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Managerial and Financial Barriers to the Green Transition

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Abstract. Using data on 10,776 firms across 22 emerging markets, we show that both credit constraints and weak green management hold back corporate investment in green technologies embodied in new machinery, equipment, and vehicles. In contrast, investment in measures to explicitly reduce emissions and other pollution is mainly determined by the quality of a firm's green management and less so by binding credit constraints. Data from the European Pollutant Release and Transfer Register reveal the environmental impact of these organizational constraints. In areas where more firms are credit constrained and weakly managed, industrial facilities systematically emit more CO_2 and pollutants. A counterfactual analysis shows that credit constraints and weak management have respectively kept CO_2 emissions 4.5% and 2.3% above the levels that would have prevailed without such constraints. This is further corroborated by our finding that in localities where banks had to deleverage more due to the global financial crisis, carbon emissions by industrial facilities remained 5.6% higher a decade later.

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1. Introduction

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

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

This paper sheds light on the qualitative and quantitative importance of these constraints by leveraging a rich new data set on 10,776 firms across 22 emerging markets. We use these data to analyze how financial and green managerial constraints hold back corporate investment in green technologies and the abatement of greenhouse gas emissions. Such organizational constraints can hamper green investments in poor countries in particular. A lack of external finance (Aghion et al. 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 growth in greenhouse gas emissions over the next three decades will come from emerging markets and developing countries (Wolfram et al. 2012). Indeed, the transition toward clean energy generation and the decarbonization of emissions-intensive sectors is of even greater importance in emerging economies, where investments prior to economic growth can ensure a green development path. Although all countries must strive to reduce emissions, investing in clean energy in emerging and developing economies stands out as a notably cost-effective approach to addressing climate change.

Our data come from unique face-to-face surveys with firm managers. The surveys give us access to information on firms' credit constraints, green management practices, and green investments. In terms of green management, we collect standardized data on firms' strategic objectives concerning the environment and climate change; whether there is a manager with an explicit mandate to deal with environmental issues; and how the firm sets and monitors targets (if any) related to energy and water use, CO_2 emissions, and other pollutants. Using these novel data, we document that green management practices vary significantly between and within countries.

In terms of green investments, we collect comprehensive data on investments in machinery and equipment upgrades; vehicle upgrades; heating, cooling, and lighting improvements; the on-site generation of green energy[1]; waste minimization, recycling, and waste management; improvements in energy and water management; and measures to control air or other pollution. We combine these survey data with pollution data from the European Pollutant Release and Transfer Register (E-PRTR). This register provides us with information on the emissions of greenhouse gases and other air pollutants by 3,387 industrial facilities in 12 countries.

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

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

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

Using this instrumentation strategy, we find that credit constraints significantly reduce green investment by firms. Credit constrained firms are about 30 percentage points less likely to make a green investment. Importantly, the effect is stronger and indeed only statistically significant for investments in green technologies embodied in more energy-efficient machinery or cleaner vehicles. This shows how credit constraints can slow the adoption of green technologies by firms.

In contrast, we find no clear impact of credit constraints on investments with an explicit focus on energy efficiency or pollution abatement, such as the on-site generation of green energy or recycling. An important distinction between investments in green technologies embedded in new machinery and vehicles, on the one hand, and measures explicitly geared toward increasing energy efficiency and abating pollution, on the other hand, is that the latter are considerably more firm-specific and in many cases site-specific. Such firm-specific assets are difficult to pledge as collateral as they have relatively limited redeployability and hence low liquidation value, especially in an emerging market context. This may help explain why firms' propensity to invest in such measures depends less on the local availability of credit.

The quality of a firm's green management, on the other hand, has a positive effect on *all* types of green investment that we distinguish in our survey data. We also find that better green management leads to a lower energy intensity of overall firm production.

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

We find that the presence of credit constraints leads to higher CO_2 emissions, whereas better green management reduces them. A counterfactual analysis shows that in the absence of local credit constraints, carbon emissions would have been 4.5% lower. Likewise, a significant upgrade in firms' green management practices, to the 75th percentile of the distribution, would have reduced carbon emissions by about 2.3%.

Last, we apply a difference-in-differences design to examine the impact of the biggest shock to financial constraints in recent history: the global financial crisis. More specifically, we argue that local banks' pre-crisis exposure to short-term wholesale funding provides exogenous variation in financial constraints in the wake of the crisis. This again allows us to assess whether credit constraints matter for environmental outcomes and, if so, whether they increase or decrease emissions. In this third part of our analysis, we find—consistent with the previous results—positive impacts of financing constraints (that is, more emissions) due to the global financial crisis. We estimate the medium-term effect of the crisis to be, on average across the countries we study, a 5.6% 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' green investments.[2] Because green 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 green 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 et al. (2010) measure management practices in more than 300 manufacturing firms in the United Kingdom. They find that better managed firms are more productive and less energy and carbon intensive. Martin et al. (2012) find similar results using a measure of green rather than general management practices. One interpretation of these results is that well-managed firms adopt modern manufacturing practices, which allows them to increase productivity by using energy more efficiently.[3] Their managers may be better informed about the costs and benefits of energy efficiency improvements and suffer less from present-biased preferences in which they focus too much on upfront costs and too little on future recurring energy savings (Allcott et al. 2014). Our contribution is to provide direct evidence, based on a large international firm-level data set, for a key mechanism through which green managerial constraints limit energy efficiency improvements in production: the reduced incidence of investments in green technologies and carbon abatement.

Second, we provide microevidence on how credit constraints deter various types of green investments. Credit-constrained firms cannot finance all economically viable projects available to them, but instead need to allocate scarce funding to projects with the highest expected net present value. Earlier evidence shows that credit constraints are responsible for reduced investment even in advanced economies with well-developed capital markets (Almeida and Campello 2007, Campello et al. 2010, Duchin et al. 2010).

The impact of credit constraints on *green* investments may be different from that of other investments—and may differ across types of green investments as well. On the one hand, many of the benefits of green investments—avoided damages from pollution—are by definition external to the firm. The benefit to the firm itself is, in contrast, likely smaller than that of alternative projects, making green projects more marginal to them. Environmental investments also often involve large upfront expenditures (Fowlie et al. 2018) and have uncertain operational cost-savings later in time. They therefore rely more on upfront funding. Payoffs are also likely contingent on current and future regulations—for example, carbon taxes—that are often surrounded by significant uncertainty, particularly in emerging economies. For these reasons, green investments may be especially sensitive to firm-level credit constraints.[4]

On the other hand, to receive bank funding, firms typically need to offer collateral. Some clean investment projects could struggle with this as the required assets are very specific to a given firm—for example, the plumbing associated with a new heating or heat recovery system—or because some of the technologies involved are new and not widespread yet, so that secondary markets do not yet exist. As a consequence, bank funding may not be available for such projects in the first place. A contraction of bank funding, and the resulting cross-firm variation in credit constraints, would consequently have little impact on those types of green projects.

Related empirical work in the United States has shown a negative relationship between credit availability and firm pollution, without observing firms' green investments as an intermediary step in the hypothesized causal chain. In particular, Levine et al. (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. Bartram et al. (2022) show how financially constrained firms in California responded to the introduction of a state-level cap-and-trade program by shifting emissions to other states. Last, Cohn and Deryugina (2018) document a negative relationship between U.S. firms' contemporaneous and lagged cash flow and the occurrence of environmental spills. Our contribution is to provide direct evidence, based on a large sample of emerging markets, for an important mechanism: credit constraints reduce firms' investments in specific types of green technologies.[5]

Third, we offer fresh evidence on the environmental consequences of financial crises. On the one hand, episodes of dysfunction in the financial system can lead to reductions in pollution in the short term simply because economic activity and energy usage decline (Sheldon 2017, De Haas and Popov 2023). Moreover, if crises force inferior-technology and energy-inefficient firms to exit the market, then the energy efficiency of the average surviving firm may improve.[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 et al. (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 microdata 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 and the context of Emerging European economies, after which we discuss our empirical approach in Section 3. Section 4 then provides the empirical results, and Section 5 concludes.

2. Background and Data

Our analysis relies on matching three data sets: (i) information from the EBRD-EIB-WB Enterprise Surveys on firms' credit constraints, green management and green investments (European Bank for Reconstruction and Development 2022); (ii) the exact location of bank branches from the EBRD Banking Environment and Performance Survey (BEPS) II (European Bank for Reconstruction and Development 2012) and data on bank funding from ORBIS; and (iii) data on pollution and emissions from the European Pollutant Release and Transfer Register (E-PRTR) (European Environment Agency 2020). After describing the context of emerging economies and green investments, this section presents each of these data sets in turn.

2.1. Background

Our focus on emerging economies is motivated by several considerations. First, although per capita energy consumption in these countries is typically still low, their rapid economic development presents significant potential for future growth in energy consumption. This highlights the need to develop models of progress that avoid the high-carbon choices pursued by other economies in the past. Unfortunately, current progress is slow: clean energy investment in emerging and developing economies declined by 8% to less than USD 150 billion in 2020.[8] By the end of the 2020s, annual capital spending on clean energy generation and the cleanup of emissions-intensive sectors in these economies needs to expand by more than seven times, to above USD 1 trillion, to put the world on track to reach net-zero emissions by 2050 (IEA 2021). This will not only require improvements in the domestic environment for clean energy investment but also international efforts to accelerate inflows of capital, both public and, especially, private.

Second, on the upside, the estimated cost of emissions reduction in these economies is approximately half that in advanced economies (IEA 2021). Green investment in emerging economies is therefore a relatively cost-effective approach to addressing climate change (Glennerster and Jayachandran 2023). This is emphasized by the volume of new equipment and infrastructure being acquired or constructed: incorporating sustainable solutions into new construction, manufacturing plants, and vehicles from the outset is more straightforward than retrofitting or adapting later on.

Third, there exist major differences in legal and institutional frameworks between advanced economies and emerging ones. These frameworks play a central role in either incentivizing or inhibiting firms to green their production structures. Three aspects determine progress in particular: the depth of the banking sector, the presence (or absence) of carbon pricing mechanisms, and the availability of consultancy services dedicated to sustainability.

Fourth, emerging markets have higher risk levels, encompassing exchange-rate fluctuations, macroeconomic uncertainties, and political instability. These elevated risks can negatively affect investments in general and green investments in particular. The latter often involve higher upfront capital expenditures and longer payback periods.

2.2. Firm-Level Data

We use the Enterprise Surveys to measure the incidence of credit constraints and firms' management practices and green investments. The surveys took place between October 2018 and August 2020 and cover 22 countries in Emerging Europe, where 13,353 firms were interviewed.[9] The Enterprise Surveys involve face-to-face interviews with the owner or main manager of registered firms with at least five employees. They are conducted by experienced teams from reputable international survey firms, and great care is taken to develop protocols to maximize the probability that respondents answer truthfully.[10] Eligible firms are selected using stratified random sampling. The strata are sector (manufacturing, retail, and other services), size (5–19, 20–99, and 100+ employees) and regions within a country. The main purpose of the survey is to measure the quality of the local business environment in terms of, for example, infrastructure, labor, and business-government relations. The survey also collects various firm characteristics and their geographic coordinates.[11]

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

2.2.1. Credit Constraints. To contextualize the credit constraints faced by firms, it is useful to understand the types of banks present and loans on offer in our sample countries. As described in Qi et al. (2023), as part of Emerging Europe's shift from socialist, centrally planned economies to market-based capitalist systems after 1989, these countries gradually established well-functioning banking sectors. After recapitalizing state-owned banks in the early 1990s, countries began privatizing them, often selling controlling interests to foreign strategic investors, primarily multinational banks from Western Europe. Many of these Western banks currently operate subsidiaries with associated branch networks, across multiple countries in this region.

When comparing the typical maturity of bank loans using data from the Enterprise Surveys, we find that in all sample countries, the banking sector is sufficiently developed to not only provide firms with working capital funding (typically less than a year in maturity), but also longer-term funding that can be used for capital expansion and investments. In particular, the median length of the most recent loan (among all firms that have at least one loan outstanding) ranges between 12 months in Azerbaijan and Ukraine to 60 months in Romania and the Slovak Republic. This compares to 24, 48, and 60 months in Italy, Portugal, and Greece, respectively.

To construct our credit constraint indicator, we combine the answers to several survey questions. First, we distinguish between firms with and without 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. Noncredit constrained firms are those that either had no need for credit or whose demand for credit was satisfied.[12] As shown in Table A.3, almost a quarter of all firms are credit constrained (22.3%).

Several other papers have used the same measure of credit constraints (Brown et al. 2011, Popov and Udell 2012, Beck et al. 2018, De Haas et al. 2023). Table A.4 relates our measure to three often-used predictors of whether a firm is financially constrained or not: an SME indicator; firm age; and whether the firm has audited financial accounts. Whether included one-by-one (columns 1–3) or jointly (column 4), we find strong correlations with our credit constrained indicator. This evidence aligns with a substantial literature describing how in developing countries, smaller and younger firms experience higher financing obstacles than larger enterprises (Demirgüç-Kunt et al. 2005, Aghion et al. 2007, Ayyagari et al. 2008). We can also use the Enterprise Surveys question in which firms were asked to rate on a five-point Likert scale "To what degree is access to finance an obstacle to the current operations of this establishment?" Using this question, we create an indicator variable that is one if the firm perceives access to finance to be at least a minor obstacle to its current operations. Column 5 in Table A.4 shows that this subjective measure of financial constraints is also highly correlated with our more objective baseline measure.

To understand the variation of our credit constraints measure, we present in Online Appendix A.1.5 several charts that display it across countries (Figure OA.1) and industries (Figure OA.2), including three European comparator countries—Greece, Italy, and Portugal—as a way to benchmark the data from emerging economies.

These charts confirm that there exists broad cross-country variation in the percentage of firms that are credit constrained, ranging from only 4.8% and 6.0% in the Czech Republic and Slovenia, respectively (both countries with relatively well-developed banking systems), to 48.8% in Ukraine. This range is wider than that across the three comparator countries, reflecting the large variation in Emerging Europe in terms of the size of banking sectors. Figure OA.2 shows that, as expected, the percentages of firms that are credit constrained are lowest in services industries such as hotels, restaurants, and ICT whereas they are considerably higher in various manufacturing sectors.

