, Vol. 20, No. 1, pp. 3–41.

Martin, Ralf, Mirabelle Muûls, Laure de Preux, and Ulrich J. Wagner (2012) "Anatomy of a Paradox: Management Practices, Organizational Structure and Energy Efficiency," *Journal of Environmental Economics and Management*, Vol. 63, pp. 208–223.

Nanda, Ramana and Tom Nicholas (2014) "Did Bank Distress Stifle Innovation during the Great Depression?," *Journal of Financial Economics*, Vol. 114, pp. 273–292.

Nordhaus, William (2019) "Climate Change: The Ultimate Challenge for Economics," *American Economic Review*, Vol. 109, No. 6, pp. 1991–2014.

Osotimehin, Sophie and Francesco Pappada (2015) "Credit Frictions and the Cleansing Effect of Recessions," *Economic Journal*, Vol. 127, pp. 1153–1187.

Pacala, Stephen and Robert H. Socolow (2004) "Stabilization Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies," *Science*, Vol. 305, pp. 968–972.

Pacca, Lucia, Alexander Antonarakis, Patrick Schroder, and Andreas Antoniades (2020) "The Effect of Financial Crises on Air Pollutant Emissions: An Assessment of the Short vs. Medium-term Effects," *Science of the Total Environment*, Vol. 698, January.

Peters, Glen P., Gregg Marland, Corinne Le Quéré, Thomas Boden, Josep G. Canadell, and Michael R. Raupach (2012) "Rapid Growth in CO2 Emissions after the 2008-2009 Global Financial Crisis," *Nature Climate Change*, Vol. 2, pp. 2–4.

Petersen, Mitchell A. and Raghuram G. Rajan (1994) "The benefits of lending relationships: Evidence from small business data," *Journal of Finance*, Vol. 49, No. 1, pp. 3–37.

Popov, Alexander and Gregory F. Udell (2012) "Cross-Border Banking, Credit Access, and the Financial Crisis," *Journal of International Economics*, Vol. 87, No. 1, pp. 147–161.

Ritchie, Hannah and Max Roser (2020) "CO_2 and Greenhouse Gas Emissions," *Our World in Data*. https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions.

Sheldon, Tamara L. (2017) "Asymmetric Effects of the Business Cycle on Carbon Dioxide Emissions," *Energy Economics*, Vol. 61, pp. 289–297.

Shelyapina, Marina G., Inocente Rodríguez-Iznaga, and Vitalii Petranovskii (2021) "Materials for CO_2, SO_x, and NO_x Emission Reduction," in Oxana Vasilievna Kharissova, Boris I. Kharisov, and Leticia M. Torres-Martínez eds. *Handbook of Nanomaterials and Nanocomposites for Energy and Environmental Applications*: Springer, Cham, pp. 2429–2458.

Stiglitz, Joseph E. and Andrew Weiss (1981) "Credit Rationing in Markets with Imperfect Information," *American Economic Journal*, Vol. 71, No. 3, pp. 393–410.

United States Environmental Protection Agency (2022) "Risk-Screening Environmental Indicators model," `https://www.epa.gov/rsei/rsei-toxicity-data-and-calculations/` (accessed 2022-02-03).

Wolfram, Catherine, Orie Shelef, and Paul Gertler (2012) "How Will Energy Demand Develop in the Developing World?," *Journal of Economic Perspectives*, Vol. 26, No. 1, pp. 119–138.

Xu, Qiping and Taehyun Kim (2022) "Financial Constraints and Corporate Environmental Policies," *The Review of Financial Studies*, Vol. 35, No. 2, p. 576–635.

