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Financial development and industrial pollution

Discussion paper [or working paper, etc.]

Financial Development and Industrial Pollution*

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Abstract

We study the impact of financial market development on industrial pollution in a large panel of countries and industries over the period 1974-2013. We find a strong positive impact of credit markets, but a strong negative impact of stock markets, on aggregate CO_2 emissions per capita. Industry-level analysis shows that stock market development (but not credit market development) is associated with cleaner production processes in technologically "dirty" industries. These industries also produce more green patents as stock markets develop. Moreover, our results suggest that stock markets (credit markets) reallocate investment towards more (less) carbon-efficient sectors. Together, these findings indicate that the evolution of a country's financial structure helps explain the non-linear relationship between economic development and environmental quality documented in the literature.

JEL classification: G10, O4, Q5.

Keywords: Financial development, industrial pollution, innovation, reallocation.

*We thank Francesca Barbiero and Alexander Stepanov for outstanding research assistance and Russell Bishop, Francesca Cornelli (discussant), Antoine Dechezleprêtre, Kathrin de Greiff, Hans Degryse, Manthos Delis, Sergei Guriev, Mikael Homanen, Luc Laeven, Steven Ongena, Alexander Plekhanov, Robert Sparrow (discussant) and participants at the 8th Development Economics Workshop (Wageningen University), the 3rd CEPR Annual Spring Symposium in Financial Economics (Imperial College Business School) and seminars at the EBRD, University of New South Wales, and Queen's University Belfast for useful comments. The opinions expressed are the authors' and not necessarily those of the EBRD, the ECB, or the Eurosystem.

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1 Introduction

The 2015 Paris Climate Conference (COP21) has put finance firmly at the heart of the debate on environmental degradation. The leaders of the G20 stated their intention to scale up so-called green-finance initiatives to fund low-carbon infrastructure and other climate solutions. A key example is the burgeoning market for green bonds to finance projects that save energy, reduce carbon emissions, or curtail pollution more generally. Other green-finance initiatives include the establishment of the British Green Investment Bank, which specializes in projects related to environmental preservation, and the creation of a green-credit department by the largest bank in the world—ICBC in China. Similar initiatives are being developed by many other industrialized and developing countries.

Somewhat paradoxically, the interest in green finance has also laid bare our limited understanding of the relation between regular finance and environmental pollution. To date, no rigorous empirical evidence exists on how finance affects industrial pollution as economies grow. Are well-developed banking sectors and stock markets detrimental to the environment as they fuel growth and the concomitant emission of pollutants? Or can financial development steer economies towards more sustainable growth by favoring clean industries over dirty ones? These are pertinent questions because most of the global transition to a low-carbon economy will need to be funded by the private financial sector if international climate goals are to be met on time (UNEP, 2011). A better understanding of how banks and stock markets affect carbon emissions can also help policy-makers to benchmark the ability of special green-finance initiatives to reduce such emissions.

To analyze the mechanisms that connect financial development, industrial composition and environmental degradation—as measured by the emission of CO_2—we exploit a 53-country, 16-industry, 40-year panel.[1] To preview our results, we find a strong positive impact of credit markets, but a strong negative impact of stock markets, on aggregate CO_2 emissions per capita. Additional findings indicate that industries that pollute more for intrinsic, technological reasons emit more carbon dioxide when credit markets develop. We find that stock markets have the opposite effect: industries that pollute more for technological reasons, produce relatively less carbon dioxide where and when stock markets grow. Our analysis also sheds light on the mechanisms that underpin these re-

[1] CO_2 emissions are widely considered to be the main source of global warming as they account for over half of all radiative forcing (net solar retention) by the earth (IPCC, 1990; 2007). The monitoring and regulation of anthropogenic CO_2 emissions is therefore at the core of international climate negotiations. CO_2 emissions also proxy for other air pollutants caused by fossil fuels such as methane, carbon monoxide, SO_2, and nitrous oxides.

sults. In particular, we show that while stock markets facilitate the adoption of cleaner technologies in polluting industries, the opposite holds true for credit markets. Auxiliary evidence from sectoral patenting data confirms that deeper stock markets (credit markets) are associated with more (less) green innovation in traditionally polluting industries, as well as with lower (higher) rates of new business creation in such industries. Moreover, our results suggest that—holding cross-industry differences in technology constant—stock markets (credit markets) tend to reallocate investment towards more (less) carbon-efficient sectors. Lastly, we find that the reduction in pollution in industries with a high natural propensity to pollute, as a result of domestic stock market development, is not mirrored by a proportionate increase in pollution by the same industries in emerging economies. This suggests that stock markets have a genuine cleansing effect on polluting industries and do not simply help such industries to outsource "dirty" technologies to pollution havens. These empirical regularities are robust to controlling for a host of potential confounding factors, such as general economic development, country-industry fixed effects, and unobservable country and industry trends.

This paper contributes to (and connects) two strands of the literature. First, we inform the debate on economic development and environmental pollution. This literature has focused mostly on the environmental Kuznets hypothesis, according to which pollution increases at early stages of development but declines once a country surpasses a certain income level. Two main mechanisms underlie this hypothesis. First, during the early stages of development, a move from agriculture to manufacturing and heavy industry is associated with both higher incomes and more pollution per capita. After some point, however, the structure of the economy moves towards light industry and services, and this shift goes hand-in-hand with a levelling off or even a reduction in pollution.[2] Second, when economies develop, breakthroughs at the technological frontier (or the adoption of technologies from more advanced countries) may substitute clean for dirty technologies and reduce pollution per unit of output (within a given sector).

While empirical work provides evidence for a Kuznets curve for a variety of pollutants, the evidence for CO_2 emissions is mixed.[3] Schmalensee, Stoker and Judson (1998) find an inverse U-

[2]Hettige, Lucas and Wheeler (1992) and Hettige, Mani and Wheeler (2000) find that the sectoral composition of an economy gets cleaner when a country reaches middle-income status and moves towards less-polluting services.

[3]Grossman and Krueger (1995) find a Kuznets curve for urban air pollution and the contamination of river basins. For a critical review of empirical research on the environmental Kuznets curve, see Dasgupta, Laplante, Wang and Wheeler (2002).

curve in the relationship between per capita GDP and CO_2 emissions while Holtz-Eakin and Selden (1995) show that CO_2 emissions go up with per capita GDP but merely stabilize when economies reach a certain income level. Our contribution is to explore the role of finance in shaping the relation between economic growth and carbon emissions. Empirical evidence on the diffusion of low-carbon technologies is still lacking (Burke et al., 2016) and our findings shed light on the role of finance in this regard.

More specifically, we assess how banks and stock markets affect the two main mechanisms that underpin the Kuznets hypothesis: a shift towards less-polluting sectors and an innovation-driven reduction in pollution within sectors. A move towards greener technologies can involve substantial investments and therefore be conditional on the availability of external finance.[4] Schumpeterian growth models, such as Aghion, Howitt and Mayer-Foulkes (2005), suggest that financial constraints can prevent firms in less-developed countries from exploiting R&D that was carried out in countries closer to the technological frontier. Financial development can then facilitate the absorption of state-of-the art technologies and help mitigate environmental pollution.

Second, our results also contribute to the literature on the relationship between financial structure and economic development. A substantial body of empirical evidence has by now established that growing financial systems contribute to economic growth in a causal sense.[5] While earlier findings suggest that the *structure* of the financial system—bank-based versus market-based—matters little for its ability to stimulate growth (Beck and Levine, 2002), more recent research qualifies this finding by showing that the impact of banking on growth declines (and the impact of securities markets on growth increases) as national income rises (Demirgüç-Kunt, Feyen and Levine, 2013; Gambacorta, Yang and Tsatsaronis, 2014). Our contribution is to assess whether the structure of the financial system matters for the degree of environmental degradation that accompanies the process of economic development.

The rest of the paper is structured as follows. Section 2 sets out the main arguments as to why banks and stock markets may have a different impact on industrial pollution. Section 3 then

[4]Levine et al. (2018) show how positive credit supply shocks in US counties, stemming from increased fracking of shale oil in other counties, reduce local air pollution. At the firm level, the authors confirm that a relaxation of credit constraints is associated with a decline in emitted toxic air pollutants. In a similar vein, Goetz (2018) finds that financially constrained firms reduced toxic emissions when their capital cost decreased as a result of the US Maturity Extension Program.

[5]For comprehensive surveys of this literature, see Levine (2005), Beck (2008), and Popov (2018).

presents our empirical methodology, after which Section 4 describes the data. Section 5 then presents the empirical results. Section 6 concludes with a discussion of our main findings.

2 Banks, stock markets, and industrial pollution

Financial structure, the relative importance of credit versus stock markets, matters if different forms of finance affect industrial pollution to a different extent or through different channels. Several theoretical arguments suggest that banks may be less suited to reducing industrial pollution than stock markets. First, banks are "dirtier" financiers to the extent that they are technologically conservative: they may fear that funding new (and possibly cleaner) technologies erodes the value of the collateral that underlies existing loans, which mostly represent old (dirtier) technologies (Minetti, 2011). Second, banks can also hesitate to finance green technologies if the related innovation involves assets that are intangible, firm-specific, and linked to human capital (Hall and Lerner, 2010). Such assets are difficult to redeploy elsewhere and therefore hard to collateralize (Carpenter and Petersen, 2002). Third, banks may also simply lack the skills to assess (green) technologies at the early stages of adoption (Ueda, 2004). In line with this skeptical view of banks as financiers of innovative technologies, Hsu, Tian and Xu (2014) provide cross-country evidence that industries that depend on external finance and are high-tech intensive are less (more) likely to file patents in countries with better developed credit (equity) markets. Fourth, banks typically operate with a shorter time horizon (the loan maturity) as compared with equity investors and are hence less interested in whether funded assets will become less valuable (or even stranded) in the more distant future. Ongena, Delis and de Greiff (2018) show that banks only very recently (after 2015) started to price the climate-policy risk of lending to firms with large fossil fuel reserves.[6]

In contrast, stock markets may be better suited to finance innovative (and greener) industries. Equity contracts are more appropriate to finance green innovations that are characterized by both high risks and high potential returns.[7] Equity investors may also care more about future pollu-

[6]Dasgupta, Laplante, Wang and Wheeler (2002) argue that banks may refuse to lend to a firm if they are worried about environmental liability. This indicates that screening by banks helps to weed out at least the (visibly) most polluting industries. Indeed, recent anecdotal evidence (Zeller, 2010) suggests that banks have started to scrutinize the dirtiest industries more as they fear the financial and reputational repercussions of lending to such firms. Yet, this narrow focus on reputational risk and environmental liability does not preclude banks with a short-term horizon from lending to less visibly polluting industries, such as those producing large amounts of greenhouse gases.

[7]Brown, Martinsson and Petersen (2017) show that while credit markets mainly foster growth in industries that rely on external finance for physical capital accumulation, equity markets have a comparative advantage in financing

tion so that stock prices rationally discount future cash flows of polluting industries.[8] Empirical evidence shows that stock markets indeed punish firms that perform badly in environmental terms (such as after environmental accidents) (Salinger, 1992) and reward those that do well in terms of environmental friendliness (Klassen and McLaughlin, 1996). Chava (2014) shows that firms with environmental concerns also tend to have fewer institutional owners.

In all, we conjecture that stock markets facilitate the adoption of cleaner technologies in polluting industries, while we expect no or less of such a role for credit markets. Ultimately, however, whether banks or stock markets are better suited to limiting or even reducing environmental pollution remains an empirical question.[9] The aim of this paper is therefore to provide robust empirical evidence on how, and how much, banks and stock markets contribute to carbon emissions at both the country and the industry level.

3 Empirical Methodology

We begin by estimating a regression where we map financial markets development into carbon dioxide emissions and where we use a country as the unit of observation. In the process, we distinguish between the effect of developments in credit markets and the effect of developments in stock markets. We estimate the following specification:

$$\frac{CO_{2c,t}}{Population_{c,t}} = \beta_1 Credit_{c,t-1} + \beta_2 Stock_{c,t-1} + \beta_3 X_{c,t-1} + \varphi_c + \phi_t + \varepsilon_{c,t} \tag{1}$$

where $\frac{CO_{2c,t}}{Population_{c,t}}$ denotes total per capita emissions of carbon dioxide in country c during year t. $Credit_{c,t-1}$ is total credit extended to the private sector by deposit money banks and other credit institutions, normalized by GDP, in country c during year $t-1$. $Stock_{c,t-1}$ is the total value of all

technology-led growth. In line with this, Kim and Weisbach (2008) find that a majority of the funds that firms raise in public stock issues is invested in R&D.