2.2.2. Green Management Practices. The Green Economy module asks firms in detail about their green management practices in four areas. The first one covers strategic objectives related to the environment and climate change. The second area looks at whether firms employ a manager with an explicit mandate to deal with green issues. Conditional on the presence of such an environmental manager, additional information is collected on whom they report to and whether they are evaluated against how well the firm performs on energy consumption, CO_2 emissions or other pollution or environmental targets.[13] The third area asks whether firms have clear and attainable environmental targets. Last, the fourth area looks at whether firms actively and frequently monitor their energy and water use, as well as CO_2 emissions and other pollutants, to reduce their environmental footprint.

We assign a score between zero and one to each question (see Online Appendix A.1.3 for details) and aggregate them to averages for each of the four areas. Last, we create an overall green management score as an unweighted average of these areas. Table A.3 confirms that *Green management* ranges by construction between zero and one (the sample maximum is below one).

We document that green management practices vary significantly between and within countries (Table OD.1 in the Online Appendix). For example, whereas almost 60% of firms monitor their energy consumption, fewer monitor carbon emissions: almost one in six firms emit CO_2, but less than half of them monitor these emissions. In terms of cross-country differences, we find, for example, that although only 7.4% of Turkish firms have strategic objectives related to the environment or climate change, this is the case for more than 30% of Slovak firms.

Figure OA.2 (b) in the Online Appendix sheds further light on the variation in green management practices across industries. A firm's sector provides a rough indication of the amount of pollution that a firm is likely to generate. A firm's willingness and ability to adopt good green management practices will therefore depend partially on its sector. Our data show that green management practices tend to be more advanced in relatively emission-intensive sectors such as chemicals; plastic and rubber; and metals and minerals. Yet, the figure also shows that these cross-industry differences are relatively muted, indicating that the strong within-country variation in firms' green management practices does not simply reflect industrial composition.

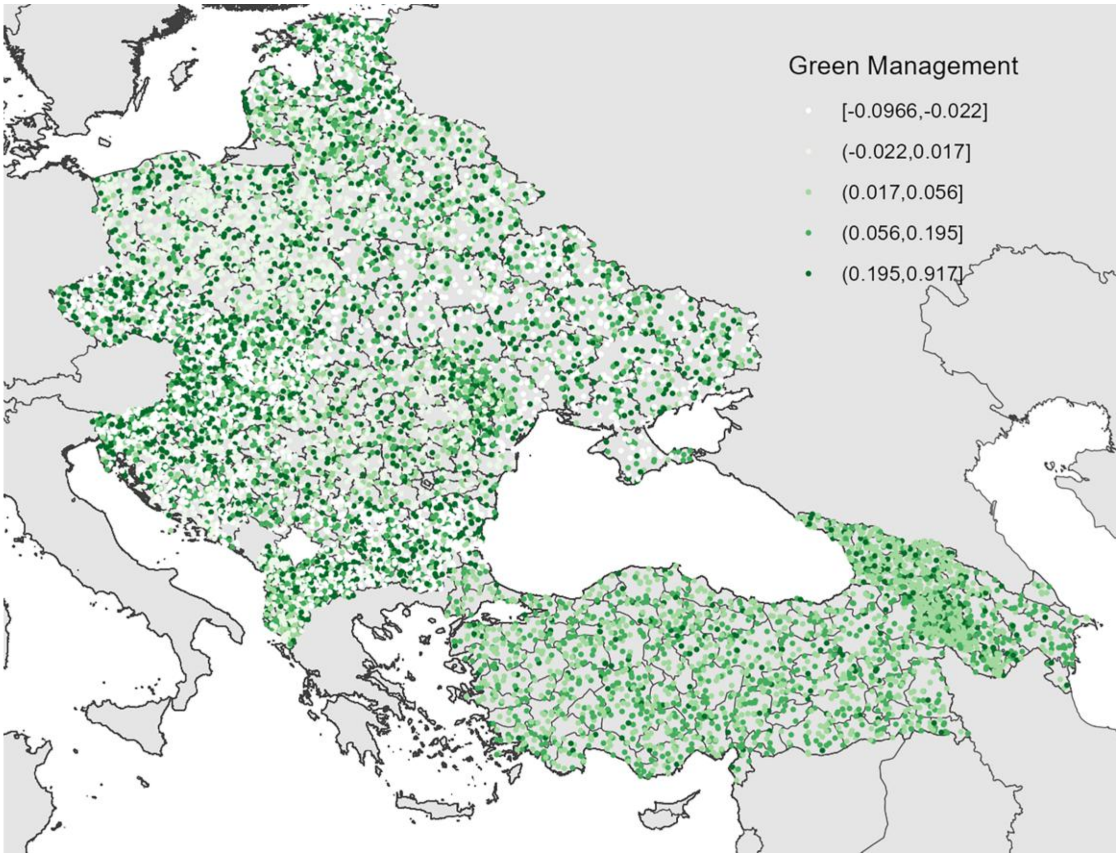
Indeed, most variation in green management practices (91%) occurs *within* countries, even when accounting for international differences in sectoral composition. Figure 1 depicts firms with low and high green management scores in every country: this is the granular variation that we will use in our empirical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

Determinants of Green Management. What determines which firms in a country are green leaders and which ones are green laggards? We can exploit the richness of our firm-level survey data to explore the cross-firm variation in green management practices in more detail. In Table A.5, we first investigate the role of internal factors—firm characteristics such as size and ownership structure—before turning to external factors and stakeholders, such as customer pressure, losses due to extreme weather, and exposure to pollution caused by other firms. Throughout this table, we sift out within-country regional variation and sector-level variation through fixed effects.[14]

Table A.5 reveals several intuitive correlational patterns in the data. First, as firms grow, they may eventually reach a size at which they are obliged to monitor emissions. They may also face pressure from consumers to reduce their impact on the environment. In line with this, column 1 of Table A.5 shows that larger and older firms have better green management. Moreover, earlier work has shown how, in particular in emerging markets, foreign ownership often reduces firm-level energy intensity by transferring cutting-edge technology, management practices and knowledge to acquired firms. This has sometimes been referred to as the "pollution halo effect" (Brucal et al. 2019). In line with this effect, we find that firms where foreign investors hold a stake of at least 25% tend, on average, to have higher green management scores than domestically owned counterparts and firms where foreign investors hold a stake of less than 25%.

Another factor is whether a firm is listed on a stock exchange. Listed firms tend to be subject to greater scrutiny and under more pressure (from institutional investors, for example) to report on ESG issues. Although listed firms make up a relatively small percentage of

Figure 1. (Color online) Geographical Distribution of Firms and the Quality of Their Green Management



Source. EBRD-EIB-WBG Enterprise Surveys.
Notes. This map shows the geographical distribution of the 10,776 firms that make up the sample used in Tables 1 and 2. Each dot represents one or several firms in a locality. Darker colors indicate higher-quality green management. Green management is measured as a score between zero and one 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 use, CO_2, and other pollutant emissions. The map shows green management scores after netting out country fixed effects (so that negative values are possible).

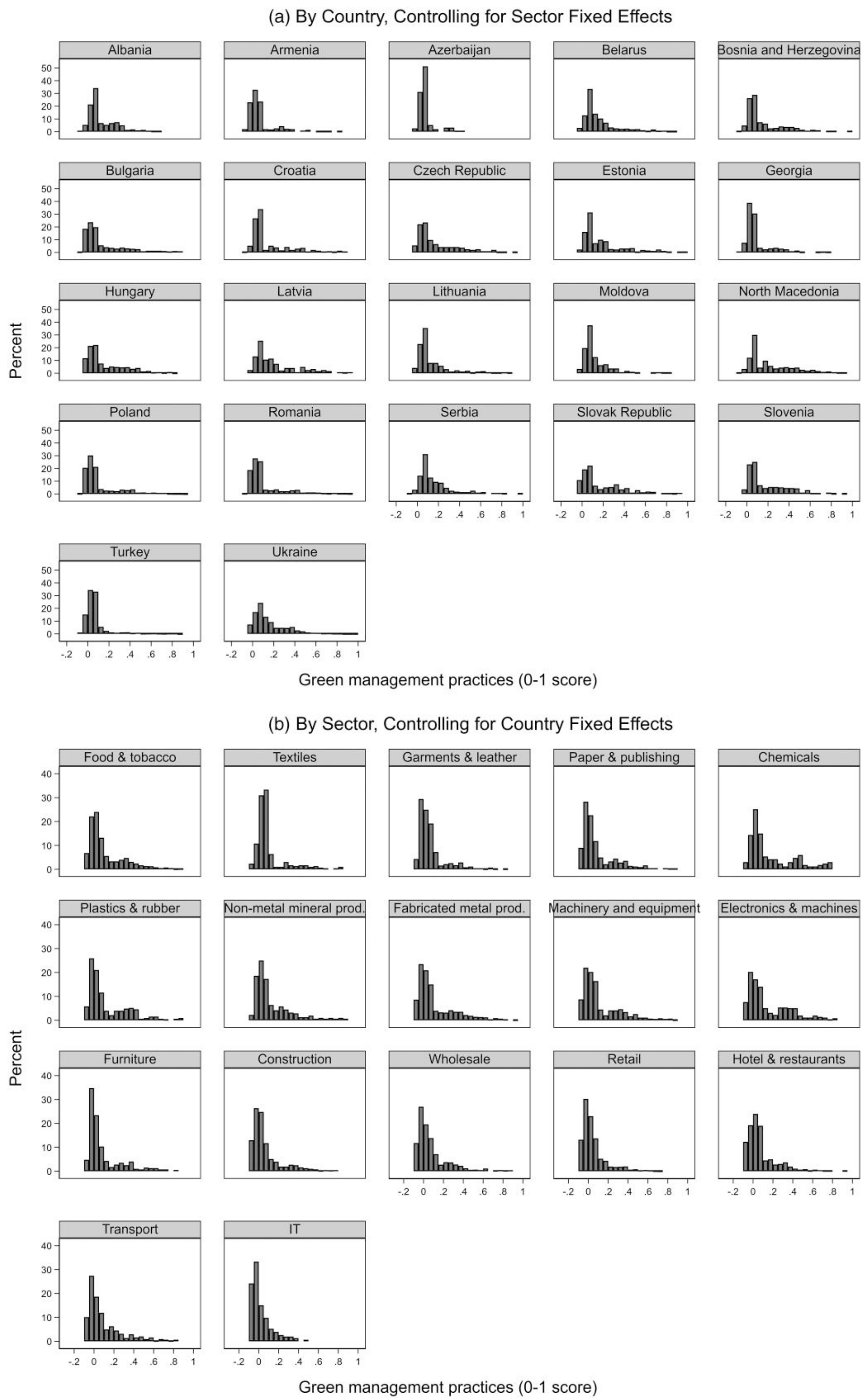
all companies in our sample, the results in Table A.5 confirm that listed firms do, on average, have better green management. In contrast, sole proprietorships and firms without audited financial accounts face the least scrutiny and tend to have lower green management scores.

The results in columns 2 and 3 of the same table explore four external forces that can influence how seriously firm management considers green issues. First, we create a dummy that indicates whether, during the last fiscal year, at least some of a firm's customers required environmental certifications or adherence to certain environmental standards as a condition to do business with the firm. We find that green management scores are, on average, considerably higher for firms experiencing such customer pressure. Indeed, the improvement in green management that is associated with facing customer pressure is almost four times that associated with foreign ownership.

Second, we have survey evidence on whether, over the last three years, the firm experienced any monetary losses due to extreme weather events (such as storms, floods, and droughts). Almost 9% of all firms in our sample experienced monetary losses due to extreme weather events. For instance, Moldova, North Macedonia, and Romania all experienced severe flooding in 2016, and heatwaves and droughts have become a common occurrence in many countries during the summer months. Similarly, severe hailstorms occurred in Croatia, Poland, Romania, and Slovenia. The results in Table A.5 show that firms that experienced such extreme weather first hand take green management issues more seriously.

Third, firms may also be affected by pollution emitted by other firms, and thus experience the negative externalities that bad management can cause. We create an indicator variable showing whether, over the last three years, a firm itself experienced monetary losses

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 10,776 firms that make up the sample used in Tables 1 and 2 by country, controlling for sector fixed effects (a) and by sector, controlling for country fixed effects (b). Sector groupings can be found in Table OB.2 in Online Appendix B.

due to pollution caused by others. We find that exposure to such pollution is correlated with better green management.

Fourth, we measure where a firm is subject to an energy tax or levy. Where energy is expensive, firms have an incentive to use less of it. The estimates in Table A.5 suggest that firms which are subject to an energy tax or levy have substantially better green management practices than firms which are not. That effect is about twice the size of the impact of foreign ownership.[15]

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

A second set of questions deals with investments that explicitly target an increase in the firm's energy efficiency and/or a reduction in pollution or other negative environmental impacts. These include improvements to heating, cooling, and lighting systems; on-site green energy generation; waste minimization, recycling, and waste management; energy and water management; and measures to control air and other pollution.[16]

A key difference between both types of investments is that the latter are considerably more firm-specific and in many cases even site specific. Such firm-specific assets are typically difficult to pledge as collateral because they are characterized by low redeployability and hence low liquidation value (Williamson 1988, Shleifer and Vishny 1992, Kim and Kung 2017) especially in an emerging market context (Liberti and Mian 2010). In contrast, assets such as new and greener vintages of vehicles and standard machinery assets are easier to liquidate and redeploy and banks tend to be more amenable to financing them.[17]

Overall, 74.6% of firms made at least one type of green investment in the past three years. Table A.3 reports that more than half of all firms made improvements to heating, cooling, or lighting systems—making this the most common type of green investment. In contrast, only 12.4% invested in green energy generation on site, possibly because such projects typically require very sizable investments.

Table OA.2 in Online Appendix A.1.5 presents a pairwise correlation matrix of the incidence of all green investments. We uncover two interesting patterns. First, *all* these correlations are positive. This reflects that some of these investments act as complements and/or that these investments respond similarly to deeper causal forces. Second, these correlations are relatively low: none of them exceeds 0.45. As intended, they thus measure clearly distinct green investments and measures.

