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Do Banks Price Environmental Transition Risks?
Evidence from a Quasi-Natural Experiment in a Chinese Province

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Abstract

This paper assesses the financial risks arising from transition toward a low-emission economy. The environmental DSGE model shows tightening environmental regulation impairs firms' balance sheets, and consequently threatens financial stability in the short term. The empirical analysis indicates that following the implmentation of Clean Air Action Plan, the default rates of high-polluting firms in a Chinese province rose by around 80 percent. Joint equity commercial banks with higher level of independence were able to appropriately price in their exposure to transition risks, while the Big Five commercial banks failed to factor in such risks.

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I. INTRODUCTION

Facing escalated physical risks of environmental degradation and climate change, a growing number of countries have either tightened their existing environmental standards or imposed entirely new environmental obligations on the business community. To engineer a transition away from unsustainable growth to eventual low-emission and sustainable development requires a massive reallocation of capital and adoption of clean production technology, which is likely to generate significant and systematic impacts on financial stability and macroeconomic conditions.

While physical risks have been investigated more extensively, transition risks are a new category and remain relatively underexplored. Against this backdrop, this paper investigates how an environmental policy, aiming at emission abatement, affects financial stability from both theoretical and empirical perspectives. In particular, we shed light on the channels through which the transition toward a low-emission economy impacts a commercial bank's balance sheet.

We first build an environmental dynamic stochastic general equilibrium (E-DSGE) model to illustrate how productive firms and financial institutions react to the imposition of policy regulations such as emission caps. The model predicts a financial accelerator mechanism through which the prevention and mitigation of emission, in the form of tightening environmental policies, leads entrepreneurs to default endogenously on the outstanding value of their debt. This occurs because environmental policies affect the value of collateral they use to pledge against borrowing, which in turn results in an excess premium on loans (i.e., the difference between contracted loan rates and risk-free rates). The model extends the financial accelerator mechanism in the spirit of Kiyotaki and Moore (1997), Bernanke et al. (1999) and Christiano et al. (2014) by including an environmental policy that aims to reduce productive firms' emissions.

For the empirical analysis, we employ Chinese Clean Air Action Plan as a quasi-natural experiment to assess the financial risks raised by the adjustment process. The year 2013 represents the starting year of China's war on air pollution. The outbreak of a PM2.5[2] crisis covering a fourth of the territory sparked outrage among the Chinese public, which eventually forced the government to enact the Clean Air Action Plan on 12 September 2013. The Action sets quantitative air quality improvement goals for the entire country within a clear time frame and requires the local governments to tighten the regulations on the manufacturing sectors, especially industries with high emission or high energy consumption.

Given that Chinese firms largely rely on debt financing, the impact of environmental regulation can easily spill over to the banking sector. This naturally raises the question of whether banks consider the environmental shock when originating or extending credit to polluting firms. If banks are well-informed economic agents, they will in principle price in the increased default probability arising from the tightened environmental regulation. If not, they will underestimate an important source of risk for the sake of offering more competitive loan rates.

[2] PM, which stands for particulate matter, contains microscopic solid particles or liquid droplets in the air. Some particles, such as dust, dirt, soot, or smoke, are large or dark enough to be seen with the naked eye. Others are so small they can only be detected using an electron microscope. PM10 and PM2.5 refers to inhalable particles, with diameters of 10 micrometers and smaller and 2.5 micrometers and smaller respectively. Particulate matter contains microscopic solids or liquid droplets that can be inhaled and cause serious health problems. The particles less than 10 micrometers in diameter can get deep into peoples' lungs or even bloodstream, causing serious health problems.

In particular, we assess how the default rates and loan spreads of firms with different level of emission intensity change following the policy implementation. To provide a clear identification and causal evidence, we employ a unique micro-level dataset containing 1.3 million loans granted to the nonfinancial firms located in Jiangsu Province to investigate how an environmental policy shock affects the default and lending spread, as well as their variations across different regions, types of firms and banks. Given that the emission intensity varies significantly across industries, we classify all the borrowers into high-polluting firms and low-polluting firms, and use the low-polluting firms as a control group. Accordingly, the Clean Air Action Plan allows us to implement a difference-in-difference (DID) estimation by using both before-and-after policy variation and cross-industry variation for identification. The empirical analysis indicates that the default risk of high polluting firms rose by around 80 percent after the policy implementation.

This finding represents salient evidence that the transition toward low emission economy has posed considerable risks on the financial stability. However, compared with the period before the Action Plan, the loan spread for high-polluting firms increases by only around 5.5 percent. Further analysis shows those joint equity commercial banks with lower degree of government intervention and better corporate governance structure were able to appropriately price their exposure to transition risks, while the state-owned banks failed to factor in such risks when extending credit to the borrowers targeted by the environmental regulation.

The transition toward low emission economy is of critical importance to achieving the goal of sustainable growth. The long term benefits of such transition are considerable, including cleaner air, improved health, reduced occurrence of natural disasters and sustainable economic growth.[3] However, such policies can generate large transition costs for the economy, inducing fragility in the banking sector arising from compromised profitability for entrepreneurs, especially in the short run. Despite the imperative needs of alleviating the potential economic fluctuations arising from such policy change, most existing studies on the transition risks are partial and usually focus on the energy sector.

Our paper complements this strand of research by providing concrete theoretical analysis and solid empirical evidence. This research enriches the existing literature from four perspectives. We build the linkage of financial market to environmental transition, incorporate the environmental risk into a DSGE model with endogenous default risk, integrate environmental factors into macroeconomy through a financial accelerator mechanism, and quantitatively gauge the impact of environmental regulation on financial stability.

The rest of the paper is organized as follows. Section II comprehensively review the literature to underscore the contribution of the paper. Section III presents the environmental DSGE model. Section IV reports the impulse responses to a tightened environmental policy. Section V provides the data source and empirical strategy. Section VI presents the empirical results, while Section VII concludes the paper.

II. CONTRIBUTION TO THE LITERATURE

This paper extends different strands of the literature. First, our work enriches the growing literature studying the linkage of financial markets to climate change and environmental risk,

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[3] See Albrizio et al. (2014), Fankhauser and Tol (2005), Greenstone and Hanna (2014), Kozluk and Zipperer (2015), and Mathiesen et al. (2011) for a detailed discussion.

which is being vigorously discussed by researchers and is increasingly on the agenda of regulators and supervisors (Carney, 2015). Trenberth et al. (2014) show that corporations' production processes are vulnerable to natural disasters, which are likely to be amplified by climate change. Bansal et al. (2016) estimate the elasticity of equity prices to temperature fluctuations and find that global warming has a significant negative effect on asset valuations. Daniel et al. (2016) and Giglio et al. (2015) claim that stock and real estate market might help guide government policies if markets efficiently incorporate climate risks. Our work is closely related to Ivanov et al. (2021) who find that with the presence of carbon pricing policy, the high-emission firms face shorter loan maturities, lower access to permanent forms of bank financing, higher interest rates, and higher participation of shadow banks in their lending syndicates. Despite the growing literature studying the direct impacts of pollution and climate change on financial assets, the research on the relationship between transition risks and financial stability are still scarce. We fill this gap by investigating the financial mechanisms through which the adjustment process toward a low-emission economy affects macroeconomy and financial sector in the short term.

Second, we contribute to the literature on endogenous default risk and the financial accelerator. Christiano et al. (2014) develop a model where entrepreneurs combine their own resources with loans to acquire raw capital, which can be converted into effective capital in a process that is characterized by idiosyncratic uncertainty (i.e. risk shocks).[4] The authors prove that these risk shocks are important drivers of business cycle fluctuations. Comerford and Spiganti (2017) assume that the government levies carbon taxes and provides green subsides to induce entrepreneurs to use zero-carbon production and find that such policies damage the balance sheets of entrepreneurs, with major macroeconomic implications due to the presence of financial frictions. Our paper is also very close to Ivanov et al. (2021) who show that cap-and-trade legislation in California leads to lower access to bank financing, higher lending rates, and higher participation of shadow banks for high-polluting firms. Different from those papers, we incorporate the environmental risk into a DSGE model with endogenous default determined through a change in the balance sheets of entrepreneurs and the current asset holdings as collateral.

Third, the paper sheds new light on the literature that incorporates environmental factors into macroeconomic analysis. Angelopoulos et al. (2010) analyze the impact of alternative environmental policy rules in a real business cycle model augmented with the assumption that only the government can engage in pollution abatement activity. Fischer and Springborn (2011) evaluate volatility and welfare costs by comparing cap-and-trade, the carbon tax, and the intensity target in a dynamic stochastic general equilibrium model with one polluting intermediate input. Heutel (2012) examines the optimal emission policy in a dynamic stochastic general equilibrium model with a pollution externality during phases of expansions or recessions. Annicchiarico and Di Dio (2015) analyze different environmental policy regimes in a new Keynesian model with nominal and real uncertainty and evaluate the transmission mechanism of shocks with the presence of nominal rigidities and a monetary authority. Tumen et al. (2016) investigate the mechanisms through which environmental taxes on fossil fuel usage affect the main macroeconomic variables in the short run. Compared with the existing literature, we develop a financial accelerator mechanism that propagates the economic consequences of environmental risk by linking entrepreneurs to banks through the collateral value.

[4] Throughout the paper, we use the terms "risk shocks" and "uncertainty shocks" interchangeably.

Last but not least, this research echoes the intriguing debate over the economic costs of environmental regulation. Early studies on the United States support the modest negative economic effect of environmental regulation on productivity, but the results are sensitive to the measurement of regulatory stringency (Jaffe et al., 1995). Focusing on the US Clean Air Act Amendments, research finds that more stringent air pollution regulation in nonattainment counties caused a sizeable reduction in the capital stock and output of pollution-intensive industries (Greenstone, 2002), a significant decline of total factor productivity (Greenstone et al., 2012), substantial losses of jobs (Greenstone, 2002; Walker, 2011) and earnings (Walker, 2013), and a decrease in births of firms in polluting industries (Becker and Henderson, 2000). On the contrary, Berman and Bui (2001a) and Berman and Bui (2001b) find that strict air pollution regulation brought a sharp increase in the total factor productivity of local oil refineries with only a slight decline in the employment. Tanaka et al. (2014) demonstrate that although environmental regulation eventually improves the economic performance of the targeted polluting firms, it takes five years for the effect on technological advancement to materialize. Finally, de Greiff et al. (2018), whose research question is closely related to us, find that banks have been charging significantly higher loan rates to fossil fuel firms with larger exposure to climate policies. Despite the inspiring progress in the empirical examinations of this debate, the evidence on the financial accelerator mechanism is still sparse. This research enriches our understanding of the impacts of environmental transition on the financial system and banks' price strategy in the short run.

III. MODEL

We develop an augmented environmental dynamic stochastic general equilibrium (E-DSGE) model similar to Bernanke et al. (1999) and Christiano et al. (2014), in which the environmental regulation is tightened to reduce emissions by productive firms. The model is characterized by an endogenous development in the credit market, through which the well-known financial accelerator mechanism propagates and amplifies the business and financial cycle. Moreover, the model allows the excess premium (i.e., the spread of entrepreneur's lending rate over the risk-free interest rate) to fluctuate with changes in level of risk or uncertainty which arise from the enforcement of specific environmental standards aiming for emission abatement. Inducing additional production cost, the risk is expected to lower firms' profitability, and consequently increases the excess premium to cover the costs of default.

The model includes several features: (i) two types of entrepreneurs, who differ in terms of the greenness of their input for the production of intermediate goods; (ii) perfectly competitive firms that combine a continuum of intermediate goods into a final good; (iii) a capital producer that converts investment goods into productive capital, subject to adjustment costs; (iv) a household sector, in which savers earn income by supplying labor to firms and get utility through the enjoyment of leisure; (v) a banking sector that channels savings from households to entrepreneurs to start new projects; and (v) a monetary authority that sets the policy rate.

A. Entrepreneurs and Defaulting Decision

The economy is populated by two groups of entrepreneurs (superscript j) operating in the green (g) and non-green (ng) sector. Each group of entrepreneurs consists of many members, indexed by $i \in [0, n^j]$, where n^j indicates the number of firms in the economy. Entrepreneurs in each group produce intermediate goods to sell to retailers. In order to finance new business, entrepreneurs in each group purchase the stock of capital, $k_{e,t}^j$ at the real price, $q_t^{j,k}$.[5] The investment opportunities are financed by either entrepreneurs' net worth, $N_{e,t+1}^j$, or bank loans, $b_{e,t+1}^j$. The balance sheet of each group of entrepreneurs is given by:

$$q_t^{j,k} k_{e,t}^j = N_{e,t+1}^j + b_{e,t+1}^j \tag{3.1}$$

The investment projects undertaken by each type of entrepreneurs are risky, as entrepreneurs choose the value of firm capital and the level of borrowing prior the realization of the project itself. Thus, the ex post gross return on capital for entrepreneurs j is given by $\omega_{t+1}^j R_{K,t+1}^j$, where the random variable $(\omega_{t+1}^j j)^i$ is an i.i.d. idiosyncratic shock which is log-normally distributed with cumulative distribution $F_{j,t}[(\omega_{t+1}^j)^i)]$.[6] The ex-post profit for each project is

$$\Pi(\omega_{t+1}^i) = \omega_{t+1}^j R_{K,t}^j q_{t+1}^{j,k} (k_{e,t+1}^j)^i - R_{z,t+1}^j b_{e,t}^j, \tag{3.2}$$

where $R_{z,t+1}$ is the gross contractual state-contingent loan rate paid to the bank by non-defaulting entrepreneurs.

The cut-off value, $\overline{\omega}_{t+1}^j$, that distinguishes between profitable and non-profitable projects is defined such that $\Pi(\omega_{t+1}^i) = 0$, which implies:

$$\overline{\omega}_{t+1}^j R_{K,t+1}^j \left(q_{t+1}^{j,k} k_{e,t+1}^j \right) = b_{e,t}^j R_{z,t+1}^j \tag{3.3}$$

Eq. 3.3 indicates that entrepreneur defaults when the ex-post value of the return to capital on new projects is lower than the loan repayment (loan value plus interest). The random variable $(\omega_{t+1}^j)^i$ describes an i.i.d. idiosyncratic shock, which can alter the realization of Eq. 3.3. If $(\overline{\omega}_{t+1}^j)^i \in [\overline{\omega}_{t+1}^j, \infty]$, entrepreneurs are solvent and repay the loan to the bank; while for loans with low realizations, $(\overline{\omega}_{t+1}^j)^i \in [0, \overline{\omega}_{t+1}^j]$, entrepreneurs declare bankruptcy and defaulting members lose their capital.[7]

Tightening environmental protection standards and climate change policies will generate negative externalities that can be internalized on a firm's balance sheet, thus altering Eq. 3.3 and generating potential losses for financial institutions and the financial system.

Entrepreneurs' Maximization Problem

Each type of entrepreneurs produces intermediate goods, $Y_{e,t}^j$, by using a Cobb-Douglas constant returns-to-scale technology that combines total factor productivity A, labor L, capital k, and clean/dirty inputs, X. Entrepreneurs operating in the green sector use clean and renewable energy, $X = E$, while entrepreneurs in the non-green sector use polluting inputs, $X = M$, to

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[5] Entrepreneurs assign equal resources to each member i to purchase capital $(k_{e,t}^j)^i$, where $\int_i (k_{e,t}^j)^i di = k_{e,t}^j$.