[8]For instance, oil company ExxonMobil recently gave in to investor demand for more disclosure of the impact of climate policies on the firm's future activities (Financial Times, 2017). A stock-market listing may nevertheless lead to short-termism and distorted investment decisions if firm managers believe that equity investors do not properly value long-term projects (Narayanan, 1985; Asker, Farre-Mensa and Ljungqvist, 2015).

[9]Chava (2014) shows how the environmental profile of a firm affects both the cost of its equity and its debt capital, suggesting that both banks and equity investors take environmental concerns into account. Higher capital costs can be an important channel through which investor concerns affect firm behavior and their pollution intensity. If higher capital costs outweigh the cost of greening the production structure, firms will switch to a more expensive but less polluting technology (Heinkel, Kraus and Zechner, 2001).

listed shares, normalized by GDP, in country c during year $t-1$. Arguably, countries with deeper credit markets also tend to have more mature stock markets, which is reflected in an unconditional correlation between $Credit_{c,t}$ and $Stock_{c,t}$ of 0.5. Nevertheless, the two variables capture qualitatively different developments—debt finance versus equity finance—which have different theoretical implications for the adoption of dirty versus clean technologies. $X_{c,t-1}$ denotes a vector of time-varying country-specific variables. Lastly, φ_c is a vector of country dummies; ϕ_t is a vector of year dummies; and $\varepsilon_{c,t}$ is an idiosyncratic error term.

The vector X includes factors that can account for a sizeable portion of the variation in cross-country CO_2 emissions. One such factor is economic development, the pollution impact of which can be positive at early stages of development as the economy utilizes the cheapest technologies available, and negative at later stages when the economy innovates to reduce pollution (the environmental Kuznets-curve argument). We account for this by including the logarithm of per-capita GDP, both on its own and squared. Another factor is macroeconomic stability, which we capture by including the level of inflation on the right-hand side of the regression. The phase of the business cycle can also have an impact on pollution levels. For example, the economy may cleanse itself from obsolete technologies during recessions. To account for this, we include proxies for recessions and for systemic banking crises.[10] Lastly, country dummies allow us to net out the impact of unobservable country-specific time-invariant influences, such as comparative advantage or appetite for regulation. The inclusion of year dummies helps to purge our estimates from the effect of unobservable global trends common to all countries in the dataset, such as the "Great Moderation" or the adoption of a new technology across countries around the same time.

Interpreting the results from Eq. (1) as causal rests on the assumption that financial development is unaffected by current or expected per-capita pollution levels, and that pollution and financial development are not affected by a common factor. The latter assumption is particularly

[10] Caballero and Hammour (1994) provide a vintage model in which production units that embody the latest technology are continuously being produced as innovation proceeds. At the same time, outdated units with inferior technology are continuously being destroyed. During a recession, outdated units are most likely to turn unprofitable and to be scrapped. (A related idea is the "pit-stop" view of recessions, according to which recessions stimulate productivity-improving activities because of their temporarily low opportunity costs (Gali and Hammour, 1991)). We argue that recessions may also involve an environmental cleansing effect as inferior-technology companies are typically also the least energy efficient ones. A recession will then prune these companies and hence improve the energy efficiency of the average (surviving) firm. Any such positive effects may be partly counterbalanced, however, if renewable energy investments are put on hold, thus delaying the introduction of cleaner technologies. Indeed, Campello, Graham and Harvey (2010) show that firms that were financially constrained during the global financial crisis cut spending on technology and capital investments and bypassed attractive investment opportunities.

questionable. For example, if global demand increases, particularly for the type of products that are produced by technologically "dirty" industries, CO_2 emissions and financial depth will increase simultaneously without there necessarily being a causal link from finance to pollution.

We address this point by employing a cross-country, cross-industry regression framework where we assess the relative impact of within-country financial development on different types of industries, depending on their technological propensity to pollute. We estimate the following model:

$$\begin{aligned}\frac{CO2_{c,s,t}}{Population_{c,t}} = \; & \beta_1 Credit_{c,t-1} \times Pollution\ intensity_s + \beta_2 Stock_{c,t-1} \times Pollution\ intensity_s \\ & + \beta_3 X_{c,s,t-1} + \varphi_{c,s} + \phi_{c,t} + \theta_{s,t} + \varepsilon_{c,s,t}\end{aligned} \tag{2}$$

where $\frac{CO2_{c,s,t}}{Population_{c,t}}$ denotes total per-capita emissions of carbon dioxide by industry s in country c during year t. As in Model (1), $Credit_{c,t-1}$ is total credit extended to the private sector by deposit money banks and other credit institutions, normalized by GDP, in country c during year $t-1$, and $Stock_{c,t-1}$ is the total value of all listed shares, normalized by GDP, in country c during year $t-1$. $Pollution\ intensity_s$ is a time-invariant, sector-specific variable that measures the average carbon dioxide emissions of sector s per unit of value added, in the global sample during the sample period. The underlying assumption is that the global average of a sector's emissions per unit of output captures the sector's global propensity to pollute. In robustness tests, we also employ a proxy for $Pollution\ intensity_s$ that captures average carbon dioxide emissions by the respective sector in the United States, over the sample period, and one based on the industry's global average air pollution per employee.

In the most saturated version of Model (1), we control for $X_{c,s,t-1}$, a vector of interactions between industry characteristics and country factors. For a start, we control for the interaction between the industry benchmark for pollution intensity and a host of time-varying country-specific factors which capture the extent of economic development (GDP per capita), the size of the market (population), and the business cycle (inflation, whether the country is experiencing a recession, and whether the country is experiencing a banking crisis). This test is aimed at controlling for the possibility that the impact of financial development on pollution is contaminated by concurrent developments in the country's economy. We also control for interactions of the country's credit and stock markets with other natural industrial benchmarks, such as the industry's dependence on external financing, the industry's growth opportunities, and the industry's asset tangibility. All these tests aim to control for the possibility that pollution intensity captures a different property of the industrial composition via which the effect of financial markets manifests itself.

Lastly, we saturate the empirical specification with interactions of country and sector dummies ($\varphi_{c,s}$), interactions of country and year dummies ($\phi_{c,t}$), and interactions of sector and year dummies ($\theta_{s,t}$). $\varphi_{c,s}$ nets out all variation that is specific to a sector in a country and does not change over time (e.g., the comparative advantage of agriculture in France). $\phi_{c,t}$ eliminates the impact of unobservable, time-varying factors that are common to all industries within a country (e.g., the population's demand for regulation). Lastly, $\theta_{s,t}$ controls for all variation that is coming from unobservable, time-varying factors that are specific to an industry and common to all countries (e.g., technological development in air transport).

In the next two steps, we test for the channels through which financial development affects overall pollution. In particular, we study the impact of financial development on (1) between-industry reallocation and (2) within-industry innovation. The first mechanism is one whereby some types of financial markets are better at reallocating investment away from technologically "dirty" towards technologically "clean" industries, holding technology constant. The second mechanism is one whereby—holding the industrial structure constant—some types of financial markets are better at improving the energy efficiency of technologically "dirty" industries, bringing them closer to their technological frontier.

We evaluate the first hypothesis using the following regression model:

$$\begin{aligned} \Delta Value\ added_{c,s,t} = \quad & \beta_1 Credit_{c,t-1} \times Pollution\ intensity_s + \beta_2 Stock_{c,t-1} \times Pollution\ intensity_s \\ & + \beta_3 X_{c,s,t-1} + \varphi_{c,s} + \phi_{c,t} + \theta_{s,t} + \varepsilon_{c,s,t} \end{aligned} \tag{3}$$

where relative to Model (2), the only change is that the dependent variable denotes the percentage change in value added between year $t-1$ and year t by industry s in country c. The evolution of this variable over time thus measures the industry's growth relative to other industries in the country. This therefore captures the degree of reallocation that takes place in the economy from technologically dirty towards technologically clean industries. Earlier work has shown how well-developed stock and credit markets make countries more responsive to global common shocks by allowing firms to better take advantage of time-varying sectoral growth opportunities (Fisman and Love, 2007). Financially developed countries increase investment more (less) in growing (declining) industries (Wurgler, 2000).

We evaluate the second hypothesis in two ways. First, we estimate the regression model:

$$\begin{aligned}\frac{CO_{2c,s,t}}{Value\ added_{c,s,t}} = {} & \beta_1 Credit_{c,t-1} \times Pollution\ intensity_s + \beta_2 Stock_{c,t-1} \times Pollution\ intensity_s \\ & + \beta_3 X_{c,s,t-1} + \varphi_{c,s} + \phi_{c,t} + \theta_{s,t} + \varepsilon_{c,s,t}\end{aligned} \tag{4}$$

where relative to Model (2), the only change is that the dependent variable denotes the total emissions of carbon dioxide by industry s in country c during year t, divided by the total value added of industry s in country c during year t. The evolution of this variable over time thus measures the industry's degree of efficiency improvement—that is, how dirty the production process is for a unit of produced output.

Lastly, we also ask whether any within-industry efficiency gains come through an enhanced propensity of technologically dirty industries to engage in patented innovation and/or in higher rates of creative destruction. To that end, we evaluate the following models:

$$\begin{aligned}\frac{Patents_{c,s,t}}{Population_{c,t}} = {} & \beta_1 Credit_{c,t-1} \times Pollution\ intensity_s + \beta_2 Stock_{c,t-1} \times Pollution\ intensity_s \\ & + \beta_3 X_{c,s,t-1} + \varphi_{c,s} + \phi_{c,t} + \theta_{s,t} + \varepsilon_{c,s,t}\end{aligned} \tag{5}$$

and

$$\begin{aligned}\frac{Establishments_{c,s,t}}{Population_{c,t}} = {} & \beta_1 Credit_{c,t-1} \times Pollution\ intensity_s + \beta_2 Stock_{c,t-1} \times Pollution\ intensity_s \\ & + \beta_3 X_{c,s,t-1} + \varphi_{c,s} + \phi_{c,t} + \theta_{s,t} + \varepsilon_{c,s,t}\end{aligned} \tag{6}$$

Here the dependent variable is either the total number of patents or a measure of "green" patents, in industry s in country c during year t, divided by the population in country c in year t (Model (5)) and the number of total establishments in industry s in country c in year t, divided by the population in country c in year t (Model (6)). The evolution of the first variable over time measures the industry's propensity to innovate away from dirty technologies. The evolution of the second one measures the rate at which the industry creates new businesses.

4 Data

This section introduces the four main data sources used in the empirical analysis. We first describe the data on carbon dioxide emissions, then the industry-level data on output and green patents, and finally the country-level data on financial development. We also discuss the matching of the industry-level data.

4.1 CO_2 emissions

We obtain data on CO_2 emissions from fuel combustion at the sectoral level from the International Energy Agency (IEA).[11] The data set contains information for 137 countries over the period 1974–2013. Information on CO_2 emissions is reported both at the aggregate level and for a total of 18 industrial sectors, which are based on NACE Rev. 1.1. These sectors encompass each country's entire economy, and not just the manufacturing sector, which is important given that some of the main CO_2-polluting activities, such as energy supply and land transportation, are of a non-manufacturing nature. The 18 sectors are: (1) Agriculture, hunting, forestry, and fishing; (2) Mining and quarrying; (3) Food products, beverages, and tobacco; (4) Textiles, textile products, leather, and footwear; (5) Wood and products of wood and cork; (6) Pulp, paper, paper products, printing, and publishing; (7) Chemical, rubber, plastics, and fuel products; (8) Other non-metallic mineral products; (9) Basic metals and fabricated metal products; (10) Machinery and equipment; (11) Transport equipment; (12) Electricity, gas, and water supply; (13) Construction; (14) Land transport – transport via pipelines; (15) Water transport; (16) Air transport; (17) Real estate, renting, and business activities; and (18) Community, social, and personal services.