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

Online Appendix A.1.5 also includes charts that display the variation in the mean of our main dependent and other independent variables across countries (Figure OA.1) and industries (Figure OA.2).[18] We observe variation across countries in terms of firms' green management practices. Firms score an average of just 0.04 (on the 0 to 1 scale) in Azerbaijan, whereas Latvian firms score on average 0.19. In terms of green investments, the most common investments are those to improve heating, cooling, or lighting, with just more than half of all firms in our sample having undertaken at least one such measure over the past three years. In contrast, relatively few firms—only 12.4%—have invested in on-site green energy generation. Green energy generation is most common in the Slovak Republic, where about one in three firms have made such investments in the recent past.

A final interesting observation based on comparing Figures OA.1 and OA.2, in the Online Appendix, is that the cross-country variation in credit constraints, green management, and green investments is considerably larger than the variation in these variables within industries.

2.3. Bank-Level Data

To implement our Instrumental Variable (IV) strategy (described in more detail in Section 3.1) and to control for local credit market conditions in both the OLS and IV estimations, we use detailed data about the banking sectors in our sample countries. First, we access the geographical coordinates of 67,559 branches operated by 609 banks in these countries. These coordinates were collected by specialized consultants as part of the second round of the EBRD Banking Environment and Performance Survey (BEPS II). The 609 banks represent 97% of all bank assets in these 22 countries in 2013, so we have a near complete bank branch footprint. As described in Section 3.1.1, we connect the firm and branch data by drawing circles with a radius of 15 km around the coordinates of each firm and then linking the firm to all branches inside that circle. This allows us to control for the number and size of the banks that make up the local credit market around each firm.

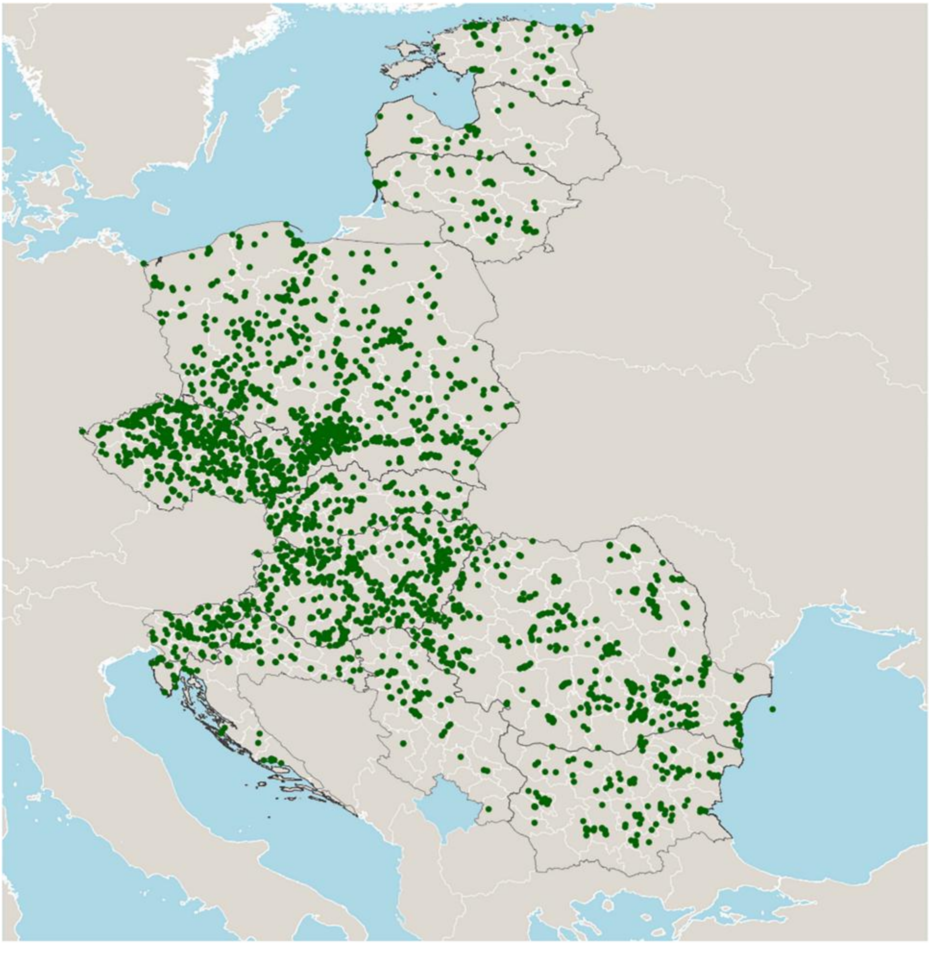
For each branch we know the bank it belongs to. We merge this information with bank balance sheet information from Bureau Van Dijk's ORBIS database (Bureau Van Dijk 2022). We download information about each bank's balance sheet in 2007, just prior to the Global Financial Crisis, in 2014 (after this crisis and the subsequent Eurozone crisis) and in 2016. We also collect information on each bank's performance during the 2014 EBA regulatory stress tests.

2.4. Pollution Data

We use the European Pollutant Release and Transfer Register (E-PRTR, version 18), which contains annual data on some 30,000 industrial facilities covering 65 economic activities across Europe. For each facility, E-PRTR reports the amounts released to air, water, and land from a list of 91 key pollutants including heavy metals, pesticides, greenhouse gases and dioxins.[19] Data are available from 2007 onward. For industrial facilities with missing information on specific releases, we assume that they were equal to threshold reporting values for that pollutant (Table OC.1 lists the pollutants and reporting thresholds).

We focus on 3,387 industrial facilities in 12 Emerging European countries in the E-PRTR that overlap with the Enterprise Surveys country sample (Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Serbia, the Slovak Republic, and Slovenia).[20] The 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. Table A.3 shows substantial variation in the types of emissions across industrial facilities. All the companies owning these facilities have at least one bank branch within a 15-km radius, allowing us to

Figure 3. (Color online) Geographical Distribution of E-PRTR Industrial Facilities in Emerging Europe



Source. European Pollutant Release and Transfer Register (E-PRTR, version 18).
Note. This map shows the geographical distribution of the 3,387 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 2015–2017.

adopt a similar empirical strategy as in the first part of our analysis.

3. Empirical Methodology

3.1. Organizational Constraints to Green Investment

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

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

Here, Y_i is an indicator equal to one if firm i made a particular type of green investment in the past three years and zero otherwise. The independent variables of interest are *Credit Constrained*, an indicator for whether the firm is credit constrained or not (see Section 2.2.1) and *Green Management*, our summary measure of a firm's green management quality (see Section 2.2.2). The vector $\mathbf{X}_i$ represents a set of control variables: the population size bracket of a firm's locality, region fixed effects, and controls about the banks located in a firm's vicinity (that is, within a 15-km radius). We also control for the number of branches in a firm's vicinity and the amount of assets held by the banks owning these branches.[21]

We start by fitting Equation (1) via OLS although this may bias our estimates of the causal impact of credit constraints and of green management on green investments. For example, it may be the case that only rapidly growing firms that want to invest, find themselves credit constrained. This could introduce an upward bias in our OLS estimates. Likewise, successful firms may be more inclined to adopt advanced management practices—including green ones. This could again bias the OLS estimates upward. An alternative concern is that firms engage in greenwashing. That is, firms that have decided not to invest in green technologies might be using aspects of green management (for example, appointing a manager in charge of climate change) as a token measure to appease regulators, investors, or concerned customers. This would introduce a downward bias in our OLS regressions. The OLS estimates may also reflect some common-method bias, as both the dependent and independent variables are derived from the same survey.[22] To deal with these potential issues, we develop several instruments.

3.1.1. Instruments for Credit Constraints. International evidence shows that due to agency costs, most small and medium-sized enterprises can only borrow from nearby banks.[23] This is especially true in many emerging markets (Popov and Udell 2012, Brown et al. 2016, Beck et al. 2018, Bircan and De Haas 2020, De Haas et al. 2023) and developing countries (Mian 2006, Canales and Nanda 2012) where distance constraints bind more and the presence of local bank branches determines small firms' access to credit. The local banking landscape near firms then imposes an exogenous geographical limitation on the banks that firms have access to (Berger et al. 2005). We build on this idea by using variation in local banks' capital availability as a plausibly exogenous driver of the credit constraints of firms.

More specifically, we consider the change in nearby banks' Tier 1 capital ratio. The Tier 1 capital ratio relates a bank's core equity capital to its risk-weighted assets. During and after the Global Financial Crisis, many banks had to improve this capital ratio within a short period of time. Since raising additional equity was costly due to the difficult situation in the global capital markets, most banks deleveraged by shrinking their risk-weighted assets, including through cuts in lending (Gropp et al. 2019).[24] 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.[25] 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).[26]

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

where b indexes bank branches.

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

It is worth noting that in these countries, a large part of the banking sector is owned by EU-based (and hence EBA-reporting) subsidiary banks. For example, in Armenia, important foreign banks are HSBC and the German Procredit Bank. For EU-owned subsidiaries we therefore calculate the difference between the EU parent bank's Tier 1 ratio under the EBA's baseline scenario and the hurdle rate.[27] The construction of our instruments thus builds on an earlier empirical literature showing how shocks to European parent banks' capitalization or to their regulatory regime influence their subsidiaries' lending in emerging Europe (Popov and Udell 2012, Ongena et al. 2013, De Haas and Van Lelyveld 2014). To create the instrument $\Delta Tier1H$, we again combine information on the geographic coordinates of both firms and the branches around them:

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

where b indexes bank branches.

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

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

Hence, we assume that any shocks ϵ_i to credit constraints affect at most firms within the same two-digit sector $s(i)$, but have no impact on other firms in the vicinity of i. Consequently, $CreditConstrainedLO_i$ becomes an indicator of local financing conditions while being quasi random. This is similar to the "leave-one-out" strategy pursued in jackknife approaches (Angrist et al. 1999).[28] For firms without any nearby firms in other sectors, we set $CreditConstrainedLO_i$ equal to zero. In the regressions, we include an indicator variable identifying such cases.

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

3.1.2. Instrument for Green Management. We construct a similar "leave-out" (LO) instrument for green management. Our motivation in this case, and the details of its construction, are slightly different. We build on the idea that depending on their (conditionally exogenous) local environment, some firms have better access to information about good green management than others (Fu 2012).[29] In particular, firms close to well managed other firms are likely to be more aware of good green management. For firm i, we can therefore compute the average green management quality of firms j in its vicinity. This will only then be exogenous with respect to ϵ_i if these firms j are not influenced by i in turn. We hence assume that knowledge about green management flows from larger to smaller firms.[30] 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.[31] For firm i, we then use the average green management scores of firms j that are within a 15-km radius and in all size deciles above i's own decile.

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

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

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

This accounts for the possibility that a firm i could respond to aspects of a (larger) firm j other than management practices. Most notably, suppose a larger firm

j in the neighborhood of i adopts a new environmental technology—solar panels. Then this adoption could directly affect firm i's knowledge set, irrespective of firm j's management quality. Of course, the latter might be causally affected by such an adoption decision as well. However, by including $\overline{Y}_{-i}$ as a control variable, we close this causal channel, thereby isolating the effect of better management quality. For firms in the top size decile, or firms without any nearby firms in higher size deciles, we set $\overline{Y}_{-i}$ equal to zero. In the regressions, we include an indicator variable identifying such cases.

This approach addresses the potential issues about leave out instruments discussed in the previous section in a somewhat different way. First, we address the exclusion restriction and the concern about simultaneity bias by our assumption that information about management practices only flows from larger to smaller firms (but not in reverse).[32] Second, we ensure conditional exclusivity by including $\overline{Y}_{-i}$ as a control variable.

3.1.3. Two-Stage Least Squares (2SLS) Approach. Using the previous instruments, our 2SLS framework comprises the first-stage equations:

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

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

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

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

3.2. Regressions of Industrial Emissions

To examine the impact of credit and managerial constraints on industrial emissions, we use data from the E-PRTR. Unfortunately, there is only limited overlap between the E-PRTR facilities and the firms in the Enterprise Surveys, so we cannot directly extend the approach outlined in the previous section. However, we can adopt a reduced form version of that approach. Specifically, we create credit constraint and green management indicators for an E-PRTR facility i by averaging the predicted credit constraint and green management quality for all firms j in the vicinity of i and that are not in the same sector as i[33]:

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

and

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

This is measured for 98.6% of all the E-PRTR facilities in our country sample. For E-PRTR facilities without any nearby firms in other sectors, we set $Credit\overline{Constraints}_i$ and $Green\overline{Management}_i$ equal to zero. In the regressions, we include an indicator variable identifying such cases. We can then estimate the following equation:

$$\log(Emissions_i) = \beta_0 + \beta_1 Credit\overline{Constraints}_i + \beta_2 Green\overline{Management}_i + \gamma' \mathbf{X_i} + \epsilon_i, \tag{11}$$

where *Emissions* is either the log of CO_2, NO_x, SO_x, or hazardous air pollutant emissions by industrial facility i, and $\mathbf{X}$ is defined analogously to Equation (1).[34] 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 (11) using data on emissions for the years 2015–2017.

3.3. Global Financial Crisis and Industrial Emissions

The third and final part of our analysis comprises a difference-in-differences design to examine the environmental impact of what is arguably the biggest shock to credit constraints in recent history: the 2007–2008 global financial crisis. Annual E-PRTR data are available from 2007 onward so that we can examine the longer-term impact of this crisis on industrial emissions across Emerging Europe.[35] In the short run, it is uncontroversial that the crisis reduced emissions along with economic activity. However, it is not clear what happened after economic activity picked up again. One can envisage three scenarios. First, emissions may simply have reverted back to precrisis levels. Second, emissions could be lower if the crisis had a cleansing effect by allowing firms to replace inefficient equipment more swiftly than would have happened otherwise. Third, emissions could have increased if—due to credit constraints—equipment and machinery was replaced more slowly or not at all.

We explore this by exploiting the fact that banks that had funded themselves with short-term and relatively unstable wholesale funding before the crisis had to deleverage more afterward. In contrast, banks that could count on a steady deposit base were more stable lenders (Iyer et al. 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 spatially varied pattern of changes in funding conditions, with industrial facilities in some localities having access to banks with stable funding whereas other facilities had to rely on banks on a steep deleveraging path (Popov and Udell 2012). Hence, with one year of pollution data from right before the crisis (2007), we can relate subsequent changes in emissions to changes in the immediate financial environment of firms. To do so, we again match each facility with all bank branches within a 15-km radius.[36] We then create a measure of the average reliance on wholesale funding in 2007, just before the global financial crisis, of these surrounding branches.