[6] We allow for idiosyncratic risk, such that $E_t[(\omega_{t+1}^j)^i] = 1$. This implies that $\log[(\omega_t^j)^i] \sim N(-\frac{\sigma^2_{\omega j,t}}{2}, \sigma^2_{\omega j,t})$, where $\sigma_{\omega j,t}$ is a time-varying standard deviation for each type of entrepreneurs, which follows an AR(1) process.

[7] This shock can be interpreted as physical risk associated to Climate change-related risk, deriving from direct damage to property or trade disruption. However, this paper focuses mainly on the impact of tightening environmental protection standards and climate change policies in line with the Action Plan implemented in China since 2013. Thus, the study of physical risk is beyond the scope of this paper.

produce intermediate goods to be sold to retailers. A fraction σ_g and a fraction σ_{ng} of total labor and capital are used in the production process for green and non-green sector, respectively.[8]

Entrepreneurs maximize the following utility function, subject to the budget constraint and the bank participation constraint:

$$\max E_0 \sum_{t=0}^{\infty} (\beta^e)^t \left[\ln \left(c^j_{e,t} \right) \right] \tag{3.4}$$

subject to:

$$c^j_{e,t} + X_t + q^{j,k}_t \left(k^j_{e,t} - (1 - \delta_k)\, k^j_{e,t-1} \right) + w^j_t L^j_t + R^j_{K,t} k^j_{e,t} + R^j_{z,t} b^j_{e,t-1} - Z^j_{e,t} + F_t$$
$$= Y^j_{e,t} + b^j_{e,t}, \tag{3.5}$$

$$b^j_{e,t} \leq m^j_{e,t}\ E_t \frac{\left(q^{j,k}_{t+1} \pi_{t+1} (1 - \delta_k)\, k^j_{e,t} \right)}{R^L_t}, \tag{3.6}$$

and

$$R^L_t b^j_{e,t} = \left\{ (1 - \mu^j) \int_0^{\overline{\omega}_{j,t+1}} \omega_{j,t+1} (1 - \delta_h)\, q^{j,k}_{t+1} k^j_{e,t} f_{t+1}(\omega_j)\, d\omega_j \right\}$$
$$+ \left\{ \int_{\overline{\omega}_{j,t+1}}^{\infty} R^j_{z,t+1} b^j_{e,t} f_{t+1}(\omega_j)\, d\omega_j \right\}, \tag{3.7}$$

where $j = (g, ng)$. β^e is the discount factor, $\pi_t = \frac{P_t}{P_{t-1}}$ is the inflation rate, $m_{e,t}^j$ is the endogenous loan-to-value ratio, μ^j is the cost that lenders pay to observe the borrower's realized return on capital,[9] $Z_{e,t}^j$ is the amount of defaulting loans, δ_k is the depreciation rate of capital stock, and F_t are real dividends paid to households.

Eq. 3.5 shows that each group of entrepreneurs produces intermediate goods, $Y_{e,t}^j$, and sells the intermediate good to retailers. The revenues are used to finance the entrepreneur's consumption, $c_{e,t}^j$, to pay wages to workers, $w_t^j L_t^j$, and to acquire extra inputs, $X = E, M$. Moreover, each period, entrepreneurs borrow, $b_{e,t}^j$, from banks to finance the acquisition of new capital for new projects, $q_t^{j,k} I_{e,t}^j = q_t^{j,k}(k_{e,t}^j - (1 - \delta_k) k_{e,t-1}^j)$. Each project financed is subject to individual contract where the financial institution charges an interest rate equal to $R_{z,t}^j$.[10]
Entrepreneurs also rent capital at the rate of R_t^k.[11] The green sector uses clean and renewable energy, E, while the non-green sector uses polluting inputs, M. As in Fischer and Springborn (2011), we assume that emissions are proportional to the use of the polluting inputs, therefore the unit of emission are equal to the quantity of inputs M.[12]
The production function of intermediate goods is given by:

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[8] $\sigma g + \sigma ng = 1$.
[9] The auditing cost, μj, includes costs associated to legal costs, auditing, accounting, and costs related to losses related to asset liquidation and disclosure of business.
[10] Loan rate Rz , t+1 j is determined at time t, after the realization of the shocks.
[11] Li and Tsou (2019) analyze the implications of lease contracts and show that the leased capital is less risky than the purchased capital through secured loans.
[12] We assume the price of intermediate inputs to be equal to 1 ($PX = 1$).

$$Y_{e,t}^{j} = A_t \left(k_{e,t-1}^{j}\right)^{\alpha} \left(L_t^{j}\right)^{1-\alpha-\gamma_j} X_t^{\gamma_j}, \tag{3.8}$$

The non-green production function is constrained on the use of polluting inputs:

$$M_t \leq \Omega_{ng,t} - \varepsilon_{M,t}$$

where $\Omega_{ng,\,t}$ is a function aiming to reduce pollution emissions, $\varepsilon_{M,\,t}$ is an environmental policy shock that aims to reduce the level of emissions during the production process, and it is given by an AR(1), such that $\varepsilon_{M,\,t} = \rho_{\varepsilon}\varepsilon_{M,\,t-1} + \epsilon_{\varepsilon,\,t}$.[13]

Similar to Fischer and Springborn (2011), the government imposes a reduction of polluting emissions in a fixed amount $\overline{M}$.[14] As a result, $\Omega_t^{ng} = \overline{M}$ and the above emission constraint becomes:

$$M_t \leq \overline{M} - \varepsilon_{M,t}. \tag{3.9}$$

Financial frictions are introduced in Eq. 3.6. Entrepreneurs borrow from the banking sector to finance their productions. They use capital to pledge against borrowing. Moreover, the model allows the possibility for entrepreneurs to endogenously default by introducing a threshold value that defines the repayment ability of the loan, as described in Eq. 3.3.

$Z_{e,\,t}^{j}$ is the amount of borrowing that entrepreneurs default, and it is given by the amount of missed loan repayments minus the seized capital stock by the banking sector:

$$Z_{e,t}^{j} = F_{j,t}\left(\overline{\omega}_t^{j}\right) R_{z,t}^{j} b_{e,t-1}^{j} - q_t^{j,k}\left(1-\delta_k\right) k_{e,t-1}^{j} G_t^{j}\left(\overline{\omega}_t^{j}\right), \tag{3.10}$$

where $F_{j,t}\left(\overline{\omega}_t^{j}\right)$ is the share of entrepreneurs who default their debt to the bank, $G_t^{j}\left(\overline{\omega}_t^{j}\right) = \int_0^{\overline{\omega}_{t+1}^{j}} \omega_{t+1}^{i,j} f_{t+1}\left(\omega^{i,j}\right) d\omega^{i,j}$ is the fraction of capital stock seized by the bank in case of default,[15] and $f(\omega_j^i)$ is the probability density function of ω_j^i.

$m_{e,\,t}^{j}$ in Eq. 3.6 is the loan-to-value ratio equal to $\left[\Gamma_{t+1}\left(\overline{\omega}_{t+1}^{j}\right) - \mu^{j} G_{t+1}\left(\overline{\omega}_{t+1}^{j}\right)\right]$, and μ^{j} is the fraction of the capital value that banks pay to monitor and seize the collateral in case of default. $\Gamma_{t+1}\left(\overline{\omega}_{t+1}^{j}\right) \equiv \overline{\omega}_{t+1}^{j}\int_{\overline{\omega}_{t+1}^{j}}^{\infty} f_{t+1}\left(\omega^{i,j}\right)\omega^{i,j} + G_{t+1}\left(\overline{\omega}_{t+1}^{j}\right)$ indicates the expected net share of capital values that lenders size in case of default.

Finally, the entrepreneur's maximization problem is subject to a bank participation constraint described in Eq. 3.7, which assumes that banks expect to earn the lending rate, R_t^L, which represents the rate that account for loan repayments and losses from defaults. It will be discussed in more details in the next Section.

[13] $\rho\varepsilon$ is the persistence parameter and $\varepsilon\varepsilon$, t is a i.i.d. white noise process with mean zero and variance $\sigma\varepsilon 2$.
[14] Alternatively, Annicchiarico and Di Dio (2015) assumes that emissions are proportional to output and environmental policies and abatement measures limit the environmental impact of production activities.
[15] As in Bernanke et al. (1999) and Forlati and Lambertini (2011), the seized housing stock is destroyed during the foreclosure process.

B. Banking Sector

We assume there is a banking sector which receives at time t deposits from domestic households, d_t, and finances loans to both types of entrepreneurs. The banker maximizes her consumption (dividends) defined as:

$$\max E_0 \sum_{t=0}^{\infty} \beta_b^t \ln\left(c_{b,t}\right), \tag{3.11}$$

subject to the flow of funds

$$c_{b,t} + \frac{R_{t-1}}{\pi_t} d_{t-1} + b_t + \Theta\left(x_t\right) = d_t + \frac{R_t^L}{\pi_t} b_{t-1} \tag{3.12}$$

and

$$\frac{x_t}{b_t} \geq \rho_b, \tag{3.13}$$

where $c_{b,t}$ denotes the banker's consumption (dividends) and β_b is its discount factor; $b_t=(\sigma_g b_{e,t}^g + \sigma_{ng} b_{e,t}^{ng})$ represents one-period bank loans extended to green and non-green firms in period t. The commercial bank capital is given by $x_t = b_t - d_t$, and the excess capital is given by $x_t = (1 - \rho_b)b_t - d_t$.

In Eq. 3.13, following Kollmann et al. (2011) and Kollmann (2013), we assume that the banking sector faces the requirement that the capital to asset ratio should be larger than the fraction of ρ_b. We assume that the bank can hold less capital than the required or desired level, but deviating from this requirement implies a cost of Θ_t, which is a function of bank's excess capital, i.e., $\Theta_t = \Theta(x_t)$.[16]

The flow of fund described in Eq. 3.12 reports the expenditure side of the banker which includes current consumption, the interest payment on deposits to households, $\frac{R_{t-1}}{\pi_t} d_{t-1}$, new business loans to the green b_e^g and non-green sector b_e^{ng}, as well as the cost of deviating from the required capital ratio $\Theta(x_t)$. The flow of income includes the household deposits and the repayment of loans by green and non-green entrepreneurs, $\frac{R_t^L}{\pi_t} b_{t-1}$. Moreover, both types of entrepreneurs can eventually default by being unable to perform their contractual obligations. Thus the bank experiences a financial loss due to the failure of obtaining its expected loan repayment of $Z_{e,t}^j$, defined previously in Eq. 3.10.

The *optimal contract* is defined as a one-period loan contract which guarantees a risk neutral bank to obtain a predetermined rate of return on its total loans to entrepreneurs. At time t, the expected return from granted loans should guarantee the bank at least the gross rate of return, R_t^L times the total loans $b_{e,t+1}^j$ to entrepreneurs. This leads to the following participation constraint:

[16] Θt is is a convex function with first derivative is $\Theta' < 0$, which implies that a higher excess capital reduces the cost of deviating from the required capital ratio, and the second derivative $\Theta'' > 0$, which implies that a higher excess capital reduces the cost but at a decreasing rate.

$$R_t^L b_{e,t}^j = \left\{ \left(1-\mu^j\right) \int_0^{\overline{\omega}_{j,t+1}} \omega_{j,t+1}^i \left(1-\delta_h\right) q_{t+1}^{j,k} \pi_{t+1} k_{e,t+1}^j f_{t+1}\left(\omega_j^i\right) d\omega_j^i \right\} + \left\{ \int_{\overline{\omega}_{j,t+1}}^{\infty} R_{z,t+1}^j b_{e,t}^j f_{t+1}\left(\omega_j^i\right) d\omega_j^i \right\}, \tag{3.14}$$

Eq. 3.14 states that the return on total loans the banking sector expects to obtain comes from the value of the capital stock, net of monitoring costs and depreciation of the defaulting entrepreneurs (the first term on the right hand side); and, from the repayment by the non-defaulting entrepreneurs (the second term on the right hand side). Once the idiosyncratic and environmental policy shocks hit the economy, the threshold values $\overline{\omega}_{t+1}^j$ and the state-contingent mortgage rate $R_{Z,t+1}^j$ are determined, to fulfill the above participation constraint.

C. Households

There is a representative household who consumes good, c_t, and supplies labor, L_t. She also saves bank deposits, d_t, in order to solve the following intertemporal problem:

$$\max E_0 \sum_{t=0}^{\infty} (\beta)^t \left[\frac{c_t^{1-\sigma_c}}{1-\sigma_c} - \frac{v_L}{\eta}\left(L_t\right)^{\eta} \right], \tag{3.15}$$

subject to the following budget constraint:

$$c_t + d_t \leq w_t L_t + \frac{R_{t-1}}{\pi_t} d_{t-1} + F_t. \tag{3.16}$$

where w_t is the real wage, σ_c is the inverse of the intertemporal elasticity of substitution for consumption goods, η is the inverse of the Frisch elasticity of work effort and υ_L is the labor disutility parameter. R_t is the free-risk nominal interest rate received on deposits and $\pi_t = P_t/P_{t-1}$ is the inflation rate. Households also receive real dividends from firms, F_t.

D. Final Goods Producers

The model assumes there is a continuum of intermediate firms indexed $n \in [0, 1]$ who transform intermediate goods $Y_t(n)$ into a final consumption good Y_t, according to a constant elasticity of substitution technology:

$$Y_t = \left[\int_0^1 Y_t(n)^{\frac{\xi-1}{\xi}} dn \right]^{\frac{\xi}{\xi-1}}, \tag{3.17}$$

where $\xi > 1$ is the elasticity of the substitution between the different intermediate goods.

Intermediate firms aggregate intermediate goods from both green and non-green firms:[17]

$$Y_t(n) = \sigma_g Y_{e,t}^g + \sigma_{ng} Y_{e,t}^{ng} \tag{3.18}$$

[17] Intermediate goods are perfect substitutes and this allows to have the same levels of intermediate goods' prices according to whether they are produced by green or non-green firms.

where σ_g and σ_{ng} represents the market share of green and non-green firms, respectively.

