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. The former effect is explained by higher growth in technologically dirty industries in countries with deeper credit markets. The latter is driven by increased innovation—in particular, a higher propensity to produce green patents—in technologically dirty industries in countries with more mature stock markets. 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.

JEL classification: G10, O4, Q5.

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

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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 various 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 impact 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 73-country, 18-industry, 39-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 dioxide in countries with better developed credit markets. We find that stock markets have the opposite effect: industries that pollute more for technological reasons, produce relatively less carbon dioxide in countries with deeper stock markets. Our analysis also sheds light on the mechanisms that

[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.

underpin these country- and industry-level results. In particular, we show—holding cross-industry differences in technology constant—that credit markets tend to reallocate investment towards less carbon-efficient sectors. In contrast, stock markets facilitate the adoption of cleaner technologies in polluting industries. Auxiliary evidence from sectoral patenting data confirms that deeper stock markets are indeed associated with more green innovation in traditionally polluting industries. All 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 debate has focused mostly on the environmental Kuznets hypothesis according to which pollution increases at early stages of development but declines once a country reaches a certain income level. Three mechanisms underlay this hypothesis. First, increasingly affluent voters may start to demand stricter anti-pollution regulation. Second, during the early stages of development, a move from agriculture to manufacturing and heavy industry is associated with both higher income 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] Third, 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). For instance, 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 technical change in the car industry towards clean innovation (electric and hybrid technologies) and away from dirty technology (internal combustion engines). Related papers stress that policy interventions may be needed to stimulate clean technologies and move countries towards sustainable growth.[3]

While empirical work provides evidence for a Kuznets curve for a variety of pollutants, the

[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] 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.

evidence for CO_2 emissions is mixed.[4] Schmalensee, Stoker and Judson (1998) find an inverse U-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. More specifically, we assess how banks and stock markets affect the main mechanisms that underpin the Kuznets hypothesis: a shift towards less-polluting sectors and an innovation-driven reduction in pollution within sectors.[5]

Second, our results 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.[6] 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.

Financial structure, the relative importance of credit versus stock markets, matters if different forms of finance impact industrial pollution to a different extent or through different channels. Several theoretical arguments suggest that banks may be less suited to reduce environmental pollution than stock markets. 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). 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,

[4]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).

[5]A move towards greener technologies can involve substantial investments and therefore be conditional on the availability of external finance. 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 foreign state-of-the art technologies and help mitigate environmental pollution.

[6]For comprehensive surveys of this literature, see Levine (2005), Beck (2008), and Popov (2017).

2010). Such assets are difficult to redeploy elsewhere and therefore hard to collateralize (Carpenter and Petersen, 2002). 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.

In contrast, stock markets may be better suited to finance innovative (and greener) industries. Equity contracts may be 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 pollution so that stock prices rationally discount future cash flows of polluting industries.[8] Stock markets indeed punish firms that perform badly in environmental terms (such as after environmental accidents) (Salinger, 1992) and reward firms that perform well in terms of environmental friendliness (Klassen and McLaughlin, 1996). Chava (2014) shows that firms with environmental concerns have fewer institutional owners. Banks, on the other hand, typically operate with a shorter time horizon (the loan maturity) and are less interested in whether funded assets will become less valuable (or even stranded) in the more distant future.[9]

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 limit or even reduce environmental pollution remains an empirical question.[10] The aim of this paper is therefore to provide robust empirical

[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 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]Dasgupta, Laplante, Wang and Wheeler (2002) argue that banks may refuse to lend to a firm if they are worried about environmental liability. This suggests that screening by banks helps to weed out at least the (visibly) most polluting industries. Indeed, recent anectodal 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.

[10]Chava (2014) shows how the environmental profile of a firm affects both the cost of its equity and 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 producting structure, firms will switch to a more expensive but less polluting technology (Heinkel, Kraus and Zechner, 2001).

evidence on how, and how much, banks and stock markets contribute to carbon emissions at both the country and the industry level.

The rest of the paper is structured as follows. Section 2 presents our empirical methodology after which Section 3 describes the data. Section 4 then presents the empirical results. Section 5 concludes with a discussion of our main findings.

2 Empirical Methodology

We begin by estimating a regression where we map financial markets development into carbon dioxide emissions while using a country as the unit of observation. We distinguish the effect of developments in credit markets from the effect of developments in stock markets by estimating the following specification:

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

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 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. Finally, 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 contains factors that can account for a sizeable portion of the variation in cross-country CO_2 emissions. One such factor is general economic development, the pollution impact of which can be positive at early stages of development as the economy utilizes the cheapest technologies available, and then negative at later stages when the economy innovates to reduce pollution (the environmental Kuznets-curve argument). We account for this possibility by including the logarithm of per-capita GDP, both on its own and squared. Another such factor is general macroeconomic stability, which we capture by including the level of inflation. The phase of the business cycle can also have an impact on pollution levels. For example, the economy may be cleansing itself from obsolete technologies during recessions. To account for this possibility, we include proxies for recessions and for systemic banking crises.[11] Finally, country dummies allow us to net out the impact of unobservable country-specific time-invariant influences, such as comparative advantage or appetite for regulation. Year dummies 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 in part 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 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 compare 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:

$$\begin{aligned}\frac{CO_{2c,s,t}}{Population_{c,t}} = \; & \beta_1 Credit_{c,t-1} \times Pollutionintensity_s + \beta_2 Stock_{c,t-1} \times Pollutionintensity_s + \\ & \beta_3 Credit_{c,t-1} \times Fin.dependence_s + \beta_4 Stock_{c,t-1} \times Fin.dependence_s + \\ & \beta_5 X_{c,s,t-1} \times Pollutionintensity_s + \varphi_{c,s} + \phi_{c,t} + \theta_{s,t} + \varepsilon_{c,s,t}\end{aligned} \qquad (2)$$

where $\frac{CO_{2c,s,t}}{Population_{c,t}}$ denotes total per-capita emissions of carbon dioxide by industry s in country

[11] Caballero and Hammour (1994) provide a vintage model in which production units that embody the latest technology are produced as innovation proceeds. At the same time, outdated units with the inferior technology are 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. 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.