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

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

where *Emissions* is either the log of CO_2, NO_x, SO_x, or hazardous air pollutant emissions by an industrial facility i in year t. ζ_i are facility fixed effects.[37] *WSFReliance* is the average reliance of local banks on wholesale funding in 2007. In the case of multifacility firms, the distance is calculated relative to the parent company. $Post_{2007}$ is a dummy variable that is one in 2008 and later years and zero 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 (12) where we split the post-2007 period into subperiods. Specifically, we split it into the period covering the Global Financial Crisis and the subsequent Eurozone crisis (2008–2013) and the period after both crises (2014–2017).

4. Empirical Results

4.1. Organizational Constraints and Green Investments

Table 1 examines the first stage of our IV framework. We regress each firm's credit constraint indicator and green management score on all four instruments in columns 1 and 2, respectively. As a further control

Table 1. Firm-Level IV Regressions: First Stage

	Columns 1–8, Table 2		Column 9, Table 2	
Variables	*Credit constrained (indicator)* [1]	*Green management (0–1 score)* [2]	*Credit constrained (indicator)* [3]	*Green management (0–1 score)* [4]
Leave-out mean credit constraints	0.226***	0.020	0.201***	0.030
	(0.036)	(0.017)	(0.040)	(0.019)
Change in average local Tier 1 ratio (% points)	0.004**	−0.001	0.003	0.000
	(0.002)	(0.001)	(0.002)	(0.001)
EBA 2014 *instrument (% points)*	−0.018***	0.002	−0.019***	0.000
	(0.007)	(0.002)	(0.007)	(0.002)
Leave-out mean green management	−0.041	0.250***	−0.032	0.266***
	(0.042)	(0.045)	(0.046)	(0.050)
Leave-out mean green investment	−0.008	0.001	−0.034	0.013
	(0.024)	(0.010)	(0.027)	(0.011)
Region fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Observations	10,776	10,776	8,643	8,643
Clusters (localities)	2,502	2,502	2,118	2,118
R^2	0.145	0.199	0.134	0.215
F test of excluded instruments	16.158	13.183	10.279	10.328
SW multivariate F test	21.510	17.418	13.898	15.234
Angrist-Pischke χ^2	65.047	52.645	42.381	48.089
Angrist-Pischke χ^2 p value	0.000	0.000	0.000	0.000
Angrist-Pischke F test	21.515	17.413	13.991	15.876
Angrist-Pischke F test p value	0.000	0.000	0.000	0.000
Angrist-Pischke R^2	0.010	0.026	0.008	0.030

Notes. This table presents the first-stage regressions corresponding to Panel B of Table 2; columns 1 and 2 are the first stage regressions for results in columns 1–8 in Panel B of Table 2 and columns 3 and 4 are the first stage regressions for results in column 9 in Panel B of Table 2. All regressions include locality-level credit market controls (log local banks' average asset size in a 15-km radius and the number of bank branches in a 15-km radius) and population size class; indicators for no firms in other sectors in a 15-km radius with data on credit constraints and green management and region and sector fixed effects. Table A.1 contains all variable definitions, Table A.3 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 *Statistical significance at the 1%, 5%, and 10% levels, respectively.

variable, we include $\overline{Y}_{-i}$, the average investment outcomes of nearby larger firms.

Column 1 displays positive and significant coefficients for the first two instruments and a negative and significant one for the third instrument. This confirms that firms are more likely to be credit constrained if companies from other sectors in their vicinity are also constrained; if nearby banks had to substantially increase their Tier 1 ratio between 2007 and 2014; and if such nearby banks performed worse during the 2014 EBA stress tests. As expected, we find no relationship between the green management instrument and firms' credit constraints in column 1.

In column 2, the green management score is positively affected by the related instrument: the average green management score of nearby larger firms. Importantly, the instruments for credit constraints are not correlated with the green management score. This supports the identifying assumption underlying our instrumentation strategy: the financial health of banks only affects the investment decisions of firms through its impact on local lending conditions.[38] We find very similar results in columns 3 and 4, the first-stage regressions for column 9 of Table 2—which considers firms' energy efficiency as an outcome. The first-stage F statistics on the excluded instruments are at or above the rule-of-thumb of 10, indicating that the instruments are reasonably but not very strong. Last, $\overline{Y}_{-i}$, the average investment outcomes of nearby larger firms, never enters statistically significantly.[39]

Next, Table 2 reports the relationship between credit constraints and green management quality, on the one hand, and various types of investment, on the other. We first show OLS estimates (based on Equation (1)) in Panel A and then the equivalent IV results in Panel B (based on Equation (7)). Standard errors are clustered by locality.[40] Each column refers to a different investment type. In column 1, we first consider an indicator that is equal to one if the firm purchased any fixed assets in the previous fiscal year (general investment).

Our IV results in Panel B indicate that credit-constrained firms are 30.3 percentage points less likely to engage in any fixed investment. A priori, it is not clear whether this extends to green investments. Green investments might not be affected by credit constraints if firms do not rely on external funding for them, for example, because these are smaller projects. Moreover, certain green investments may simply be mandated by strict regulation. Firms therefore have to implement them, finding the necessary funds irrespective of credit constraints (and perhaps foregoing other investments instead).

The IV results reveal that different types of green investments relate very differently to credit constraints. It is primarily investments in green technologies embodied in general fixed assets that are affected. Credit-constrained firms are 36 and 36.2 percentage points less likely to invest in greener machinery/equipment and vehicle upgrades, as shown in columns 2 and 3, respectively. In sharp contrast, the point estimates are much smaller and not statistically significant for investments that explicitly target lower emissions or pollution (columns 4–8), such as green energy generation or improvements in waste and recycling facilities.[41] As explained in Section 2.1.3, this stark difference likely reflects that the latter types of investments and measures are more firm specific and in many cases even site specific. Such assets are typically difficult to pledge as collateral because they are characterized by low redeployability and hence low liquidation value (Williamson 1988, Shleifer and Vishny 1992, Kim and Kung 2017) especially in an emerging market context (Liberti and Mian 2010). In contrast, assets such as new and greener vintages of vehicles and standard machinery assets are easier to liquidate and redeploy and banks tend to be more amenable to financing them. It is therefore only for those investments that local credit supply shocks have a meaningful impact in firms' ability to finance these assets.[42]

Turning to the effect of green management practices, we find for *all* investment types a significant positive impact. A one-standard-deviation increase in the green management score increases the likelihood of green investment by between 18.1 and 31.8 percentage points. Unlike for credit constraints, the effect size is broadly the same for the different investment types. That is, when a firm is better managed in a green sense, it is not only more likely to invest in measures to directly reduce its carbon and other pollutant emissions but also to integrate environmental considerations in more standard investment decisions.[43] Again, the impact found with IV is larger than using OLS.[44] Although we cannot conclusively determine what causes this difference, it may reflect that at least some firms use green management as a superficial substitute for green investments, as discussed in Section 3. Figure 4 summarizes the IV coefficients of Table 2 (Panel B).[45]

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

A few additional points are worth discussing in relation to these results. First, it is remarkable that for investments in machinery and vehicles that embody

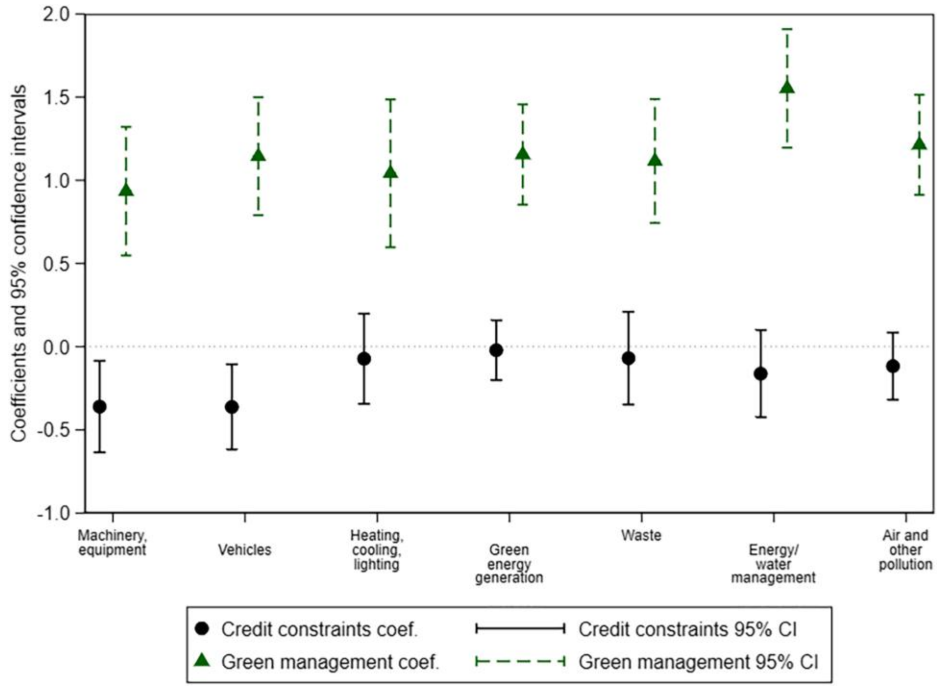
Table 2. Firm-Level Credit Constraints, Green Management, and Green Investments

Variables	*Fixed asset investment (indicator)* [1]	*Machinery, equipment upgrades* [2]	*Vehicle upgrades* [3]	*Improved heating/cooling/lighting* [4]	*Green energy generation* [5]	*Waste and recycling* [6]	*Energy/water management* [7]	*Air/other pollution control* [8]	*Log (energy cost per sales)* [9]
				Panel A: OLS					
Credit constrained	−0.100***	−0.046***	−0.053***	−0.044***	−0.015	−0.036***	−0.031***	−0.000	0.010
	(0.013)	(0.012)	(0.012)	(0.013)	(0.010)	(0.011)	(0.011)	(0.010)	(0.040)
	[0.000]	[0.001/0.000]	[0.000/0.000]	[0.004/0.000]	[0.184/0.083]	[0.006/0.003]	[0.008/0.007]	[0.968/0.956]	[0.843]
Green management	0.444***	0.677***	0.615***	0.708***	0.581***	0.763***	1.054***	0.926***	−0.040
	(0.032)	(0.032)	(0.034)	(0.030)	(0.037)	(0.030)	(0.031)	(0.028)	(0.105)
	[0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.722]
R^2	0.183	0.192	0.176	0.226	0.167	0.243	0.268	0.261	0.202
				Panel B: IV					
Credit constrained	−0.296**	−0.325**	−0.328**	−0.076	−0.028	−0.105	−0.179	−0.099	0.590
	(0.142)	(0.141)	(0.130)	(0.140)	(0.094)	(0.145)	(0.132)	(0.104)	(0.557)
	[0.079]	[0.063/0.026]	[0.027/0.023]	[0.612/0.996]	[0.812/0.996]	[0.441/0.996]	[0.225/0.423]	[0.387/0.996]	[0.290]
Green management	1.060***	0.923***	1.143***	1.055***	1.146***	1.129***	1.555***	1.207***	−1.785***
	(0.257)	(0.198)	(0.180)	(0.228)	(0.155)	(0.189)	(0.182)	(0.154)	(0.554)
	[0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.000/0.000]	[0.001]
R^2	0.118	0.145	0.093	0.217	0.088	0.228	0.225	0.239	0.132
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,776	10,776	10,776	10,776	10,776	10,776	10,776	10,776	8,643
Clusters (localities)	2,502	2,502	2,502	2,502	2,502	2,502	2,502	2,502	2,118

Notes. This table presents OLS (Panel A) and instrumental variables (Panel B) regressions to estimate the relation between, on the one hand, firm-level credit constraints and the quality of green management and, on the other hand, firm-level investments in columns 1–8 and firm-level log energy cost per sales in column 9. All regressions include locality-level credit market controls (log local banks' average asset size in a 15-km radius and the number of bank branches in a 15-km radius); population size class and region and sector fixed effects. Table A.1 contains all variable definitions, Table A.3 provides summary statistics, Table OB.1 provides information on regions, and Table OB.2 on sectors. The square brackets contain, first, p values taking into account spatial correlation following Colella et al. (2019) and, second, p values under Bonferroni-Holm multiple hypothesis testing. Table 1 provides the first stage of the IV regressions in Panel B. Robust standard errors are clustered by locality and shown in parentheses.

***, ** and *Statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 4. (Color online) Firm-Level Credit Constraints, Green Management, and Green Investments



Notes. This figure summarizes the IV coefficients of Table 1, Panel B, columns 2–8, which represent estimates of the relation between, on the one hand, firm-level credit constraints and the quality of green management and, on the other hand, firm-level green investments. Table A.1 contains all variable definitions, and Table A.3 provides summary statistics. Whiskers represents 95% confidence intervals (CI).

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

Second, one may ask whether there is something special about green management that differs from general good management. For a subsample of firms, we have data on general management practices based on questions from the U.S. Census Bureau's Management and Organizational Practices Survey (MOPS).[46] We can therefore perform a "horse race" between firms' general management practices and their green management quality as drivers of green investment behavior. We present these results in Table OD.14, Online Appendix D.3. Importantly, they indicate that it is specifically green management that drives green investment. In contrast, it is general management that drives the results for general investment in column 1 of Table 2. This indicates that although green and general management are somewhat positively correlated ($p = 0.36$), they are nevertheless distinct management 'technologies' that each affect firms' investment activity in different ways.

Third, investment in greener technologies embodied in new equipment, machinery, and vehicles does not necessarily equate desirable environmental outcomes. Such investments may lead to a net increase in emissions, especially given our finding of a nonsignificant effect of credit constraints on energy costs per sale. The same could be true for the green management effect on such embodied green investments. Moreover, although we find that green management also affects "pure" green investments and energy costs per sale, we might be concerned that the impact of these investments on pollution outcomes is rather minimal. Hence, we explore in the following sections the impact on actual greenhouse gas emissions.