From standard profit maximization, input demand for the intermediate good i is obtained as:

$$Y_t(n) = \left(\frac{P_t(n)}{P_t}\right)^{-\xi} Y_t, \tag{3.19}$$

where $P_t(n) = \sigma_g P_{e,t}{}^{g}(n) + \sigma_{ng} P_{e,t}{}^{ng}(n)$ and P_t is the CES-based final (consumption) price index given by

$$P_t = \left[\int_0^1 P_t(n)^{1-\xi} dn\right]^{\frac{1}{1-\xi}}. \tag{3.20}$$

We assume a Calvo price-setting mechanism and retailers adjust each period their prices with a probability $(1-\theta)$. $P_t{}^*(n)$ is the price that retailers are able to adjust. Thus, retailers maximize the following expected profit:

$$\max E_t \sum_{k=t}^{\infty} (\beta_s \theta)^{k-t} \frac{U_{C_{st+k}}}{U_{C_{st}}} \left\{ \left(\frac{P_t^*(n)}{P_{t+k}} - \frac{X_t}{X_{t+k}} \right) Y_{t+k}^*(n) \right\}$$

where $Y_{t+k}^*(i) = \left(\frac{P_t^*(i)}{P_{t+k}}\right)^{-\xi} Y_{t+k}$. X_t is the markup of final over intermediate goods and in steady state is equal to $X = \xi/(\xi-1)$. The Calvo price evolves according to the following:

$$P_t = \left[\theta P_{t-1}^{\xi} + (1-\theta)\left(P_t^*\right)^{(}1-\xi)\right]^{\frac{\xi}{\xi-1}}. \tag{3.21}$$

Combining these two last equations, and after log-linearizing, we can obtain the following expression for the Phillips curve:

$$\hat{\pi}_t = \beta_s E_t \hat{\pi}_{t+1} - \kappa \hat{X}_t, \tag{3.22}$$

with

$$\kappa = \frac{(1-\theta)(1-\beta)\theta}{\theta}.$$

E. Capital Producers

Capital producers combine a fraction of the final goods purchased from retailers as investment goods, $i_{k,t}$, with the existing capital stock, $k_t = \sum_j \sigma_j k_{e,t}{}^j$, in order to produce new capital. Existing capital is subject to an adjustment cost specified as $\frac{\psi_k}{2}\left(\frac{i_{k,t}}{k_{t-1}} - \delta_k\right)^2 k_{t-1}$, where ψ_k governs the slope of the capital producers' adjustment cost function. Capital producers choose the level of $i_{k,t}$ that maximizes their profits

$$\max_{i_{k,t}} q_t^k i_{k,t} - \left(i_{k,t} + \frac{\psi_k}{2}\left(\frac{i_{k,t}}{k_{t-1}} - \delta_k\right)^2 k_{t-1} \right).$$

From profit maximization, it is possible to derive the supply of capital

$$q_t^k = \left[1 + \psi_k \left(\frac{i_{k,t}}{k_{t-1}} - \delta_k\right)\right], \tag{3.23}$$

where $q_t^k = \sum_j \sigma_j q_t^{j,k}$ is the relative price of capital. In the absence of investment, adjustment costs, q_t^k, is constant and equal to one. The usual capital accumulation equation defines aggregate capital investment:

$$i_{k,t} = k_t - \left(1 - \delta_k\right) k_{t-1}. \tag{3.24}$$

F. Monetary Policy

The Central Bank follows a Taylor-type rule that reacts to changes in inflation expectations and the output gap:

$$\frac{R_t}{\overline{R}} = \left(\frac{R_{t-1}}{\overline{R}}\right)^{\phi_R} \left(\frac{\pi_t}{\overline{\pi}}\right)^{\phi_\pi (1-\phi_R)} \left(\frac{Y_t}{y}\right)^{\phi_Y (1-\phi_R)} \tag{3.25}$$

where ϕ_π is the coefficient on inflation in the feedback rule, ϕ_Y is the coefficient on output, and ϕ_R determines the degree of interest rate smoothing.

G. Market Clearing Conditions

The market will be cleared according to the equations

$$Y_t = C_t + i_{k,t} + E_t + M_t + \Sigma_j \mu^j G_{t+1}\left(\overline{\omega}_{j,t+1}\right) q_{t+1}^{j,k}\left(1 - \delta_k\right) k_{e,t}^j \Big) \tag{3.26}$$

$$C_t = c_t + \sigma_g c_{e,t}^g + \sigma_{ng} c_{e,t}^{ng} + c_{b,t} \tag{3.27}$$

$$k_t = \sum_j \sigma_j k_{e,t}^j \tag{3.28}$$

$$L_t = \sum_j \sigma_j L_t^j \tag{3.29}$$

$$b_t = \sum_j \sigma_j b_{e,t}^j \tag{3.30}$$

$$q_t^k = \sum_j \sigma_j q_t^{j,k} \quad . \tag{3.31}$$

H. Parameterization

In this research, the time unit is measured in quarters. The parametrization follows standard values used in the real business cycle literature and long-term statistics for China, and they are reported in Table 1.[18] The discount factor $\beta = \beta_b$ is set to 0.93 to target the average Chinese one-year official lending rate of financial institutions of 7.4 percent over the period of 1991–2012. Similar to Iacoviello (2015), we assume entrepreneurs face a lower discount factor relative to savers, thus $\beta^e = 0.92$.

Our production function follows a Cobb-Douglas specification with constant returns to scale and the capital share, α, equal to 0.46. This figure is consistent with the empirical finding of Ng (2015) who calibrated a value of 0.54 for the labor income share in after-tax value-added of the good sector, using the Chinese Input–Output Tables (in 1992, 1995, 1997, 2000, 2002, 2005, 2007, and 2010). According to Huang (2005), Fan et al. (2016), Bai et al. (2006) and Niu et al.

[18] We do not calibrate the idiosyncratic risk shock as we do not consider it. The variable ω is introduced to allow for entrepreneurs' defaulting behavior.

(2018), we set the capital depreciation rate δ_k as 0.025, and the adjustment cost parameter on investments as 6.7.

Table 1. Parameters' Values

Parameter	Description	Value
β	Households Discount factor	0.93
β^e	Entrepreneurs Discount factor	0.92
σ_c	Elasticity of substitution for consumption	1.353
ν_L	Labor disutility parameter	1
η	Labor supply aversion	2
δ_k	Capital depreciation parameter	0.025
ψ_k	Capital adjustment cost	6.7
α	Capital Share	0.46
γ_g	Energy Inputs Share	0.099
γng	Pollution Inputs Share	0.09
ϑ	Intensity Target coefficient	0.05
$F_j(\overline{\varpi}^{\,g})$	Probability of default (Green)	0.009
$F_j(\overline{\varpi}^{\,ng})$	Probability of default (Non-Green)	0.010
ξ	Price Elasticity of Demand for Good n	6
θ	Calvo's Price Parameter for Nominal Rigidities	0.568
ρ_R	Monetary Policy Inertia	0.73
ρ_Y	Monetary Policy Reaction to Y	0.109
ρ_π	Monetary Policy Reaction to π	1.487
β_b	Banks Discount factor	0.93
ρ_b	Banks Capital ratio	0.08
Θ	Cost of deviation from the required capital ratio	0.25
μ_j	Monitoring Cost	0.21
σ_g	Size of Green Firms	0.3
ρ_M	Persistency of Environ. Policy shock	0.97
σ_M	Standard deviation on Environ. Policy shock	0.01

The share of clean energy and pollution emission in the production function, γ_j, is equal to 0.099 so that averaged energy expenditures account for 12 percent of GDP.[19] Following Fischer and Springborn (2011) and Xiao et al. (2018), we assume the size of green firms be 0.3, while the intensity target coefficient, ϑ, be to 0.05, a value smaller than γ_j . As in Zhao et al. (2016), the inverse elasticity of labor supply, η, is set equal to 2 and the coefficient of relative risk aversion, σ_c, is set to be 1.353. We follow estimates by Ng (2015) in setting the price elasticity ξ equal to 6 and the Calvo probability to adjust prices, θ, equal to 0.568. Those values indicate moderate levels of stickiness in the Chinese goods market. For the monetary policy parameters of the Taylor rule, we follow Ng (2015) and Justiniano et al. (2015)[20] to set the coefficient for the interest rate inertia, ρ_R, to be 0.73, the reaction to the output gap, ρ_Y to be 0.109, and the reaction to inflation ρ_π to be 1.487.

[19] Source: Global Energy Data - Enerdata.

[20] Justiniano et al. (2015) set ρR equal to 0.8, ρY equal to 0.125, and $\rho\pi$ equal to 1.5. Alternatively, Zhao et al. (2016) set higher parameters (ρR = 0.9, ρY = 0.59, $\rho\pi$ = 1.8).

According to the World Bank data, the Chinese banking regulator imposes a required bank capital ratio equal to 0.08. The bank cost parameter for deviating from capital requirements is set equal to 0.25, as in Kollmann et al. (2011). Following Christiano et al. (2014), we set the value of monitor cost as 0.21, and it is the same for both entrepreneurs. The data for default rates comes from the corporate credit database collected by the China Banking and Insurance Regulatory Commission (CBIRC). Using the statistics from Table 2, we set the average probability of default, $F_j\left(\overline{\omega}^j\right)$ to be 0.009 and 0.010 for the green and non-green sector, respectively. In order to achieve a 20 percent decrease in the emissions, the persistence of the environmental policy shock and its standard deviation is equal to 0.97 and 0.01 respectively.

IV. IMPULSE RESPONSES

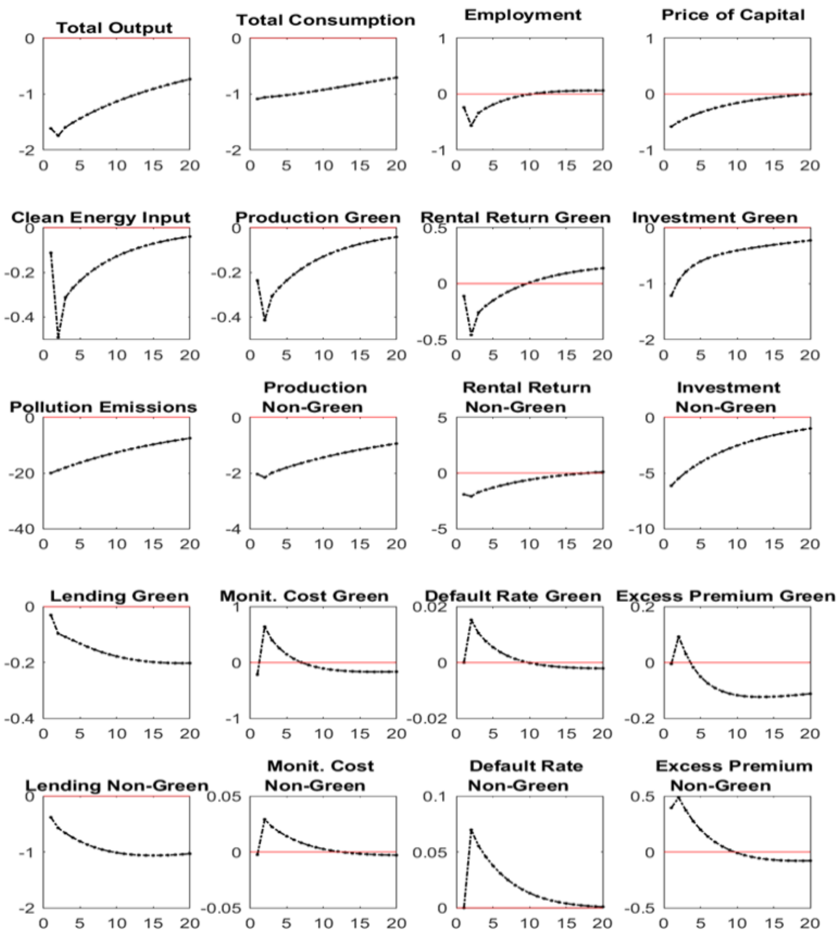
This section presents results on simulated impulse responses under the scenario that the government enhances regulatory environmental standards to reduce the pollution emissions. Consequently, the pollution constraint, $\overline{M}$ should decrease by 20 percent.[21] The impulse responses show a percentage deviation from the initial steady state over a 20-quarter period under the environmental policy scenario.

Figure 1 shows that such policy enforcement dampens the productivity of non-green sectors by around 2 percent as the emission cap requires firms to cut the nongreen inputs in the production process. Consequently, entrepreneurs in non-green sectors decrease their investments and the price of capital drops accordingly. Less investment also leads to lower rental return on capital, as the demand for renting capital declines. Lower production compromises a firm’s profitability and hence its ability to repay part of or all the interest and principal of a loan. Further, the fall in the collateral value of non-green entrepreneurs induce them to cut their demand for funds. All these changes in the price of capital, capital stock and borrowing affect the entrepreneurs’ return on capital and the cut-off value, $\overline{\omega}^{ng}$, that endogenously determines the entrepreneurs’ failure to repay outstanding loans due to the rising costs of complying with environmental protection policies.

Figure 2 shows that the cut-off value increases for both types of entrepreneurs, with higher impact on the non-green sector which is the target of environmental regulation (See solid line). This increase in the cut-off value reflects the movement of $\overline{\omega}$ which is plotted in Figure 3. The left side corresponds to the distribution of default probabilities for the non-green sector, while the right side refers to the green sector. Figure 3 indicates that when the government tightens the environmental standards, the probability of default increases due to a movement to the right of the $\overline{\omega}$. Hence, the default, measured by the shaded area, increases by the amount corresponding to the diagonal lines. However, the environmental policy shock leads to a change in the cut-off value also for the green sector. See dashed-dotted line in Figure 2. The increase in the cut-off value is smaller relative to the non-green sector, reflecting a smaller movement to the right, as described in the right side of Figure 3.

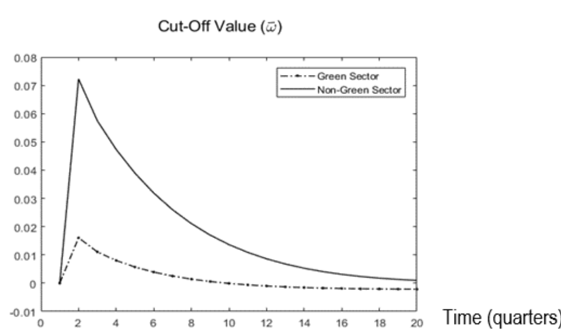
[21] Specifically, the impulse response analysis reports simulation to one standard deviation negative shock to *M*.

Figure 1. Environmental Shock to Decrease Pollution Emissions



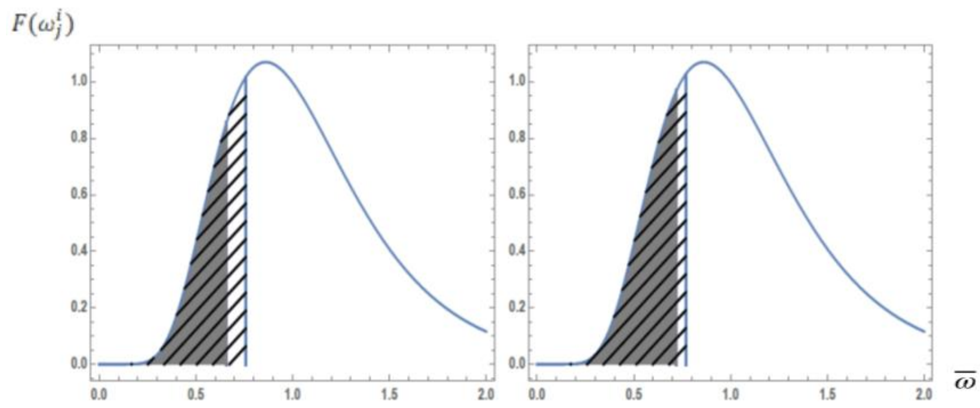
Note: This figure presents results on simulated impulse responses under the scenario that the government determines to cut the emission by 20 percent. The horizontal axis plots the quarters following the enactment of the policy. The vertical axis reflects the percentage deviations from steady state values.