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 propensity to pollute. $Fin.\ dependence_s$ is the difference between capital expenditures and cash flow, normalized by cash flows, for large listed firms in the United States. This is consistent with the Rajan and Zingales (1998) approach of using data on unconstrained firms in an economy with deep and liquid financial markets to proxy for a sector's natural dependence on external financing. In accordance with this approach, 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.

The regression includes interactions of time-varying country-specific and industry-specific variables, captured by vector $X_{c,s,t-1}$. Such variables include interactions of different types of financial development with sector-specific technological characteristics, such as external finance dependence. Finally, 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). Finally, $\theta_{s,t}$ controls for all variation 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 evaluate the impact of financial development on across-industry reallocation and within-industry innovation. These tests are derived from the theoretical argument that some forms of finance—such as equity finance—are better at, first, reallocating investment away from technologically "dirty" towards technologically "clean" industries, and, second, at bringing industries closer to their technological frontier, resulting in less pollution per unit of production.

We evaluate the first hypothesis using the following regression model:

$$
\begin{aligned}
\Delta Valueadded_{c,s,t} = \quad & \beta_1 Credit_{c,t-1} \times Pollutionintensity_s + \beta_2 Stock_{c,t-1} \times Pollutionintensity_s + \\
& \beta_3 Credit_{c,t-1} \times Fin.dependence_s + \beta_4 Stock_{c,t-1} \times Fin.dependence_s + \\
& \beta_5 X_{c,s,t-1} \times Pollutionintensity_s + \varphi_{c,s} + \phi_{c,t} + \theta_{s,t} + \varepsilon_{c,s,t}
\end{aligned} \tag{3}
$$

where relative to Model (2), the dependent variable now is the percentage change in value added between year $t-1$ and year t by industry s in country c. The evolution of this variable thus measures the industry's growth relative to other industries in the country. This captures the reallocation in the economy from technologically "dirty" towards technologically "clean" industries. Earlier work shows how well-developed stock and credit markets make countries more responsive to global common shocks by allowing firms to take advantage of time-varying sectoral growth opportunities (Fisman and Love, 2007).

We evaluate the second hypothesis using the following regression model:

$$
\begin{aligned}
\frac{CO_{2c,s,t}}{Valueadded_{c,s,t}} = \quad & \beta_1 Credit_{c,t-1} \times Pollutionintensity_s + \beta_2 Stock_{c,t-1} \times Pollutionintensity_s + \\
& \beta_3 Credit_{c,t-1} \times Fin.dependence_s + \beta_4 Stock_{c,t-1} \times Fin.dependence_s + \\
& \beta_5 X_{c,s,t-1} \times Pollutionintensity_s + \varphi_{c,s} + \phi_{c,t} + \theta_{s,t} + \varepsilon_{c,s,t}
\end{aligned} \tag{4}
$$

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 innovation away from "dirty" technologies. We use carbon dioxide emissions per unit of value added as a proxy for within-industry technological evolution. In an alternative specification aimed at gauging more directly the impact of various types of finance on within-industry innovation, we use the number of "green" patents as the dependent variable.

3 Data

This section describes 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.

3.1 CO_2 emissions

We obtain data on CO_2 emissions from fuel combustion at the sectoral level from the International Energy Agency (IEA).[12] 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 product; (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.

The data set contains a maximum of 98,640 observations, however, there are 36,042 missing observations. We next proceed to produce a data set that consists of countries that each have a fair representation of industries with non-missing CO_2 data. To that end, we drop countries that have less than 10 sectors with at least 10 years of CO_2 emissions data. This results in the exclusion of 64 countries, and so the final data set consists of 73 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) and (2).

3.2 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

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

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. Therefore, we can 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 73 countries and 21 sectors while the other one contains 33 countries and 62 sectors. The main tests in the paper are based on the former data set with a view of 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.

3.3 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. 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 inventions. Second, we take the country of residence of the inventors as the reference country. If a patent has multiple inventors from different countries, 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.[13]

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.[14]

We then calculate three patent variables by country, sector, and year. "Green patents" measures all granted patents that belong to the EPO Y02/Y04S climate change mitigation technology

[13] 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.

[14] PATSTAT also classifies patents according to NACE 2. A drawback of this classification is that it covers only 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.

(CCMT) tagging scheme. CCMTs include technologies to reduce the amount of greenhouse gas emitted 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. "Green patents (excluding transportation and waste)" counts all granted patents that belong to the EPO Y02/Y04S scheme with the exception of Y02T (Climate change mitigation technologies related to transportation) and Y02W (Climate change mitigation technologies related to solid and liquid waste treatment). The resulting group consists primarily of 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); capture, storage, sequestration or disposal of greenhouse gases (Y02C); alternative (none fossil) energy sources (Y02E); and smart grids (Y04S). Finally, "Green patents (production in energy intensive sectors)" counts patents that belong only to the Y02P category.

3.4 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 credits 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. Finally, it counts credit from all financial institutions rather than only deposit money banks. The 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).

3.5 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 industrial 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 18 industrial sectors with data on both carbon dioxide emissions and on industrial output. While some sectors are uniquely matched between IEA and UNIDO/STAN, other industrial sectors 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 5.87 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. The median country in the data set has a population of 15.3 million and annual inflation of 2.3 percent. On average, a country is in a recession once every five years and in a banking crisis once every eight years.

The industry-level data from UNIDO show that the median industry emits 85 metric tons of carbon dioxide per year, and 1 metric ton per 1000$ of value added. Over the sample period, the median industry grows by 1.3 percent per year, and constitutes about 5 percent of total manufacturing. These values are more or less consistent across the UNIDO and STAN data sets. However, the median STAN industry records emissions twice as large as 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 0.078 such patents per 1 million people in the global sample, and 0.145 per 1 million people in the OECD sample.