We next produce a data set consisting of countries that each have a fair representation of industries with non-missing CO_2 data. We drop countries that have fewer than 10 sectors with at least 10 years of CO_2 emissions data. This excludes 84 countries so that the final data set consists of 53 countries with at least 10 sectors with at least 10 years of CO_2 emissions data. We combine the country-level and the industry-level data on CO_2 emissions with data on each country's population, which allows us to construct the dependent variables in Models (1), (2), and (5).

[11] Eighty percent of anthropogenic CO_2 emissions are due to the combustion of fossil fuels (Pepper et al., 1992).

4.2 Industry value added

To calculate the dependent variables in Models (3) and (4), we need industry-level data on value added. We obtain those from two sources. The first one is the United Nations Industrial Development Organization (UNIDO) data set, which contains data on value added in manufacturing (21 industries) for all countries in the IEA data set. The second one is the OECD's STAN Database for Structural Analysis which provides data on value added for all sectors (62) in the economy, but it only covers 33 OECD countries. We can therefore calculate proxies for CO_2 emissions per unit of value added, for value added growth, and for each sector's share of total output in the country, for two separate data sets. Both cover the period 1974–2013 and one contains 53 countries and 16 sectors while the other comprises 33 countries and 62 sectors. The main tests in the paper are based on the former data set with a view to maximizing country coverage, but we also include tests based on the latter data set, in order to maximize sectoral coverage. We winsorize the data on value added growth at a maximum of 100 percent growth and decline. In order to make overall value added by the same industry comparable across countries, we first convert all nominal output into USD and then deflate it to create a time series of real industrial output.

4.3 Green patents

We use the Patent Statistical database (PATSTAT) of the European Patent Office (EPO) to calculate the number of green patents across countries, sectors, and years. PATSTAT is the largest international patent database. Because of an average delay in data delivery and processing in PATSTAT of 3.5 years, our patent data end in 2013. To create our patent variables, we follow the methodological guidelines of the OECD Patent Statistics Manual. First, we take the year of the application as the reference year unless a priority patent was submitted in another country. In the latter case, the reference year is the year of the original priority filing. This ensures that we closely track the actual timing of inventive performance. Second, we take the country of residence of the inventors as the reference country. If a patent has multiple inventors from different countries, we use fractional counts (i.e., every country is attributed a corresponding share of the patent). Third, every patent indicator is based on data from a single patent office and we use the United States as the primary patent office.[12]

PATSTAT classifies each patent according to the International Patent Classification (IPC). We round this very detailed classification to 4-character IPC codes and use the concordance table of Lybbert and Zolas (2014) to convert IPC 4-character sectors into ISIC 2-digit sectors.[13] We then calculate the sum of all green patents in a particular country, sector, and year. The resulting variable, *Green patents*, measures all granted patents that belong to the EPO Y02/Y04S climate change mitigation technology (CCMT) tagging scheme. CCMTs include technologies to reduce the amount of greenhouse gas emitted into the atmosphere when producing or consuming energy. The Y02/Y04S scheme provides the most reliable method for identifying green patents and has become the standard in studies on green innovation. We count all granted patents that belong to the EPO Y02/Y04S CCMT tagging scheme. This includes Y02P patents, which concern innovations that make production in a number of energy-intensive sectors more energy efficient. Y02P also includes green technologies applicable across sectors, such as those relating to the efficient use of energy and flexible manufacturing systems. The other categories included are green inventions related to buildings and home appliances (Y02B), alternative (none fossil) energy sources (Y02E), and smart grids (Y04S). Lastly, we also count patents in Y02T (Climate change mitigation technologies related to transportation) and Y02W (Climate change mitigation technologies related to solid and liquid waste treatment).

4.4 Country-level data

Our first measure of financial development, *Credit*, is the ratio of credit extended to the private sector to GDP. The numerator is the value of total credit by financial intermediaries to the private sector (lines 22d and 42d in the IMF International Financial Statistics), and so this measure excludes credit by central banks (which may reflect political rather than economic considerations). It also excludes credit to the public sector and cross claims of one group of intermediaries on another. Lastly, it counts credit from all financial institutions rather than only deposit money banks. The

[12] In unreported robustness checks, we calculate patent indicators based on EPO data (which are only available after 1978). The correlation coefficients between US and EPO based indicators range between 0.75 and 0.81.

[13] PATSTAT also classifies patents according to NACE 2. A drawback of this classification is that it only covers manufacturing. Given that the scope of our analysis is broader, we do not use this as our baseline approach but only in robustness checks. To ensure comparability between both approaches, we convert NACE 2 into ISIC 3.1. The correlation coefficients between both types of indicators vary between 0.93 and 0.98.

data come from Beck et al. (2016) and are available for all countries in the data set.

The second measure, *Stock*, is the ratio of stock market capitalization to GDP. In practice, what goes in the numerator is the value of all traded stocks in the economy, so this is a measure of the total value of traded stock, not of the intensity with which trading occurs. These data too come from Beck et al. (2016) and are available for all countries in the data set.

Chart 1 plots the per-year sample average of these two explanatory variables between 1974 and 2013. This shows that stock market development strongly lags credit market development over time. The growth of credit markets is more gradual, while stock markets are prone to steep booms and busts. In terms of ratio to GDP, stock markets have only overtaken credit markets for a brief period during the dot-com bubble of the 1990s and in the run-up to the global financial crisis during the early to mid-2000s.

In addition to these two variables, we use data on real per capita GDP, on population, on inflation, and on recessions (calculated as an instance of negative GDP growth) from the World Development Indicators. Data on systemic banking crises come from Laeven and Valencia (2013).

4.5 Concordance and summary statistics

Our data are available in different industrial classifications. The original IEA data on carbon dioxide emissions are classified across 18 industrial sectors, using IEA's classification. The UNIDO and STAN data on value added are classified in 2-digit industrial classes using the ISIC classification. This calls for a concordance procedure to match the disaggregated ISIC sectors with the broader IEA sectors. The matching results in a total of 16 industrial sectors with data on both carbon dioxide emissions and industrial output. While some sectors are uniquely matched between IEA and UNIDO/STAN, others result from the merging of ISIC classes. For example, ISIC 15 "Food products and beverages" and ISIC 16 "Tobacco products" are merged into ISIC 15–16 "Food products, beverages, and tobacco", to be matched to the corresponding IEA industry class.

Table 1 summarizes the data. At the country level, we use aggregate CO_2 emissions (in tons), divided by the country's population. The average country emits 6.87 metric tons of CO_2 per capita. The summary of the financial development proxies shows that while countries typically have more developed credit than stock markets, stock market development is more dispersed. The data on GDP per capita make it clear that the data set contains a good mix of developing countries, emerging markets, and industrialized economies (see Appendix Table A2 for a list of all sample countries). The median country in the data set has a population of 16.3 million and annual inflation of 2.3 percent. On average, a country is in a recession once every five years, and it experiences a banking crisis once every eight years.

The industry-level data from UNIDO show that the median industry emits 0.08 metric tons of carbon dioxide per capita per year, and 1 metric ton per million USD of value added. Over the sample period, the median industry grows by 1 percent per year and makes up about 4.8 percent of total manufacturing. These values are relatively consistent across the UNIDO and STAN data sets. However, the median STAN industry records larger per capita emissions than the median UNIDO industry because the two heaviest polluters—ISIC 40 and 41 "Electricity, gas, and water supply" and ISIC 60 "Land transport – transport via pipelines"—are not manufacturing industries. In terms of green patents, the average country-industry produces around 0.1 such patents per 1 million people in the global sample, and 0.16 per 1 million people in the OECD sample.

Table 2 presents the concordance key to match 62 ISIC classes into 16 IEA ones. It also summarizes, by sector, the main industrial benchmark in the paper, "Pollution intensity", calculated as the average per capita emissions of carbon dioxide by all firms in the respective sector across the world and over the whole sample period.

5 Empirical Results

This section consists of six subsections. Section 5.1 investigates the effect of credit and stock market development on aggregate pollution. In Section 5.2, we then assess the impact of both types of finance on industry-level pollution, distinguishing between technologically "dirty" and "clean" industries. Section 5.3 investigates the degree to which between-industry reallocation and within-industry efficiency improvements explain the statistical association between finance and emissions. Section 5.4 provides robustness tests while Section 5.5 analyzes the impact of finance on patented technological innovation as well as business creation at the industry level. Lastly, in Section 5.6 we test whether the cleansing effect of stock market development in advanced countries reflects the outsourcing of pollution to emerging markets.

5.1 Financial development and pollution: Aggregate results

Table 3 reports our baseline results for the impact of financial markets development on carbon dioxide emissions, using aggregate data. We estimate different versions of Model (1) in the full panel of 73 countries for the period 1974-2013. This results in a maximum of 2,847 data points (given the lagged structure of the analysis). However, because financial data, pollution data, and country controls are not available for each country-year, the number of observations is reduced to 1,571 in the regression without country-specific controls, and down to 1,451 in the regressions with country controls. Country and year dummies purge our estimates from the impact of unobservable country-specific time-invariant influences and from the effect of unobservable global trends.

In column (1), we regress country-level per capita pollution on the size of credit markets, proxied by the ratio of credit extended to the private sector to GDP (*Credit*). The results strongly suggest that growing credit markets are associated with higher levels of CO_2 pollution. Numerically, the point estimate implies that going from the 10th to the 90th percentile of the sample, credit market development increases aggregate CO_2 emissions by 0.5 tons per capita, or by one-tenth of a sample standard deviation. The effect is significant at the 1 percent statistical level.

In column (2), we regress country-level per capita pollution on the size of stock markets, proxied by the ratio of stock market capitalization to GDP (*Stock*). We record the opposite effect to the one in column (1): larger stock markets are associated with substantially lower levels of CO_2 pollution. Numerically, the point estimate implies that going from the 10th to the 90th percentile of the sample, stock market development reduces aggregate CO_2 emissions by 0.3 tons per capita, or by one-sixteenth of a sample standard deviation. This effect is significant at the 5 percent level.

In column (3), we include both measures of financial development. We confirm that credit markets and stock markets have a simultaneous and statistically significant, but opposite, effect on carbon dioxide emissions. Deeper credit markets increase, while deeper stock markets reduce, overall pollution from CO_2. The regression with the two financial variables and with country and year dummies explains 0.95 of the variation in per capita carbon dioxide emissions.

Next, we include controls for other time-varying country-specific characteristics. First, we account for the fact that financial development is correlated with general economic development, and so the former may simply pick up the effect of a general increase in wealth on the demand for pollution. However, when we add GDP per capita to the regression (column (4)), we find that this is not the case: while the economies of richer countries generate more per capita pollution, the positive effect of credit markets and the negative impact of stock markets still obtain, with undiminished economic and statistical strength.

The same is true in column (5) where we add the square term of GDP per capita. We confirm the standard environmental Kuznets curve whereby per capita CO_2 emissions first increase and then decrease with economic development. More specifically, this specification indicates that carbon emissions start to decline at an annual income of around USD 40k which is the 85th percentile in our country-level income distribution. This is in line with earlier estimates by Holtz-Eakin and Selden (1995) who find a peak in CO_2 emissions at a per capita GDP of around USD 35k.

In this regression, we also include a number of other controls, which turn out to have the expected sign. In particular, both recessions and banking crises are associated with lower per capita CO_2 emissions. There are two potential explanations for this effect. For one, overall output goes down during a recession or a crisis, reducing overall pollution too. Second, the economy may be using the downturn to purge itself from obsolete (that is, relatively dirty) technologies (Schumpeter, 1912; Caballero and Hammour, 1994). Crucially, the positive effect of credit markets and the negative effect of stock markets are still recorded in this most saturated specification. Numerically, the point estimates imply that going from the 10th to the 90th percentile of the sample, credit market development increases aggregate CO_2 emissions by 0.28 of a sample standard deviation, and that going from the 10th to the 90th percentile of the sample, stock market development reduces aggregate CO_2 emissions by 0.12 of a sample standard deviation.

