Do Banks Price Environmental Risk? Evidence from a Quasi Natural Experiment in China

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Abstract

This paper maps the risk arising from the transition to a low-emission economy and studies its transmission channels within the financial system. The environmental dynamic stochastic general equilibrium (E-DSGE) model shows that tightening environmental regulations deteriorates firms' balance sheet, as it internalizes the pollution costs, which consequentially accelerates the risks that the financial system faces. The empirical study, which employs the Clean Air Action that the Chinese government launched in 2013 as a quasi-experiment, supports the theoretical implications. The analysis of a unique dataset containing 1.3 million loans shows that the default rates of high-polluting firms rose by around 50% along their environmental policy exposure. At the same time, loan spread charged to such firms increased by 5.5% thereafter, indicating that the banks do price the environment-related risks, but not sufficiently.

Keywords: Environmental DSGE Model, Clean Air Action, Lending Spread, Default Rate.

JEL Codes: E32, E50, Q43, H23.

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"If some companies and industries fail to adjust to this new world, they will fail to exist."[1]

1 Introduction

The risks that environmental degradation and climate change pose for the stability of the financial system has been increasingly recognized (Bank of England (2019)). Physical risks arising from weather events such as more frequent or severe storms, floods and droughts dramatically increase the financial value at risk by destroying the assets like homes, offices and factories. Meanwhile, transition risks arising from changes in environmental policy and production technology requires a massive reallocation of capital and is likely to have significant and system-wide impacts on financial stability and might adversely affect macroeconomic conditions (Network for Greening the Financial Systems (2019)). While the physical risks have been discussed for many years, transition risks are a relatively new category and remain underexplored. This paper fills this gap by investigating the mechanisms through which an environmental policy, aiming at improving air quality, affects macroeconomy and financial sector. In particular, it sheds light on the channels through which the transition toward a low-emission economy transmit to a commercial bank's balance sheet. As the regulations internalize the environmental costs, firms will face certain constraints on the cash flows and balance sheets, which will potentially weaken their solvency and consequently increase the risks facing the financial system.

A growing number of countries are implementing a wide range of new rules and regulations that either tighten their existing environmental standards or impose entirely new environmental obligations on the business community. The long term benefits of such transition toward clean production are considerable, including cleaner air, improved health, reduced occurrence of natural disasters and sustainable economic growth.[2]. 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. Moderating the potential economic fluctuations arising from such policy change is hence of critical importance. However, most existing studies on the transition risks are partial and usually focus on the energy sector.

This paper analyzes the economic and financial impacts of the transition towards low emission economy in the short term. We address this issue from both theoretical and empirical perspectives. We first develop an environmental dynamic stochastic general equilibrium (E-DSGE) model to illustrate how productive firms and financial institutions react to the imposition of environmental policy tools such as emission caps or intensity targets. We then employ a quasi-natural experiment to size the financial

[1] Open letter on climate-related financial risks, by Mark Carney (Governor of Bank of England) and Franois Villeroy de Galhau (Governor of Banque de France), available at `https://www.bankofengland.co.uk/news/2019/april/open-letter-on-climate-related-financial-risks`.

[2] See Fankhauser and Tol (2005), Mathiesen, Lund, and Karlsson (2011), Albrizio, Botta, Koźluk, and Zipperer (2014), Greenstone and Hanna (2014) and Kozluk and Zipperer (2015)

risks escalated by the adjustment process. In particular, we assess how the default rates and loan spread of firms with different level of emission intensity change following the Air Pollution Prevention and Control Action Plan (thereafter the Clean Air Action) that the Chinese government launched in 2013. This policy sets the national wide air pollution abatement target, with a special emphasis on the key regions of Beijing, Tianjin and Hebei (BTH), the Yangtze River Delta (YRD) and the Pearl River Delta (PRD).[3] This is the first time that the Chinese government has set quantitative air quality improvement goals with a clear time limit.

Our theoretical model sheds light on 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, Gertler, and Gilchrist (1999) and Christiano, Motto, and Rostagno (2014) by including an environmental policy that aims to reduce productive firms emissions. In particular, the financial accelerator mechanism assumes the existence of a dynamic feedback process between the value of capital and the level of borrowing, which can deplete when firms face tightening emission standards. The model assumes the existence of an optimal contract, which implies that entrepreneurs repay the debt to the bank if the value of their outstanding debt is lower than the value of the capital that they own. The tightening of environmental regulations on the use of polluting inputs in the production process reduces the asset values and expected return on projects. Consequently, entrepreneurs find themselves struggling and become unwilling or unable to perform their duties in line with the contractual conditions, as the repayment of debt is too costly relative to the rate of return. As the risk of default rises, the banking system will inevitably bear a financial loss due to its failure to obtain the expected earnings. Indeed, being aware of borrowers' increasing exposure to environmental regulations, financial institutions, facing balance sheet distress, will charge higher lending rates as they internalize the environmental risks.