Appendices

Table A1: Variable Definitions and Data Sources

Variable name	**Variable definition**	**Source**
Tables 1-2		
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
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
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
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	Z-score 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
Listed	1 if firm is a shareholding firm with shares traded in the stock market; 0 otherwise	ES

Continued on next page

Variable name	Table A1 – continued from previous page Variable definition	Source
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
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
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 2 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
Local mean green management	Averages of the predicted values of green management from Table 2 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

Continued on next page

	Table A1 – continued from previous page	
Variable name	**Variable definition**	**Source**
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**		
	Tables 1-2	Table 3	Table 4
Albania	281	0	0
Armenia	373	0	0
Azerbaijan	192	0	0
Belarus	540	0	0
Bosnia and Herz.	270	0	0
Bulgaria	625	130	72
Croatia	303	95	0
Czech Rep.	399	686	377
Estonia	261	71	37
Georgia	408	0	0
Hungary	723	525	285
Latvia	244	29	11
Lithuania	310	63	39
Moldova	269	0	0
North Macedonia	296	0	0
Poland	1,091	922	689
Romania	559	485	244
Serbia	272	60	0
Slovak Rep.	369	182	113
Slovenia	366	140	100
Turkey	1,523	0	0
Ukraine	1,178	0	0
Total	*10,852*	*3,388*	*1,967*

Source: EBRD-EIB-WBG Enterprise Surveys for Tables 1-2 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]
Tables 1-2						
Fixed asset investment	10,852	0.451	0.000	0.498	0.000	1.000
Green investment	10,852	0.746	1.000	0.435	0.000	1.000
Machinery, equipment upgrades	10,852	0.470	0.000	0.499	0.000	1.000
Vehicle upgrades	10,852	0.340	0.000	0.474	0.000	1.000
Improved heating / cooling / lighting	10,852	0.553	1.000	0.497	0.000	1.000
Green energy generation	10,852	0.124	0.000	0.330	0.000	1.000
Waste and recycling	10,852	0.396	0.000	0.489	0.000	1.000
Energy/water management	10,852	0.344	0.000	0.475	0.000	1.000
Air / other pollution control	10,852	0.199	0.000	0.399	0.000	1.000
Credit constrained	10,852	0.225	0.000	0.417	0.000	1.000
Green management	10,852	0.066	-0.310	1.033	-1.908	6.980
Exporter	10,852	0.253	0.000	0.435	0.000	1.000
Publicly listed	10,852	0.064	0.000	0.245	0.000	1.000
Sole proprietorship	10,852	0.162	0.000	0.369	0.000	1.000
Audited	10,852	0.342	0.000	0.474	0.000	1.000
Age (log)	10,852	2.789	2.944	0.690	0.000	5.323
No. bank branches ('000)	10,852	0.199	0.064	0.337	0.001	2.379
Local banks' average asset size in 2007 (log)	10,852	15.200	15.230	1.545	11.320	17.620
Leave-out mean credit constraints	10,852	0.220	0.167	0.214	0.000	1.000
Change in local average Tier 1 ratio (% points)	10,852	2.041	1.456	7.905	-35.880	44.600
Leave-out mean green management	10,852	0.278	0.000	0.749	-1.317	6.980
No data on leave-out mean credit constraints	10,852	0.009	0.000	0.092	0.000	1.000
No data on leave-out mean green management	10,852	0.146	0.000	0.353	0.000	1.000
Table 3						
Log (air pollutants + 1)	10,164	18.570	18.430	0.579	0.000	23.220
Log (CO_2 emissions + 1)	10,164	18.560	18.420	0.549	18.420	23.220
Log (GHG emissions +1)	10,164	18.560	18.420	0.579	0.000	23.220
Log (Non-GHG emissions +1)	10,164	13.860	13.750	0.457	0.000	18.820
Air pollutants (kg, hyperbolic sine)	10,164	36.450	36.170	1.157	-0.693	45.740
CO_2 emissions (kg, hyperbolic sine)	10,164	36.430	36.150	1.099	36.150	45.740
GHG emissions (kg, hyperbolic sine)	10,164	36.430	36.150	1.159	-0.693	45.740
Non-GHG emissions (kg, hyperbolic sine)	10,164	27.040	26.810	0.913	-0.693	36.950
Local mean credit constraints	10,164	0.146	0.107	0.121	-0.018	0.635
Local mean green management	10,164	0.100	0.072	0.296	-0.703	0.977
Listed company (indicator)	10,164	0.051	0.000	0.220	0.000	1.000
Delisted company (indicator)	10,164	0.055	0.000	0.227	0.000	1.000
Log (firm age + 1)	10,164	3.011	3.091	0.726	0.000	5.576
No. bank branches ('000)	10,164	0.199	0.065	0.292	0.001	1.223
Local banks' average asset size in 2007 (log)	10,164	16.140	16.310	0.778	12.820	17.340