Figure 2. Change in $\overline{\omega}$ due to Tightness of Environmental Standards



Indeed, the rise of default rate for the green sector is described by the diagonal lines area minus the shaded area. As a result, default rates increase by around 7.5 percent and 1.8 percent for the non-green and green sector, respectively. The existence of asymmetric information between bankers and entrepreneurs triggers banks to charge higher non-state contingent rates in face of expected higher monitoring costs, thus the excess premium, expressed as the difference between contractual rates and risk-free rate, increases by around 0.5 percent and 0.1 percent for the non-green and green sector, respectively.

Figure 3. Distribution of Default Probabilities ($F(\omega_j^i)$) and Tightness of Environmental Standards



Note: Non-Green Sector (Left side); Green Sector (Right side).

Through a capital channel, banks cut the supply of loans as they face a reduction in bank capital due to higher default rates and a lower price of capital. As a result, banks deleverage because the value of the assets in their balance sheet decline. This mechanism is reinforced by a bank funding channel, through which banks charge higher lending rates also to green entrepreneurs in order to recover from the losses resulting from higher monitoring costs and the forgone loan repayments. Higher borrowing cost leads green entrepreneurs to lower their demand for external funds, making production and investment in the green sector slow down. Also clean energy inputs decrease as green entrepreneurs produce less. Ultimately, some green entrepreneurs can experience a lower return on new projects and a drop in their asset prices, affecting their ability to repay their debt. Indeed, even if in smaller values, default rates in the green sector increase as well as in the non-green sector. This result is in line with the findings of the European Banking Federation (EBF), reporting that Industrial and Commercial Bank of China tends to have lower default rates to loans to green businesses relative to those in the non-green loans.[22]

To sum up, the main simulation results reveal that the economic impact of environmental policy, aiming at reducing pollution in the non-green sector, can spill over to the green sector through the banking sector which tends to charge higher cost of borrowing to cover increased monitoring cost, as well as a large negative spillover on asset prices.

V. DATA AND EMPIRICAL STRATEGY

To provide further supporting evidence to the theoretical implications of the *E*-DSGE model, we employ the Clean Air Action Plan that the Chinese government launched in 2013 as a quasi-natural experiment to examine the financial impacts of tightening environmental regulations in

[22] See https://www.ebf.eu/wp-content/uploads/2017/09/Green-Finance-Report-digital.pdf.

the short term. The background information on the Clean Air Action Plan and Chinese banking industry are provided in Appendix 1.

A. Data Sources and Summary Statistics

Our data come from a corporate credit database that the China Banking and Insurance Regulatory Commission (CBIRC) Jiangsu Office established. With a population of 80.4 million in 2018 and an area of 102,600 km^2, Jiangsu is one of the most densely populated provinces in China. Thanks to its large and well-developed manufacturing sector, it is one of China's fastest developing provinces over recent decades. As of 2018, Jiangsu had a GDP of US$1.377 trillion (or RMB9.2 trillion), the second highest in China (just after Guangdong), but greater than those of Mexico and Indonesia. However, with an economic structure in which the secondary industry accounts for around 40 percent of GDP and home to many of the world's leading exporters of electronic equipment, chemicals and textiles, Jiangsu faces serious environmental degradation. In 2013, the annual industrial SO_2 and CO_2 emissions per unit of land area are 8.48 and 19.51 tonnes per square kilometer, respectively.[23]

Moreover, this coastal province offers an ideal setting for us to investigate how the process of adjustment toward low emission economy affects the financial risks because it has a diverse economy with various types of banks. On one hand, GDP per capita of the six prefectures varies widely between US$7,000 and US$20,000, representing different levels of economic development. On the other hand, various types of banks such as the Big Five commercial banks,[24] joint-equity commercial banks, foreign banks, city commercial banks, rural commercial banks, rural credit cooperative, are operating in this jurisdiction. According to the newest statistics released by CBIRC, the total asset of commercial banks in Jiangsu Province amounts to RMB 16782 billion (around US$2,494 billion), accounting for 8 percent of the whole commercial banking industry in the country as of 2018.[25]

This dataset contains around 1.3 million commercial loans that all banks operating in six prefectures within Jiangsu province granted to all non-financial firms during the period of 2010 to 2016, allowing us to identify the causal effect of environmental policy on the stability of the financial system by exploiting the variations across prefectures, banks, industries and borrowing firms. Since the database includes all loans that the banks granted within the jurisdiction, we eliminate concerns about sample selection.[26]

The number of borrowers in this dataset amounts to around 100,000 firms, covering all industrial sectors in accordance with the classification defined by the Chinese government. This information allows us to identify the borrowers belonging to the highly polluting industries that the Clean Air Action Plan targets. Besides the comprehensive coverage, the dataset provides

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[23] The figures are calculated from China Environmental Yearbook.

[24] Big Five refers to the five biggest state-owned commercial banks, including the Bank of China, China Construction Bank, Industrial and Commercial Bank of China, Agricultural Bank of China, and Bank of Communications, all of which are among the largest banks in the world.

[25]The figures are calculated from the statistics released on websites of CBIRC (http://www.cbrc.gov.cn/chinese/home/docView/C990691733D644B39582DEFA3EF1EF69.html) and CBIRC Jiangsu Office (yrlhttp://www.cbrc.gov.cn/jiangsu/docPcjgView/8AB96DDF7DDF487C95D1D4D4FB8FC0E1/600811.html)

[26] In China, due to the needs of risk management, banks usually do not grant loans to firms located in other regions. This is because local banks have more information of local firms, while monitoring the borrowing firms located in other regions is too costly. This risk management practice is consistent with the recent literature highlighting the importance of geographical distance in explaining loan rates and monitoring costs for borrowing firms (Degryse and Ongena, 2005).

detailed loan-level information, specifically a unique firm identifier, firm-level fundamentals (e.g., age, size, ownership and location), banks' information (e.g., the ownership, the names and location of branches), and loan-level characteristics (e.g., loan amount, maturity, credit guarantee, issuing date, and loan delinquency status).

The banks update a loan's information mandatorily with a monthly frequency throughout its whole life cycle. In this way, we can trace the repayment of loans and determine whether the banks properly price the risk of default, which the environmental regulation might escalate. In addition to default, loan spread is the other main outcome variable. Following the existing literature, we measure the loan spread by the percentage deviation of the lending rate of each loan from the benchmark rate. This calculation allows us to rule out the change of the credit cost arising from adjustment of benchmark interest rate. Given that the commercial loans granted by the local banks reflect the market response to the environmental risk in a better way, we remove all the loans granted by the development bank, policy banks and foreign banks from our analysis.[27]

Table A1 in Appendix 2 provides the summary statistics for the loans issued between 1 September 2012 and 31 December 2014. The repayment status of loans granted during this period of time was traced up to 31 March 2016. Overall, the 52 commercial banks, including Big Five, 12 joint equity commercial banks, 1 postal saving bank, 8 city commercial banks, and 27 rural commercial banks, granted 452,208 loans to 60,856 firms during this period of time. The mean borrowing rate is 7.4 percent, which is 23.4 percent higher than the benchmark rate of 6 percent. The average amount of borrowing is RMB 7.93 million. In terms of maturity, 93.6 percent of loans are short term borrowing. There are various types of loans, among which 45 percent are secured loans with collateral and around 40 percent are loans with a guarantee. With an average age of 10.41 years, 84.4 percent of borrowers are micro and small firms, 12.3 percent are medium-sized firms and 3.3 percent are big firms.[28]The Big Five and rural commercial banks are the major lenders, accounting for 34.7 percent and 38.9 percent of loans respectively.

B. Empirical Strategy

This paper employs the Clean Air Action Plan that Jiangsu province implemented in January 2014 as a quasi-natural experiment to evaluate the financial risks posed by the transition toward low emission economy.[29] We rely on the DID approach to infer the impact of tightened environmental regulation on default and lending spread of bank loans. DID analysis consists of comparing the pre-post difference in an outcome variable between a treatment and a control group. Specifically, for each loan, we classify the borrowers belonging to the highly polluting industries defined by the Clean Air Action Plan (Jiangsu version) as our treatment group, while the rest as the control group.[30] This approach has an advantage over simply comparing the outcome before and after the regulatory shock because there might be before-after differences in the outcome that are due to broader trends. This is why having a comparison group, which is

[27] We exclude the loans by foreign banks due to two reasons. On the one hand, the share of foreign bank assets in total banking asset is as small as 1.3%; on the other hand, the regulation on the foreign banks is also different from that on the local banks.

[28] A firm's size is defined as small and micro, medium, or large, based on *The Standards of SMEs* jointly issued by China's Ministry of Industry and Information Technology, National Bureau of Statistics, National Development and Reform Commission, and Ministry of Finance.

[29] The Clean Air Action Plan was implemented up to 2019. It was thereafter replaced by stricter environmental regulations.

[30] The high polluting industries targeting by the Clean Air Action Plan (Jiangsu version) include steel, cement, thermal power, textile, chemical, petrochemical, nonferrous metal melting, sintering pellet, ferroalloy, steel rolling, coking, coating and plating, pharmaceutical, plastic, furniture, building materials, automotive repair and maintenance.

unexposed (or less exposed) to the policy shock, allows us to capture this trend and thus better estimate a counterfactual.

Table 2 compares the descriptive statistics between the control and treatment groups. The 52 commercial banks grant 351,888 loans to the low polluting firms and 100,320 loans to the highly polluting firms respectively. The lending rate is similar across two groups of firms. However, the average loan amount borrowed by the low polluting firms is much larger than that by highly polluting firms. The term of maturity and loan type are similar between the treatment and control groups. Regarding the firm size, big firms account for 3.7 percent of low polluting borrowers and 2 percent of high polluting borrowers. In terms of lenders' structure, local banks including the city commercial banks and rural commercial banks grant 58.4 percent of loans to highly polluting firms and the rest 50.7 percent of loans to low polluting firms.

Overall, we find that the treatment and control groups are comparable. Within this framework, we implement the DID analysis to compare the default rate and loan spread of the high-polluting firms that the Clean Air Action Plan specially targets with those of low-polluting firms with less exposure to the regulation. If the financial institutions like banks are aware of the environmental transition risks, their lending decisions regarding the high-polluting firms should differ from those regarding the other firms. We obtain our DID estimators measuring the effect of the environmental policy shock on the financial stability using the following model:

$$y_{lbft} = \beta_0 + \beta_1 Action + \beta_2 Action * Treat + \beta_3 Treat + \beta_4 L_{lt} + \beta_5 F_{ft} + \beta_6 X_c + u_{lbft} \tag{5.1}$$

One of our main outcome variables is the repayment of loan *l* that bank *b* grants to firm *f* at time *t*. It equals 1 if defaulted, and 0 otherwise. The other is loan spread calculated as the percentage deviation of lending rate from the benchmark rate.

To identify the policy effect, we need to impose a time window to ensure that the change in default or loan spread is indeed induced by the Clean Air Action Plan. We divide our sample into three subperiods. We define the time between 1 September 2012 and 10 September 2013 as the before-policy adoption period (or pre-regulation period). On 12 September 2013, the central government enacted the national Clean Air Action Plan, while on 4 January 2014, Jiangsu provincial government launched its local version of the Action. We define this period of time as the interim period and the time period between 6 January 2014 and 31 December 2014 as the after-treatment (post-regulation) period. Accordingly, the dummy variable, *Action*, takes the value of 1 if a bank loan was granted during the post-regulation period, and 0 during the pre-regulation period. In the robustness check, we incorporate all these three time periods into the multi-period DID analysis.

The dummy variable, *Treat*, takes the value of 1 if a bank grants a loan to a firm in the high-polluting industries, and 0 otherwise. The interaction term between *Action* and *Treat* is our main variable of interest. Its coefficient, β_2, measures the difference in default or loan spread between the treatment (high-polluting firms) and the control group (low-polluting firms) after the implementation of the Clean Air Action Plan. In contrast, β_1 measures the difference between the post- and pre-regulation period for the control group, and β_3 measures the difference between the treatment and control group during the pre-period. Thus, the DID coefficient β_2 removes biases in the post period comparison between the treatment and the control group that could be due to permanent differences between the control and the treatment groups, as well as biases resulting from comparisons over time in the treatment group that could be the result of trends. β_0 is a vector of fixed effects, and u is the remainder disturbance. L and F are vectors of loan and firm characteristics, respectively, that might affect the cost of loans.

At the prefecture-level, we control for regional macroeconomic variables (X_c), including the share of the secondary and tertiary industry in GDP, and real GDP per capita of the prefecture where a borrowing firm is located. At the loan level, we control for the borrowed amount, which we measure as the logarithm of the absolute value, the maturity and the type of loans. We also control the characteristics of borrowers that might affect the loan spread and default probability of loans, including the firm age, ownership, size, credit rating, among others.

As we described in Appendix 1, the Clean Air Action Plan clearly aims to abate the emission of high-polluting sector. Industrial upgrading and restructuring were enforced for industries of high emission, high energy consumption, or with backward productivity or excess capacity. This should induce banks to adjust their lending decision and risk management according to the industry of borrowing firms. Hence, we cluster the standard errors on the industry level to address the potential concern of residual correlation. As a robustness check, we also cluster the standard errors on the bank and bank-year level to reflect the potential correlation across banks. The results are report in Table A2 and A3 in Appendix 2.

The existing literature acknowledge that the default probability is mainly attributable to two factors. One is the ex-ante idiosyncratic shocks faced by the firms, for example, misallocation of loans to dirty industries. The other is ex-post poor credit risk management. Schoenherr (2019) shows politically connected private firms get more loans but less monitoring, which leads to worse loan outcomes. In China, the banking sector, which is dominated by the stated-owned banks, prefers lending to state-owned enterprises (SOEs) because of the explicit or implicit guarantees provided by the government (Brandt and Li, 2003; Cull and Xu, 2003; Cull et al., 2015; Qian, 1996; Ru, 2018). As a result, SOEs enjoy a borrowing advantage on bank loans despite their lower average productivity compared to the private sector (Cull et al., 2015; Song et al., 2011).

To factor in the influence of ownership, we classify the borrowing firms into several categories, including state-owned enterprises, collectively owned enterprises, private enterprises, limited liability enterprises, incorporated enterprises, joint venture enterprises and foreign enterprises. In the baseline DID regression, we control both the ownership of firms and bank fixed effect. Further, we implement the DDD analysis and subsample analysis in section 6.2.1 and 6.2.2 to infer the heterogenous impact of environmental regulation on the financial stability across different types of firms and banks.