Table 2 presents the concordance key to match 62 ISIC classes into 18 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. Table 2 also reports the other industry benchmark, "External dependence", calculated in the spirit of Rajan and Zingales (1998) and obtained from Duygan-Bump, Levkov and Montoriol-Garriga (2015).

4 Empirical Results

This section is split into four subsections. Section 4.1 investigates the effect of credit and stock market development on aggregate pollution. In Section 4.2, we then assess the impact of both types of finance on industry-level pollution, distinguishing between technologically "dirty" and "clean" industries. Section 4.3 investigates the degree to which across-industry reallocation and within-industry innovation explain the statistical association between finance and emissions. We also analyze the impact of finance on patented innovation at the industry level. Finally, Section 4.4 provides robustness tests.

4.1 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 deeper credit markets are associated with higher levels of CO_2 pollution. Numerically, the point estimate implies that going from the 10^{th} to the 90^{th} 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 levels on the size of stock markets, proxied by the ratio of total 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 10^{th} to the 90^{th} 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 in the regression. 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, and 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 in 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 also include the square term of GDP per capita. In this case, we confirm the standard environmental Kuznets-curve effect whereby per capita CO_2 emissions first increase and then decrease with the degree of 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, most of 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).

4.2 Financial development and pollution: Industry-level results

We next turn to evaluating the evidence from the analysis of the sector-level data. The evidence based on 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, or economies with better growth opportunities in polluting sectors may be developing their financial markets earlier. These issues are only imperfectly addressed by the matrix of country and year dummies and by the country-specific controls in the previous sub-section.

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. Our main proxy is the global industry-specific average CO_2 emissions per unit of output, calculated across all countries and years in the sample (see Table 2). The underlying 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 is then that an industry's pollution intensity in a country with few regulatory impediments and with deep and liquid financial markets reflects the industry's "natural" propensity to pollute (unaffected by regulatory arrangements or by credit constraints).

In Table 4, we evaluate Model (2) to test whether technologically "dirty" sectors emit more carbon dioxide than technologically "clean" sectors in countries with better developed financial markets. The estimates in column (1) strongly suggest that industries which pollute relatively more for inherent, technological reasons, generate relatively higher carbon dioxide emissions in countries with better developed credit markets. This effect is significant at the 5 percent 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 technological reasons, produce relatively lower carbon dioxide emissions in countries with deeper stock markets. This effect is significant at the 10 percent level. We also note that sectors which constitute a larger share of the overall economy—in terms of value added—pollute more per capita than relatively smaller sectors (although the related coefficients are imprecisely estimated). In both cases, we control for the interaction of the country's financial structure with the industry's external financial dependence, and we find that it does not explain any portion of the variation in carbon dioxide emissions in a particular country-industry over time.

The opposite effects of the two types of financial markets still obtain when we include them together in the regression (column (3)). In this case, the numerical impact of credit markets is around 50 percent higher than 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 percentage from the same base. In this way, the estimates in column (3) of Table 4 mirror conceptually those in column (3) of Table 3.

Finally, we test for 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. More specifically, 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 covariates reported in column (3). We report the results in column (4) of Table 4. We indeed find that some of these country-specific variables matter in a material way. For example, technologically dirty industries exhibit lower levels of CO_2 pollution per capita in larger countries (in terms of population). The business cycle also affects per capita pollution: technologically dirty industries generate more pollution per capita when inflation (and presumably, growth) is higher, and less pollution per capita during a recession or banking crisis.

Importantly, the main results recorded in columns (1)–(3) survive in this fully saturated specification. We still find that per capita carbon dioxide emissions increase relatively more in "dirty" sectors in countries with better developed credit markets, and decline relatively more in "dirty" sectors in countries with deeper stock markets. Both effects are significant at least at the 10 percent level, and they are also economically meaningful. For example, the coefficient on the interaction of pollution intensity and stock market development (-0.2636) suggests that moving from the 25^{th} to the 75^{th} percentile of stock market development is associated with a decline in CO_2 emissions per capita in an industry at the 75^{th} percentile of pollution intensity—relative to an industry at the 25^{th} percentile of pollution intensity—of 0.025, which is equal to 6 percent of the sample mean.

Crucially, all regressions in Table 4 (and thereafter) are saturated with interactions of country-sector dummies, country-year dummies, and sector-year dummies. Their inclusion ensures that the effect we measure 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.

4.3 Financial development and pollution: Channels

4.3.1 Cross-industry reallocation

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." We also established that the former result is not simply a level effect, i.e., industries do not pollute more simply because they grow faster with credit market deepening.

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 technologies constant—stock markets reallocate investment towards, and credit markets reallocate investment away from, relatively "clean" industrial sectors. The second one is within-industry technological innovation. We next test whether either or both of these channels are indeed operational.

In Table 5, we test for the first channel by running Model (3) on our data. The dependent variable is the growth in value added in a particular industry in a particular country during a particular year. 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 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.

Column (1) provides no evidence of a differential impact of credit markets on growth across technologically dirty versus clean industries. While the coefficient on the interaction term is positive, implying that technologically "dirty" industries grow faster in countries with deeper credit markets, the effect is nowhere near any meaningful level of statistical significance. Similarly, in column (2), we find no evidence that "dirty" industries grow faster in countries with larger stock markets. However, once we estimate the effect of the two types of finance jointly, we find an impact of credit markets on the growth of dirty industries (column (3)). This effect is significant at the 10 percent level. Encouragingly, it coexists with a positive impact of credit markets on growth in financially dependent industries, a result in line with prior research (e.g., Rajan and Zingales, 1998).