Continued on next page

Table A3 – continued from previous page

	N	Mean	Median	Std. Dev.	Min	Max
	[1]	[2]	[3]	[4]	[5]	[6]
No data on local mean credit constraints / green management	10,164	0.014	0.000	0.116	0.000	1.000
Table 4						
Log (air pollutants + 1)	21,637	18.680	18.430	0.741	18.430	24.350
Log (CO_2 emissions + 1)	21,637	18.670	18.420	0.743	18.420	24.350
Log (GHG emissions +1)	21,637	18.670	18.420	0.742	18.420	24.350
Log (Non-GHG emissions +1)	21,637	13.960	13.750	0.617	13.750	19.930
Air pollutants (kg, hyperbolic sine)	21,637	36.670	36.170	1.482	36.170	48.010
CO_2 emissions (kg, hyperbolic sine)	21,637	36.640	36.150	1.486	36.150	48.010
GHG emissions (kg, hyperbolic sine)	21,637	36.650	36.150	1.484	36.150	48.010
Non-GHG emissions (kg, hyperbolic sine)	21,637	27.230	26.810	1.235	26.810	39.160
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.

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1836	Lindsay E. Relihan	Is online retail killing coffee shops? Estimating the winners and losers of online retail using customer transaction microdata
1835	Anna D'Ambrosio Vincenzo Scrutinio	A few Euro more: benefit generosity and the optimal path of unemployment benefits
1834	Luke Inman Ralf Martin Dennis Verhoeven	Knowledge spillovers from clean and emerging technologies in the UK
1833	Tommaso Sonno Davide Zufacchi	Epidemics and rapacity of multinational companies
1832	Andreas Teichgraeber John Van Reenen	A policy toolkit to increase research and innovation in the European Union
1831	Antonin Bergeaud Jean-Benoît Eyméoud Thomas Garcia Dorian Henricot	Working from home and corporate real estate
1830	Simon Briole Marc Gurgand Éric Maurin Sandra McNally Jenifer Ruiz-Valenzuela Daniel Santín	The making of civic virtues: a school-based experiment in three countries
1829	Niklas Gohl Peter Haan Claus Michelsen Felix Weinhardt	House price expectations
1828	Max Marczinek Stephan Maurer Ferdinand Rauch	Trade persistence and trader identity - evidence from the demise of the Hanseatic League

1827	Laura Alfaro Cathy Bao Maggie X. Chen Junjie Hong Claudia Steinwender	Omnia Juncta in Uno: foreign powers and trademark protection in Shanghai's concession era
1826	Thomas Sampson	Technology transfer in global value chains
1825	Nicholas Bloom Leonardo Iacovone Mariana Pereira-López John Van Reenen	Management and misallocation in Mexico
1824	Swati Dhingra Thomas Sampson	Expecting Brexit
1823	Gabriel M. Ahlfeldt Duncan Roth Tobias Seidel	Optimal minimum wages
1822	Fernando Borraz Felipe Carozzi Nicolás González-Pampillón Leandro Zipitría	Local retail prices, product varieties and neighborhood change
1821	Nicholas Bloom Takafumi Kawakubo Charlotte Meng Paul Mizen Rebecca Riley Tatsuro Senga John Van Reenen	Do well managed firms make better forecasts?
1820	Oriana Bandiera Nidhi Parekh Barbara Petrongolo Michelle Rao	Men are from Mars, and women too: a Bayesian meta-analysis of overconfidence experiments
1819	Olivier Chanel Alberto Prati Morgan Raux	The environmental cost of the international job market for economists

The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
Website: http://cep.lse.ac.uk Twitter: @CEP_LSE