Fourth, in the Online Appendix, Table OA.3, we provide a pairwise correlation matrix with our indicator of whether a firm is credit constrained, the various components we use to construct this indicator variable, and the green management score. Importantly, the pairwise correlation between credit constrained and green management is only -0.026. This table also shows negligible correlations between green management and the components used to construct our credit-constrained variable: loan needed (correlation is 0.06); rejected (−0.01); and discouraged (−0.10). In addition, when we rank all firms in our data set according to their green-management score and then group them into terciles, we find that, in the top tercile (i.e., firms with the best green management practices) 21% of these firms are credit constrained. This number is very similar for the terciles with average and low green management skills at 24% and 22%. This mitigates concerns about multicollinearity driving some of our (null) results as regards the relationship between credit constraints and certain investment types.

Finally, we show that the results are not driven by the group of countries for which reporting emissions in the E-PRTR (presented in Section 2.4) is binding.[47] In the Online Appendix, Table OD.10, we interact the two explanatory variables of interest, credit constraints and green management practices, with an E-PRTR dummy that is one for firms located in an E-PRTR–reporting country. Neither the interaction terms with credit constraint nor with green management are statistically significant and our baseline effects remain. Interestingly, column 9 shows that the negative relationship between green management and log energy costs per unit of sales is driven mostly by E-PRTR countries. It may be that better management only translates into lower energy costs when there are sufficient complementarities with country-level institutional frameworks, in line with recent work by Schweiger and Stepanov (2022).

4.2. Organizational Constraints and Facility-Level Emissions

Because there is no comprehensive pollution data available for the firms used in the previous analysis, we now move to the E-PRTR facility-level data that we introduced in Section 2.4. Table 3 presents estimates of Equation (11) to explain facility emissions through local variation in credit constraints and green management quality.[48] 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% of all greenhouse gas emissions in our sample during 2007–2017. 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 et al. 2021): they cause acid deposition, which deteriorates soil and water quality and damages forests, crops and other vegetation. Third, we

Table 3. Credit Constraints, Green Management, and Facility-Level Emissions

Variables	*CO_2* [1]	*NO_x* [2]	*SO_x* [3]	*Hazardous air pollutants* [4]
Local mean credit constraints	0.314**	0.332*	0.283*	0.016
	(0.143)	(0.170)	(0.147)	(0.041)
Local mean green management	−0.518**	−0.538**	−0.295	0.027
	(0.222)	(0.250)	(0.214)	(0.057)
Region fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Observations	10,161	10,161	10,161	10,161
Clusters (facilities)	3,387	3,387	3,387	3,387
R^2	0.070	0.094	0.100	0.035

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 and 2017. For each E-PRTR facility, values for the variables *Local mean credit constraints* and *Local mean green management* are calculated as averages of the predicted values from Table 1 across all firms in other sectors within a 15-km radius around the industrial facility or, in the case of multifacility firms the parent company. If there are no such firms within a 15-km radius, the value is set to zero. All regressions include indicators for the years 2016 and 2017; 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 around the industrial facility or, in the case of multifacility firms the parent company); an indicator for missing local mean credit constraints/green management value (set to zero in the variable itself); locality size controls; and region and sector fixed effects. Table A.1 contains all variable definitions, and Table A.3 provides summary statistics. Bootstrapped standard errors are clustered by facility and shown in parentheses.

***, ** and *Statistical significance at the 1%, 5%, and 10% levels, respectively.

investigate hazardous air pollutants that can cause cancer and other diseases. These impacts are often highly localized. We calculate this outcome as the weighted sum of all air releases in E-PRTR for which inhalation toxicity weights are available in the U.S. Environmental Protection Agency's Risk-Screening Environmental Indicators model (U.S. Environmental Protection Agency 2022) (see Table OC.1 for availability and inhalation toxicity weights).

The results in Table A.3 support the hypothesis that in localities where firms are more credit constrained and less well managed, industrial facilities emit more CO_2, NO_x, and SO_x during 2015–2017. We include year, sector, and regional fixed effects so that this finding holds when comparing facilities within the same sector or subnational region. The local credit constraints pick up spatial variation in the earlier tightening of local lending conditions as banks shored up their Tier 1 capital ratios after 2007. This indicates that the reduction in the supply of bank lending during and immediately after the global financial crisis was associated with a worse performance in terms of facilities' carbon emissions and other air pollutants in the subsequent years. Our earlier results provide a mechanism to explain this: the worsening of credit conditions during the crisis resulted in lower green investments in the subsequent years and as a result more pollution. To be more precise, our results in Table 2 suggest that credit constraints may have held firms back from investing in new and significantly greener vintages of machinery, equipment, and vehicles.[49]

Moreover, the quality of green management in firms near a facility is associated with fewer plant-level emissions of CO_2 and NO_x (with the coefficient for SO_x imprecisely estimated). Here too, our findings suggest that firms' green management practices tend to spill over to other firms and facilities in their vicinity who then reduce their air pollution and CO_2 emissions.

There is only a small and statistically insignificant impact of local credit constraints and green management on the facility emissions of hazardous air pollutants (Table 3, column 4). This may reflect that in our sample of EU countries, the emissions of hazardous pollutants are subject to strict regulations. Evidence from the United States shows that financial constraints only impact firms' toxic emissions when local regulation is rather lax and hence provides firms with discretion in terms of trading off investments in pollution abatement versus other investments (Xu and Kim 2022).

How quantitatively important are the effects we find? How do the credit constraint effects compare with the green management ones? We explore this by considering two counterfactual scenarios. First, we examine how much emissions would fall in the absence of credit constraints, that is, if $\textit{Credit}\overline{\textit{Constraints}}_i$ was equal to zero for all firms. Second, we examine the impact of increasing the quality of firms' green management. We implement this by applying the green management score of the firm at the 75th percentile as a benchmark. That is, we counterfactually set the green management score of firms below the 75th percentile equal to the 75th percentile value. This implies a reduction in average 2015–2017 aggregate CO_2 emissions by 4.5% when removing credit constraints altogether and by 2.3% when improving green management practices. The equivalent numbers for NO_x and SO_x are reductions of 4.7 and 4.0%, respectively, for the impact of credit constraints and reductions of 2.4 and 1.3%, respectively, for the impact of better green management.[50]

4.3. Global Financial Crisis and Industrial Emissions

Another way to gauge the empirical relevance of credit constraints is to explore the global financial crisis, one of the biggest financial shocks in living memory. Table 4 reports results from our difference-in-differences specification as described in Equation (12). We focus on the same emissions as in Table 3. The first four columns provide results from the basic difference-in-differences set up. The negative and significant estimates for the *Post 2007* dummy indicate a secular decline in industrial emissions during and after the financial crisis. Yet, the interaction term of interest—between the *Post 2007* dummy and local banks' precrisis reliance on wholesale funding—shows that this decline was significantly weaker for industrial facilities surrounded by branches of banks that were more vulnerable to funding shortages. The estimated coefficients are positive, large, and statistically significant, at least at the 10% level.[51] All else equal, total emissions of CO_2, NO_x, and SO_x were on average 4.0%, 4.2%, and 6.3% higher than they would have been without credit constraints.[52] In this setup, we also find statistically significant but economically small impacts on hazardous air pollutants (2.3% higher than without credit constraints).

In columns 5–8, we replicate the difference-in-differences analysis but split the postperiod into an early (2008–2013) and later (2014–2017) time window.[53] We find that the CO_2 and NO_x emission differences between facilities surrounded by affected versus less affected banks only emerge during 2014–2017, whereas the SO_x and hazardous air pollutant emission differences already emerge during 2008–2013 but become even stronger during 2014–2017. This lag may reflect, somewhat speculatively, that it takes several years for variation in local credit conditions to translate into differences in green investments and, ultimately, in carbon and other emissions.

Figure 5 illustrates the impact of local credit shocks on facility emissions for each sample year. We interact year dummies with the *WSFReliance* variable and plot these coefficients. In line with the second part of Table 4, this

Table 4. Local Credit Shocks and Industrial Emissions

Variables	CO_2 [1]	NO_x [2]	SO_x [3]	*Hazardous air pollutants* [4]	CO_2 [5]	NO_x [6]	SO_x [7]	*Hazardous air pollutants* [8]
Local banks' reliance on wholesale funding	−0.056	−0.868*	−3.915**	−1.164	0.097	−0.357	−2.818*	−0.616
	(0.443)	(0.482)	(1.537)	(0.884)	(0.348)	(0.429)	(1.481)	(0.528)
Post 2007 × Local banks' reliance on wholesale funding	0.079*	0.084*	0.121**	0.046**				
	(0.046)	(0.046)	(0.053)	(0.021)				
Post 2007	−0.056**	−0.092***	−0.128***	−0.027**				
	(0.023)	(0.023)	(0.028)	(0.013)				
2008–2013 × Local banks' reliance on wholesale funding					0.054	0.051	0.093**	0.041**
					(0.040)	(0.038)	(0.048)	(0.020)
2014–2017 × Local banks' reliance on wholesale funding					0.115*	0.135**	0.176**	0.063**
					(0.059)	(0.064)	(0.069)	(0.027)
2008–2013					−0.039**	−0.061***	−0.093***	−0.024**
					(0.019)	(0.019)	(0.024)	(0.012)
2014–2017					−0.080***	−0.140***	−0.190***	−0.036**
					(0.029)	(0.033)	(0.036)	(0.016)
Facility fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,934	3,934	3,934	3,934	5,901	5,901	5,901	5,901
Clusters (facilities)	1,967	1,967	1,967	1,967	1,967	1,967	1,967	1,967
R^2	0.007	0.042	0.051	0.004	0.008	0.041	0.053	0.004

Notes. This table presents OLS regressions to estimate the relation between local bank-funding shocks and the log transformation of facility-level emissions of CO_2, NO_x, SO_x, and hazardous air pollutants (using inhalation toxicity weights from EPA's Risk-Screening Environmental Indicators (RSEI) model, see Online Appendix C, Table OC.1 for details). Missing pollutant emissions are replaced with the pollutant reporting threshold. The sample consists of all facilities present in E-PRTR in all years between 2007 and 2017. 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 multifacility firms the parent company. 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 around the industrial facility or, in the case of multifacility firms the parent company) and facility fixed effects. Table A.1 contains all variable definitions, and Table A.3 provides summary statistics. Standard errors are clustered by facility and shown in parentheses.

***, ** and *Statistical significance at the 1%, 5%, and 10% levels, respectively.

figure shows how the effects on emissions become economically and statistically more pronounced in later years (especially in earlier years, the annual estimates are not significant). This increasingly strong effect is consistent with (but does not provide conclusive evidence for) our proposed mechanism: It takes time for green investments to materialize and thus for differential access to bank credit to result in differing levels of air pollution. The data do not allow us to assess the presence of pretrends, although for a subsample of facilities we have data for the year 2004 (but not for 2005–2006). Reassuringly, Figure OD.2 in Online Appendix D.5 demonstrates an absence of significant effects in the pretreatment year 2004 for CO_2, NO_x, and hazardous air pollutants.

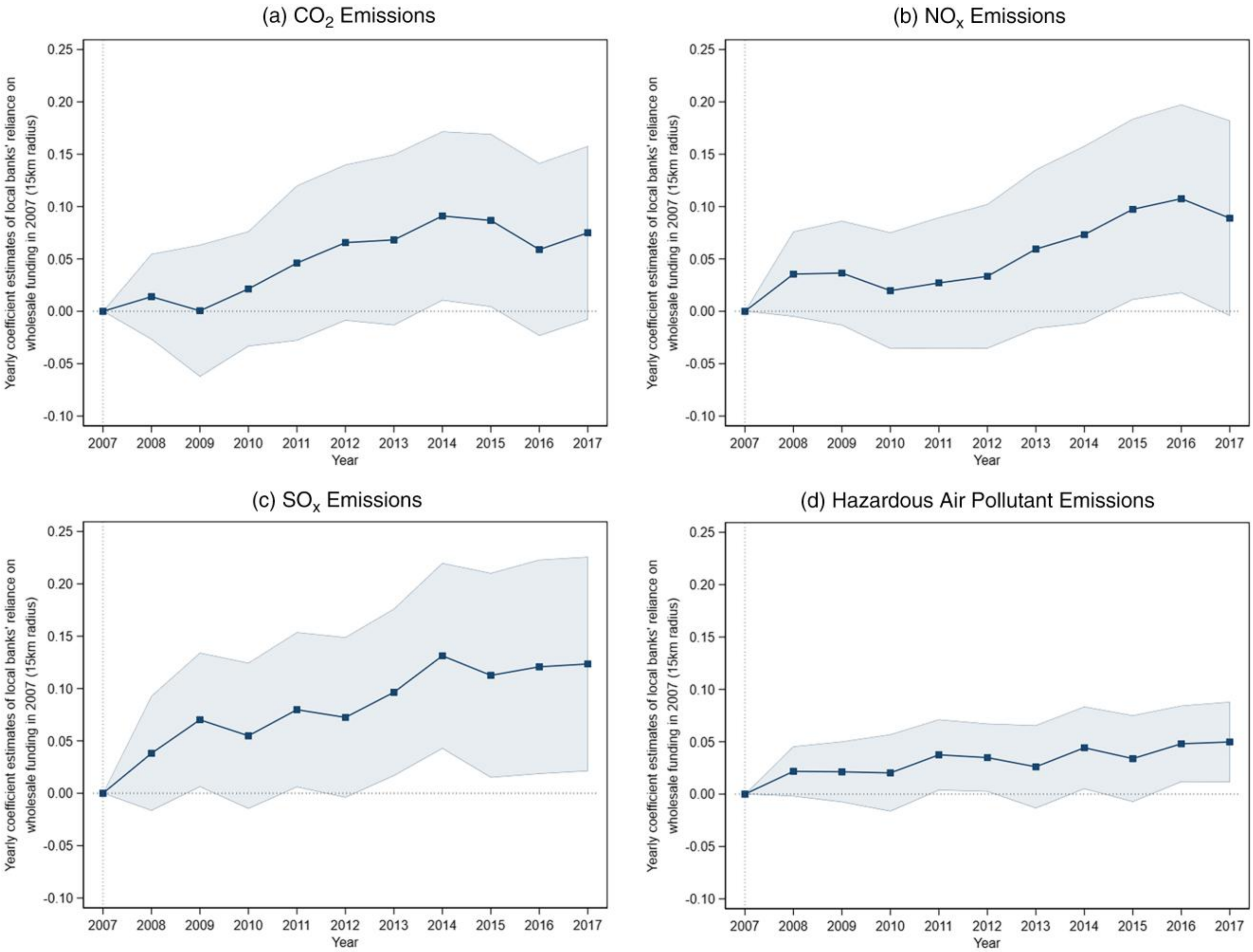
Lastly, Figure 6 provides a quantification of the cumulative impact of local bank-funding shocks on one of our main outcomes, CO_2 emissions. The solid line shows the actual decline in carbon emissions, whereas the dotted line represents the counterfactual that would have emerged in the absence of credit 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 to 5.6% above the level they would have been in the absence of crisis-related financial frictions. The equivalent numbers for NO_x, SO_x, and hazardous air pollutants are 6.7%, 9.5%, and 3.7%, respectively. These figures are remarkably similar to the counterfactual figures reported for credit constraints in the previous section, despite the very different econometric design.