Our empirical tests demonstrate that financial development is to a large extent responsible for the inverse-U shape of the environmental Kuznets curve. Because stock markets only catch up with credit markets at later stages of development (see Chart 1), our results imply that the pattern of per-capita pollution over time is intimately related to the sequential development of different types of financial markets. We thus conclude that the evolution of financial structure helps explain the non-linear relationship between economic development and environmental quality that has been documented in the literature (e.g., Grossman and Krueger, 1995).

5.2 Financial development and pollution: Industry-level results

We next turn to evaluating evidence based on an analysis of the sector-level data. The evidence derived from aggregate data reported in the previous sub-section may be problematic for several reasons. Conceptually, incomplete risk-sharing may prevent the aggregate economy from behaving like a representative agent (Attanasio and Davis, 1996). Econometrically, both financial development and industrial pollution could be driven by any of a long list of common omitted variables that financial sector development could merely be a proxy of. Economies with better growth opportunities in polluting sectors may be developing their financial markets earlier as well. These issues are only imperfectly addressed by the matrix of country and year dummies and by the country-specific controls in the previous subsection.

To address these issues, we adapt the cross-country cross-industry methodology first suggested by Rajan and Zingales (1998) to evaluate the sectoral channels through which financial markets affect industrial pollution. We start by constructing a proxy for the industry's natural propensity to pollute that is exogenous to pollution in each particular industry-country. The main proxy we use is the industry-specific average CO_2 emissions per unit of output, calculated across all countries and years in the sample. The assumption is that a global average reflects the technological frontier of an industry rather than its performance in an individual country. In robustness tests, we follow Rajan and Zingales (1998) more closely and calculate each industry's average CO_2 emissions per unit of output in the United States. The assumption in this case is that an industry's pollution intensity in a country with few regulatory impediments and with deep and liquid financial markets reflects the industry's inherent propensity to pollute and is unaffected by regulatory arrangements or by credit constraints.

In Table 4, we evaluate Model (2) to test whether technologically dirty sectors produce higher carbon dioxide emissions than technologically clean sectors in countries with growing financial markets. The estimates in column (1) strongly suggest that industries that pollute relatively more for inherent, technological reasons, generate relatively higher carbon dioxide emissions in countries with expanding credit markets. This effect is significant at the 1-percent statistical level and is economically meaningful, too. In column (2), we find that stock markets have the exact opposite effect: industries that pollute relatively more for technology-related reasons, produce relatively lower carbon dioxide emissions in countries with deepening stock markets. Once again, the effect is significant at the 1 percent statistical level. We also note that sectors that constitute a larger share of the overall economy—in terms of value added—pollute more per capita than relatively smaller sectors.

The opposite effects of the two types of financial markets still obtain when we include them together (column (3)). In this case, the numerical impact of credit markets is almost twice as high as that of stock markets. This suggests that pollution in a country will increase materially if private credit and stock market capitalization simultaneously increase by the same factor. In this way, the estimates in column (3) of Table 4 mirror conceptually those in column (3) of Table 3.

Crucially, all regressions in Table 4 (and thereafter) are saturated with interactions of country-sector dummies, country-year dummies, and sector-year dummies. The inclusion of these makes sure that the effect we measure in the data is not contaminated by unobservable factors that are specific to a sector in a country and that do not change over time, by unobservable time-varying factors that are common to all industries within a country, and to unobservable, time-varying factors that are specific to an industry and common to all countries.

5.3 Financial development and pollution: Channels

Our main finding so far is that per capita carbon dioxide emissions increase with credit market development and decline with stock market development, more so in industries that are technologically dirty. This naturally raises the question via which channels credit translates into higher, and equity into lower, industrial pollution. There are two such potential channels. The first one is cross-industry reallocation whereby—holding technology constant—stock markets reallocate investment towards, and credit markets reallocate investment away from, relatively clean industrial sectors. The second channel is within-industry technological innovation whereby—holding the industrial structure constant—industries over time adopt more efficient (in our case, cleaner) technologies. If this channel is at play, our results would imply that access to equity finance facilitates the process of within-industry technological innovation, while access to credit slows it down by perpetuating firms' use of inefficient (dirty) technologies and/or by facilitating the adoption of such technologies. In what follows, we test for whether any of the two, or both, channels are indeed operational.

5.3.1 Cross-industry reallocation

In Table 5, we test the first channel by running Model (3) on our data. By doing so, we replicate Table 4, but this time the dependent variable is the growth in value added in a particular industry in a particular country during a particular year. As before, all regressions are saturated with interactions of country-sector dummies, country-year dummies, and sector-year dummies. In this case, a negative coefficient on the interaction term of interest would imply that financial development results in a reallocation of investment away from technologically dirty industries. This test is conceptually similar to Wurgler (2000) who finds that in countries with deeper financial markets, investment is higher in booming than in declining sectors.

In all specifications, we find that larger sectors grow more slowly, a result in line with theories of growth convergence. In a country-industry setting, this effect also mirrors the canonical work in this line of research by Rajan and Zingales (1998). Turning to the main variables of interest, in column (1), we find that technologically dirty sectors grow faster in countries with growing credit markets. However, the effect is not significant at any traditional level of statistical significance. In column (2), we find that dirty industries grow more slowly (or, conversely, that clean industries grow faster) in countries with expanding stock markets. This effect is significant at the 10-percent statistical level. Once we estimate the effect of the two types of financial development jointly (column (3)), we find that both continue to exert the already documented effects (positive in the case of credit markets, and negative in the case of stock markets). In this case, both effects are significant at the 10-percent statistical level.

We conclude that there is evidence to confirm the conjecture that—holding cross-industry differences in technology constant—credit markets promote a reallocation of investment towards dirtier sectors. This can partially explain the positive impact of growing credit markets on per capita pollution that we find in Table 4. At the same time, the opposite holds for stock markets and this helps explain the decline in per-capita CO_2 emissions by technologically dirty industries in countries with deepening stock markets.

5.3.2 Within-industry efficiency improvement

In Table 6, we test the second channel by estimating Model (4) on our data. In this model, the dependent variable is CO_2 emissions per unit of value added, rather than CO_2 emissions per capita. Once again, all regressions are saturated with interactions of country-sector dummies, country-year dummies, and sector-year dummies. In this case, a negative coefficient on the interaction term of interest would imply that financial development results in a technological improvement within an environmentally dirty industry, regardless of its level of overall growth.

In column (1), we find evidence of declining levels of within-industry technological innovation as credit markets develop. In particular, in countries with growing credit markets, and relative to clean sectors, dirty sectors exhibit higher levels of CO_2 per unit of value added. The effect is significant at the 5-percent statistical level. We next look at the independent effect of stock markets on pollution per unit of output. The evidence in column (2) suggests that stock markets have the opposite effect: pollution levels per unit of value added decline in dirty sectors, relative to clean ones, in countries with deepening stock markets. This effect is significant at the 1-percent statistical level, and it is numerically stronger than the effect of credit markets. Once we juxtapose the two types of financial development, we find that both effects still obtain, and both are statistically significant (column (3)). The magnitude of the point estimates implies that the impact of stock markets on pollution per unit of output is considerably more powerful than that of credit markets. In particular, CO_2 emissions per unit of value added would decrease if a country was to double the overall size of its financial system, while holding constant the ratio of credit to stock markets.

The evidence in Table 6 suggests that stock markets facilitate the adoption of cleaner technologies in polluting industries. There is weaker evidence for the opposite effect in countries with developing credit markets. This evidence thus helps explain the negative impact of stock markets, and the positive effect of credit markets, on per capita pollution documented in Table 4.[14]

[14] We find a consistent picture when we instead include the overall size of a country's financial system (that is, stock and credit markets combined) and financial structure (that is, the ratio between the size of the stock and credit market) as explanatory variables. While a growing financial system benefits relatively dirty industries, this effect becomes smaller when stock markets develop faster than credit markets (Appendix Table A3).

5.4 Financial development and pollution: Robustness

5.4.1 Controlling for other country- and industry-specific factors

We next test the robustness of our results to the impact of a host of country factors that could impact industry-specific emission levels and that are correlated with financial development. First, we take all country-specific variables included in column (5) of Table 3, interact them with each sector's benchmark technological pollution intensity, and include them alongside the main covariates. We do so in all regressions, in order to saturate the model with a number of potential channels which may operate alongside financial structure, such as economic development, market size, and the business cycle.

We also include interactions of *Credit* and *Stock* with three additional industry-specific benchmarks. The first one is *External dependence*, proxied as in Rajan and Zingales (1998) by the difference between investment and cash flow. Data come from Duygan-Bump et al. (2015). This variable controls for the possibility that the financial structure operates through the industry's natural reliance on external financing, and not through its propensity to pollute. The second benchmark is *Growth opportunities*, measured as the industry's global average sales growth in a particular year. The interaction of this benchmark with the country's financial structure controls for the possibility that changes in credit and equity financing result in changes in pollution through the channel of global growth opportunities. The third benchmark is *Asset tangibility*, measured as the ratio of an industry's tangible assets to total assets. Data come from Braun (2003). The interaction of this benchmark with the size of credit and stock markets accounts for the possibility that, for instance, the impact of financial structure on pollution by dirty industries reflects that such industries are also more reliant on tangible assets which credit markets are more likely to fund. We add the three industry benchmarks to the regression, one by one, in order to evaluate their independent impact on pollution intensity.

Similar to Table 3, Table 7 indicates that a number of country-specific factors are significantly correlated with pollution. For example, CO_2 emissions are lower in richer countries, both per-capita (columns (1)–(3)) and per-unit of output (columns (7)–(9)). Per capita pollution also declines with market size (columns (1)–(3)). The business cycle exerts a similar effect on pollution levels as recorded in Table 3: per capita pollution is higher during the expansion phase of the cycle (proxied by higher inflation), and it is lower during the contraction phase (proxied by whether the country is in a recession or experiencing a banking crisis).

The impact of the alternative industry benchmarks is nuanced. We find that industries dependent on external finance pollute more per capita as credit markets develop, but less in countries with deepening stock markets (column (1)). Industries facing better global growth opportunities pollute more, both per capita (column (2)) and per unit of output (column (8)), in countries with expanding stock markets. Lastly, there is some evidence that part of the positive impact of credit markets on pollution in technologically dirty industries operates through these sectors' differential reliance on tangible assets (column (3)).

Importantly, the main results recorded in columns (1)–(3) survive in this more saturated specification. We still find that per capita carbon dioxide emissions increase relatively more in dirty sectors in countries with growing credit markets, and decrease in countries with deepening stock markets (columns (1)–(3)). Technologically clean industries grow faster in countries with expanding stock markets but this effect is only significant in one case out of three (column (4)). Lastly, the efficiency gains from more developed stock markets are not sensitive to adding the full range of country and industry controls (columns (7)–(9)). The documented effect continues to be economically significant, too. For example, the coefficient on the interaction of pollution intensity and stock market development in column (1) (-0.1445) suggests that moving from the 25th to the 75th percentile of stock market development is associated with a decline in CO_2 emissions per capita in an industry at the 75th percentile of pollution intensity—relative to an industry at the 25th percentile of pollution intensity—of 0.030. This equals 7.2% of the sample mean.[15]

[15] We also find that the main results in the paper survive once we control for the impact of country-industry-specific fuel subsidies (Appendix Table A4). Fuel subsidies may blunt firms' incentives to make their production technology more energy efficient, even when firms can access stock markets to finance such green investments. Relatedly, Newell, Jaffe and Stavins (1999) find that oil price increases stimulate innovation to make air conditioners more energy efficient while Aghion et al. (2016) show how higher fuel prices redirect the car industry towards clean innovation (electric and hybrid technologies) and away from dirty technology (internal combustion engines). Other papers stress that policy interventions may be needed to stimulate clean technologies and move countries towards sustainable growth. Acemoglu, Aghion, Bursztyn and Hemous (2012) and Acemoglu, Akcigit, Hanley and Kerr (2016) develop endogenous growth models with directed technical change in which sustainable growth depends on temporary carbon taxes and research subsidies that redirect innovation towards clean technologies.