This result survives in column (4) where we add interactions of the rest of the country-specific factors with the sectors' propensity to pollute. In this specification, the positive impact of credit markets on the growth in technologically dirty industries is significant at the 5 percent level. We conclude that there is strong evidence to confirm the conjecture that—holding cross-industry differences in technology constant—credit markets promote a reallocation of investment towards dirtier sectors, explaining the positive impact of credit markets on per capita pollution that we found in Table 4. Finally, note that all specifications indicate that larger sectors grow more slowly, a finding in line with theories of growth convergence.

4.3.2 Within-industry innovation

In Table 6, we test the second channel by running Model (4) on our data. We investigate the role of within-industry technological innovation whereby 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 facilitating the adoption (or prolonging the use) of less efficient ("dirty") technologies. Our dependent variable is now CO_2 emissions per unit of value added. Once again, all regressions are saturated with interactions of country-sector dummies, country-year dummies, and sector-year dummies.

In column (1), we find evidence of slower within-industry technological innovation as credit markets develop. In particular, in countries with deeper 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 ten percent level. We next look at the separate effect of stock markets on pollution per unit of output. The evidence in column (2) suggests that stock markets have the opposite effect: pollution per unit of value added declines in "dirty" sectors, relative to "clean" ones, in countries with better developed stock markets. Once we juxtapose the two types of finance, the effect of stock markets still obtains, while the effect of credit markets, albeit positive, is no longer statistically significant (column (3)).[15] The same is true in column (4) where we add interactions of the rest of the country-

[15] In unreported tests, we hypothesize that the impact of each type of finance on pollution at later stages of financial development goes in the opposite direction of its contribution early on. We find some evidence that the effect of credit markets on pollution per unit of output is non-linear. At very high levels of credit market development, further credit growth is associated with a substantial deterioration in within-industry pollution efficiency. The lack of a precise statistical association between credit market development and pollution per unit of output may therefore mask a

specific factors with the sectors' natural propensity to pollute. The evidence thus strongly suggests that stock markets facilitate the adoption of cleaner technologies in polluting industries, while there is no evidence for any such cleansing role for developing credit markets. This finding helps explain the negative impact of stock markets on per-capita pollution that we found in Table 4.

While it is plausible that growing stock markets reduce pollution in relatively dirty industries by stimulating the development of cleaner production techniques, we have not yet provided direct evidence to support this conjecture. We now address this gap by exploiting detailed data on industrial patenting. In particular, we make use of a uniquely comprehensive global data set, PATSTAT, which reports patents classified according to the International Patent Classification (IPC). For the countries and industries in our sample, we calculate three measures of green innovation. The first one, "Green patents", measures all granted patents that belong to the EPO Y02/Y04S climate change mitigation technology (CCMT) tagging scheme. The second 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 (CCMT related to transportation) and Y02W (CCMT 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); capture, storage, sequestration or disposal of greenhouse gases (Y02C); alternative (none fossil) energy sources (Y02E), and smart grids (Y04S). The third variable, "Green patents (production in energy intensive sectors)", counts patents that belong only to the arguably most important category, Y02P.

Table 7 reports estimates from tests where we estimate Model (2) with each of the three patent variables as the dependent variable. Our data provides no strong evidence that the total production of green patents in a dirty industry is related to the country's financial structure (column (1). However, our data strongly indicate that the number of green patents (excluding transportation and waste) increases relatively more in technologically dirty industries in countries with deeper stock markets (column (2)). The effect is significant at the 10 percent statistical level, and economically meaningful, too. The coefficient of 0.0657 indicates that moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of stock market development is associated with an increase in the number of patents generated by an industry at the 75$^{\text{th}}$ percentile of pollution intensity—relative to an industry at the 25$^{\text{th}}$ percentile of pollution intensity—by 0.0063 patents per million people, which is equal to 10 percent of the

U-shaped relationship between the two.

sample mean. Moreover, the number of green patents (production in energy intensive sectors) in relatively dirty industries increases particularly strongly with stock market development. This effect is significant at the 5 percent statistical level. Overall, the results in Table 7 provide convincing and direct evidence that increased innovation is an important channel through which stock market development helps heavily polluting industries to become greener over time.

4.4 Financial development and pollution: Robustness

4.4.1 Robustness to a different pollution-intensity measure

We now subject our main results to a number of robustness tests. First, we check whether our results are robust to changing the definition of our main pollution measure. Our industry-specific 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 levels than the industry's technology would imply. Another possibility 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 US is a prime example of one such country. [16]

To bring this idea to the analysis, we calculate 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 0.82, and only two industries move within the ranking of industries in terms of industrial pollution per unit of value added. With this new benchmark in hand, we re-estimate Models (3) and (4), and report the results in Table 8.

In column (1), we find that CO_2 emissions per unit of value added are significantly lower in technologically dirty industries in countries with more developed stock markets. Similar to Table 6,

[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 green-house gases, including emission trading schemes for CO_2 and SO_2, taxes on CO_2, taxes on the industrial use of diesel, etc. 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/.

column (4), this effect is significant at the 1 percent statistical level. The impact of credit markets is negative, albeit not significant. In column (2), we find that technologically dirty industries grow relatively faster in countries with deeper credit markets. This effect is significant at the 5 percent statistical level, and is fully consistent with the evidence in Table 5, column (4). As before, larger industries tend to grow more slowly, which is consistent with theories of economic convergence, as well as with prior evidence. We conclude that our main results are not driven by a particular choice of a benchmark for pollution intensity.