The theoretical analysis of this research is related to Fischer and Springborn (2011) who incorporate environmental policy into a real business cycle model in which the total production is a function of capital, labor and polluting inputs. Within this framework, emissions are proportional to the use of polluting inputs and constrained by permit allocations so as to determine the maximum emission output ratio. We extend their model by assuming that a fixed cap on emissions constrains polluting inputs. This setting is consistent with the Chinese Clean Air Action that the government implemented in 2013 with the aim of improving the air quality in Chinese cities through varying

[3] Due to the short sample period (the Action Plan has been implemented only since 2013), we are unable to estimate or simulate the E-DSGE model. Therefore, the quasi-experimental analysis helps us to support the theoretical implications that a more restrictive climate change policy leads to environmental risk and loan defaults.

targets. The model assumes that higher production would generate more polluting emissions, which would then increase the shadow price of emission permits due to the fixed cap. A shock arising from a more severely tightened emission cap leads the output to fall as firms use fewer pollutant inputs, and the return on capital to decline as well. In contrast to Fischer and Springborn (2011), our model assumes that in each period entrepreneurs acquire new capital by borrowing new loans from financial intermediaries. The production function converts new capital into consumption goods, which households buy. The earned income and capital gains give entrepreneurs the capacity to repay their outstanding loans. However, a tightened constraint on emissions would reduce entrepreneurs' profit, compromise firms liquidity, and endogenously raise the risk of default.

In addition to the theoretical analysis, this research provides the clear identification and causal evidence by employing a unique micro-level dataset in a difference-in-difference (DID) setting to investigate how an environmental policy shock affects the default and lending spread, as well as their variations across different types of firms and banks. More specifically, we exploit the Clean Air Action that the Chinese government implemented in 2013 as a quasi-natural experiment. The Action sets quantitative air quality improvement goals for the entire country within a clear time frame. By 2017, the annual average concentration of coarse particulate matter (PM10) in urban area shall decrease by 10% compared with 2012, with the number of days with good air quality shall increase gradually. Moreover, it sets higher target for the key regions. During the same period of time, the annual average concentration of fine particulate matter (PM2.5) in Beijing-Tianjin-Hebei (BTH), the Yangtze River Delta (YRD), and the Pearl River Delta (PRD) shall decrease by 25%, 20%, and 15% respectively. To achieve these targets, the Action requires the local governments to tighten the regulations on heavily polluting industries. 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 rate.

The issue of endogeneity hampers the inference of the causal impact of an environmental policy on financial stability. For example, some unknown factors, like economic conditions, may affect the policy implementation and bank lending simultaneously. We employ several strategies to address the methodological challenge. First, we follow the recent literature, Jiménez, Ongena, Peydró, and Saurina (2012) for instance, by using a unique micro-level dataset that contains 1.3 million loans that all types of banks granted to all non-financial firms located in six prefectures within Jiangsu province during the period of 2010 to 2016, moderating the concern that an analysis based only on macro data or bank-level data may suffer from omitted-variables bias. Second, 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 allows us to implement a difference-in-difference (DID) estimation by using both before-and-after policy variation and cross-industry variation for identification. In other words, we compare the before-and-after change in the lending spread and default rates of firms with different pollution intensities. Moreover, considering that DID may not exclude time-varying variables that may bias the estimates, we further strengthen our identification by fielding loan and firm-time characteristics and several fixed effects. For example, we include the important fixed effects of *bank*year* to saturate the model with time-varying supply-side characteristics that might affect the loan spread and *city*year* to control for yearly city-specific shocks.

To understand whether the risks of lending to high polluting firms change following the policy enforcement, we trace the repayment status of loans granted during our sample period and find that the default risk of high polluting firms rose by around 50% after the policy implementation. However, compared with the period before the Action Plan, the loan spread for high-polluting firms increases by only around 5.5%. These finding represents salient evidence that the transition toward low emission economy has posed large risks on the financial stability. Although the banks are aware of such risks by raising the lending rate, but not to a degree comparable with the increased default rate. Further analysis indicates that the effects of the Clean Air Action vary across firms of different sizes. Both the lending spread and the default rate show largest treatment effects for the small and micro enterprises. Moreover, banks facing fewer government interventions are able to price the environmental risks more appropriately.