5.4.2 Robustness to alternative pollution-intensity measures

We next subject our results to a set of robustness tests where we employ alternative industry proxies for pollution intensity. Our industry benchmark for pollution intensity may be an imperfect proxy for the industry's "true" propensity to pollute. Recall that the benchmark we have used so far is based on average CO_2 emissions per unit of output over the sample period, in the global sample. This benchmark could be distorted if in many countries regulation is stringent and/or polluting firms are credit constrained, resulting in lower pollution than the industry's technology would imply.

One alternative is to calculate this variable on the basis of pollution per unit of output in one particular country that is simultaneously characterized by a relatively lax regulatory environment and deep financial markets. Consistent with the original idea in Rajan and Zingales (1998), the United States is a prime example of such a country.[16] To bring this idea to the analysis, we first calculate for each industry an alternative benchmark for pollution intensity using only US data on average CO_2 emissions per unit of output over the sample period. The correlation between the two benchmarks is 0.92, suggesting that the ranking of industries in terms of inherent propensity to pollute is not a feature of one particular pollution-intensity measure.

Second, we use the measure of pollution per worker developed by the World Bank's Industrial Pollution Projection System (IPPS). IPPS was developed from a database of environmental and economic data for about 200,000 facilities spanning 1,500 product categories with different operating technologies and pollutants. We focus on air pollution in the form of sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), volatile organic compounds, and total particulates. This measure therefore complements our CO_2 baseline measure of air pollution. We use IPPS values with respect to employment based on the same level of industry aggregation that we use in the rest of the paper. IPPS is an especially useful tool to estimate pollution load in developing countries where sufficient data for mass balance calculations from production processes are not available.

With these two new benchmarks in hand, we re-estimate Models (2)—(4), and report the results in Table 8. The reported results are in remarkable agreement with our previous estimates.

[16]The OECD publishes two Environmental Policy Stringency (EPS) indices, one for the energy sector and one for the economy as a whole. These indices measure the stringency of regulation to mitigate greenhouse gases, including emission trading schemes for CO_2 and SO_2, taxes on CO_2, taxes on the industrial use of diesel, and so on. According to 2012 data, the American EPS index for the energy sector was among the five lowest across the OECD while the economy-wide EPS index was in the bottom half. Over the period 1990-2012, the US economy-wide index value was typically below the OECD average and never among the top 10 OECD countries. Source: https://stats.oecd.org/.

In columns (1) and (2), we find that CO_2 emissions per capita are significantly higher (lower) in technologically dirty industries in countries with more developed credit markets (stock markets). Both effects are significant at least at the 5-percent statistical level. These results fully confirm the evidence in Table 4, and suggest that the impact of financial development on industrial pollution is independent of the benchmark used to classify industries as either dirty or clean. We also document weak evidence that growing stock markets are associated with slower growth in technologically dirty industries when we use US data to construct the industry benchmark for pollution intensity (column (3)). Lastly, we confirm our prior results on the relationship between financial structure and production efficiency: technologically dirty sectors emit more CO_2 per unit of output in countries with growing credit markets, while the opposite is true of countries with deepening stock markets (columns (5) and (6)).

5.4.3 Finance and pollution at later stages of development

A remaining question is whether our results are driven by a particular sample choice. Our findings so far are based on the UNIDO sample which features more countries (53) but fewer sectors (9 manufacturing ones).[17] The UNIDO sample contains many developing countries and emerging markets. Therefore, this particular sample choice may produce empirical regularities that are driven by the manufacturing industry in countries with relatively low levels of financial development.

We now make a different sample choice. First, we only focus on those country-years where both the level of credit market development and stock market development is above the 25th percentile. In that way, we make sure that we capture empirical regularities that are not driven by financial imperfections at early stages of financial development.

Second, we replicate our tests in the OECD sample, using data from STAN. This alternative data set allows us to run our tests on a sample of fewer countries (33) but more sectors (16), encompassing the whole economy with the exception of services. This is potentially important because the four heaviest polluters according to Table 2—the sectors "Electricity, gas, and water supply", "Land transport – transport via pipelines", "Water transport" and "Air transport"—are not part of manufacturing. In this way, we make sure that our results are not driven by a special

[17] Together with primary industry, the manufacturing sector accounts for almost 40 per cent of worldwide greenhouse gas emissions (Martin, de Preux and Wagner, 2014).

relationship between finance and pollution in the manufacturing sector.

With this strategy in hand, we replicate the most saturated versions of Models (2), (3), and (4)—that is, the ones with country-sector dummies, country-year dummies, and sector-year dummies. We report the results from these tests in Table 9. We find that the stage of overall financial development does not matter much, as all previous results are confirmed in a sample excluding countries at very low levels of financial development. We continue to find that credit markets increase per capita pollution levels, owing to a reduction in within-industry efficiency, and that stock markets reduce per capita pollution levels, owing to a simultaneous reduction in the size of dirty industries and an increase in within-industry efficiency (columns (1)–(3)).

When we move to the OECD sample, we find that deeper stock markets are still associated with a reduction in per-capita pollution levels (column (4)), and that this result is fully driven by an increase in within-industry efficiency (column (6)). However, we now find that controlling for stock market development, deeper credit markets are also associated with a reduction in per capita pollution levels (column (4)). This effect is due to relatively faster growth in technologically clean industries (column (5)).

The evidence in Table 9 thus suggests that the negative impact of stock markets on industrial pollution is not a feature of a sample dominated by lower-income countries or by economies at early stages of financial development. However, the impact of credit markets on industrial pollution appears to reverse at later stages of development, suggesting that overall financial development exerts a positive impact on environmental quality once countries reach a certain income level.

5.5 Financial development, innovation, and new business creation

In the previous sections, we found that CO_2 emissions per unit of output decline with stock market development, relatively more in technologically dirty industries. The intuitive interpretation of this result is that it reflects the propensity of dirty industries to innovate more in countries where more of their financing comes from equity markets. Such an effect could come from two different directions: either existing companies upgrade their technology, or older companies in possession of less efficient technologies are displaced by younger, more technologically innovative companies (that is, creative destruction in the spirit of Schumpeter, 1912).

We now aim to provide direct evidence for this conjecture. We start by exploring the link between financial development and innovation in technologically ”dirty” sectors. To that end, we incorporate in our analysis data on industrial patenting for our sample countries. We use of a uniquely comprehensive global dataset on patents, PATSTAT, which reports patents classified according to the International Patent Classification (IPC). For the countries and industries in our sample, we calculate four separate variables. The first one, “Total patents”, measures all patents granted to an industry in a country, regardless of the patent's underlying technological contribution. The second one, “Green patents”, measures all granted patents that belong to the EPO Y02/Y04S climate change mitigation technology (CCMT) tagging scheme. The third one, “Green patents (excluding transportation and waste)”, counts all granted patents that belong to the EPO Y02/Y04S CCMT tagging scheme, with the exception of Y02T (Climate change mitigation technologies related to transportation) and Y02T (Climate change mitigation technologies related to solid and liquid waste treatment). The resulting group of patents consists of patents related to energy efficiency (Y02P), buildings and home appliances (Y02B), alternative (none fossil) energy sources (Y02E), and smart grids (Y04S). The fourth variable, “Green patents (energy intensive sectors)”, counts patents that belong only to the arguably most important category of patents when it comes to green innovation, Y02P.

With these data in hand, we now proceed to estimate Model (5). Table 10 reports the resulting estimates. This table follows the logic of Tables (4)–(6) whereby we first test for the effect of credit markets and stock markets separately and then jointly. The results indicate that patenting in technologically dirty industries declines with credit market development. This is the case both for total patents (column (1)) and for various green patent aggregates (columns (2)–(4)). At the same time, the number of green patents per capita increases relatively more in technologically dirty industries in countries with deeper stock markets. This effect is only significant at the 10-percent statistical level, but is consistent across all three specifications (columns (2)–(4)). These results complement those of Hsu, Tian and Xu (2014), who show that industries that depend on external finance and are high-tech intensive are less (more) likely to file patents in countries with better developed credit (equity) markets. We find that credit and stock markets also have contrasting effects on the ability of polluting industries to become greener through innovation.

These effects are economically meaningful, too. For example, the coefficient of 0.0529 in column (2) suggests that moving from the 25th to the 75th percentile of stock market development is associated with an increase in the number of green patents generated by an industry at the 75th percentile of pollution intensity—relative to one at the 25th percentile of pollution intensity—of 0.0049 patents per million, which is equal to 8% of the sample mean. [18]

Next, we turn to the question of new business creation. For each of the 18 industrial sectors, UNIDO reports, by year, the total number of establishments. We divide by total population and take the logarithm of the resulting value. We then estimate Model (6) where, in the context of a fixed-effect regression, the impact on the dependent variable can be understood as a change in the growth rate of total establishments. Building on the evidence we have shown so far, we also do this for three different samples: the full sample, the sample of countries at later stages of financial development, and the sample of OECD countries at later stages of financial development.

The evidence reported in Table 11 unequivocally suggests that a higher degree of credit market development is associated with a higher rate of new business creation in technologically "dirty" industries. The economic magnitude of this effect is meaningful, too. For example, the coefficient on the interaction of pollution intensity and credit market development in column (1) (0.0707) suggests that moving from the 25th to the 75th percentile of credit market development is associated with an increase in the number of establishments per capita in an industry at the 75th percentile of pollution intensity—relative to an industry at the 25th percentile of pollution intensity—of 0.015. This corresponds to one-fifth of a sample standard deviation. Stock markets, at the same time, have the opposite effect: the number of establishments declines in technologically "dirty" industries with deeper stock markets, in particular in countries at later stages of financial development. The combined evidence in Tables 10 and 11 thus suggests that financial structure affects differentially the rates of creative destruction in technologically dirty and in technologically clean industries, pointing to a robust channel linking financial development and industrial pollution.

5.6 Financial development and industrial pollution: The role of outsourcing

One final concern that we need to address is that much of the decline in domestic industrial pollution as a result of stock market development is driven by the outsourcing of "dirty" industries to emerging economies. Because funding through stock markets is ultimately provided by individual

[18] As many country-industry-year cells are empty, we also estimate this table using logit regressions on the basis of a sample of non-zero observations. The results in Appendix Table A5 are broadly in line with those reported here.

investors with their own social objectives, stock markets may be more sensitive to the financing of firms that perform badly in environmental terms (Salinger, 1992; Klassen and McLaughlin, 1996). One unintended consequence of this social objective may be that firms close domestic operations, but open foreign ones, under the assumption that poor environmental performance away from home will be more acceptable (or less observable) to their investors. If so, then the decline in pollution domestically would be neutralized by a proportionate increase in pollution in emerging markets, making for a null effect from a global point of view.

To test this hypothesis, we modify Models (1)–(3) in the following way. First, we focus on the 10 major emerging markets: Argentina, Brazil, China, India, Indonesia, Mexico, Poland, Russia, South Africa, and Turkey. Next, we take US stock market development as a benchmark, and interact, for all of these 10 emerging markets, the US-specific stock market development with the industry-specific pollution intensity. In this regression, the inclusion of Industry×Year fixed effects is not possible because the industry trend is collinear with the interaction of US stock market development and the industry benchmark for its propensity to pollute.

As a second way to address the same question, we postulate that a country is more likely to be affected by stock market developments in close and large financial centers. This is consistent with gravity models in finance and trade which have demonstrated that distance matters for financial and commercial relationships between two countries (e.g., Frankel, Stein, and Wei, 1995; Frankel and Romer, 1999; Martin and Rey, 2004). We therefore calculate the distance from each of the 10 emerging markets' capitals to each of the three main global financial centers (New York, London, and Tokyo). Then, for each of the 10 emerging markets, we calculate a distance-weighted aggregate stock market development. This specification results in a measure of core stock market development that varies across time and emerging market, allowing for the inclusion of Industry×Year fixed effects.

The estimates from these modified versions of Models (1)–(3) are reported in Table 12. The data fail to reject the hypothesis that stock market development in the US (Panel A) or in the three core financial centers (Panel B) has an impact on technologically "dirty" industries' propensity to pollute in emerging markets. In particular, we find no increase in CO_2 emissions per capita (column (1)), in growth rates (column (2)), and in CO_2 emissions per unit of output (column (3)) in such industries in emerging markets, relative to technologically "clean" ones. We conclude that the reduction in pollution in industries with a high natural propensity to pollute, as a result of domestic stock market development, is not mirrored by a proportionate increase in pollution by the same industries in emerging economies.