4.4.2 Robustness to a different sample

Finally, we perform a robustness test to check whether our results are driven by a particular sample choice. Our results so far are based on the UNIDO sample which features more countries (73) but fewer sectors (9 manufacturing ones). We now 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 (18), encompassing the whole economy. This is potentially important because the five heaviest polluters in Table 2—the sectors "Agriculture, hunting, forestry, and fishing," "Electricity, gas, and water supply," "Land transport – transport via pipelines," "Water transport," and "Air transport"—are not part of manufacturing. Once again, we replicate the most saturated versions of Models (3) and (4)—the ones with country-sector dummies, country-year dummies, sector-year dummies, and interactions of the remaining country-specific factors with the sectors' natural propensity to pollute. We also do so using our main proxy for pollution intensity (replicating Tables 5 and 6) as well as our alternative proxy (replicating Table 8).

We report the results from these tests in Table 9. In the first set of tests, using our principle proxy for pollution intensity (based on a global average), we find that financial markets exert no effect on either CO_2 emissions per unit of value added (column 1) or industry growth (column 2). However, once we employ our alternative benchmark for pollution intensity (based on US data), we find that technologically dirty industries grow relatively more slowly in countries with deeper stock markets (column 4). This suggests that the impact of stock markets on reallocation away from naturally dirty industries is not necessarily a feature of a sample dominated by lower-income countries.

5 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 quantify this role, we study the relationship between financial market 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, stock markets have the exact opposite effect: industries that pollute relatively more for technological reasons, produce relatively less carbon dioxide in countries with deeper 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 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, while there is no evidence for any such effect due to the development of credit markets. Further analysis of sectoral patenting data confirms that deeper stock markets are associated with more green innovation in traditionally polluting industries. Moreover, we also show that—holding cross-industry differences in technology constant—credit markets tend to reallocate investment towards dirtier sectors, while there is no such evidence for stock markets. All 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.

In sum, our findings indicate that not only financial development, but financial structure, too, has an important effect on environmental quality. This suggests that countries with a bank-based financial system that aim to "green" their economy through specific green-finance initiatives, such as the promotion of green bonds, should consider stimulating the development of conventional private and public equity markets as well. This holds in particular 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 banks' lending practices.[17] Strict adherence to these principles can also make governmental climate change policies more effective by accelerating capital reallocation and investment in lower-carbon technologies.

[17]The Carbon Principles are guidelines to assess the risks in financing electric power projects in terms of climate change. The Climate Principles comprise a similar but broader framework. Finally, 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 for projects with greenhouse gas emissions above a certain threshold to implement measures to reduce such emissions.

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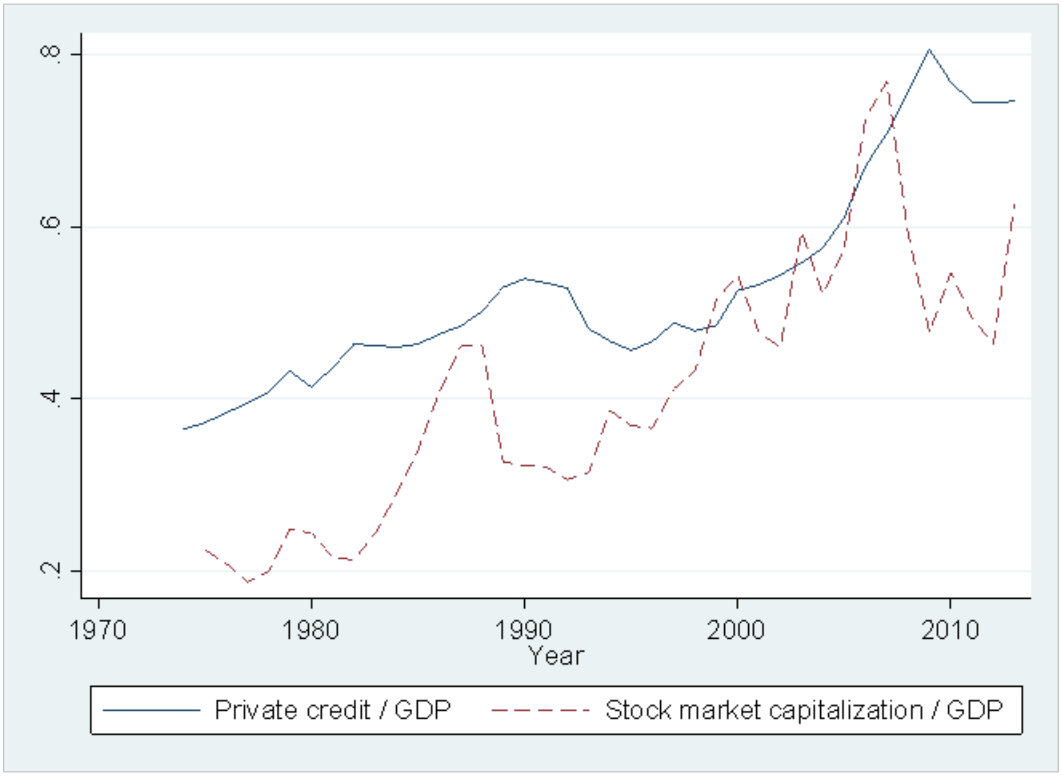
Chart 1. Credit markets and stock markets over time



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

Table 1. Summary statistics

Variable	Mean	Median	St. dev.	Min	Max
Country-level					
CO_2 per capita	5.872	5.123	5.118	0.025	45.036
Credit/GDP	0.546	0.434	0.431	0.009	2.625
Stock/GDP	0.458	0.303	0.521	0.001	9.969
GDP per capita	17,875	9,002	19,080	327	110,001
Population (mln.)	66.186	15.308	179.469	0.215	1357.380
Inflation	0.030	0.023	0.034	-0.047	0.620
Recession	0.224	0.000	0.417	0.000	1.000
Banking crisis	0.122	0.000	0.327	0.000	1.000
Industry-level (UNIDO)					
CO_2 per capita	0.419	0.085	1.065	0.000	29.264
CO_2 per unit of value added	0.002	0.001	0.004	-0.032	0.126
Growth in value added	0.015	0.013	0.191	-1.000	1.000
Green patents (total)	0.078	0.000	0.530	0.000	23.754
Green patents (excluding transportation and waste)	0.063	0.000	0.511	0.000	21.108
Green patents (production in energy intensive sectors)	0.026	0.000	0.180	0.000	10.487
Industry share	0.061	0.048	0.056	0.000	0.783
Industry-level (OECD)					
CO_2 per capita	0.591	0.153	1.309	0.000	29.264
CO_2 per unit of value added	0.001	0.001	0.010	-0.030	0.617
Growth in value added	0.014	0.017	0.126	-1.000	1.000
Green patents (total)	0.145	0.000	0.722	0.000	23.754
Green patents (excluding transportation and waste)	0.124	0.000	0.698	0.000	21.108
Green patents (production in energy intensive sectors)	0.049	0.000	0.245	0.000	10.487
Industry share	0.074	0.036	0.105	0.001	0.897