In addition to ownership, other factors could play critical roles in shaping the credit risk management by banks (Ang et al., 2000; Berger and Udell, 1995; Petersen, 2004). For example, the number of banks from which the firm obtains loans could affect bank's monitoring costs; the length of a firm's relationship with its primary bank affects bank's ability to monitor; and the firm's size of debt affects bank's incentives to monitor. Based on the data availability, we adopt three control variables in eq (5.1) to capture the potential influences of all these factors on lending risk, including: (i) number of financial institutions from which a firm has borrowed at time *t*; (ii) number of times that a firm has borrowed from bank *b* at time *t*; and (iii) the amount of the loan and the size of a firm.[31]

A potential identification challenge of our DID estimation could be the presence of omitted variable bias resulting from other risk characteristics of banks and firms. Since default and credit costs might vary across banks and regions, we control the fixed effects of time, industry, bank and the prefecture where a borrowing firm is located. In addition, the time-varying supply-side policies of banks might drive the results. The fact that in our data every bank gives multiple loans within the sample period, allows us to control *bank*year* fixed effects, which saturate the model from supply-side explanations of the findings. The usual time-varying firm-specific characteristics mitigate the concerns. Considering that some factors like the environmental governance capacity and the technological progress may vary across cities over time, we also add *prefecture*year* fixed effects to the specification to control for yearly city-specific shocks. Thus, along with the fielding of our model with firm-year indicators of risk and performance, it is unlikely that coefficient β_2 would capture anything other than a shift due to the environmental policy exposure of high-polluting firms vis-*à*-vis low-polluting firms.

[31] Given that the level of assets of borrowing firms is not available in our dataset, we use the amount of loan and the size of a firm as the proxy to reflect a bank's incentives to monitor.

Table 2. Summary Statistics, Low Polluting versus Highly Polluting Industries

	low-polluting					high-polluting				
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Lending spread	351888	0.231	0.274	-0.398	1.998	100320	0.243	0.239	-0.398	1.998
Lending rate	351888	0.074	0.016	0.034	0.191	100320	0.074	0.015	0.034	0.180
Benchmark interest rate (percent)	351888	5.980	0.233	5.600	6.550	100320	5.955	0.218	5.600	6.550
Loan default	333865	0.010	0.098	0	1	99404	0.010	0.102	0	1
Loan amount (CNY 10 thousand)	351888	885	2678	5	210000	100320	468	1115	5	93500
Maturity										
Short term loan	351888	0.922	0.268	0	1	100320	0.983	0.129	0	1
Mid-long term loan	351888	0.078	0.268	0	1	100320	0.017	0.129	0	1
Loan type										
Secured loan	351888	0.446	0.497	0	1	100320	0.445	0.497	0	1
Fiduciary loan	351888	0.031	0.172	0	1	100320	0.019	0.135	0	1
Loan on guarantee	351888	0.389	0.488	0	1	100320	0.426	0.494	0	1
Pledged loan	351888	0.079	0.270	0	1	100320	0.072	0.258	0	1
Discount loan	351888	0.055	0.229	0	1	100320	0.038	0.192	0	1
Firm size										
Micro and small enterprises	351888	0.832	0.374	0	1	100320	0.885	0.319	0	1
Medium-sized Enterprises	351888	0.131	0.337	0	1	100320	0.095	0.294	0	1
Big Enterprises	351888	0.037	0.188	0	1	100320	0.020	0.140	0	1
Company age (Year)	351888	10.24	5.95	1	60	100320	11.04	4.90	1	37
Bank type										
Big five	351888	0.362	0.481	0	1	100320	0.296	0.456	0	1
Joint-stock commercial banks	351888	0.131	0.338	0	1	100320	0.120	0.325	0	1
City commercial banks	351888	0.146	0.353	0	1	100320	0.098	0.297	0	1
Rural commercial banks	351888	0.361	0.480	0	1	100320	0.486	0.500	0	1
Local Economic structure										
Share of secondary industry	351888	0.508	0.021	0.442	0.541	100320	0.511	0.018	0.442	0.541
Share of tertiary industry	351888	0.449	0.029	0.380	0.484	100320	0.456	0.027	0.380	0.484
GDP per capita (CNT Yuan)	351888	96834	29500	31827	129926	100320	106863	26834	31827	129926

Note: This table compares the summary statistics of the key variables between low polluting and highly polluting firms for the sample period between 1 September 2012 and 31 December 2014 when the loans were granted. The repayment status of the loans were traced up to 31 March 2016. We report the summary statistics for the main outcome variables including the default and the lending spread which is calculated as the percentage deviation of lending rate from the benchmark rate; the loan-level characteristics including loan amount, maturity, and types; the firm-level fundamentals including age, size and ownership; types and ownership of banks; and local economic structure and GDP per capita.

VI. EMPIRICAL RESULTS

A. Baseline Analysis

To understand whether the risks of lending to high polluting firms changed following the policy enforcement, we trace the repayment status of loans granted during our sample period up to March 2016 and implement the DID estimation on the default rate. All the specifications control for the loan and borrowing firms' characteristics, the relationship between a firm and its lending banks, the regional macroeconomic factors, the benchmark interest rate and the different types of fixed effects. The standard errors are clustered at the industry level.

The baseline estimation results reported in column (1) to (3) of Table 3 are consistent across different specifications. The coefficients for the interaction term between *Action* and *Treat* are positively significant. The magnitude of the coefficients indicates that the default risk of high-polluting firms rose by around 0.75-0.77 percentage points after the policy implementation. Comparing with the mean default rate of 1 percent for the whole sample, this is equivalent to almost 80 percent increase in the default rate. In addition, higher likelihoods of default are associated with loans with shorter terms of maturity, or loans granted to private or small and micro enterprises. Moreover, the probability of default rises as the number of borrowing banks increases, reflecting the difficulty of monitoring the multi-bank firms.

With such a considerable increase in the probability of default, it is natural for banks to charge higher risk premiums on the firms heavily exposed to the Clean Air Action Plan. To understand whether the banks are aware of the transition risks, we implement the DID estimation on the lending spread relative to the benchmark rate and report the results in column (4) to (6) of Table 3. The model specifications are similar to Eq. (5.1). We control for the loan and borrowers' characteristics, the regional macroeconomic factors, benchmark interest rate and different types of fixed effects.

Consistent with the theoretical analysis, the coefficient on our main variable of interest, the interaction term, is positively significant, suggesting that the Clean Air Action Plan makes the lending spread to polluting firms significantly increase by 1.3 percentage points, which is equivalent to 5.5 percent of the mean lending spread. This implies that the banks have priced the potential risks associated with escalated environmental regulations. However, comparing with the considerable increase in the default rate, the increase in the loan spread seems not sufficient.[32] Banks tend to charge lower interest rate for the loans with larger amounts and guarantees, but higher interest on small and medium sized enterprises. Moreover, the loan spread declines as the number of borrowing banks increases, reflecting the competition effect.

[32] After the policy was enforced, the default probability of high-polluting firms rose by around 0.75–0.77 percentage points, or 12.6 percent to 12.9 percent compared with the benchmark interest rate of 5.975 percent (0.75 percent/5.975 percent—0.77 percent/5.975 percent). The interest rate shall also increase by around 14 percent to cover the increased default risk.

Table 3. Clean Air Action Plan, Default and Loan Spread, Baseline DID Estimation Result

		Default			Loan spread	
VARIABLES	(1)	(2)	(3)	(4)	（5）	（6）
Action*Treat	0.0076**	0.0077**	0.0075**	0.0137**	0.0127**	0.0135**
	(0.0033)	(0.0030)	(0.0031)	(0.0056)	(0.0052)	(0.0053)
Treat	-0.0019	-0.0021	-0.0019	0.0020	0.0020	0.0021
	(0.0017)	(0.0015)	(0.0015)	(0.0023)	(0.0021)	(0.0021)
Ln(Loan amount)	-0.0005	-0.0004	-0.0005	-0.0112***	-0.0109***	-0.0112***
	(0.0004)	(0.0004)	(0.0004)	(0.0019)	(0.0020)	(0.0019)
Short-term loan	-0.0052	-0.0069	-0.0053	0.0230*	0.0215*	0.0230*
	(0.0057)	(0.0058)	(0.0058)	(0.0125)	(0.0123)	(0.0126)
Fiduciary loan	0.0092*	0.0089**	0.0092*	-0.0883***	-0.0896***	-0.0883***
	(0.0044)	(0.0040)	(0.0044)	(0.0052)	(0.0059)	(0.0052)
Loan on guarantee	-0.0031	-0.0033	-0.0031	-0.0821***	-0.0826***	-0.0821***
	(0.0023)	(0.0022)	(0.0023)	(0.0090)	(0.0091)	(0.0090)
Pledged loan	-0.0038*	-0.0034	-0.0038*	-0.1707***	-0.1684***	-0.1705***
	(0.0021)	(0.0021)	(0.0021)	(0.0175)	(0.0180)	(0.0175)
Discount loan	-0.0047**	-0.0044**	-0.0047**	-0.0888***	-0.0876***	-0.0888***
	(0.0019)	(0.0019)	(0.0019)	(0.0034)	(0.0031)	(0.0034)
Micro and small enterprises	0.0103***	0.0101***	0.0103***	0.0408**	0.0408**	0.0407**
	(0.0016)	(0.0017)	(0.0016)	(0.0187)	(0.0188)	(0.0185)
Medium-sized enterprises	0.0050***	0.0049***	0.0050***	-0.0025	-0.0016	-0.0026
	(0.0010)	(0.0010)	(0.0010)	(0.0104)	(0.0106)	(0.0103)
Firm age	-0.0012***	-0.0012***	-0.0012***	0.0018*	0.0017*	0.0018*
	(0.0003)	(0.0003)	(0.0003)	(0.0009)	(0.0009)	(0.0009)
Firm age Sq.	0.0000**	0.0000***	0.0000**	-0.0000**	-0.0000**	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ln(times of borrowing)	-0.0009*	-0.0006	-0.0009*	-0.0232***	-0.0216***	-0.0232***
	(0.0005)	(0.0004)	(0.0005)	(0.0030)	(0.0029)	(0.0030)
Number of borrowing banks	0.0020***	0.0019***	0.0020***	-0.0063***	-0.0066***	-0.0063***
	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)
Collective Enterprises	0.0082*	0.0081*	0.0082*	-0.0098	-0.0082	-0.0096
	(0.0042)	(0.0042)	(0.0041)	(0.0089)	(0.0082)	(0.0088)
Private Enterprises	0.0076***	0.0075***	0.0075***	0.0004	0.0023	0.0005
	(0.0014)	(0.0014)	(0.0014)	(0.0104)	(0.0102)	(0.0104)
Limited liability Enterprises	0.0112***	0.0110***	0.0111***	-0.0051	-0.0035	-0.0050
	(0.0018)	(0.0019)	(0.0018)	(0.0107)	(0.0101)	(0.0106)
Incorporated Enterprises	0.0023*	0.0022*	0.0024*	-0.0289	-0.0268	-0.0287
	(0.0012)	(0.0012)	(0.0012)	(0.0167)	(0.0165)	(0.0167)
Joint venture Enterprises	0.0105***	0.0102***	0.0104***	-0.0314**	-0.0308**	-0.0314**
	(0.0019)	(0.0020)	(0.0019)	(0.0120)	(0.0117)	(0.0120)
Foreign Enterprises	0.0106***	0.0102***	0.0106***	-0.0580***	-0.0568***	-0.0579***
	(0.0020)	(0.0020)	(0.0020)	(0.0102)	(0.0097)	(0.0102)
Other Enterprises	0.0051*	0.0052*	0.0051	-0.0020	-0.0006	-0.0020
	(0.0029)	(0.0029)	(0.0030)	(0.0122)	(0.0122)	(0.0123)
Share of secondary industry	0.0176	0.2706		-1.1867	6.2985***	
	(0.3482)	(0.6499)		(1.5524)	(1.4571)	
Share of tertiary industry	0.1764	0.5666		2.1499	8.3362***	
	(0.3140)	(0.5776)		(1.5416)	(1.7424)	
Log(GDP per capita)	0.0072	-0.0198		0.8189***	0.5684***	
	(0.0831)	(0.1051)		(0.0778)	(0.1260)	
Benchmark interest rate	0.0051***	0.0055***	0.0052***	0.0041	0.0066	0.0042
	(0.0010)	(0.0010)	(0.0009)	(0.0083)	(0.0079)	(0.0083)
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y
Observations	433269	433269	433269	452208	452208	452208
R2	0.018	0.021	0.018	0.485	0.495	0.486
Adjusted R2	0.017	0.021	0.018	0.485	0.495	0.486

Note: This table shows DID estimates of the effect of the Clean Air Action Plan on the default and loan spread of high-polluting firms relative to low-polluting firms, respectively. The dependent variable is default for columns (1) to (3), and loan spread for columns (4) to (6). Treat is a dummy variable marking all firms belonging to the high-polluting industries targeted by the Clean Air Action Plan. Action is a dummy variable marking the post treatment period (6 Jan 2014 and 31 Dec 2014). All specifications contain loan, firm and macro-level controls. All the loans were granted between 1 September 2012 and 31 December 2014. We trace the repayment status of these loans up to 31 March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the industry level and reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

In the interest of brevity, we note only the role of control variables that have the most significant effects on the lending spread and default. Borrowers who are private or small in size are more likely to default and pay higher borrowing rate. A firm having longer relationship with the bank, which is proxied by the logarithm of number of times that a firm has borrowed from this bank, is less likely to default and pays lower interest rate, indicating that relationship is valuable in reducing borrowers' incentives to default and hence the monitoring cost. The firms who are able to borrow from larger number of banks are more likely to default, confirming the difficulty of monitoring the credit risk of multi-bank firms. However, probably driven by bank competition for borrowers, multi-bank firms pay lower interest rate for the loans.

B. Cross-sectional Variations

The baseline results show the average effect of the Clean Air Action Plan on the lending spread and default. The higher environmental risk may change a bank's behavior in other ways. For example, a bank may adopt different pricing strategies for different segments of its loan portfolios. Banks of different size may have different capacities for risk management. Simply focusing on the average value would conceal the changes in the default and lending cost of different components of loan portfolios. The detailed structure of our bank data enables us to investigate these issues. We now explore whether the relationship uncovered in Table 3 varies cross-sectionally along certain observable dimensions.

Firm Size and Ownership

It seems plausible that the effect of the Clean Air Action Plan should vary across firms of different sizes, because environmental protection is expensive. Facing tightened environmental regulation, the high-polluting firms need additional financial resources to adopt clean production technology and pollution abatement facilities to meet the regulation targets. However, these activities compete with investment in marketing, capacity expansion, and new products development (Cohn and Deryugina, 2018; Kim and Xu, 2017). Given that small companies often have fewer financial resources and face tighter capital constraints than large companies, a change in environmental regulation will induce larger adverse impacts on small firms' profitability, especially in the short term. If banks are well-informed economic agents, in principle, they should price the environmental risk differently across firms of different sizes.

To test this hypothesis, we first classify the borrowing firms into three categories according to their size and use the large firms as the reference group. We then estimate a difference-in-difference-in-differences (DDD) equation as below

$$\begin{gathered} y_{lbft} = \beta_0 + \beta_1 Action * Treat + \beta_2 Action * Treat * Size_f + \beta_3 Action * Size_f \\ + \beta_4 Treat + \beta_5 L_{lt} + \beta_6 F_{ft} + \beta_7 X_c + u_{lbft} \end{gathered} \tag{6.1}$$

In this equation, the interaction of original DID term with the dummy of firm size ($Size_f$) is the variable of main interest. The definition of other variables remains the unchanged. Panel A of Table 4 reports the coefficient estimates that we obtained from a DDD specification. Consistent with the view that the impacts of environmental regulation are stronger for smaller firms, the

DDD estimates for both lending spread and the default rate show the largest treatment effects for the small and micro enterprises.