5. Conclusions

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

The analysis in this paper, based on newly collected data on 10,776 firms across 22 countries, shows how credit constraints continue to hamper firms' implementation of greener technologies. The negative impact of credit constraints is particularly true for green investments

Figure 5. (Color online) Local Credit Shocks and Industrial Emissions, 2007–2017



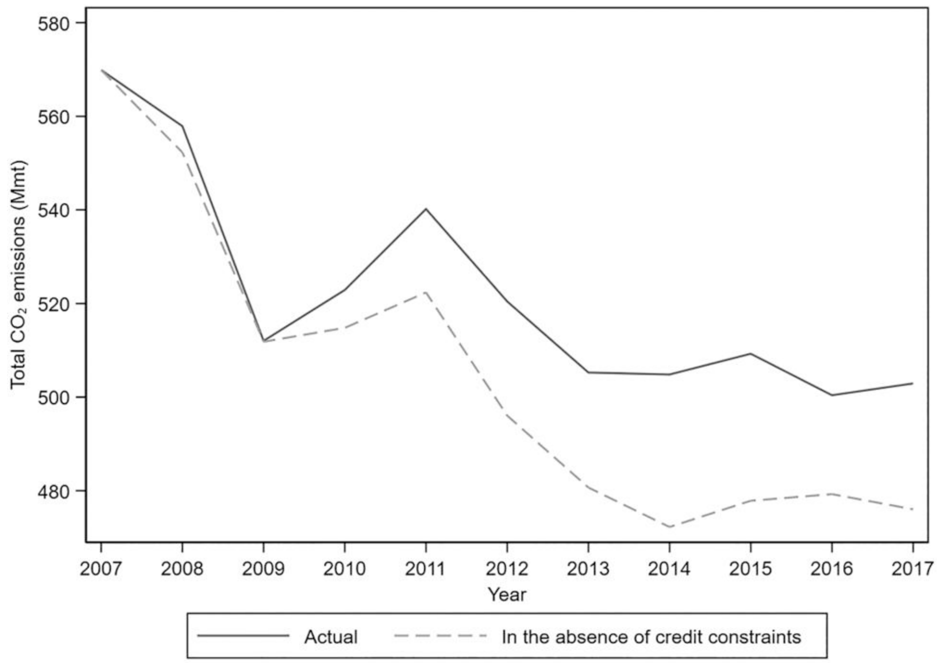
Notes. These charts summarize the coefficient estimates of difference-in-differences regressions explaining the impact of local bank-funding shocks on CO_2 emissions (log kg, (a)), NO_x emissions (log kg, (b)), SO_x emissions (log kg, (c)), and hazardous air pollutant emissions (log using toxicity weights, (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 multifacility 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 2007–2017 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 15-km radius and the number of bank branches in a 15-km radius around the industrial facility or, in the case of multifacility firms the parent company); and facility and year fixed effects.

embodied in more general investments such as machinery and vehicle upgrades. In contrast, investments in assets and measures to explicitly reduce pollution and emissions depend less on local variation in access to credit, likely reflecting that banks are less amenable to fund firm- and site-specific assets that are relatively difficult to redeploy.

Analysis of data from the European Pollutant Release and Transfer Register (E-PRTR) reveals the environmental consequences of these credit constraints: a substantially slower decline in CO_2 and other industrial emissions. Our results thus reveal how financial crises can slow down the process of decarbonization of economic production. They should also caution against excessive optimism about the potential green benefits of economic slowdowns such as during the global financial crisis or the recent COVID-19 pandemic, which—like any big recession—led to reductions in emissions. Our results suggest that such short-term reductions might come at the cost of longer-term increases in emissions if they are associated with more severe credit-market frictions that delay or prevent clean investments.

Our analysis also shows that deficient green management tends to hamper green investments across the board, and that they affect more types of investment than credit constraints do. These results suggest that comparatively low-cost measures—such as developing and implementing an environmental strategy; setting and monitoring environmental targets; and putting a

Figure 6. Actual and Counterfactual CO_2 Emissions, 2007–2017



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(a). Mmt, millions of tons.

manager in charge of climate change and environmental issues—can increase firms' green investments and ultimately decrease their emission of greenhouse gases and pollutants.

Although our analysis is conducted in the context of emerging European economies, our results are likely to be portable to many other emerging markets and developing countries. The relatively developed (and mostly foreign-owned) banking sector and sectoral composition are common enough in other economies—most notably in Latin America—to ensure the external validity of our findings. Even other peripheral European countries with bank-based financial systems, such as Italy, Greece, or Portugal, are likely to have small- and medium-sized firms that fare comparably to those in our analysis in terms of both credit constraints and green management practices, reinforcing the external validity of our findings to developed economies. Conversely, there are countries in Southeast Asia where the role of state banks implies more widely available credit (Banerjee and Duflo 2014), and for which our results might be less applicable.

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

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Appendices

Table A.1. Variable Definitions and Data Sources

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

Table A.1. (Continued)

Variable name	Variable definition	Source
Firm age	Log of firm age (from when it was registered)	ES
No. bank branches	Number of bank branches within a 15-km 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 15-km 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 15-km 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 capital ratio of banks with branches within a 15-km radius of the firm in 2014 (weighted by the number of bank branches) and the average Tier 1 capital ratio of banks with branches within a 15-km radius of the firm in 2007 (weighted by the number of bank branches).	BEPS II, Orbis, and ES
EBA 2014 *instrument (% points)*	Difference between the 2016 baseline scenario Tier 1 ratio and 8% hurdle rate of banks with branches within a 15-km radius of the firm (weighted by the number of bank branches). For banks that were not included in the 2014 European Banking Authority stress test, the actual 2016 Tier 1 ratio is used	BEPS II, European Banking Authority (2014), Orbis, and ES
Leave-out mean green management	Green management instrument obtained by averaging the green management of firms in higher size deciles in a 15-km radius around the firm	ES
Leave-out mean green investment	Green investment control variable obtained by averaging the green investment of firms in higher size deciles in a 15-km radius around the firm	ES
Tables 3 and 4		
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
NO_x emissions	Total quantity of NO_x emissions released by the facility into the air in kg; missing values set to threshold	E-PRTR v18
SO_x emissions	Total quantity of SO_x emissions released by the facility into the air in kg; missing values set to threshold	E-PRTR v18
Hazardous air pollutants emissions	The weighted sum of releases of all pollutants released to air available in E-PRTR v18 for which inhalation toxicity weights are available in the United States Environmental Protection Agency (EPA)'s Risk-Screening Environmental Indicators (RSEI) model version 2.3.9 (https://www.epa.gov/rsei/rsei-toxicity-data-and-calculations); missing values of included pollutants released to air is set to threshold	E-PRTR v18
Local mean credit constraints	Averages of the predicted values of credit constraints from Table 1 across all firms in a 15-km radius around the industrial facility or, in the case of multifacility 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 1 across all firms in a 15-km radius around the industrial facility or, in the case of multifacility 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 multifacility firms the parent company, logged	Orbis
No. bank branches	Number of bank branches within a 15-km radius around the industrial facility or, in the case of multifacility firms the parent company	E-PRTR v18, BEPS II, Orbis

Table A.1. (Continued)

Variable name	Variable definition	Source
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 multifacility 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 15-km radius around the industrial facility or, in the case of multifacility 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

Note. ES, EBRD-EIB-WBG Enterprise Surveys; BEPS II, second round of the Banking Environment and Performance Survey; E-PRTR, European Pollutant Release and Transfer Register.

Table A.2. Sample Breakdown by Country

	Number of unique firms and facilities			
Countries	Table 2 (columns 1–8) and Table 1 (columns 1–2)	Table 2 (column 9) and Table 1 (columns 3–4)	Table 3	Table 4
Albania	281	283	0	0
Armenia	347	327	0	0
Azerbaijan	154	81	0	0
Belarus	540	469	0	0
Bosnia and Herzegovina	270	181	0	0
Bulgaria	625	438	130	72
Croatia	303	293	95	0
Czech Republic	399	399	686	377
Estonia	261	257	71	37
Georgia	406	385	0	0
Hungary	723	627	525	285
Latvia	244	230	29	11
Lithuania	310	279	63	39
Moldova	269	280	0	0
North Macedonia	296	232	0	0
Poland	1,091	255	922	689
Romania	559	585	485	244
Serbia	272	190	59	0
Slovak Republic	369	388	182	113
Slovenia	366	309	140	100
Türkiye	1,523	1,399	0	0
Ukraine	1,168	756	0	0
Total	10,776	8,643	3,387	1,967

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

Table A.3. Summary Statistics

Variables	*N* [1]	Mean [2]	Median [3]	Standard deviation [4]	Minimum [5]	Maximum [6]
Table 2 (columns 1–8) and Table 1 (columns 1–2)						
Fixed asset investment	10,776	0.451	0.000	0.498	0.000	1.000
Machinery upgrade	10,776	0.470	0.000	0.499	0.000	1.000
Vehicle upgrade	10,776	0.341	0.000	0.474	0.000	1.000
Heat/cool/light	10,776	0.553	1.000	0.497	0.000	1.000
Green energy generation	10,776	0.125	0.000	0.330	0.000	1.000

Table A.3. (Continued)

Variables	N [1]	Mean [2]	Median [3]	Standard deviation [4]	Minimum [5]	Maximum [6]
Waste and recycling	10,776	0.397	0.000	0.489	0.000	1.000
Energy/water management	10,776	0.344	0.000	0.475	0.000	1.000
Air/other pollution control	10,776	0.199	0.000	0.399	0.000	1.000
Credit constrained	10,776	0.223	0.000	0.416	0.000	1.000
Green management (0-1 score)	10,776	0.119	0.031	0.178	0.000	0.949
Exporter status (indicator)	10,776	0.253	0.000	0.435	0.000	1.000
Listed firm (indicator)	10,776	0.064	0.000	0.245	0.000	1.000
Sole proprietorship (indicator)	10,776	0.161	0.000	0.367	0.000	1.000
Audited financial accounts (indicator)	10,776	0.343	0.000	0.475	0.000	1.000
Log (firm age)	10,776	2.790	2.944	0.690	0.000	5.323
No. bank branches ('000)	10,776	0.200	0.064	0.338	0.001	2.379
Local banks' average asset size in 2007 (log)	10,776	15.217	15.226	1.533	11.324	17.622
Leave-out mean credit constraints	10,776	0.220	0.167	0.213	0.000	1.000
Change in average local Tier 1 ratio (% points)	10,776	5.262	4.591	7.191	−21.701	47.358
EBA 2014 *instrument (% points)*	10,776	5.376	4.686	3.050	−0.420	22.035
Leave-out mean green management	10,776	0.140	0.102	0.140	0.000	0.932
Leave-out mean green investment	10,776	0.666	0.824	0.365	0.000	1.000
No data on leave-out mean credit constraint	10,776	0.008	0.000	0.089	0.000	1.000
No data on leave-out green management	10,776	0.145	0.000	0.353	0.000	1.000
No data on leave-out green investment	10,776	0.143	0.000	0.350	0.000	1.000
Table 2 (column 9) and Table 1 (columns 3–4)						
Log (energy cost per sales)	8,643	−3.812	−3.758	1.399	−10.597	0.405
Credit constrained	8,643	0.220	0.000	0.414	0.000	1.000
Green management (0-1 score)	8,643	0.120	0.031	0.176	0.000	0.970
Exporter status (indicator)	8,643	0.255	0.000	0.436	0.000	1.000
Listed firm (indicator)	8,643	0.067	0.000	0.250	0.000	1.000
Sole proprietorship (indicator)	8,643	0.143	0.000	0.350	0.000	1.000
Audited financial accounts (indicator)	8,643	0.362	0.000	0.481	0.000	1.000
Log (firm age)	8,643	2.794	2.944	0.684	0.000	5.323
No. bank branches ('000)	8,643	0.168	0.059	0.284	0.001	2.379
Local banks' average asset size in 2007 (log)	8,643	15.177	15.228	1.591	11.324	17.622
Leave-out mean credit constraints	8,643	0.217	0.167	0.208	0.000	1.000
Change in average local Tier 1 ratio (% points)	8,643	5.522	5.162	7.610	−21.701	47.358
EBA 2014 *instrument (% points)*	8,643	5.612	4.813	3.266	−0.420	22.035
Leave-out mean green management	8,643	0.142	0.105	0.141	0.000	0.932
Leave-out mean green investment	8,643	0.672	0.833	0.363	0.000	1.000
No data on leave-out mean credit constraint	8,643	0.008	0.000	0.086	0.000	1.000
No data on leave-out green management	8,643	0.143	0.000	0.350	0.000	1.000
No data on leave-out green investment	8,643	0.141	0.000	0.348	0.000	1.000
Table 3						
Log (CO_2 emissions)	10,161	18.560	18.421	0.550	18.421	23.216
Log (NO_x emissions)	10,161	11.686	11.513	0.616	11.513	16.717
Log (SO_x emissions)	10,161	12.051	11.918	0.574	11.918	18.668
Log (Hazardous air pollutant emissions)	10,161	22.412	22.397	0.141	22.397	25.583
CO_2 emissions (kg, hyperbolic sine)	10,161	36.428	36.148	1.099	36.148	45.740
NO_x emissions (kg, hyperbolic sine)	10,161	22.680	22.333	1.232	22.333	32.741
SO_x emissions (kg, hyperbolic sine)	10,161	23.409	23.144	1.149	23.144	36.642
Hazardous air pollutant emissions (kg, hyperbolic sine)	10,161	44.131	44.100	0.283	44.100	50.474
Local mean credit constraints	10,161	0.146	0.109	0.122	−0.060	0.600
Local mean green management	10,161	0.131	0.133	0.056	−0.030	0.288
Listed company (indicator)	10,161	0.051	0.000	0.220	0.000	1.000
Delisted company (indicator)	10,161	0.055	0.000	0.227	0.000	1.000
Log (firm age + 1)	10,161	3.013	3.091	0.727	0.000	5.576
No. bank branches ('000)	10,161	0.199	0.065	0.292	0.001	1.223
Local banks' average asset size in 2007 (log)	10,161	16.139	16.309	0.777	12.823	17.342
No data on local credit constraints/green management	10,161	0.014	0.000	0.116	0.000	1.000
Table 4						
Log (CO_2 emissions)	21,637	18.669	18.421	0.743	18.421	24.350
Log (NO_x emissions)	21,637	11.817	11.513	0.838	11.513	17.574
Log (SO_x emissions)	21,637	12.178	11.918	0.822	11.918	19.898