Notes: The paper summarizes the data used in the paper. 'CO_2 per capita' denotes aggregate or industry-specific emissions of carbon dioxide, in tons, divided by the country's population. 'Credit/GDP' denotes the ratio of credit to the private sector to the country's GDP. 'Stock/GDP' denotes the ratio of the value of all listed stocks to the country's GDP. 'GDP per capita' denotes the country's per-capita GDP. 'Population (mln.)' denotes the country's population, in millions of inhabitants. 'Inflation' denotes the annual change in the country's consumer price inflation (CPI). 'Recession' is a dummy variable equal to one if the country is experiencing negative GDP growth. 'Banking crisis' is a dummy equal to one if the country is experiencing a systemic banking crisis. 'CO_2 per unit of value added' denotes aggregate or industry-specific emissions of carbon dioxide, in tons, divided by the industry's value added. 'Growth in value added' denotes industry-specific growth in value added. 'Green patents' denotes the number of green patents in a country-industry-year, per 1 mln. population. 'Green patents (excluding transportation and waste)' 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. 'Green patents (production in energy intensive sectors)' denotes the number of patents in energy-intensive sectors in a country-industry-year, per 1 mln. population. 'Industry share' denotes the share in value added of the industry out of the whole economy.

Table 2. Industry benchmarks

ISIC code	Industry name	Pollution intensity	External dependence
01—05	Agriculture, hunting, forestry, and fishing	3.639	-1.430
10—14	Mining and quarrying	0.136	0.193
15—16	Food products, beverages, and tobacco	0.175	-0.309
17—19	Textiles, textile products, leather, and footwear	0.165	-0.028
20	Wood and products of wood and cork	0.094	-0.023
21—22	Pulp, paper, paper products, printing, and publishing	0.207	-0.016
23—25	Chemical, rubber, plastics, and fuel products	0.287	0.106
26	Other non-metallic mineral products	0.980	-0.960
27—28	Basic metals and fabricated metal products	0.568	-0.067
29—33	Machinery and equipment	0.057	-0.058
34—35	Transport equipment	0.061	-0.108
40—41	Electricity, gas, and water supply	5.076	0.240
45	Construction	0.031	0.570
60	Land transport – transport via pipelines	2.689	1.000
61	Water transport	7.379	0.670
62	Air transport	3.229	0.480
70—74	Real estate, renting, and business activities	0.246	0.240
75—99	Community, social, and personal services	0.088	-0.550

Notes: This table summarizes, by industry, the main benchmarks used in the paper. ‘Pollution intensity’ denotes the average value, over the entire sample period, of each industry’s CO2 emissions per value added in the global sample. This variable is based on CO_2 per unit of value added (as in Table 1) multiplied by 1,000. ‘External dependence’ denotes the industry’s reliance on external finance in the United States (from Duygan-Bump et al., 2015).

Table 3. Financial development and aggregate pollution

	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	0.95	0.95	0.95	0.96	0.96

Notes: This table reports estimates from OLS regressions. The dependent variable is 'CO_2 per capita' which denotes aggregate emissions of carbon dioxide, in tons. 'Credit/GDP' denotes the 1-perod lagged ratio of credit to the private sector to the country's GDP. 'Stock/GDP' denotes the 1-period lagged ratio of the value of all listed stocks to the country's GDP. 'GDP per capita' denotes the country's per-capita GDP. 'Population (mln.)' denotes the country's population, in millions of inhabitants. 'Inflation' denotes the annual change in the country's CPI. 'Recession' is a dummy variable equal to one if the country is experiencing negative GDP growth. 'Banking crisis' is a dummy equal to one if the country is experiencing a systemic banking crisis. 'CO_2 per value added' denotes the ratio of the industry's total emissions of carbon dioxide to its value added. All regressions include fixed effects as specified. Robust standard errors are included in parentheses, where ***, **, and * denote significance at the 1, 5, and 10 percent statistical level, respectively.

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

	CO_2 emissions per capita			
	(1)	(2)	(3)	(4)
Credit/GDP × Pollution intensity	0.2459**		0.3599*	0.4428**
	(0.1242)		(0.1989)	(0.2283)
Stocks/GDP × Pollution intensity		-0.2516*	-0.2235*	-0.2636*
		(0.1371)	(0.1214)	(0.1430)
Credit/GDP × External dependence	0.0003		0.0004	0.0005
	(0.0002)		(0.0004)	(0.0004)
Stocks/GDP × External dependence		-0.0003	-0.0002	-0.0003
		(0.0002)	(0.0002)	(0.0002)
Log GDP per capita × Pollution intensity				-0.0000
				(0.0004)
Log Population × Pollution intensity				-0.0025*
				(0.0014)
Inflation × Pollution intensity				0.0024**
				(0.0010)
Recession × Pollution intensity				-0.0001*
				(0.0001)
Banking crisis × Pollution intensity				-0.0002*
				(0.0002)
Industry share	0.0009	0.0013	0.0012	0.0020
	(0.0006)	(0.0009)	(0.0008)	(0.0014)
Country × Industry dummies	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes
No. Observations	10,550	8,697	8,498	8,090
R-squared	0.764	0.761	0.767	0.770