Table 4. Clean Air Action Plan, Default and Loan Spread, DDD Estimation by Firms' Characteristics

	Default			Loan spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A DDD by firm size						
Action*Treat* Medium-sized Enterprises	0.0086***	0.0081***	0.0084***	0.0431**	0.0410**	0.0426**
	(0.0025)	(0.0026)	(0.0026)	(0.0201)	(0.0190)	(0.0196)
Action*Treat* Micro and Small Enterprises	0.0158***	0.0155***	0.0155***	0.0555*	0.0520*	0.0547**
	(0.0024)	(0.0024)	(0.0026)	(0.0265)	(0.0264)	(0.0257)
Treat	-0.0019	-0.0021	-0.0019	0.0021	0.0022	0.0022
	(0.0017)	(0.0015)	(0.0015)	(0.0024)	(0.0022)	(0.0022)
Action*Treat	-0.0071	-0.0068	-0.0069	-0.0394*	-0.0375	-0.0390*
	(0.0042)	(0.0040)	(0.0043)	(0.0224)	(0.0217)	(0.0219)
Action* Medium-sized Enterprises	-0.0031	-0.0011	-0.0027	-0.0212	-0.0119	-0.0210
	(0.0018)	(0.0019)	(0.0020)	(0.0134)	(0.0127)	(0.0130)
Action*Micro and Small Enterprises	-0.0035*	0.0006	-0.0034	-0.0134	0.0084	-0.0119
	(0.0019)	(0.0020)	(0.0021)	(0.0190)	(0.0220)	(0.0178)
Observations	433269	433269	433269	452208	452208	452208
R^2	0.018	0.021	0.018	0.486	0.496	0.486
Adjusted R^2	0.017	0.021	0.018	0.485	0.495	0.486
Panel B DDD by firms' ownership						
Action*Treat*SOEs	-0.0045**	-0.0026	-0.0047**	0.0253	0.0441**	0.0253
	(0.0018)	(0.0022)	(0.0018)	(0.0179)	(0.0204)	(0.0179)
Treat	-0.0019	-0.0021	-0.0019	0.0020	0.0021	0.0021
	(0.0017)	(0.0015)	(0.0015)	(0.0023)	(0.0022)	(0.0022)
Action*Treat	0.0076**	0.0077**	0.0075**	0.0137**	0.0125**	0.0135**
	(0.0033)	(0.0030)	(0.0031)	(0.0057)	(0.0053)	(0.0055)
Action* SOEs	0.0004	-0.0021	0.0011	0.0010	-0.0119	0.0023
	(0.0029)	(0.0033)	(0.0028)	(0.0125)	(0.0154)	(0.0123)
Observations	433269	433269	433269	452208	452208	452208
R2	0.018	0.021	0.018	0.485	0.495	0.486
Adjusted R2	0.017	0.021	0.018	0.485	0.495	0.486
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y

Note: Panel A of this table compares DID estimates of the Clean Air Action Plan on the default and loan spread by the size of borrowing firms. The reference group is big firms. Panel B compares DID estimates of the Clean Air Action Plan on the default and loan spread by the ownership of borrowing firms. The reference group is non state-owned enterprises (SOEs). The dependent variable is default for columns (1) to (3), and loan spread for columns (4) to (6). All the loans were granted between 1 September 2012 and 31 December 2014. We trace the repayment status of these loans up to 31 March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the industry level and reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

In China, the ownership of borrowing firms has important implications for the risk of lending. To factor in the influence of ownership, we classify the borrowing firms into SOEs and non-SOEs and implement the DDD analysis with the following equation

$$y_{lbft} = \beta_0 + \beta_1 Action * Treat + \beta_2 Action * Treat * Ownership_f + \beta_3 Action * Ownership_f$$
$$+\beta_4 Treat + \beta_5 L_{lt} + \beta_6 F_{ft} + \beta_7 X_c + u_{lbft} \tag{6.2}$$

In this equation, the interaction of original DID term with the dummy of firm *f*'s ownership (*Ownership$_f$*) is the variable of main interest, enabling us to investigate the heterogenous impact of environmental regulation on the financial stability across different types of firms. The DDD estimation results are reported in Panel B of Table 4. Compared with non-SOEs, the probability of default for SOEs is relatively lower following the implementation of Clean Air Act. This is probably due to the implicit or explicit guarantees provided by the government to SOEs, which is widely recognized by Brandt and Li (2003); Cull and Xu (2003); Cull et al. (2015); Qian (1996); Ru (2018).

Bank Size and Ownership

Considering that different banks may price environmental risks differently, we classify all the banks into three groups according to their size and ownership. The first group contains the Big Five while the second group is the joint equity commercial banks (JECBs). Compared with the Big Five, JECBs are more competitive, profit oriented, and performance conscious due to a lower degree of government intervention, flexible personnel management, and overall better corporate governance structure. The rest are mainly local banks, including rural commercial banks and city commercial banks. Their main business is to finance small and medium-sized rural or urban enterprises and individuals, and their lending policies were heavily affected by the local authorities. We interact the bank type dummy with the original DID term and implement DDD analysis with the equation as follow

$$y_{lbft} = \beta_0 + \beta_1 Action * Treat + \beta_2 Action * Treat * Type_b + \beta_3 Action * Type_b$$
$$+\beta_4 Treat + \beta_5 L_{lt} + \beta_6 F_{ft} + \beta_7 X_c + u_{lbft} \tag{6.3}$$

In this equation, the interaction of original DID term with the dummy of bank *b*'s ownership (*Type$_b$*) is the variable of main interest. The results that Panel A of Table 5 reports show that compared with small banks and the Big Five, JECBs significantly increase the lending spread for highly polluting industries when their default rate rose following the implementation of the Action. This might imply that when banks like JECBs are allowed to make business decisions independently, they are able to price the environmental risks more appropriately. Facing tough competition for customers and heavy government intervention, the small banks might have limited capacity of raising the lending rate despite the accelerated default risks triggered by the tightened environmental regulation.

Table 5. Clean Air Action Plan, Default and Loan Spread, DDD Estimation by Banks' Characteristics

	Default			Loan spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A DDD by bank size and ownership						
Action*Treat*Big Five	0.0028*	0.0026	0.0027	0.0009	0.0087*	0.0006
	(0.0016)	(0.0015)	(0.0017)	(0.0052)	(0.0044)	(0.0054)
Action*Treat*JECBs	0.0101***	0.0111***	0.0100***	0.0477***	0.0556***	0.0475***
	(0.0017)	(0.0018)	(0.0018)	(0.0047)	(0.0058)	(0.0045)
Treat	-0.0021	-0.0021	-0.0021	0.0009	0.0023	0.0008
	(0.0017)	(0.0015)	(0.0016)	(0.0025)	(0.0021)	(0.0023)
Action*Treat	0.0058*	0.0055**	0.0059*	0.0100*	0.0028	0.0101*
	(0.0031)	(0.0025)	(0.0028)	(0.0053)	(0.0045)	(0.0049)
Action* Big Five	0.0031***		0.0037***	0.0312***		0.0321***
	(0.0007)		(0.0007)	(0.0055)		(0.0059)
Action* JECBs	0.0048***		0.0055***	0.0091		0.0108
	(0.0016)		(0.0015)	(0.0093)		(0.0087)
Observations	433269	433269	433269	452208	452208	452208
R2	0.018	0.021	0.018	0.486	0.496	0.487
Adjusted R2	0.018	0.021	0.018	0.486	0.495	0.487
Panel B DDD by banks' greenness						
Action*Treat*Green	0.0049***	0.0050***	0.0047***	0.0136***	0.0215***	0.0134***
	(0.0015)	(0.0015)	(0.0016)	(0.0032)	(0.0024)	(0.0034)
Treat	-0.0021	-0.0021	-0.0021	0.0008	0.0022	0.0007
	(0.0017)	(0.0015)	(0.0016)	(0.0025)	(0.0021)	(0.0023)
Action*Treat	0.0058*	0.0055**	0.0058*	0.0101*	0.0028	0.0102**
	(0.0030)	(0.0025)	(0.0028)	(0.0053)	(0.0045)	(0.0048)
Action*Green	0.0036***		0.0042***	0.0252***		0.0264***
	(0.0006)		(0.0006)	(0.0030)		(0.0032)
Observations	433269	433269	433269	452208	452208	452208
R2	0.018	0.021	0.018	0.486	0.495	0.487
Adjusted R2	0.018	0.021	0.018	0.486	0.495	0.486
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y

Note: Panel A of this table compares DID estimates of the Clean Air Action Plan on the loan spread and default by the ownership and size of lending banks. The reference group is urban and rural commercial banks which are relatively small in size. JECBs refers to the joint equity commercial banks. Big Five are the five largest state-owned commercial banks. Panel B compares DID estimates of the Clean Air Action Plan on the loan spread and default by "Greenness" of lending banks. "Green" refers to the banks that disclose the amount of green credit to the CBRC regularly. All the loans were granted between 1 September 2012 and 31 December 2014. We trace the repayment status of these loans up to 31 March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the industry level and reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Green vs Non-green Banks

In principle, "environmentally-friendly" or "green banks" should align their business strategy with environmental/climate principles, be more sensitive to the change of environmental regulation and demand a larger compensation for the environmental transition risk (de Greiff et al. (2018)). Since July 2013, aiming to promote green finance, CBRC requested the 21 banks to report the amount of green lending twice a year.[33] Big Five, 12 JECBs and the Postal Saving Bank are all on the list. With this compulsory requirement, we assume these banks shall be aware

[33] The English version of the document can be found in this link https://www.pkulaw.com/en_law/54b335e6db91bf5ebdfb.html.

of the financial risks arising from environmental regulations and treat them as the green banks. This hypothesis is tested by the following equation

$$y_{lbft} = \beta_0 + \beta_1 Action * Treat + \beta_2 Action * Treat * Green_b + \beta_3 Action * Green_b + \beta_4 Treat + \beta_5 L_{lt} + \beta_6 F_{ft} + \beta_7 X_c + u_{lbft} \quad (6.4)$$

In this specification, we examine the role of banks' greenness using a triple interaction between *Action, Treat,* and *Green*. The estimation results are reported in Panel B of Table 5. The positive and significant coefficients on the DDD interaction term indicate that green banks charge higher loan prices to high-polluting firms that face higher environmental policy risk.

City Regulation Heterogeneity

Although the Clean Air Action Plan was a nationwide policy, the regional-decomposed targets varied greatly in terms of regulatory stringency. It imposes a higher emission abatement target for the three regions of Beijing-Tianjing-Hebei, the Pearl River Delta and the Yangtze River Delta. Among the six prefectures in our database, three are located in the Yangtze River Delta while the rest three are outside of the region. The environmental regulation stringency index that Huang et al. (2020) calculate also indicates that the three cities located in the Yangtz River Delta face stricter environmental regulations than the other three prefectures. We hence denote the cities in the Yangtze River Delta as highly-regulated cities and the rest as lightly-regulated cities, and implement the DDD analysis with the following equation.

$$y_{lbft} = \beta_0 + \beta_1 Action * Treat + \beta_2 Action * Treat * Stringency_c + \beta_3 Action * Stringency_c + \beta_4 Treat + \beta_5 L_{lt} + \beta_6 F_{ft} + \beta_7 X_c + u_{lbft} \quad (6.5)$$

The interaction of original DID term with the dummy of city c's regulation stringency ($Stringency_c$) is the variable of main interest. The DDD estimation results that Table A4 in Appendix 3 reports show that the lending spread has increased by a larger degree in the highly- regulated cities. Although the DDD estimates for the default are insignificant, the sign is positive and consistent with our expectations.

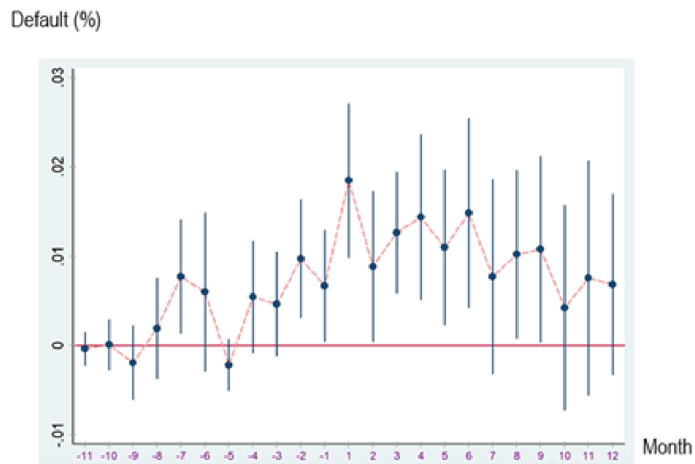
C. Dynamics of Environmental Regulation and Financial Stability

We further explore the dynamics of the relation between environmental regulation and financial stability. Instead of simply interacting the treatment dummy with the post-regulation dummy, we interact the treatment dummy with each month's dummy to trace out the month-by-month effects of environmental regulation on default. We exclude the month when the Clean Air Action Plan (Jiangsu version) was enacted, thus estimating the dynamic effect of environmental regulation on financial stability relative to the time when the policy was implemented. We consider a 23-month window, spanning from 11 months before the Clean Air Action Plan was implemented (1 September 2012 to 1 September 2013) until 12 months after it was enforced (6 January 2014 to 31 December 2014).

Figure 4 plots the estimation result for default that accounts for time, bank and prefecture effect, at the 90 percent confidence intervals. The estimate shows that the interaction terms between the treatment dummy and the month dummy are mostly insignificant prior to the policy enforcement.

This indicates that there are no measurable differences in the default rate between the control and the treatment groups in the pre-treatment period. Moreover, the impact of environmental regulation materializes quickly. The coefficient on the interaction term significantly rose to 0.02 on the first month after the policy's implementation.

Figure 4. The Dynamic Impact of the Clean Air Action Plan on Default



Note: The figure plots the impact of the Clean Air Action Plan on default. The horizontal axis plots the months before and after the Plan was enacted. The vertical axis reflects the default rate. We consider a 23-month window, spanning from 11 months before the Clean Air Action Plan was implemented until 12 months after it was enforced. We control year, bank and prefecture fixed effect.

We note the default rate for clean versus dirty industries exhibited slight difference a couple of months before the Clean Air Action Plan was announced by the Central government. The outbreak of "PM2.5 crisis" in early 2013 had forced the government to take actions like closing the heavily polluting firms in mega cities before the nationwide Clean Air Action Plan was announced in September 2013, whose negative economic effect could later spill over to the financial sector.[34] But the massive and nation-wide transition toward low emission production, especially for the manufacturing sector, starts after the Clean Air Action Plan came into force.

D. Robustness Checks

In this subsection, we conduct various robustness tests on our baseline results. Considering that a bank may have negotiated the loan contract before the enactment of the Clean Air Action Plan, we lag the policy implementation time by 30 and 60 days,[35] respectively, to determine whether the policy influenced the default and loan spread immediately. We report the results in Panel A and B of Table 6 respectively. We also try different time windows, including 10 months (1 September 2012 to 30 June 2013) or 9 months of pre-policy period (1 September 2012 to 30 April 2013) for the loan issuance.[36] Our findings are in line with the baseline results, indicating the significant increase in the default and loan spread following the enforcement of Clean Air Action Plan.