6 Conclusion

The rapid growth of green finance, and the myriad associated policy initiatives, contrasts sharply with the paucity of the existing evidence on the impact of conventional finance on carbon emissions and other forms of pollution. To help quantify this role, we study the relationship between financial development and industrial pollution in a large panel data set of countries and industries over the period 1974–2013. We find a strong positive impact of credit markets, but a strong negative impact of stock markets, on aggregate CO_2 emissions per capita. When further analyzing the impact of financial development on industries that pollute relatively more for intrinsic technological reasons, we find that such industries emit relatively more carbon dioxide in countries with larger credit markets. At the same time, such dirty industries produce relatively less carbon dioxide in countries with deepening stock markets. This first set of results can be interpreted in light of the Kuznets-curve argument that industrial pollution follows an inverse-U shape over the development cycle. Our empirical setting addresses this issue head on by juxtaposing the effects of bank and market intermediation. As stock markets tend to develop at later stages of development than credit markets, our findings show that financial development directly contributes to the concave shape of industrial pollution over time.

We next study the mechanisms that underpin these country- and industry-level results. We find strong evidence for the conjecture that stock markets facilitate the adoption of cleaner technologies in polluting industries. At the same time, credit market development reduces within-industry pollution efficiency. Further analysis of sectoral patenting data confirms that deeper stock markets (credit markets) are associated with more (less) green innovation in traditionally polluting industries, as well as with lower (higher) rates of new business creation in those industries. We also document weak evidence that—holding cross-industry differences in technology constant—credit markets tend to reallocate investment towards dirtier sectors, while the opposite is true for stock markets. These empirical regularities are broadly robust to controlling for a host of potential confounding factors, such as general economic development, market size, and the business cycle, country-industry fixed effects, and unobservable country and industry trends.

In sum, our findings indicate that not only financial development, but also financial structure has an important effect on environmental quality. This suggests that countries with a bank-based financial system that aim to green their economy, such as through the promotion of green bonds or other green-finance initiatives, should consider stimulating the development of conventional equity markets as well. This holds especially for middle-income countries where carbon dioxide emissions may have increased more or less linearly during the development process. There, according to our findings, stock markets could play an important role in making future growth greener, in particular by stimulating innovation that leads to cleaner production processes within industries.

In parallel, countries can take measures to counterbalance the tendency of credit markets to (continue to) finance relatively dirty industries. Examples include the green credit guidelines and resolutions that China and Brazil introduced in 2012 and 2014, respectively, to encourage banks to improve their environmental and social performance and to lend more to firms that are part of the low-carbon economy. From an industry perspective, adherence to the so-called Carbon Principles, Climate Principles, and Equator Principles should also contribute to a gradual greening of bank lending.[19] Strict adherence to these principles can also make governmental climate change policies more effective by accelerating capital reallocation and investment towards lower-carbon technologies.

[19]The Carbon Principles are guidelines to assess the climate change risks of financing electric power projects. The Climate Principles comprise a similar but broader framework. Lastly, the Equator Principles are a risk management framework to assess and manage environmental and social risk in large projects. Equator Principle banks commit not to lend to borrowers that do not comply with their environmental and social policies and procedures, and to require borrowers with greenhouse gas emissions above a certain threshold to implement measures to reduce such emissions.

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Table 1: Summary statistics

Variable	Mean	Median	St. dev.	Min	Max
Country-level					
CO_2 per capita	6.872	6.289	5.288	0.105	45.036
Credit/GDP	0.608	0.505	0.433	0.009	2.129
Stock/GDP	0.481	0.339	0.454	0.001	2.651
GDP per capita	20,731	13,221	19,665	366	110,001
Population (mln.)	73.793	16.282	197.712	0.355	1,357.380
Inflation	0.028	0.023	0.027	-0.047	0.382
Recession	0.209	0.000	0.407	0.000	1.000
Banking crisis	0.128	0.000	0.334	0.000	1.000
Industry-level (UNIDO)					
CO_2 emissions per capita	0.439	0.078	1.187	0.000	29.264
CO_2 emissions per value added	0.002	0.001	0.006	-0.052	0.257
Growth in value added	0.010	0.012	0.175	-1.000	1.000
Total patents per capita	1.980	0.000	11.953	0.000	275.901
Green patents per capita	0.099	0.000	0.618	0.000	21.131
Green patents per capita (excl. transport and waste)	0.078	0.000	0.528	0.000	20.850
Green patents per capita (energy intensive sectors)	0.034	0.000	0.203	0.000	10.487
Establishments per 1000 capita	0.234	0.080	0.436	0.000	6.525
Industry share	0.061	0.048	0.056	0.000	0.783
Fuel subsidies	9.647	1.082	42.186	-129.594	413.833
Industry-level (OECD)					
CO_2 emissions per capita	0.562	0.119	1.379	0.000	29.264
CO_2 emissions per value added	0.001	0.001	0.005	-0.023	0.217
Growth in value added	0.008	0.011	0.126	-1.000	1.000
Total patents per capita	3.290	0.000	15.330	0.000	275.901
Green patents per capita	0.162	0.000	0.788	0.000	21.131
Green patents per capita (excl. transport and waste)	0.129	0.000	0.678	0.000	20.850
Green patents per capita (energy intensive sectors)	0.057	0.000	0.260	0.000	10.487
Establishments per 1000 capita	0.305	0.127	0.512	0.000	6.525
Industry share	0.074	0.036	0.105	0.001	0.897
Fuel subsidies	0.381	0.235	15.512	-129.594	74.508

Notes: This table summarizes the data used in the paper. Appendix Table A1 contains all variable definitions.

Table 2: Industry benchmarks

ISIC code	Industry name	Pollution intensity	External dependence
01-05	Agriculture, hunting, forestry, and fishing	0.218	-1.430
10-14	Mining and quarrying	0.129	0.193
15-16	Food products, beverages, and tobacco	0.202	-0.309
17-19	Textiles, textile products, leather, and footwear	0.128	-0.028
20	Wood and products of wood and cork	0.115	-0.023
21-22	Pulp, paper, paper products, printing, and publishing	0.229	-0.016
23-25	Chemical, rubber, plastics, and fuel products	0.525	0.106
26	Other non-metallic mineral products	1.134	-0.960
27	Basic metals	1.712	-0.067
28-33	Fabricated metal products, machinery, and equipment	0.040	-0.058
34-35	Transport equipment	0.068	-0.108
40-41	Electricity, gas, and water supply	8.083	0.240
45	Construction	0.037	0.570
60	Land transport transport via pipelines	3.000	1.000
61	Water transport	7.320	0.670
62	Air transport	3.845	0.480

Notes: This table summarizes, by industry, the main benchmarks used in the paper. Appendix Table A1 contains all variable definitions.

Table 3: Financial development and aggregate pollution

Dependent variable	CO_2 emissions per capita				
	(1)	(2)	(3)	(4)	(5)
Credit/GDP	0.0004***		0.0005**	0.0006***	0.0013***
	(0.0001)		(0.0002)	(0.0002)	(0.0002)
Stocks/GDP		-0.0003**	-0.0003**	-0.0002**	-0.0006***
		(0.0001)	(0.0001)	(0.0001)	(0.0002)
Log GDP per capita				0.0025***	0.0137***
				(0.0004)	(0.0027)
Log GDP per capita squared					-0.0006***
					(0.0002)
Log Population					-0.0014
					(0.0010)
Inflation					0.0008
					(0.0009)
Recession					-0.0002**
					(0.0001)
Banking crisis					-0.0006***
					(0.0001)
Country dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
No. Observations	2,184	1,608	1,571	1,571	1,451
R-squared	0.950	0.950	0.950	0.960	0.960

Notes: This table reports estimates from OLS regressions. The dependent variable is 'CO_2 emissions per capita' which denotes aggregate emissions of carbon dioxide, in tons. All regressions include fixed effects as specified. Robust standard errors are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 4: Financial development and industry-level pollution per capita

Dependent variable	CO_2 emissions per capita		
	(1)	(2)	(3)
Credit/GDP × Pollution intensity	0.1286***		0.2065***
	(0.0390)		(0.0487)
Stocks/GDP × Pollution intensity		-0.1411***	-0.1167**
		(0.0484)	(0.0457)
Industry share	0.0082***	0.0159***	0.0146***
	(0.0026)	(0.0052)	(0.0048)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes
No. Observations	9,806	8,309	8,124
R-squared	0.764	0.761	0.773

Notes: The table reports estimates from OLS regressions. The dependent variable is 'CO_2 emissions per capita' which denotes industry-specific emissions of carbon dioxide, in tons, per capita. Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 5: Cross-industry reallocation

Dependent variable	Growth in value added		
	(1)	(2)	(3)
Credit/GDP × Pollution intensity	0.1917		0.2402*
	(0.1654)		(0.1694)
Stocks/GDP × Pollution intensity		-0.2448*	-0.2346*
		(0.1445)	(0.1477)
Industry share	-0.0705***	-0.0951***	-0.0975***
	(0.0087)	(0.0144)	(0.0147)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes
No. Observations	10,216	8,371	8,188
R-squared	0.510	0.547	0.548

Notes: The table reports estimates from OLS regressions. The dependent variable is 'Growth in value added' which denotes industry-specific growth in value added. Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 6: Industry-level pollution per unit of output

Dependent variable	CO_2 emissions per value added		
	(1)	(2)	(3)
Credit/GDP × Pollution intensity	0.8583**		0.5180*
	(0.3443)		(0.2979)
Stocks/GDP × Pollution intensity		-1.1267***	-1.1415***
		(0.2379)	(0.2415)
Industry share	-0.0069	0.0041	0.0006
	(0.0052)	(0.0069)	(0.0072)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes
No. Observations	9,338	7,875	7,702
R-squared	0.836	0.843	0.844

Notes: The table reports estimates from OLS regressions. The dependent variable is 'CO_2 emissions per value added' which denotes industry-specific emissions of carbon dioxide, in tons, per unit of value added. Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 7: Financial development and industry-level pollution: Additional controls

Dependent variable	CO_2 emissions per capita			Growth in value added			CO_2 emissions per unit of value added		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Credit/GDP × Pollution intensity	0.3202***	0.2449***	0.2195***	0.2345	0.1611	0.1443	0.2299	0.1621	0.1482
	(0.0735)	(0.0559)	(0.0492)	(0.2154)	(0.1896)	(0.1847)	(0.3547)	(0.3111)	(0.2871)
Stocks/GDP × Pollution intensity	-0.1445**	-0.1004**	-0.0921**	-0.2716*	-0.1660	-0.0802	-0.8093***	-0.8524***	-0.8551***
	(0.0589)	(0.0424)	(0.0372)	(0.1839)	(0.1558)	(0.1444)	(0.2561)	(0.2322)	(0.2356)
Credit/GDP × External dependence	0.0004***			0.0004			0.0004		
	(0.0001)			(0.0003)			(0.0004)		
Stocks/GDP × External dependence	-0.0002**			-0.0005			0.0003		
	(0.0001)			(0.0003)			(0.0003)		
Credit/GDP × Growth opportunities		-0.0048***			0.0044			-0.0039	
		(0.0012)			(0.0063)			(0.0029)	
Stocks/GDP × Growth opportunities		0.0023**			0.0048			0.0079***	
		(0.0010)			(0.0047)			(0.0030)	
Credit/GDP × Asset tangibility			0.0007***			0.0003			0.0005
			(0.0002)			(0.0013)			(0.0009)
Stocks/GDP × Asset tangibility			-0.0003*			-0.0019**			-0.0003
			(0.0002)			(0.0009)			(0.0007)
Log GDP per capita × Pollution intensity	-0.0004**	-0.0004**	-0.0004**	-0.0005	-0.0006	-0.0005	-0.0038***	-0.0038***	-0.0038***
	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0005)	(0.0005)	(0.0012)	(0.0012)	(0.0012)
Log Population × Pollution intensity	-0.0008***	-0.0008***	-0.0008***	-0.0002	-0.0002	-0.0002	0.0035	0.0035	0.0035
	(0.0002)	(0.0002)	(0.0002)	(0.0008)	(0.0008)	(0.0008)	(0.0025)	(0.0025)	(0.0025)
Inflation × Pollution intensity	0.0006***	0.0006***	0.0006***	0.0003	0.0004	0.0003	0.0003	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0021)	(0.0021)	(0.0021)	(0.0049)	(0.0049)	(0.0049)
Recession × Pollution intensity	-0.0001***	-0.0001***	-0.0001***	0.0000	0.0000	0.0000	0.0002	0.0002	0.0002
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Banking crisis × Pollution intensity	-0.0001***	-0.0001***	-0.0001***	0.0002	0.0002	0.0002	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0003)
Industry share	0.0171***	0.0170***	0.0168***	-0.1179***	-0.1182***	-0.1192***	-0.0082	-0.0084	-0.0086
	(0.0060)	(0.0060)	(0.0059)	(0.0176)	(0.0176)	(0.0177)	(0.0073)	(0.0073)	(0.0074)
Country × Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	7,751	7,751	7,751	7,780	7,780	7,780	7,353	7,353	7,353
R-squared	0.781	0.778	0.778	0.544	0.544	0.544	0.837	0.837	0.837