Notes: The table reports estimates from OLS regressions. The dependent variable is 'CO_2 per capita' which denotes industry-specific emissions of carbon dioxide, in tons, per capita. 'Credit/GDP' denotes the 1-period lagged ratio of credit to the private sector to the country's GDP. 'Stock/GDP' denotes the 1-period lagged ratio of the value of all listed stocks to the country's GDP. 'Pollution intensity' denotes the average value, over the entire sample period, of each industry's CO_2 emissions per value added, for all countries in the sample. 'External dependence' denotes the industry's reliance on external finance in the United States (from Duygan-Bump et al., 2015). 'GDP per capita' denotes the country's 1-period lagged per-capita GDP. 'Population (mln.)' denotes the country's 1-period lagged population, in millions of inhabitants. 'Inflation' denotes the 1-period lagged annual change in the country's CPI. 'Recession' is a 1-period lagged dummy variable equal to one if the country is experiencing negative GDP growth. 'Banking crisis' is a 1-period lagged dummy equal to one if the country is experiencing a systemic banking crisis. 'Industry share' denotes the 1-period lagged share in value added of the industry out of the whole economy. 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 * denote significance at the 1, 5, and 10 percent statistical level, respectively.

Table 5. Financial development and industry-level pollution: Cross-industry reallocation

	Growth in value added			
	(1)	(2)	(3)	(4)
Credit/GDP × Pollution intensity	42.7918		66.6957*	92.2664**
	(39.9675)		(34.1098)	(34.8751)
Stocks/GDP × Pollution intensity		-19.1766	-10.2843	14.4775
		(28.7199)	(29.3627)	(37.7150)
Credit/GDP × External dependence	0.0615		0.0845**	0.0947**
	(0.0400)		(0.0354)	(0.0371)
Stocks/GDP × External dependence		-0.0542*	-0.0467	-0.0133
		(0.0242)	(0.0272)	(0.0357)
Log GDP per capita × Pollution intensity				-0.0887
				(0.1389)
Log Population × Pollution intensity				0.1802
				(0.2316)
Inflation × Pollution intensity				-0.9599
				(0.9673)
Recession × Pollution intensity				0.0635
				(0.0594)
Banking crisis × Pollution intensity				-0.0272
				(0.0442)
Industry share	-1.5594***	-1.7707***	-1.7678***	-2.1991***
	(0.2059)	(0.1896)	(0.2013)	(0.2101)
Country × Industry dummies	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes
No. Observations	11,066	8,831	8,630	8,190
R-squared	0.493	0.500	0.504	0.499

Notes: The table reports estimates from OLS regressions. The dependent variable is 'CO_2 per unit of value added' which denotes industry-specific emissions of carbon dioxide, in tons, per unit of value added. 'Credit/GDP' denotes the 1-period lagged ratio of credit to the private sector to the country's GDP. 'Stock/GDP' denotes the 1-period lagged ratio of the value of all listed stocks to the country's GDP. 'Pollution intensity' denotes the average value, over the entire sample period, of each industry's CO_2 emissions per value added, for all countries in the sample. 'External dependence' denotes the industry's reliance on external finance in the United States (from Duygan-Bump et al., 2015). 'GDP per capita' denotes the country's 1-period lagged per-capita GDP. 'Population (mln.)' denotes the country's 1-period lagged population, in millions of inhabitants. 'Inflation' denotes the 1-period lagged annual change in the country's CPI. 'Recession' is a 1-period lagged dummy variable equal to one if the country is experiencing negative GDP growth. 'Banking crisis' is a 1-period lagged dummy equal to one if the country is experiencing a systemic banking crisis. 'Industry share' denotes the 1-period lagged share in value added of the industry out of the whole economy. 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 * denote significance at the 1, 5, and 10 percent statistical level, respectively.

Table 6. Financial development and industry-level pollution per unit of output

	CO_2 emissions per unit of value added			
	(1)	(2)	(3)	(4)
Credit/GDP × Pollution intensity	1.2302*		0.4741	-0.7509
	(0.6564)		(0.3988)	(0.7804)
Stocks/GDP × Pollution intensity		-1.4191***	-1.4626***	-1.2532***
		(0.3742)	(0.3546)	(0.1863)
Credit/GDP × External dependence	0.0006		0.0004	-0.0003
	(0.0005)		(0.0004)	(0.0004)
Stocks/GDP × External dependence		-0.0001	-0.0001	0.0001
		(0.0004)	(0.0003)	(0.0002)
Log GDP per capita × Pollution intensity				-0.0034
				(0.0034)
Log Population × Pollution intensity				0.0134***
				(0.0034)
Inflation × Pollution intensity				0.0198
				(0.0157)
Recession × Pollution intensity				0.0000
				(0.0006)
Banking crisis × Pollution intensity				0.0016**
				(0.0006)
Industry share	-0.0109**	-0.0112*	-0.0113*	-0.0048**
	(0.0037)	(0.0052)	(0.0053)	(0.0016)
Country × Industry dummies	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes
No. Observations	10,127	8,324	8,133	7,750
R-squared	0.792	0.867	0.868	0.878

Notes: The table reports estimates from OLS regressions. The dependent variable is 'CO_2 per unit of value added' which denotes industry-specific emissions of carbon dioxide, in tons, per unit of value added. 'Credit/GDP' denotes the 1-period lagged ratio of credit to the private sector to the country's GDP. 'Stock/GDP' denotes the 1-period lagged ratio of the value of all listed stocks to the country's GDP. 'Pollution intensity' denotes the average value, over the entire sample period, of each industry's CO_2 emissions per value added, for all countries in the sample. 'External dependence' denotes the industry's reliance on external finance in the United States (from Duygan-Bump et al., 2015). 'GDP per capita' denotes the country's 1-period lagged per-capita GDP. 'Population (mln.)' denotes the country's 1-period lagged population, in millions of inhabitants. 'Inflation' denotes the 1-period lagged annual change in the country's CPI. 'Recession' is a 1-period lagged dummy variable equal to one if the country is experiencing negative GDP growth. 'Banking crisis' is a 1-period lagged dummy equal to one if the country is experiencing a systemic banking crisis. 'Industry share' denotes the 1-period lagged share in value added of the industry out of the whole economy. 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 * denote significance at the 1, 5, and 10 percent statistical level, respectively.