Table A.3. (Continued)

Variables	N [1]	Mean [2]	Median [3]	Standard deviation [4]	Minimum [5]	Maximum [6]
Log (Hazardous air pollutant emissions)	21,637	22.424	22.397	0.182	22.397	25.884
CO_2 emissions (kg, hyperbolic sine)	21,637	36.645	36.148	1.486	36.148	48.007
NO_x emissions (kg, hyperbolic sine)	21,637	22.941	22.333	1.676	22.333	34.456
SO_x emissions (kg, hyperbolic sine)	21,637	23.662	23.144	1.643	23.144	39.102
Hazardous air pollutant emissions (kg, hyperbolic sine)	21,637	44.155	44.100	0.365	44.100	51.075
Local banks' reliance on wholesale funding in 2007 (share)	21,637	0.501	0.479	0.093	0.321	1.362
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	2.921	2.944	0.820	0.000	5.576
No of bank branches in '000, 15-km dist, in 2011	21,637	0.174	0.056	0.270	0.001	1.223
Local banks' average asset size in 2007 (log)	21,637	16.237	16.372	0.697	14.122	17.342

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.
Note. Table A.1 contains all variable definitions.

Table A.4. Credit Constraints and Firm Size, Age, and Audited Accounts Status

	Dependent variable: *Credit constrained* (indicator)				
Variables	[1]	[2]	[3]	[4]	[5]
SME (indicator)	0.060***			0.043***	
	(0.011)			(0.012)	
Log (firm age)		−0.020***		−0.013**	
		(0.006)		(0.006)	
Audited financial accounts (indicator)			−0.056***	−0.042***	
			(0.010)	(0.010)	
Access to finance is an obstacle to current operations (indicator)					0.195***
					(0.011)
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	10,776	10,776	10,776	10,776	10,775
Clusters (localities)	2,502	2,502	2,502	2,502	2,502
R^2	0.137	0.135	0.137	0.139	0.177

Notes. This table presents the regression of credit constraints indicator on proxies for credit constraints: indicator for small- and medium-sized firm, log of firm age and an indicator for audited financial accounts. All regressions include population size class and region and sector fixed effects. "Access to finance is an obstacle to current operations" is an indicator variable that is one if the firm perceives access to finance to be at least a minor obstacle to its current operations; zero otherwise. Table A.1 contains all other variable definitions, Table A.3 provides summary statistics, Table OB.1 provides information on regions, and Table OB.2 provides information on sectors. Robust standard errors are clustered by locality and shown in parentheses.
***, ** and *Statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.5. Determinants of Green Management Quality

	Dependent variable: *Green management*		
Variables	[1]	[2]	[3]
SME (indicator)	−0.075***	−0.057***	−0.037***
	(0.006)	(0.005)	(0.005)
Log (firm age)	0.010***	0.008***	0.008**
	(0.003)	(0.002)	(0.003)
At least 25% foreign ownership (indicator)	0.042***	0.037***	0.031***
	(0.007)	(0.007)	(0.007)
Exporter status (indicator)	0.033***	0.024***	0.017***
	(0.006)	(0.005)	(0.005)
Listed firm (indicator)	0.028***	0.024***	0.025***
	(0.009)	(0.008)	(0.009)
Sole proprietorship (indicator)	−0.017***	−0.013***	−0.014*

Table A.5. (Continued)

Variables	Dependent variable: *Green management* [1]	[2]	[3]
	(0.005)	(0.004)	(0.008)
Audited financial accounts (indicator)	0.059***	0.040***	0.025***
	(0.005)	(0.004)	(0.005)
Customer pressure (indicator)		0.158***	0.162***
		(0.009)	(0.009)
Monetary losses due to extreme weather events (indicator)		0.053***	0.052***
		(0.008)	(0.009)
Monetary losses due to pollution not generated by the firm (indicator)		0.098***	0.096***
		(0.015)	(0.017)
Subject to energy tax or levy (indicator)		0.068***	0.070***
		(0.010)	(0.009)
General management			0.180***
			(0.014)
Region fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Observations	10,776	10,776	6,133
Clusters (localities)	2,502	2,502	1,790
R^2	0.239	0.376	0.419

Notes. This table presents the regression of green management on its determinants. All regressions include population size class and region and sector fixed effects. Table A.1 contains all variable definitions, Table A.3 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 *Statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.6. Firm-Level Credit Constraints, Green Management, and Investment-Intensive Margin

Variables	Dependent variable: *Made at least one type of green investment* [1]	*Made green machinery or vehicle investment* [2]	*Number of different types of green investment (1–7)* [3]
Panel A: OLS			
Credit constrained	−0.029***	−0.048***	−0.179***
	(0.011)	(0.012)	(0.053)
Green management	0.514***	0.662***	4.114***
	(0.028)	(0.029)	(0.126)
R^2	0.211	0.201	0.316
Panel B: IV			
Credit constrained	−0.084	−0.334**	−1.166*
	(0.113)	(0.137)	(0.630)
Green management	0.526***	1.024***	7.337***
	(0.157)	(0.188)	(0.717)
R^2	0.235	0.148	0.167
Region fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Observations	10,776	10,776	8,045
Clusters (localities)	2,502	2,502	2,096

Notes. This table presents the regression of green management on its determinants. All regressions include population size class and region and sector fixed effects. Table A.1 contains all variable definitions, Table A.3 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 *Statistical significance at the 1%, 5%, and 10% levels, respectively.

Endnotes

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

[2] Hottenrott et al. (2016) provide an overview of the literature on the determinants of firm investment in green technologies, whereas Cagno et al. (2013) propose a taxonomy of barriers to industrial energy efficiency improvement.

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

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

[5] Accetturo et al. (2022) show for a sample of Italian firms that positive credit supply shocks lead to a higher propensity to invest in green technologies.

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

[7] Prior work shows how financial crises, and the associated reduction in bank lending, tighten corporate credit constraints and reduce investment in R&D and fixed assets (Campello et al. 2010, Duchin et al. 2010, Nanda and Nicholas 2014).

[8] Drawing on data from the International Energy Agency (IEA), a comparative overview of the progress made in various regions shows that Emerging Europe's energy investment as a share of GDP, although declining, is higher than that of Latin America, Africa, or Asia.

[9] Our final sample contains 10,776 firms with nonmissing values for all the required variables. Table A.2 presents a breakdown by country, whereas Table A.3 contains summary statistics for all variables. Online Appendix A2 describes the Enterprise Surveys methodology and discusses survey response rates. All relevant survey questions can be found in Online Appendix A.1.

[10] Surveyors fill out a debriefing survey in which they rate for each interview the perceived truthfulness of the answers received: only in 80 cases was the veracity of some of the answers questioned. Our results are robust to excluding these observations.

[11] In robustness tests (Online Appendix, Table OD.7), we use firm-level controls such as age and dummy variables for whether the firm is publicly listed, a sole proprietorship, an exporter, and whether an auditor reviews its financial statements.

[12] 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".

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

[14] We also ran regressions where we either include regional and sector fixed effects or include our full set of firm-level covariates. Doing so reveals that the R^2 becomes nearly three times larger (an increase from 0.13 to 0.38) when we add firm-level covariates on top of the fixed effects. This confirms that the substantial variation in firms' green management practices does not simply reflect industrial composition.

[15] All these results hold when controlling for general management quality (column 3).

[16] See Table A.1 for definitions.

[17] The Green Economy module was introduced to the firm manager as follows: "Now I would like to consider the last module of the questionnaire that deals with questions related to this establishment's environmental signature, such as its exposure to environmental impacts, environmental policy and regulations". The question on green investments (question BMGC.23 in Online Appendix A.1.2) was only asked after this introduction and after the respondent had answered several other questions about green topics (such as the firm's green management practices, its energy use, and its exposure to extreme weather and other environmental impacts). We are therefore confident that in this section—as intended—respondents only offered information about investments in upgrading machinery, equipment, and/or vehicles that contained an explicit and substantial green component.

[18] Moreover, means, medians, standard deviations, minimum and maximum based on the whole sample are provided in Table A.3.

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

[20] Table A.2 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 2015–2017 as this period is closest to the rollout of the Enterprise Surveys, on which we base our vicinity measures of green management practices.

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

[22] One reassurance is that the variables are based on questions using different scale endpoints. Green investments reflect straightforward Yes/No questions, whereas credit constraints and green management practices combine various underlying questions, each with unambiguous and prespecified answers. This minimizes the risk of anchor and social desirability effects (Podsakoff et al. 2003, Chang et al. 2020).

[23] For example, the median Belgian SME borrower in Degryse and Ongena (2005) was located 2.5 km from the lending bank branch and borrows often from only one bank (Degryse et al. 2019). In the U.S. data of Petersen and Rajan (1994) and Agarwal and Hauswald (2010), the corresponding median distances were 3.7 and 4.2 km, respectively.

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

[25] 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.

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

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

[28] Similar approaches have been used in a number of other studies including Fisman and Svensson (2007), Aterido et al. (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."

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

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

[31] 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.

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

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

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

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

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

[37] In robustness checks, we use a hyperbolic sine transformation of emissions. This leads to similar results (see Table OD.16 in Online Appendix D).

[38] In the Online Appendix, Tables OD.8 (first stage) and OD.9 (second stage), we provide an alternative specification where the first-stage regressions predicting Credit Constrained and Green Management are run as separate equations that include only the relevant instruments for each of the endogenous variables. This manual estimation of the two-stage procedure requires us to bootstrap the standard errors in the second-stage regressions. A comparison of our baseline Table 1 and the Online Appendix, Table OD.8, shows no material difference in terms of the strength of the key instruments. The size of the estimated coefficients is very similar also. Likewise, a comparison of the baseline IV results in Table 2 with those in the Online Appendix, Table OD.9, shows only minor differences in terms of statistical or economic significance.

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

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

[41] The OLS results suggest a smaller impact for credit constraints across all asset types. Although it is challenging to pin down precisely what causes this difference, it may at least partly reflect attenuation bias, for example because rapidly growing (and investing) firms are more likely to experience credit constraints.

[42] Although no information is available on the size of the investment made, Table A.6 shows that credit constraints also impact the intensive margin measured as the number of green investments. The dependent variable in column 1 is an indicator 1 if the firm made at least one type of investment in the last three years and, in column 2, if it made at least one upgrade of vehicles, machinery, or equipment. In column 3, the dependent variable counts the number of different types of green investments, ranging from 1 to 7.

[43] As described for credit constraints, Table A.6 shows that better green management also affects green investment on the intensive margin.

[44] Our results are robust to alternative ways of summarizing the various questions on green management practices into one Green management explanatory variable. As presented in Online Appendix D.2, using z-scores or two alternative principal component analyses (PCAs) yields virtually unchanged results. This is shown in Tables OD.4, OD.5, and OD.6.

[45] The explanatory power of our green management and credit constrained variables is substantial. Across specifications, these two variables add on average 69% to the R^2 when we add them in addition to the regional fixed effects, sector fixed effects, and locality-level control variables (66% when we compare adjusted R^2s).

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

[47] As shown in the Online Appendix, Table OD.11, credit constraints are about twice as prevalent in non–E-PRTR countries, where financial markets are less developed, than in E-PRTR countries. Firms in non-E-PRTR countries also tend to have a lower green management score and are slightly less likely to make green investments.

[48] The dependent variables are transformed as $log(Emissions)$. Results are robust to using a hyperbolic sine transformation (see Table OD.15 in Online Appendix D). As explained previously, 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.

[49] To the extent that we underestimate (in Table 2) the role of credit constraints in slowing down firm-level investment in true green investments, this channel may also underpin the estimates in the first line of Table 3.

[50] Compared with Table 2 where we exploit firm-level variation, the contribution of our two locality-level variables to the overall explanatory power is lower in Table 3: On average, these variables boost the R^2 by about 1.5% (1.3% when we compare adjusted R^2s).

[51] In Table 4, the standard locality-level controls and the fixed effects contribute very little in terms of explanatory power, with the R^2 being close to zero. This means that the marginal contribution of our local bank funding variables is very large.

[52] This is calculated as $100 * \sum_{i,t=2008-17} e^{log(Emissions_i)} - \sum_{i,t=2008-17} [e^{log(Emissions_i)} - e^{log(Emissions_i - \beta_2 WSFReliance_{15km,i})}] * \{\sum_{i,t=2008-17} [e^{log(Emissions_i)} - e^{log(Emissions_i - \beta_2 WSFReliance_{15km,i})}]\}^{-1}$.

[53] The number of observations increases in these columns compared with the first four columns. In the first columns, the regressions are based on a panel where each facility is observed twice. This gives us $1{,}967 \times 2 = 3{,}934$ observations. In the last four columns, we split the postperiod further into two subperiods so that we now have $1{,}967 \times 3 = 5{,}901$ observations.

References

Accetturo A, Barboni G, Cascarano M, Garcia-Appendini E, Tomasi M (2022) Credit supply and green investments. Preprint, submitted April 26, http://dx.doi.org/10.2139/ssrn.4093925.