Notes: The table reports estimates from OLS regressions. In columns (1)-(3), the dependent variable is 'CO_2 emissions per capita' which denotes the industry's emissions of carbon dioxide, in tons, per capita; in columns (4)-(6), the dependent variable is 'Growth in value added' which denotes the industry's annual growth in value added; and in columns (7)-(9), the dependent variable is 'CO_2 emissions per unit of value added' which denotes the industry's emissions of carbon dioxide, in tons, per unit of value added. Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the industry level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 8: Alternative benchmarks for pollution intensity

Dependent variable	CO_2 emissions per capita		Growth in value added		CO_2 emissions per unit of value added	
	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP × Pollution intensity (US)	0.2620***		0.2852		0.5918*	
	(0.0618)		(0.2219)		(0.3842)	
Stocks/GDP × Pollution intensity (US)	-0.1522**		-0.3301*		-1.4694***	
	(0.0595)		(0.1939)		(0.3098)	
Credit/GDP × Pollution intensity (WB)		0.0001***		0.0001		0.0002*
		(0.0000)		(0.0002)		(0.0001)
Stocks/GDP × Pollution intensity (WB)		-0.0001**		-0.0001		-0.0008***
		(0.0000)		(0.0002)		(0.0002)
Industry share	0.0151***	0.0153***	-0.1029***	-0.0968***	-0.0004	0.0031
	(0.0051)	(0.0051)	(0.0155)	(0.0148)	(0.0076)	(0.0072)
Country × Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	7,811	8,124	7,901	8,188	7,415	7,702
R-squared	0.773	0.769	0.549	0.548	0.843	0.842

Notes: The table reports estimates from OLS regressions. In columns (1)-(2), the dependent variable is 'CO_2 emissions per capita' which denotes the industry's emissions of carbon dioxide, in tons, per capita; in columns (3)-(4), the dependent variable is 'Growth in value added' which denotes the industry's annual growth in value added; and in columns (5)-(6), the dependent variable is 'CO_2 emissions per value added' which denotes the industry's emissions of carbon dioxide, in tons, per unit of value added. Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 9: Finance and industry-level pollution at later stages of financial development

Dependent variable	CO_2 emissions per capita	Growth in value added	CO_2 emissions per value added	CO_2 emissions per capita	Growth in value added	CO_2 emissions per value added
		Full sample			OECD sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP × Pollution intensity	0.2967***	0.0150	0.8306**	-0.0423**	-0.0656*	0.1444
	(0.0760)	(0.2037)	(0.3605)	(0.0169)	(0.0341)	(0.1343)
Stocks/GDP × Pollution intensity	-0.1089**	-0.3750**	-0.9731***	-0.0188*	0.0018	-0.0955*
	(0.0538)	(0.1697)	(0.3298)	(0.0117)	(0.0270)	(0.0597)
Industry share	0.0179***	-0.0938***	-0.0011	0.0113***	-0.0341***	-0.0102***
	(0.0066)	(0.0207)	(0.0085)	(0.0034)	(0.0039)	(0.0030)
Country × Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	5,452	5,415	5,122	6,857	6,755	6,146
R-squared	0.767	0.587	0.803	0.950	0.449	0.757

Notes: The table reports estimates from OLS regressions. In columns (1) and (4), the dependent variable is 'CO_2 emissions per capita' which denotes the industry's emissions of carbon dioxide, in tons, per capita; in columns (2) and (5), the dependent variable is 'Growth in value added' which denotes the industry's annual growth in value added; and in columns (3) and (6), the dependent variable is 'CO_2 emissions per value added' which denotes the industry's emissions of carbon dioxide, in tons, per unit of value added. Industry-specific data come from UNIDO and STAN. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 10: Financial development and green innovation

Dependent variable	Total patents per capita	Green patents per capita	Green patents per capita (excl. transport and waste)	Green patents per capita (energy intensive sectors)
	(1)	(2)	(3)	(4)
Credit/GDP × Pollution intensity	-0.0011**	-0.3339***	-0.3814***	-0.0955***
	(0.0005)	(0.1162)	(0.1159)	(0.0289)
Stocks/GDP × Pollution intensity	-0.0003	0.0529*	0.0499*	0.0381*
	(0.0006)	(0.0382)	(0.0329)	(0.0268)
Industry share	0.0002***	0.0083*	0.0103**	0.0024
	(0.0001)	(0.0045)	(0.0042)	(0.0024)
Country × Industry dummies	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes
No. Observations	8,640	8,640	8,640	8,640
R-squared	0.907	0.762	0.720	0.688

Notes: The table reports estimates from OLS regressions. In column (1), the dependent variable is 'Total patents per captia' which denotes the number of total patents in a country-industry-year, per 1 mln. population; in column (2), the dependent variable is 'Green patents per capita' which denotes the number of green patents in a country-industry-year, per 1 mln. population; in column (3), the dependent variable is 'Green patents per capita (excl. transport and waste)' which denotes the number of patents in the most climate-change-intensive technologies in a country-industry-year, per 1 mln. population, excluding patents related to transportation and to wastewater treatment and waste management; and in column (4), the dependent variable is 'Green patents per capita (energy intensive sectors)' which denotes the number of patents in energy-intensive sectors in a country-industry-year, per 1 mln. population. Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 11: Financial development and new business creation

Dependent variable	Establishments per 1000 capita		
	Full sample	Later stages of development	Later stages of development and OECD
	(1)	(2)	(3)
Credit/GDP × Pollution intensity	0.0707***	0.0530***	0.0592**
	(0.0161)	(0.0178)	(0.0241)
Stocks/GDP × Pollution intensity	-0.0091	-0.0652***	-0.0536***
	(0.0184)	(0.0151)	(0.0195)
Industry share	0.0115***	0.0088***	0.0048***
	(0.0015)	(0.0014)	(0.0012)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes
No. Observations	7,025	4,942	3,726
R-squared	0.939	0.961	0.961

Notes: The table reports estimates from OLS regressions. The dependent variable is 'Establishments per 1000 capita' which denotes the total number of establishments per 1000 capita. Industry-specific data come from UNIDO and STAN. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table 12: Financial development and pollution: Outsourcing

Panel A. US financial development

Dependent variable	CO_2 emissions per capita	Growth in value added	CO_2 emissions per value added
	(1)	(2)	(3)
Credit/GDP (US) × Pollution intensity	-0.0079	-0.548	-3.5078***
	(0.0199)	(0.5188)	(0.8327)
Stocks/GDP (US) × Pollution intensity	-0.0142	0.3425	-0.1405
	(0.0175)	(0.4524)	(0.7463)
Industry share	0.0017***	-0.1198***	-0.0764**
	(0.0006)	(0.0254)	(0.0308)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
No. Observations	1,709	1,863	1,626
R-squared	0.881	0.505	0.861

Panel B. Distance-weighted average of US, UK, and Japanese financial development

Dependent variable	CO_2 emissions per capita	Growth in value added	CO_2 emissions per value added
	(1)	(2)	(3)
Credit/GDP (US, UK, JP) × Pollution intensity	-0.0158	-1.3369	-10.822**
	(0.0207)	(2.0855)	(4.657)
Stocks/GDP (US, UK, JP) × Pollution intensity	-0.0094	-1.7816	0.2649
	(0.0216)	(1.6000)	(2.459)
Industry share	0.0017***	-0.1139***	-0.0916***
	(0.0006)	(0.0258)	(0.0329)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes
No. Observations	1,709	1,857	1,613
R-squared	0.881	0.621	0.921

Notes: The table reports estimates from OLS regressions. In column (1), the dependent variable is 'CO_2 emissions per capita' which denotes the industry's emissions of carbon dioxide, in tons, per capita; in column (2), the dependent variable is 'Growth in value added' which denotes the industry's annual growth in value added; and in column (3), the dependent variables is 'CO_2 emissions per value added' which denotes the industry's emissions of carbon dioxide, in tons, per unit of value added. The sample is restricted to the 10 major emerging markets (Argentina, Brazil, China, India, Indonesia, Mexico, Poland, Russia, South Africa, and Turkey). 'Credit/GDP (US)' denotes the 1-period lagged ratio of credit to the private sector to GDP in the US. Stock/GDP (US)' denotes the 1-period lagged ratio of the value of all listed stocks to GDP in the US. 'Credit/GDP (US, UK, JP)' denotes the 1-period lagged ratio of credit to the private sector to GDP in the US, UK, and Japan, weighted by air distance to the respective country. 'Stock/GDP (US, UK, JP)' denotes the 1-period lagged ratio of the value of all listed stocks to GDP in the US, UK, and Japan, weighted by air distance to the respective country. Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Appendix

Table A1: Variable definitions and sources

Variable	Definition	Data source
CO_2 emissions per capita	Country or industry-level emissions of carbon dioxide, in tons, divided by the countrys population	IEA; WDI
CO_2 emissions per value added	Country or industry-level emissions of carbon dioxide, in tons, divided by value added	IEA; UNIDO; STAN
Growth in value added	Industry-specific growth in value added	UNIDO; STAN
Industry share	One-period lagged value added of the industry as a share of the whole economy	UNIDO
Pollution intensity	Average value, over the sample period, of an industry's CO_2 emissions per value added, for all countries in the sample	IEA; UNIDO; STAN
Pollution intensity (US)	Average value, over the sample period, of an industry's CO_2 emissions per value added in the United States	IEA; UNIDO; STAN
Pollution intensity (WB)	Per-output emissions of SO_2, NO_2, CO, volatile organic compounds, and particulates in an industry	IPPS
External dependence	An industry's capital expenditures minus cash flow from operations divided by capital expenditures (in the US)	Duygan-Bump et al. (2015)
Growth opportunity	Sales growth of an industry in the US (sample average)	STAN
Asset tangibility	Average ratio of tangible assets to total assets in an industry	Braun (2003)
Credit/GDP	One-period lagged ratio of private-sector credit to GDP	Beck et al. (2016)
Stock/GDP	One-period lagged ratio of value of all listed stocks to GDP	Beck et al. (2016)
Log GDP per capita	Gross Domestic Product per capita of a country (log)	WDI
Log Population (mln.)	Countrys population, in millions of inhabitants (log)	WDI
Inflation	One-period lagged annual change in consumer price inflation	WDI

Continued on next page.

Table A1 cont.: Variable definitions and sources

Variable	Definition	Data source
Recession	Dummy=1 if the country is experiencing negative GDP growth in a given year; 0 otherwise (one-period lagged)	WDI
Banking crisis	Dummy=1 if the country is experiencing a systemic banking crisis in a given year; 0 otherwise (one-period lagged)	Laeven and Valencia (2013)
Total patents per capita	No. of patents in a country-industry-year, per 1 million population	PATSTAT
Green patents per capita	No. of green patents in a country-industry-year, per 1 million population	PATSTAT
Green patents per capita (excl. transport and waste)	No. of patents in the most climate-change-intensive technologies in a country-industry-year, per 1 million population, excluding patents related to transportation and to wastewater treatment and waste management	PATSTAT
Green patents per capita (energy intensive sectors)	No. of patents in energy-intensive sectors in a country-industry-year, per 1 million population.	PATSTAT
Establishments per 1000 capita	No. of establishments in a country-industry-year, per 1,000 population.	UNIDO
Fuel subsidies	Post-tax fossil fuel subsidy per $1000 of output (2011)	IMF Energy Subsidies Template

Notes: This table provides definitions and data sources for all variables used in the paper. WDI: World Development Indicators. IPPS: Industrial Pollution Projection System (World Bank). IEA: International Energy Agency. STAN: STAN Dataset for Structural Analysis (OECD).