[34] A media report in Chinese can be found in this link https://www.chinanews.com/df/2013/05-10/4805172.shtml.
[35] We talked to some bank managers. According to their information, it usually takes around 1 month for a loan application to be approved or rejected.
[36] The results are available upon request.

After the Clean Air Action Plan was enforced, both the central and local governments continue to employ various policy tools to abate the emission. For example, in late 2015, the Political Bureau of the CPC Central Committee issued the Overall Plan of Ecological Civilization System Reform while the Fifth Plenary Session of the 18th CPC Central Committee further underscored the plan of establishing a green finance system. Moreover, Jiangsu province raised its standard of discharge levies in 2016. To eliminate these potential noises, we check the loans issued before 31 Dec 2014 and trace their repayment status by 30 June 2015 and 31 December 2015 respectively, and implement the DID analysis. The results reported in Table A5 in Appendix 2 are consistent with the baseline results, confirming the increased default risks induced by the Clean Air Action Plan.

Given that there are around 4 months of time lag between the enactment of the national version and the enactment of Jiangsu version of Clean Air Action Plan, we implement the multiple-period DID analysis as an additional sensitivity test. We integrate all three periods of time into the analysis, specifically the pre-regulation period between 1 September 2012 and 10 September 2013, the interim period between 11 September 2013 and 5 January 2014, and the post-regulation period between 6 January 2014 and 31 December 2014. Accordingly, we create a new dummy variable, Action1, which takes the value of 1 if a bank granted a loan during the interim period, and 0 otherwise. Its interaction with Treat measures the policy effects over different periods of time. Panel C of Table 6 reports the estimation results. The coefficient for the interaction term between Action1t and Treat is smaller in size for the loan spread and default, indicating that the banks operating in Jiangsu province did not fully adjust its pricing strategy until the local government enforced its own version of the Clean Air Action Plan. This is consistent with the reality that the Clean Air Action Plan was centrally-planned and regionally-decomposed. After the announcement of the nationwide Action, the provinces signed Letters of Responsibility with the Ministry of Environmental Protection and then issued their own version of Action to set the reduction goals for annual average concentrations of PM10 or PM2.5. Compared with the national version, the local version of the Action gave a clearer signal of tightened environmental regulation to the firms and banks.

This paper employs DID analysis to infer the financial impact of the Clean Air Action Plan. However, our estimation results might be susceptible to the endogeneity concern arising from selection bias. For example, banks might choose firms from different sectors as customers to moderate their exposure to the environmental risk that the Action has escalated. To address this concern, we identify the firms that have borrowed both before and after the enforcement of the Action to construct a firm level panel dataset. We further restrict our sample to those firms that have borrowed from the same bank both before and after the implementation of the Action. Table 7 presents the DID estimation results on these two panels. The results are in line with the baseline estimation, although the magnitude of the coefficients for the loan spread decline.

We perform the placebo tests aiming at validating the main result of Clean Air Action Plan on default risk and loan spreads. In Panel A of Table 8, we re-estimate the main specifications for the loans issued during the time period of 1 January 2011 to 10 September 2013, assuming that a change in environmental policy had taken place on 1 January 2012. The DID coefficients are not significant neither for default nor for loan spread, validating the conclusion of this research.

Table 3 shows that low-polluting and high-polluting loans are comparable. Given that default is a dummy variable, we employ the propensity score matching (PSM), a non-parametric technique, developed by Rosenbaum and Rubin (1983) and Heckman et al. (1998) to construct matched samples based on observed characteristics. For each loan listing, we use a number of loan and borrowers' characteristics to generate a propensity score. We match each loan granted to a high-polluting firm with a loan granted to a low polluting firm based on the similarity of propensity scores computed by Kernel nearest neighbor matching approach. The estimation results are reported in Panel B of Table 8. Consistent with the baseline results, the default probability and lending spread for high-polluting firms both rose following the implementation of the Clean Air Action Plan.

Table 6. **Clean Air Action Plan, Default and Loan Spread, Different Time Specification**

	Default			Loan spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A lagged by 30 days						
Action lag(30)*Treat	0.0073*	0.0073**	0.0071**	0.0131**	0.0123**	0.0128**
	(0.0036)	(0.0031)	(0.0034)	(0.0056)	(0.0053)	(0.0054)
Treat	-0.0020	-0.0022	-0.0019	0.0023	0.0021	0.0024
	(0.0018)	(0.0016)	(0.0016)	(0.0022)	(0.0021)	(0.0021)
Observations	422929	422929	422929	433137	433137	433137
R^2	0.019	0.024	0.019	0.482	0.493	0.483
Adjusted R^2	0.019	0.024	0.019	0.482	0.493	0.482
Panel B lagged by 60 days						
Action lag(60)*Treat	0.0074*	0.0075**	0.0072*	0.0125**	0.0119**	0.0121**
	(0.0037)	(0.0032)	(0.0035)	(0.0056)	(0.0052)	(0.0053)
Treat	-0.0019	-0.0021	-0.0019	0.0025	0.0022	0.0027
	(0.0017)	(0.0016)	(0.0016)	(0.0022)	(0.0021)	(0.0021)
Observations	410673	410673	410673	420090	420090	420090
R2	0.019	0.024	0.019	0.481	0.493	0.482
Adjusted R2	0.019	0.024	0.019	0.481	0.492	0.482
Panel C multiple-period DID						
Action1*Treat	0.0046***	0.0044***	0.0045**	0.0116***	0.0115***	0.0113***
	(0.0015)	(0.0013)	(0.0016)	(0.0033)	(0.0032)	(0.0035)
Action*Treat	0.0077**	0.0078**	0.0077**	0.0138**	0.0130**	0.0135**
	(0.0032)	(0.0028)	(0.0030)	(0.0055)	(0.0053)	(0.0053)
Action	0.0024**	0.0026**	0.0024**	0.0146***	0.0160***	0.0148***
	(0.0011)	(0.0012)	(0.0011)	(0.0042)	(0.0042)	(0.0042)
Action1	0.0017***	0.0019***	0.0018***	0.0047***	0.0048***	0.0046***
	(0.0005)	(0.0005)	(0.0005)	(0.0013)	(0.0013)	(0.0013)
Treat	-0.0022	-0.0023	-0.0022	0.0016	0.0015	0.0018
	(0.0015)	(0.0014)	(0.0014)	(0.0023)	(0.0023)	(0.0022)
Observations	501066	501066	501066	523216	523216	523216
R2	0.018	0.021	0.018	0.491	0.500	0.491
Adjusted R2	0.018	0.021	0.018	0.491	0.500	0.491
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y

Note: Panel A of this table reports DID estimates on the effect of the Clean Air Action Plan on the default and loan spread where the implementation time of the Action is lagged by 30 days. Panel B reports DID estimates on the effect of the Clean Air Action Plan on the default and loan spread where the implementation time of the Action is lagged by 60 days. Panel C reports the multiple-period DID estimates on the effect of the Clean Air Action Plan on the default and loan spread. The dependent variable is default for columns (1) to (3), and loan spread for columns (4) to (6). *Action*1, is a dummy that takes the value of 1 if a bank loan is granted during the interaction period (between 11 September 2013 and 5 January 2014), and 0 otherwise. The dependent variable is default for columns (1) to (3), and loan spread for columns (4) to (6). All the loans were granted between 1 September 2012 and 31 December 2014. We trace the repayment status of loans granted during our post-treatment period up to 31 March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the industry level and reported in parentheses (* p < 0.10, ** p< 0.05, *** p < 0.01).

Table 7. Clean Air Action Plan, Default and Loan Spread, Panel Data Analysis

	Default			Loan spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A Firms borrowed both before and after the Action						
Action*Treat	0.0027**	0.0035***	0.0028***	0.0063**	0.0058**	0.0061**
	(0.0010)	(0.0009)	(0.0009)	(0.0023)	(0.0021)	(0.0023)
Treat	0.0001	-0.0004	0.0000	0.0071***	0.0069***	0.0072***
	(0.0004)	(0.0004)	(0.0003)	(0.0014)	(0.0011)	(0.0015)
Observations	382639	382639	382639	394973	394973	394973
R2	0.018	0.022	0.018	0.490	0.499	0.490
Adjusted R2	0.018	0.021	0.018	0.490	0.499	0.490
Panel B Firms borrowed from the same bank both before and after the Action						
Action*Treat	0.0014*	0.0024***	0.0016**	0.0033**	0.0035**	0.0035**
	(0.0008)	(0.0007)	(0.0007)	(0.0015)	(0.0015)	(0.0014)
Treat	0.0002	-0.0002	0.0001	0.0073***	0.0072***	0.0072***
	(0.0005)	(0.0005)	(0.0004)	(0.0016)	(0.0014)	(0.0019)
Observations	330938	330938	330938	337052	337052	337052
R2	0.013	0.017	0.013	0.535	0.547	0.535
Adjusted R2	0.013	0.016	0.013	0.535	0.547	0.535
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y

Note: Panel A of this table reports DID estimates for a sample of firms that borrowed both before and after the Action was implemented. Panel B reports DID estimates for a sample of firms that borrowed from the same bank both before and after the Action was implemented. The dependent variable is default for columns (1) to (3), and loan spread for columns (4) to (6). Treat is a dummy variable marking all firms belonging to the high-polluting industries targeted by the Clean Air Action Plan. Action is a dummy variable marking the post treatment period (6 January 2014 and 31 December 2014). All the loans were granted between 1 September 2012 and 31 December 2014. We trace the repayment status of these loans up to 31 March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the industry level and reported in parentheses (* p < 0.10, ** p< 0.05, *** p < 0.01).

Table 8. Placebo Test and PSM Estimation

	default			Loan spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A Placebo Test						
Action*Treat	-0.0039	-0.0031	-0.0041	-0.0014	0.0011	-0.0004
	(0.0033)	(0.0026)	(0.0033)	(0.0012)	(0.0013)	(0.0024)
Treat	0.0027	0.0022	0.0028	0.0055***	0.0037***	0.0048**
	(0.0023)	(0.0019)	(0.0023)	(0.0010)	(0.0011)	(0.0019)
Observations	589410	589410	589410	602693	602693	602693
R^2	0.025	0.029	0.025	0.511	0.526	0.513
Adjusted R^2	0.024	0.029	0.025	0.510	0.526	0.512
Panel B Propensity Score Matching						
Action*Treat	0.0060***	0.0058***	0.0059***	0.0120***	0.0093**	0.0118***
	(0.0018)	(0.0018)	(0.0018)	(0.0037)	(0.0039)	(0.0037)
Treat	-0.0008	-0.0008	-0.0007	-0.0002	0.0009	-0.0002
	(0.0010)	(0.0010)	(0.0010)	(0.0019)	(0.0019)	(0.0019)
Observations	198790	198790	198790	200632	200632	200632
R^2	0.022	0.026	0.023	0.484	0.492	0.484
Adjusted R^2	0.022	0.025	0.022	0.483	0.491	0.483
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y

Note: Panel A of this table shows placebo tests. We re-estimate the main specifications for the loans issued during the time period of 1 January 2011 to 10 September 2013, assuming that a change in environmental policy had taken place on 1 January 2012. Panel B shows PSM estimation results. We match each loan granted to a high-polluting firm with a loan granted to a low-polluting firm based on the similarity of propensity scores computed by Kernel nearest neighbor matching approach. Treat is a dummy variable marking all firms belonging to the high-polluting industries targeted by the Clean Air Action Plan. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the industry level and reported in parentheses (* $p < 0.10$, ** $p< 0.05$, *** $p < 0.01$).

VII. Conclusions

The imperative to understand the short-term impacts of a transition toward a low-emission economy motivates us to investigate the mechanisms through which an environmental policy, aiming for pollution abatement, affects the financial stability. We first employ an environmental dynamic general equilibrium (*E*-DSGE) model to show how banks react to the imposition of environmental policy tools such as emission abatement. In the empirical analysis, we use the Clean Air Action Plan that the Chinese government launched in September 2013 as a quasi-natural experiment to investigate the impact of transition on the banking sector in a Chinese province. We use a unique micro-level big dataset that contains 1.3 million commercial loans that all types of commercial banks operating in six Chinese prefectures granted to all non-financial firms. The difference-in-difference estimation indicates that following the policy implementation the default rates of lending to the high-polluting firms that the Plan targets dramatically increased by 80 percent. At the same time, loan spreads of these lending also rose, but at a much smaller degree.

The DDD analysis on the banks' ownership imply those joint equity commercial banks with lower degree of government intervention and better corporate governance structure were able to appropriately price their exposure to transition risks, while the state-owned banks failed to factor in such risks when extending credit to the borrowers targeted by the environmental regulation. Our empirical evidence is consistent with the theoretical implications of the environmental dynamic general equilibrium (E-DSGE) model which predicts higher default and lending rates when the model includes environmental policy shift such as the implementation of emission cap.

The solid findings of this research suggest that transition toward low emission economy is a source of structural change which significantly affects all economic sectors and financial stability. While urgent action is desirable for environmental improvement, an orderly and smooth transition providing adequate time for production technology adjustment could minimize these risks. In addition, financial institutions should be aware of potential risks arising from the environmental adjustment process and embed them in their risk management and pricing strategies. Given that maintaining financial stability is within the mandates of central banks and financial regulators, it is necessary for them to integrate the monitoring of environment and climate change-related financial risks into the prudential supervision to ensure the resilience of the financial system to the potential risks.

APPENDIX I.

BACKGROUND: CLEAN AIR ACTION PLAN AND THE BANKING INDUSTRY IN CHINA

CLEAN AIR ACTION PLAN

The main identification of this paper comes from the exogenous policy shock that the enforcement of Clean Air Action Plan induced in 2013, which set the road map for air pollution control for the next five years in China.

The year 2013 represents the start year of China's war on air pollution. On 1 January 2013, the Chinese government began publishing the air quality index (AQI), which measures fine particulate matter (PM2.5) per cubic meter, in real time in 74 cities throughout the country, making the worsening pollution quantifiable and visible to the public. Shortly thereafter, a massive fog and haze broke out in a fourth of China's territory, affecting about 600 million people.

In mid-January, the Air Quality Index (AQI) in Beijing soared as high as 993, far exceeding the levels that the index defines as extremely dangerous. The population-weighted mean concentration of PM2.5 for China as a whole was 54 µg/m3 in that year, with almost all the population living in areas exceeding the World Health Organization (WHO) Air Quality Guideline (Brauer, Freedman, Frostad, Van Donkelaar, Martin, Dentener, Dingenen, Estep, Amini, Apte, et al. (2016)). The haze with its unprecedentedly high index of PM2.5 concentration and extremely low visibility attracted global media attention and sparked outrage among the Chinese public, which eventually turning to be the "PM2.5 crisis."