Agarwal S, Hauswald R (2010) Distance and private information in lending. *Rev. Financial Stud.* 23(7):2757–2788.

Aghion P, Fally T, Scarpetta S (2007) Credit constraints as a barrier to the entry and post-entry growth of firms. *Econom. Policy* 22(52): 732–779.

Aghion P, Howitt P, Mayer-Foulkes D (2005) The effect of financial development on convergence: Theory and evidence. *Quart. J. Econom.* 120:73–222.

Allcott H, Greenstone M (2012) Is there an energy efficiency gap? *J. Econom. Perspective* 26(1):3–28.

Allcott H, Mullainathan S, Taubinsky D (2014) Energy policy with externalities and internalities. *J. Public Econom.* 112:72–88.

Almeida H, Campello M (2007) Financial constraints, asset tangiblity, and corporate investment. *Rev. Financial Stud.* 20(5):1429–1460.

Angrist JD, Imbens GW, Krueger AB (1999) Jackknife instrumental variables estimation. *J. Appl. Econometrics* 14(1):57–67.

Aterido R, Hallward-Driemeier M, Pagés C (2011) Big constraints to small firms' growth? Business environment and employment growth across firms. *Econom. Development Culture Change* 59(3):609–647.

Atkin D, Chaudhry A, Chaudry S, Khandelwal AK, Verhoogen E (2017) Organizational barriers to technology adoption: Evidence from soccer-ball producers in Pakistan. *Quart. J. Econom.* 132(3):1101–1164.

Ayyagari M, Demirgüç-Kunt A, Maksimovic V (2008) How important are financing constraints? The role of finance in the business environment. *World Bank Econom. Rev.* 22(3):483–516.

Bai J, Jin W, Serfling M (2022) Management practices and mergers and acquisitions. *Management Sci.* 68(3):2141–2165.

Banerjee AV, Duflo E (2014) Do firms want to borrow more? Testing credit constraints using a directed lending program. *Rev. Econom. Stud.* 81(2):572–607.

Bartram SM, Hou K, Kim S (2022) Real effects of climate policy: Financial constraints and spillovers. *J. Financial Econom.* 143(2):668–696.

Beck T, Degryse H, De Haas R, Van Horen N (2018) When arm's length is too far: Relationship banking over the credit cycle. *J. Financial Econom.* 127(1):174–196.

Berger AN, Miller NH, Petersen MA, Rajan RG, Stein JC (2005) Does function follow organizational form? Evidence from the lending practices of large and small banks. *J. Financial Econom.* 76(2):237–269.

Berkouwer SB, Dean JT (2022) Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households. *Amer. Econom. Rev.* 112(10):3291–3330.

Betz T, Cook SJ, Hollenbach FM (2018) On the use and abuse of spatial instruments. *Political Anal.* 26(4):474–479.

Bircan Ç, De Haas R (2020) The limits of lending? Banks and technology adoption across Russia. *Rev. Financial Stud.* 33(2):536–609.

Bloom N, Van Reenen J (2007) Measuring and explaining management practices across firms and countries. *Quart. J. Econom.* 122(4):1351–1408.

Bloom N, Genakos C, Martin R, Sadun R (2010) Modern management: Good for the environment or just hot air? *Econom. J. (London)* 120(544):551–572.

Bloom N, Eifert B, Mahajan A, McKenzie D, Roberts J (2013) Does management matter? Evidence from India. *Quart. J. Econom.* 128(1):1–51.

Brown M, Guin B, Kirschenmann K (2016) Microfinance banks and financial inclusion. *Rev. Finance* 20(3):907–946.

Brown M, Ongena S, Popov A, Yeşin P (2011) Who needs credit and who gets credit in Eastern Europe? *Econom. Policy* 26(65):93–130.

Brucal A, Javorcik B, Love I (2019) Good for the environment, good for business: Foreign acquisitions and energy intensity. *J. Internat. Econom.* 121:103247.

Bureau Van Dijk (2022) Orbis. Accessed January 20, 2022, https://orbis.bvdinfo.com/.

Burke M, Craxton C, Kolstad C, Onda C, Allcott H, Baker E, Barrage L, et al. (2016) Opportunities for advances in climate change economics. *Science* 352(6283):292–293.

Caballero RJ, Hammour ML (1994) The cleansing effect of recessions. *Amer. Econom. Rev.* 84(5):1350–1368.

Cagno E, Worrell E, Trianni A, Pugliese G (2013) A novel approach for barriers to industrial energy efficiency. *Renewable Sustainable Energy Rev.* 19:290–308.

Campello M, Graham JR, Harvey CR (2010) The real effects of financial constraints: Evidence from a financial crisis. *J. Financial Econom.* 97(3):470–487.

Canales R, Nanda R (2012) A darker side to decentralized banks: Market power and credit rationing in SME lending. *J. Financial Econom.* 105(2):353–366.

Cavallo E, Galiani S, Noy I, Pantano J (2013) Catastrophic natural disasters and economic growth. *Rev. Econom. Statist.* 95:1549–1561.

Chang S-J, Van Witteloostuijn A, Eden L (2020) Common method variance in international business research. Eden L, Nielsen BB, Verbeke A, eds. *Research Methods in International Business. JIBS Special Collections* (Palgrave Macmillan, Cham, London).

Cohn JB, Deryugina T (2018) Firm-level financial resources and environmental spills. NBER Working Paper No. 24516, National Bureau of Economic Research, Cambridge, MA.

Colella F, Lalive R, Sakalli SO, Thoenig M (2019) Inference with arbitrary clustering. IZA Discussion Paper No. 12584, Institute of Labor Economics (IZA), University of Bonn, Bonn, Germany.

Commander S, Svejnar J (2011) Business environment, exports, ownership, and firm performance. *Rev. Econom. Statist.* 93(1):309–337.

De Haas R, Popov A (2023) Finance and green growth. *Econom. J. (London)* 133(650):637–668.

De Haas R, Van Lelyveld I (2014) Multinational banks and the global financial crisis: Weathering the perfect storm? *J. Money Credit Bank.* 46(S1):333–364.

De Haas R, Lu L, Ongena S (2023) Close competitors? Bilateral bank competition and spatial variation in firms' access to credit. *J. Econom. Geography* 23(6):1237–1271.

Degryse H, Ongena S (2005) Distance, lending relationships, and competition. *J. Finance* 60(1):231–266.

Degryse H, De Jonghe O, Jakovljević S, Mulier K, Schepens G (2019) Identifying credit supply shocks with bank-firm data: Methods and applications. *J. Financial Intermediary* 40:100813.

Demirgüç-Kunt A, Maksimovic V, Beck T (2005) Financial and legal constraints to firm growth: Does size matter? *J. Finance* 60:125–139.

Duchin R, Ozbas O, Sensoy BA (2010) Costly external finance, corporate investment, and the subprime mortgage credit crisis. *J. Financial Econom.* 97:418–435.

European Bank for Reconstruction and Development (2012) EBRD banking environment and performance survey II. Accessed January 20, 2022, https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html.

European Bank for Reconstruction and Development (2022) EBRD-EIB-WBG enterprise surveys 2018-20. Accessed January 20, 2022, https://www.beeps-ebrd.com/data/2018-2020/.

European Banking Authority (2014) Results of 2014 EU-wide stress test: Aggregate results. Accessed November 2, 2023, https://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2014.

European Environment Agency (2020) European pollutant release and transfer register (E-PRTR) database version 18. Accessed January 15, 2022, 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.

Eyring V, Gillett NP, Achuta Rao KM, Barimalala R, Barreiro Parrillo M, Bellouin N, Cassou C, et al. (2021) Human influence on the climate system. Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, et al. 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, Cambridge, UK).

Felbermayr G, Gröschl J (2014) Naturally negative: The growth effects of natural disasters. *J. Development Econom.* 111:92–106.

Fisman R, Svensson J (2007) Are corruption and taxation really harmful to growth? Firm level evidence. *J. Development Econom.* 83(1):63–75.

Fowlie M, Greenstone M, Wolfram C (2018) Do energy efficiency investments deliver? Evidence from the Weatherization Assistance Program. *Quart. J. Econom.* 133(3):1597–1644.

Fu X (2012) Foreign direct investment and managerial knowledge spillovers through the diffusion of management practices. *J. Management Stud.* 49(5):970–999.

Glennerster R, Jayachandran S (2023) Think globally, act globally: Opportunities to mitigate greenhouse gas emissions in low-and middle-income countries. *J. Econom. Perspective* 37(3):111–135.

Goetz M (2019) Financing conditions and toxic emissions. LIF-SAFE Working Paper No. 334, Leibniz Institute for Financial Research, Leibniz, Germany.

Granja J, Leuz C, Rajan RG (2022) Going the extra mile: Distant lending and credit cycles. *J. Finance* 77(2):1259–1324.

Greenstone M, Hornbeck R, Moretti E (2010) Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *J. Political Econom.* 118(3):536–598.

Gropp R, Mosk T, Ongena S, Wix C (2019) Banks' response to higher capital requirements: Evidence from a quasi-natural experiment. *Rev. Financial Stud.* 32(1):266–299.

Guiso L, Sapienza P, Zingales L (2004) Does local financial development matter? *Quart. J. Econom.* 119(3):929–969.

Hottenrott H, Rexhauser S, Veugelers R (2016) Organisational change and the productivity effects of green technology adoption. *Resources Energy Econom.* 43:172–194.

Howell ST (2017) Financing innovation: Evidence from R&D grants. *Amer. Econom. Rev.* 107(4):1136–1164.

IEA (2021) Financing clean energy transitions in emerging and developing economies. Report, World Energy Investment, IEA, Paris.

Iyer R, Peydró JL, da Rocha-Lopes S, Schoar A (2013) Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007–2009 crisis. *Rev. Financial Stud.* 27(1):347–372.

Kim H, Kung H (2017) The asset redeployability channel: How uncertainty affects corporate investment. *Rev. Financial Stud.* 30(1):245–280.

Levine R, Lin C, Wang Z, Xie W (2018) Bank liquidity, credit supply, and the environment. NBER Working Paper No. 24375, National Bureau of Economic Research, Cambridge, MA.

Liberti JM, Mian AR (2010) Collateral spread and financial development. *J. Finance* 65(1):147–177.

Lyon TP, Maxwell JW (2011) Greenwash: Corporate environmental disclosure under threat of audit. *J. Econom. Management Strategy* 20(1):3–41.

Martin R, Muûls M, de Preux L, Wagner UJ (2012) Anatomy of a paradox: Management practices, organizational structure and energy efficiency. *J. Environment. Econom. Management* 63:208–223.

McKenzie D (2021) I'm not a fan of leave-one-out/spatial instruments. *World Bank Development Impact Blog* (October 18), https://blogs.worldbank.org/impactevaluations/im-not-fan-leave-one-outspatial-instruments.

Mian A (2006) Distance constraints: The limits of foreign lending in poor economies. *J. Finance* 61(3):1465–1505.

Nanda R, Nicholas T (2014) Did bank distress stifle innovation during the great depression? *J. Financial Econom.* 114:273–292.

Nordhaus W (2019) Climate change: The ultimate challenge for economics. *Amer. Econom. Rev.* 109(6):1991–2014.

Ongena S, Popov A, Udell GF (2013) When the cat's away the mice will play: Does regulation at home affect bank risk-taking abroad? *J. Financial Econom.* 108(3):727–750.

Osotimehin S, Pappada F (2015) Credit frictions and the cleansing effect of recessions. *Econom. J. (London)* 127:1153–1187.

Pacala S, Socolow RH (2004) Stabilization wedges: Solving the climate problem for the next 50 years with current technologies. *Science* 305:968–972.

Pacca L, Antonarakis A, Schroder P, Antoniades A (2020) The effect of financial crises on air pollutant emissions: An assessment of the short vs. medium-term effects. *Sci. Total Environment.* 698:133614.

Peters GP, Marland G, Le Quéré C, Boden T, Canadell JG, Raupach MR (2012) Rapid growth in CO_2 emissions after the 2008–2009 global financial crisis. *Nature Climate Change* 2:2–4.

Petersen MA, Rajan RG (1994) The benefits of lending relationships: Evidence from small business data. *J. Finance* 49(1):3–37.

Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP (2003) Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psych.* 88(5):879.

Popov A, Udell GF (2012) Cross-border banking, credit access, and the financial crisis. *J. Internat. Econom.* 87(1):147–161.

Qi S, De Haas R, Ongena S, Straetmans S (2023) Move a little closer? Information sharing and the spatial clustering of bank branches. Working Paper No. 223, European Bank of Reconstruction and Development, London.

Ritchie H, Roser M (2020) CO_2 and greenhouse gas emissions. Accessed February 3, 2022, https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions.

Schweiger H, Stepanov A (2022) When good managers face bad incentives: Management quality and fuel intensity in the presence of price distortions. *Energy Policy* 164:112827.

Sheldon TL (2017) Asymmetric effects of the business cycle on carbon dioxide emissions. *Energy Econom.* 61:289–297.

Shelyapina MG, Rodríguez-Iznaga I, Petranovskii V (2021) Materials for CO_2, SO_x, and NO_x emission reduction. Kharissova OV, Kharisov BI, Torres-Martínez LM, eds. *Handbook of Nanomaterials and Nanocomposites for Energy and Environmental Applications* (Springer, Cham, Switzerland), 2429–2458.

Shleifer A, Vishny RW (1992) Liquidation values and debt capacity: A market equilibrium approach. *J. Finance* 47(4):1343–1366.

Sundquist J (2021) How to use spatial instruments. Accessed February 3, 2022, https://jame ssundquist.github.io/website/docs/How_to_Use_Spatial_Instruments.pdf.

U.S. Environmental Protection Agency (2022) Risk-screening environmental indicators model. Accessed February 3, 2022, https://www.epa.gov/rsei/rsei-toxicity-data-and-calculations/.

Williamson OE (1988) Corporate finance and corporate governance. *J. Finance* 43(3):567–591.

Wolfram C, Shelef O, Gertler P (2012) How will energy demand develop in the developing world? *J. Econom. Perspective* 26(1): 119–138.

Xu Q, Kim T (2022) Financial constraints and corporate environmental policies. *Rev. Financial Stud.* 35(2):576–635.