Table 7. Financial development and industry-level pollution: Green innovation

	Green patents	Green patents (excluding transportation and waste)	Green patents (production in energy intensive sectors)
	(1)	(2)	(3)
Credit/GDP × Pollution intensity	-0.8705	-1.1390	-0.1868
	(0.8974)	(1.1289)	(0.2009)
Stocks/GDP × Pollution intensity	0.0710	0.0657*	0.0474**
	(0.0607)	(0.0430)	(0.0168)
Industry share	0.0022	0.0023	0.0005
	(0.0018)	(0.0018)	(0.0003)
Country × Industry dummies	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes
No. Observations	8,554	8,554	8,554
R-squared	0.765	0.726	0.728

Notes: The table reports estimates from OLS regressions. The dependent variable is the number of green patents in a country-industry-year, per 1 mln. population (column 1); 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 2); and the number of patents in energy-intensive sectors in a country-industry-year, per 1 mln. population (column 3). 'Credit/GDP' denotes the 1-period lagged ratio of credit to the private sector to the country's GDP. 'Stock/GDP' denotes the 1-period lagged ratio of the value of all listed stocks to the country's GDP. 'Pollution intensity' denotes the average value, over the entire sample period, of each industry's CO_2 emissions per value added, for all countries in the sample. 'Industry share' denotes the share in value added of the industry out of the whole economy. Industry-specific data come from UNIDO. All regressions include the rest of the control variables from Tables 4—6, as well as fixed effects as specified. Standard errors clustered at the industry level are included in parentheses, where ***, **, and * denote significance at the 1, 5, and 10 percent statistical level, respectively.

Table 8. Financial development and industry-level pollution: Alternative benchmark for pollution intensity

	CO_2 emissions per unit of value added	Growth in value added
	(1)	(2)
Credit/GDP × Pollution intensity	-1.1167	117.6650**
	(1.0233)	(45.4247)
Stocks/GDP × Pollution intensity	-1.4093***	32.9612
	(0.3084)	(49.4247)
Industry share	-0.0048**	-2.2005***
	(0.0015)	(0.2089)
Country × Industry dummies	Yes	Yes
Country × Year dummies	Yes	Yes
Industry × Year dummies	Yes	Yes
No. Observations	7,750	8,190
R-squared	0.878	0.499

Notes: The table reports estimates from OLS regressions. The dependent variable is 'CO_2 per value added' which denotes the ratio of the industry's total emissions of carbon dioxide to its value added (column 1) and 'Growth in value added' which denotes the industry's annual growth in value added (column 2). 'Credit/GDP' denotes the 1-period lagged ratio of credit to the private sector to the country's GDP. 'Stock/GDP' denotes the 1-period lagged ratio of the value of all listed stocks to the country's GDP. 'Pollution intensity' denotes the average value, over the entire sample period, of each industry's CO2 emissions per value added in the US. 'Industry share' denotes the share in value added of the industry out of the whole economy. Industry-specific data come from UNIDO. All regressions include the rest of the control variables from Tables 4—6, as well as fixed effects as specified. Standard errors clustered at the industry level are included in parentheses, where ***, **, and * denote significance at the 1, 5, and 10 percent statistical level, respectively.

Table 9. Financial development and industry-level pollution: OECD sample

	CO2 emissions per unit of value added	Growth in value added	CO2 emissions per unit of value added	Growth in value added
	Main model		Alternative benchmark for pollution intensity	
	(1)	(2)	(3)	(4)
Credit/GDP × Pollution intensity	0.1534	-5.4265	0.0858	-3.2203
	(0.2008)	(4.9400)	(0.1330)	(4.0628)
Stocks/GDP × Pollution intensity	0.0917	-1.6247	0.0353	-2.4657***
	(0.1731)	(1.7190)	(0.0751)	(0.7960)
Industry share	-0.0068	-0.4538**	-0.0068	-0.4538**
	(0.0060)	(0.1943)	(0.0060)	(0.1951)
Country × Industry dummies	Yes	Yes	Yes	Yes
Country × Year dummies	Yes	Yes	Yes	Yes
Industry × Year dummies	Yes	Yes	Yes	Yes
No. Observations	9,702	10,056	9,702	10,056
R-squared	0.602	0.387	0.601	0.387

Notes: The table reports estimates from OLS regressions. The dependent variable is 'CO_2 per value added' which denotes the ratio of the industry's total emissions of carbon dioxide to its value added (columns 1 and 3), and 'Growth in value added' which denotes the industry's annual growth in value added (columns 2 and 4). 'Credit/GDP' denotes the 1-period lagged ratio of credit to the private sector to the country's GDP. 'Stock/GDP' denotes the 1-period lagged ratio of the value of all listed stocks to the country's GDP. 'Pollution intensity' denotes the average value, over the entire sample period, of each industry's CO_2 emissions per value added, for all countries in the sample (columns 1—2) or the average value, over the entire sample period, of each industry's CO_2 emissions per value added in the US (columns 3—4). 'Industry share' denotes the share in value added of the industry out of the whole economy. Industry-specific data come from UNIDO. All regressions include the rest of the control variables from Tables 4—6, as well as fixed effects as specified. Standard errors clustered at the industry level are included in parentheses, where ***, **, and * denote significance at the 1, 5, and 10 percent statistical level, respectively.