Eight months after the widely-reported air pollution episode, on 12 September 2013, China's State Council released the Action Plan for Air Pollution Prevention and Control. As a crucial step forward in fighting against air pollution, the Clean Air Action Plan sets the road map for the next five years with a focus on three key regions -– Beijing-Tianjin-Hebei (Jing-Jin-Ji), the Yangtze River Delta (YRD) and the Pearl River Delta (PRD). By 2017, for all the second- and third-tier cities, the annual average concentration of F should decline by at least 10 percent compared with the 2012 level, and the number of days with clean air should increase. At the same time, the annual average concentration of PM2.5 should fall by 25 percent, 20 percent, and 15 percent respectively, for the three key regions. For Beijing, the annual average concentration of PM2.5 should remain at the 60 µg/m3 level.

This was for the first time that the Chinese government had set quantitative air quality improvement goals for key regions with a clear time limit and key actions covering all the major aspects of air quality management. The new Air Pollution Prevention and Control Law that took effect on January 1, 2016 later reinforced the Clean Air Action Plan. It addresses pollution sources from coal, heavily polluting industries, vehicles, marine vessels and agricultural machinery, as well as the construction and food industries. Due to the urgency of severe air pollution, the stringency of the Action and the degree of its implementation are unprecedented (Sheehan and Sun, 2014).

The main body of the Plan specified the key targets, strategies, and measures, in many cases in the form of administrative orders from the government. After the nationwide Clean Air Action Plan was announced, each provincial unit signed Letters of Responsibility with the Ministry of Environmental Protection and then issued its own version of Action by setting the reduction goals for annual average concentrations of PM10 or PM2.5. It sets clear target for the strategies and measures at the regional, sub-regional, sectoral, and sometimes firm levels, divides the responsibilities for achieving the targets and implements the measures effectively among governmental departments.

Manufacturing sectors are among the foci of the Plan. Industrial upgrading and restructuring are enforced for industries of high emission, high energy consumption, or with backward productivity or excess capacity with the strategies including end-of-pipe measures,[37] optimizing the industrial structure, promoting cleaner production and eco-industrial parks, and adjusting the structure of the energy supply and consumption. The application and upgrading of the removal technologies of SO_2, NO_2, particulate matters, and volatile organic compounds (VOCs) in key polluting sectors will be mandatory. The emission intensity in key industries should reduce by over 30 percent. Outdated production lines and small polluting firms should close. The entry requirements of highly polluting and energy-consuming sectors, such as iron and steel, cement, electrolytic aluminum, and coking, require strengthening, and the formulation of ban lists for the construction and expansion of industrial projects in these sectors is necessary. It should be compulsory to carry out environmental impact assessment (EIA) and energy-saving examination before the construction, transformation, and expansion of industrial projects. The approval of an EIA should take into account the total emissions of SO_2, NO_2, particulate matters, and VOCs as prerequisites. Banks should not be allowed to provide loans to projects that have failed to pass an EIA and energy saving examinations.

The Plan forbids regions and industrial sectors that have failed to achieve air pollution reduction goals from building new projects that would emit the same nonattainment pollutant. It also sets targets in terms of the structure of energy consumption to reduce coal consumption and promote renewable energy sources. It provides annual implementation plans under the multi-year plans. It specifies the targets, measures, and projects that require completion within each year. It expects the governmental departments to seek policy, funding, and technological support from corresponding ministries or departments of higher-level governments. It is also possible to establish special plans targeting major polluting sectors.

BANKING INDUSTRY IN CHINA

Banks play a very important role in the Chinese economy as most Chinese firms largely rely on bank debt financing. The total assets of the Chinese banking system amount to 268.2 trillion yuan (or US$38.9 trillion) by the end of 2018. It is roughly 3 times the size of the countries annual GDP and overtakes the eurozone's banking assets.

Before 1978, the banking system in China was a mono-bank system. A single bank, the People's Bank of China (PBoC), functioned both as a central bank and as a commercial bank, in charge of all businesses such as deposits, lending, foreign exchange, and monetary policy. As part of economic reforms, the financial system has become more diversified since 1978. The establishment of four state-owned specialized banks in 1983 aimed to take charge of commercial businesses. The Industrial and Commercial Bank of China (ICBC) focused on the corporate lending, the Agriculture Bank of China (ABC) aimed to promote the economic development in the rural areas, the Bank of China (BOC) specialized in the foreign exchange business, and the China Construction Bank (CCB) was responsible for construction and infrastructure developments. At the same time, the mandate of PBoC was changed to that of a traditional central bank.

[37] End-of-pipe measures are pollution control technologies that remediate contaminated flows of air just before the effluent can enter the environment.

In addition to these four state-owned specialized banks, various types of financial institutions started to emerge in the late 1980s. Established in 1987, the Bank of Communications (BoCom) was the first joint equity banks in China. Although BoCom is technically a joint equity bank, it is more or less the same as the Big Four in terms of the regulation and political hierarchy. Both the four state-owned banks and BoCom are under the direct control of the central government and are held by the Ministry of Finance and a sovereign wealth fund – the China Investment Corporation. These Big Five belong to the top tier of China's banking system, controlling for approximately 45 percent of the market share. The second tier contains the 12 joint equity commercial banks (JECBs), which are also mainly state-owned, while they have far fewer branches than the big five banks and banks operate their businesses relatively locally. The rest of the financial institutions such as rural credit cooperatives, city commercial banks, trust and investment companies, finance companies, foreign banks, belong to the third tier.

After the entry of the WTO in 2001, the Chinese financial system experienced several further reforms. In 2003, the government established the Chinese Banking Regulatory Commission (CBRC) to monitor commercial bank operations. To improve the corporate governance of banks, it allowed the four state-owned banks to go to public from 2005 to 2010, and encourage city commercial banks to bring in foreign strategic investors, go public, reconstruct, and operate across regions.

In 2006, the government completely opened the RMB business to foreign banks. The entry of foreign banks improves the efficiency of the Chinese banking system (Xu, 2011). As a result of reforms, the proportion of assets of state-owned commercial banks decreased from 58.03 percent in 2003 to 37.29 percent in 2016, while the assets of joint-stock commercial banks increased from 10.70 percent in 2003 to 18.72 percent in 2016. According to the latest statistics released by China Banking and Insurance Regulatory Commission (CBIRC), which replaced the CBRC in April 2018, there were 4,588 financial institutions by the end of 2018, including 134 city commercial banks, 1,427 rural commercial banks, 1,616 village banks, 812 rural credit cooperative, 115 foreign banks, among others.[38]

[38] The figures used in the paragraph come from China Banking Regulatory Commission AnnualReports published in various years.

APPENDIX II.

Table A1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Lending spread	470105	0.234	0.266	-0.398	1.998
Lending rate	470105	0.074	0.016	0.034	0.191
Benchmark interest rate	470105	0.060	0.229	5.600	6.550
Loan default	450760	0.010	0.099	0	1
Loan amount (CNY 10 thousand)	470105	788	2411	5	210000
Maturity					
Short term loan	470105	0.936	0.244	0	1
Mid and long-term loan	470105	0.064	0.244	0	1
Loan type					
Secured loan	470105	0.446	0.497	0	1
Fiduciary loan	470105	0.028	0.165	0	1
Loan on guarantee	470105	0.397	0.489	0	1
Pledged loan	470105	0.078	0.267	0	1
Discount loan	470105	0.052	0.221	0	1
Firm size					
Micro and Small enterprises	470105	0.844	0.363	0	1
Medium-sized enterprises	470105	0.123	0.328	0	1
Big enterprises	470105	0.033	0.179	0	1
Company age (Year)	470105	10.38	5.74	1	60
Firm ownership					
State-owned enterprises	470105	0.013	0.112	0	1
Collective enterprises	470105	0.009	0.096	0	1
Private enterprisess	470105	0.882	0.378	0	1
Limited liability enterprises	470105	0.688	0.463	0	1
Incorporated enterprises	470105	0.021	0.143	0	1
Joint venture enterprises	470105	0.036	0.186	0	1
Foreign enterprises	470105	0.036	0.186	0	1
Other enterprises	470105	0.024	0.154	0	1
Bank type					
Big five	470105	0.348	0.476	0	1
Joint-stock commercial banks	470105	0.128	0.334	0	1
City commercial banks	470105	0.134	0.341	0	1
Rural banks	470105	0.390	0.488	0	1
Local Economic structure					
Share of secondary industry	470105	0.510	0.021	0.442	0.541
Share of tertiary industry	470105	0.450	0.029	0.380	0.484
GDP per capita (CNT Yuan)	470105	98616	29225	31827	129926

Note: This table presents the summary statistics of the key variables for the sample period running from 1 August 2012 to 31 December 2014 when the loans were granted. We report the summary statistics for the main outcome variables including the default and the lending spread which is calculated as the percentage deviation of its lending rate from the benchmark rate; the loan-level characteristics including loan amount, maturity, and types; the firm-level fundamentals ofage and size; types and ownership of banks; and local economic structure and GDP per capita.

Table A2. Clean Air Action Plan, Default and Loan Spread, Cluster on Bank Level

	(1)	(2)	(3)	(4)	(5)	(6)
		default			Loan spread	
Action*Treat	0.0084***	0.0084***	0.0083***	0.0132**	0.0121**	0.0131**
	(0.0027)	(0.0025)	(0.0026)	(0.0052)	(0.0046)	(0.0053)
Treat	-0.0022*	-0.0024**	-0.0022**	0.0026	0.0026	0.0026
	(0.0011)	(0.0010)	(0.0011)	(0.0039)	(0.0036)	(0.0039)
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y
Observations	450760	450760	450760	470105	470105	470105
R^2	0.018	0.023	0.019	0.487	0.497	0.488
Adjusted R^2	0.018	0.022	0.018	0.487	0.497	0.488

Note: This table shows DID estimates of the effect of the Clean Air Action Plan on the default and loan spread of high- polluting firms relative to low-polluting firms respectively. The dependent variable is default for columns (1) to (3),and loan spread for columns (4) to (6). Treat is a dummy variable marking all firms belonging to the high-pollutingindustries targeted by the Clean Air Action Plan. Action is a dummy variable marking the post treatment period (6 Jan 2014 and 31 Dec 2014). All specifications contain loan, firm and macro-level controls. All the loans were granted between 1 August 2012 and 31 December 2014. We trace the repayment status of these loans up to 31 March 2016.The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the bank level and reported in parentheses (* p < 0.10, ** p< 0.05, *** p < 0.01)

Table A3. Clean Air Action Plan, Default and Loan Spread Cluster on Bank Year Level

	(1)	(2)	(3)	(4)	(5)	(6)
		default			Loan spread	
Action*Treat	0.0084***	0.0084***	0.0083***	0.0132**	0.0121*	0.0131**
	(0.0025)	(0.0025)	(0.0024)	(0.0059)	(0.0062)	(0.0058)
Treat	-0.0022**	-0.0024**	-0.0022**	0.0026	0.0026	0.0026
	(0.0011)	(0.0011)	(0.0010)	(0.0031)	(0.0030)	(0.0031)
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y
Observations	450760	450760	450760	470105	470105	470105
R^2	0.018	0.023	0.019	0.487	0.497	0.488
Adjusted R^2	0.018	0.022	0.018	0.487	0.497	0.488

Note: This table shows DID estimates of the effect of the Clean Air Action Plan on the default and loan spread of high- polluting firms relative to low-polluting firms respectively. The dependent variable is default for columns (1) to (3),and loan spread for columns (4) to (6). Treat is a dummy variable marking all firms belonging to the high-pollutingindustries targeted by the Clean Air Action Plan. Action is a dummy variable marking the post treatment period (6 Jan 2014 and 31 Dec 2014). All specifications contain loan, firm and macro-level controls. All the loans were granted between 1 August 2012 and 31 December 2014. We trace the repayment status of these loans up to 31 March 2016.The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the bank*year level andreported in parentheses (* p < 0.10, ** p< 0.05, *** p < 0.01).

Table A4. Clean Air Action Plan, Default and Loan Spread by Local Regulation Stringency

	Default			Loan spread		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Action*Treat* high regulated cities	0.0032***	0.0027***	0.0030**	0.0072*	0.0081**	0.0072
	(0.0011)	(0.0009)	(0.0011)	(0.0039)	(0.0034)	(0.0043)
Treat	-0.0022	-0.0024	-0.0022	0.0028	0.0026	0.0027
	(0.0016)	(0.0015)	(0.0015)	(0.0020)	(0.0019)	(0.0019)
Action*Treat	0.0056	0.0062*	0.0057*	0.0066*	0.0051	0.0067**
	(0.0033)	(0.0032)	(0.0029)	(0.0035)	(0.0062)	(0.0031)
Action* high regulated cities	-0.0010	-0.0072		0.0039	-0.0096	
	(0.0032)	(0.0050)		(0.0070)	(0.0146)	
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed effect			Y			Y
Observations	450760	450760	450760	470105	470105	470105
R2	0.018	0.023	0.019	0.487	0.497	0.488
Adjusted R2	0.018	0.022	0.018	0.487	0.497	0.488

Note: This table compares DID estimates of the Clean Air Action Plan on the default and loan spread by the stringency of environmental regulation across cities. The reference group is cities with lax regulation. The dependent variable is default for columns (1) to (3), and loan spread for columns (4) to (6). Treat is a dummy variable marking all firmsbelonging to the high-polluting industries targeted by the Clean Air Action Plan. Action is a dummy variable marking thepost treatment period (6 January 2014 and 31 December 2014). All the loans were granted between 1 August 2012 and 31 December 2014. We trace the repayment status of loans granted during our post-treatment period up to 31 March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the industry level and reported in parentheses (* p < 0.10, ** p< 0.05, *** p < 0.01).

Table A5. Clean Air Action Plan, Default and Loan Spread, Different Time Specification

	Default_30 Jun 2015			Default_31 Dec 2015		
Action*Treat	0.0051**	0.0044**	0.0050**	0.0083**	0.0078**	0.0082**
	(0.0023)	(0.0018)	(0.0021)	(0.0034)	(0.0029)	(0.0031)
Treat	-0.0017*	-0.0015*	-0.0017*	-0.0020	-0.0019	-0.0019
	(0.0010)	(0.0008)	(0.0009)	(0.0014)	(0.0013)	(0.0013)
Observations	450760	450760	450760	450760	450760	450760
R^2	0.011	0.014	0.011	0.017	0.021	0.017
Adjusted R^2	0.011	0.013	0.011	0.017	0.021	0.017
Control variables	Y	Y	Y	Y	Y	Y
Industry fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y			Y		
Bank fixed effect	Y		Y	Y		Y
Prefecture fixed effect	Y	Y		Y	Y	
Bank*year fixed effect		Y			Y	
Prefecture*year fixed Effect			Y			Y

Note: This table shows DID estimates of the effect of the Clean Air Action Plan on the default of high-polluting firms relative to low-polluting firms. The dependent variable is default. Treat is a dummy variable marking all firms belonging to the high-polluting industries targeted by the Clean Air Action Plan. Action is a dummy variable marking thepost treatment period (6 Jan 2014 and 31 Dec 2014). All specifications contain loan, firm and macro-level controls.All the loans were granted between 1 August 2012 and 31 December 2014. We trace the repayment status of these loans up to 30 June 2015 and 31 December 2015 respectively. Column (1)-(3) report the estimation on default by 30June 2015 and column (4)-(6) report the estimation on default by 31 December 2015. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at the industry level and reported in parentheses (* p< 0.10, ** p< 0.05, *** p < 0.01).

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