This paper relates to different strands of the literature. First, the paper contributes to the literature that incorporates environmental factors into macroeconomy. Angelopoulos, Economides, and Philippopoulos (2010) analyze the impact of alternative environmental policy rules in a real business cycle model augmented with the assumptions that pollution occurs as a by-product of production process, and 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, Unalmis, Unalmis, and Unsal (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, this paper develops a financial accelerator mechanism that propagates the economic consequences of environmental risk by linking entrepreneurs to banks through the collateral value.

Second, we contribute to the literature on endogenous default and financial accelerator. Christiano, Motto, and Rostagno (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. Similarly, Cesa-Bianchi and Fernandez-Corugedo (2018) study the effect of macro uncertainty and micro uncertainty in a financial accelerator DSGE model with sticky prices. Forlati and Lambertini (2011), Quint and Rabanal (2014) and Rabitsch and Punzi (2017) integrate risk shocks into the mortgage market, showing that default occurs endogenously when the housing investment risk increases. Spiganti, Comerford, et al. (2017) analyze the interaction between climate change policy and macroeconomic stabilization to exhibit the financial accelerator mechanism and fire sales of fossil fuel asset arising from carbon bubble. In particular, they assume that the government levies carbon taxes and provides green subsides to induce entrepreneurs to use zero carbon production technology, and find that such policies damage the balance sheets of entrepreneurs, with major macroeconomic implications due to the presence of financial frictions. Relative to those papers, the present paper incorporates the environmental risk into a DSGE models with endogenous default determined through a change in the balance sheets of entrepreneurs and the current asset holdings as collateral.

Third, our empirical work enriches the growing literature studying the linkage of financial market to climate change and environmental risk. The potential effect of such risk on financial stability is vigorously discussed by researchers and increasingly enters the agenda of regulators and supervisors (Carney (2015)). Trenberth, Dai, Van Der Schrier, Jones, Barichivich, Briffa, and Sheffield (2014) show that corporations' production processes are vulnerable to natural disasters which is likely to be amplified by climate change. Bansal, Ochoa, and Kiku (2016) estimate the elasticity of equity prices to temperature fluctuations and find that global warming has a significantly negative effect on asset valuations. Daniel, Litterman, and Wagner (2016) and Giglio, Maggiori, Stroebel, and Weber (2015) claim that stock and real estate market might help guide government policies if markets efficiently incorporate climate risks. De Greiff, Delis, and Ongena (2018) suggest that the non-pricing of environmental policy exposure of fossil fuel firms leads to a carbon bubble. Hong, Li, and Xu (2019) show that prolonged drought in a country, measured by the Palmer Drought Severity Index (PDSI) from climate studies, forecasts both declines in profitability ratios and poor stock returns for food companies in that country. Dafermos, Nikolaidi, and Galanis (2018) report that climate change can have severe effects on financial stability by increasing the rate of default resulting from lower firms' profitability or lower asset prices, which they attribute to portfolio reallocation in the case of environmental damage. 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. This paper fills 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.

[4]Throughout the paper, I 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. The insightful review of the early studies based on the context of the United States supports the modest negative effect of environmental regulation on productivity, but the results are sensitive to the measurement of regulatory stringency and challenged by the endogeneity issue (Jaffe, Peterson, Portney, Stavins, et al. (1995)). Focusing on the Clean Air Act Amendments in the United States, 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, List, and Syverson (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 in the Los Angeles Air Basin around the 1980s brought a sharp increase in the total factor productivity of local oil refineries with only a slight decline in the employment. Morgenstern, Pizer, and Shih (2002) also demonstrate that the employment effect of environmental regulation around the 1980s was insignificant in four heavily polluting industries in the United States. Krüger (2015) estimates, through a quasi-experiment, that the firms that a regulation most heavily affects experience significantly positive valuation effects. Tanaka, Yin, and Jefferson (2014) demonstrate that although environmental regulation eventually improve the economic performance of the targeted polluting firms, it takes five years for the effect on technological advancement to materialize. Despite the inspiring progress in the empirical examinations of this debate, the evidence on the financial accelerator mechanism of environmental regulations is still sparse. The evidence that this paper provides enriches our understanding of the impacts of environmental transition on the financial system and banks' pricing strategy in response to a change in environmental policies in the short run.

The rest of the paper is organized as follows. Section 2 presents the baseline theoretical model. Section 3 reports the theoretical impulse responses to a tightened environmental policy. Section 4 provides the background information on the Clean Air Action and banking industry in China. Section 5 outlines the data source and empirical strategy. Section 6 presents the empirical results, while Section 7 concludes.