Table A2: List of countries and average financial development

Country	Credit / GDP	Stock / GDP	CO_2 per capita
Albania	0.161		1.513
Argentina	0.149	0.094	3.541
Australia	0.660	0.731	15.682
Austria	0.817	0.156	7.535
Azerbaijan	0.085	0.001	3.811
Belarus	0.152		6.240
Belgium	0.468	0.403	10.769
Brazil	0.352	0.334	1.468
Bulgaria	0.429	0.092	6.141
Canada	0.969	0.976	15.848
Chile	0.558	0.904	2.681
Colombia	0.290	0.254	1.309
Costa Rica	0.245	0.075	1.092
Croatia	0.468	0.294	3.946
Czech Republic	0.479	0.180	11.643
Denmark	0.792	0.356	10.396
Estonia	0.495	0.231	12.256
FYR of Macedonia	0.296	0.067	4.345
Finland	0.630	0.656	10.693
France	0.768	0.403	6.296
Germany	0.917	0.282	11.188
Greece	0.487	0.369	6.556
Hungary	0.368	0.186	6.104
India	0.276	0.445	0.734
Indonesia	0.279	0.246	0.944
Ireland	0.737	0.518	8.835
Italy	0.629	0.306	6.689
Japan	1.610	0.646	8.402
Kazakhstan	0.238	0.152	11.404
Lithuania	0.278	0.152	4.159
Luxembourg	0.922	1.027	25.911
Mexico	0.192	0.198	3.349
Morocco	0.329	0.354	0.954
Netherlands	0.845	0.614	9.950
New Zealand	0.684	0.386	6.638
Norway	0.679	0.349	7.018
China	0.936	0.329	3.247
Philippines	0.324	0.482	0.739
Poland	0.346	0.193	9.292
Portugal	0.856	0.302	3.926
Russian Federation	0.229	0.363	10.908
Slovak Republic	0.417	0.567	8.160
Slovenia	0.454	0.190	7.307
South Africa	0.991	1.420	7.249
Spain	0.951	0.666	5.622
Sweden	0.949	0.607	6.072
Switzerland	1.336	1.392	5.889
Thailand	0.855	0.542	1.892
Turkey	0.200	0.206	2.582
Ukraine	0.288	0.173	7.237
United Kingdom	0.969	0.890	9.165
United States	1.315	0.829	19.189
Zambia	0.078	0.122	0.332

Table A3: Financial development and industry-level pollution per capita

Dependent variable	CO_2 emissions per capita	Growth in value added	CO_2 emissions per value added
	(1)	(2)	(3)
Log (Credit/GDP + Stocks/GDP)	0.1026***	0.1484	-0.1845
× Pollution intensity	(0.0242)	(0.1850)	(0.2015)
Log (Stocks/GDP / Credit/GDP)	-0.0197**	-0.0609	-0.4960**
× Pollution intensity	(0.0083)	(0.0631)	(0.1476)
Industry share	0.0146***	-0.0932***	-0.0004
	(0.0048)	(0.0135)	(0.0068)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes
No. Observations	8,288	8,382	7,867
R-squared	0.771	0.549	0.850

Notes: The table reports estimates from OLS regressions. In column (1), the dependent variable is 'CO_2 emissions per capita' which denotes the industrys emissions of carbon dioxide, in tons, per capita; in column (2), the dependent variable is 'Growth in value added' which denotes the industry's annual growth in value added; and in column (3), the dependent variable is 'CO_2 emissions per value added' which denotes the industry's emissions of carbon dioxide, in tons, per unit of value added. Industry-specific data come from IEA and UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * denote significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table A4: Finance and industry-level pollution: Controlling for fuel subsidies

Dependent variable	CO_2 emissions per capita	Growth in value added	CO_2 emissions per value added
	(1)	(2)	(3)
Credit/GDP × Pollution intensity	0.1986***	0.2490*	0.5105*
	(0.0488)	(0.1715)	(0.3016)
Stocks/GDP × Pollution intensity	-0.1022**	-0.1854	-1.0517***
	(0.0436)	(0.1508)	(0.2391)
Credit/GDP × Fuel subsidies	0.0001**	-0.0051	-0.0057
	(0.0000)	(0.0045)	(0.0058)
Stocks/GDP × Fuel subsidies	0.0001**	-0.0019	-0.0129**
	(0.00002)	(0.0037)	(0.0060)
Industry share	0.0144***	-0.0986***	0.0011
	(0.0048)	(0.0149)	(0.0072)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes
No. Observations	7,981	8,040	7,564
R-squared	0.775	0.551	0.846

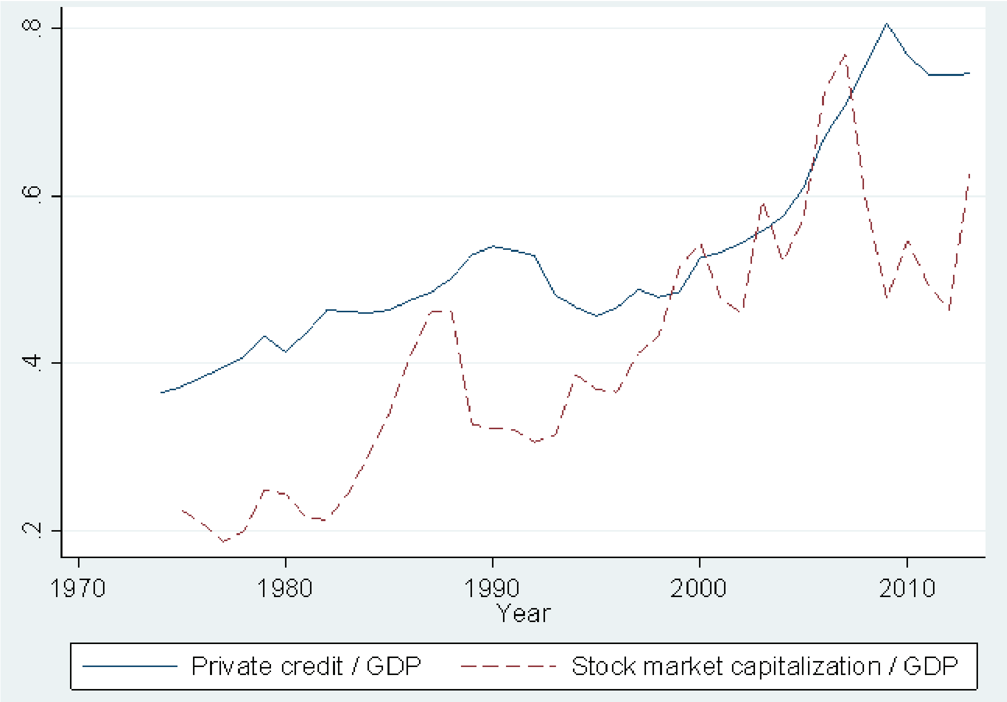
Notes: The table reports estimates from OLS regressions. In column (1), the dependent variable is 'CO_2 emissions per capita' which denotes the industry's emissions of carbon dioxide, in tons, per capita; in column (2), the dependent variable is 'Growth in value added' which denotes the industry's annual growth in value added; and in column (3), the dependent variable is 'CO_2 emissions per value added' which denotes the industry's emissions of carbon dioxide, in tons, per unit of value added. Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Table A5: Financial development and green innovation

Dependent variable	Total patents per capita	Green patents per capita	Green patents per capita (excl. transport and waste)	Green patents per capita (energy intensive sectors)
	(1)	(2)	(3)	(4)
Credit/GDP	-0.7551	-0.0732	-0.4770	-0.8420
× Pollution intensity	(0.9489)	(0.7532)	(0.7518)	(1.0091)
Stocks/GDP	3.0516**	1.0799*	2.2915***	0.6348
× Pollution intensity	(1.2468)	(0.6843)	(0.7718)	(0.7972)
Industry share	0.1081**	0.0085*	0.0197***	0.0862*
	(0.0489)	(0.0045)	(0.0048)	(0.0508)
Country × Industry dummies	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes
No. Observations	1,524	3,147	3,002	2,849
Pseudo R-squared	0.450	0.450	0.450	0.450

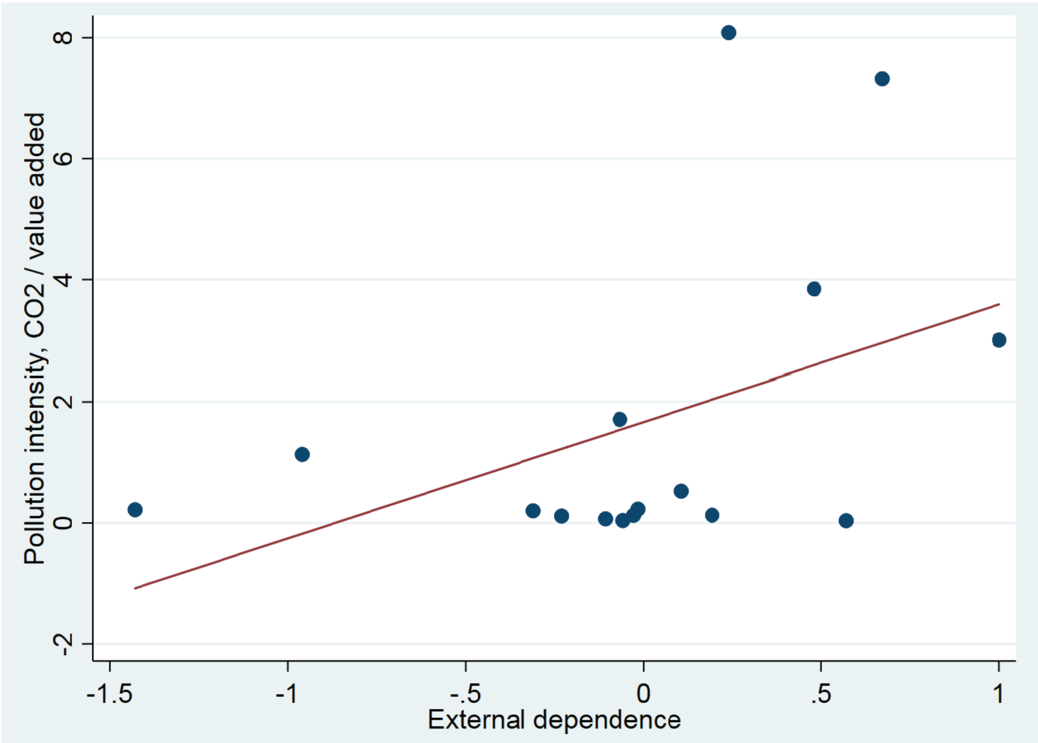
Notes: The table reports estimates from Logit regressions. The dependent variable is the number of total patents in a country-industry-year, per 1 mln. population (column (1)); the number of green patents in a country-industry-year, per 1 mln. population (column (2)); the number of patents in the most climate-change-intensive technologies in a country-industry-year, per 1 mln. population, excluding patents related to transportation and to wastewater treatment and waste management (column (3)); and the number of patents in energy-intensive sectors in a country-industry-year, per 1 mln. population (column (4)). Industry-specific data come from UNIDO. All regressions include fixed effects as specified. Standard errors clustered at the country-year level are included in parentheses, where ***, **, and * indicate significance at the 1, 5, and 10 percent statistical level, respectively. Appendix Table A1 contains all variable definitions.

Chart 1: Credit markets and stock markets over time



Notes: The chart plots sample-average Private credit / GDP and Stock market capitalization / GDP between 1974 and 2013.

Chart 2: Pollution intensity vs. external financial dependence



Notes: The chart plots industry-level external finance dependence (horizontal axis) against pollution intensity (vertical axis).