2 Model

We develop a dynamic stochastic general equilibrium (DSGE) model with an environmental policy that aims to reduce pollution emissions by productive firms. The model includes several features: (i) a household sector, (ii) a production sector, (iii) a capital producer, (iv) two types of entrepreneurs, (v) a banking sector and (v) a monetary authority.

2.1 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. In order to finance new business, entrepreneurs in each group purchase the stock of capital, $k^j_{e,t}$ at the real price, q^k_t. Entrepreneur assigns equal resources to each member i to purchase capital $(k^j_{e,t})^i$, where $\int_i (k^j_{e,t})^i di = k^j_{e,t}$. The investment opportunities are financed by either entrepreneurs' net worth, $N^j_{e,t+1}$, and bank loans, $b^j_{e,t+1}$. The balance sheet of each group of entrepreneurs is given by:

$$q^k_t k^j_{e,t} = N^j_{e,t+1} + b^j_{e,t+1} \tag{2.1}$$

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 $\omega^j_{t+1} R^j_{K,t+1}$, where the random variable $(\omega^j_{t+1})^i$ is an i.i.d. idiosyncratic shock which is log-normally distributed with cumulative distribution $F_{j,t}[(\omega^j_{t+1})^i)]$.[5] The ex-post profit for each project is $\Pi(\omega^i_{t+1}) = \omega^j_{t+1} R^{K,j}_t q^k_{t+1} (k^j_{e,t+1})^i - R^j_{z,t+1} b^j_{e,t}$, where $R_{z,t+1}$ the gross contractual state-contingent loan rate paid to the bank by non-defaulting entrepreneurs.

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

$$\bar{\omega}^j_{t+1} R^j_{K,t+1} (q^k_{t+1} k^j_{e,t+1}) = b^j_{e,t} R^j_{z,t+1} \tag{2.2}$$

Eq. 2.2 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 interests). The random variable $(\omega^j_{t+1})^i$ describes an i.i.d. idiosyncratic shock, which can alter the realization of Eq. 2.2. If $(\bar{\omega}^j_{t+1})^i \in \left[\bar{\omega}^j_{t+1}, \infty\right]$, entrepreneurs are solvent and repay the loan to the bank; while for loans with low realizations, $(\bar{\omega}^j_{t+1})^i \in \left[0, \bar{\omega}^j_{t+1}\right]$, entrepreneurs declare bankruptcy and defaulting members loose their capital.[6] However, tightening of environmental protection standards and climate change policies, will generate negative externalities that can be internalized on a firm's balance sheet, thus altering Eq. 2.2 and generating potential losses for financial institutions and the financial system.

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

[6]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.

Entrepreneurs Maximization Problem.

Each type of entrepreneurs produces intermediate goods, $Y^j_{e,t}$, 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 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.[7]

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

$$\max E_0 \sum_{t=0}^{\infty} (\beta^e)^t \left[ln(c^j_{e,t}) \right] \tag{2.3}$$

subject to:

$$\begin{gathered} c^j_{e,t} + X_t + q^j_t(k^j_{e,t} - (1-\delta_k)k^j_{e,t-1}) + w^j_t L^j_t + R^{j,K}_t k^j_{e,t} + R^j_{z,t} b^j_{e,t-1} - Z^j_{e,t} \\ = Y^j_{e,t} + b^j_{e,t}, \end{gathered} \tag{2.4}$$

$$b^j_{e,t} \leq m^j_{e,t}\ E_t \frac{(q^{j,k}_{t+1}\pi_{t+1}(1-\delta_k)k^j_{e,t})}{R^L_t}, \tag{2.5}$$

and

$$\begin{aligned} R^L_t b^j_{e,t} = & \left\{ (1-\mu^j) \int_0^{\bar{\omega}_{j,t+1}} \omega_{j,t+1}(1-\delta_h) q^{j,k}_{t+1} k^j_{e,t} f_{t+1}(\omega_j) d\omega_j \right\} \\ & + \left\{ \int_{\bar{\omega}_{j,t+1}}^{\infty} R^j_{z,t+1} b^j_{e,t} f_{t+1}(\omega_j) d\omega_j \right\}, \end{aligned} \tag{2.6}$$

where $j = (g, ng)$. β^e is the discount factor, $(1-\delta_k)$ is the depreciation rate of capital stock. Eq. 2.4 shows that each group of entrepreneurs produces intermediate goods, $Y^j_{e,t}$, and sells the intermediate good to a retailer at a price $P^j_{e,t}$. The revenues are used to finance the entrepreneur's consumption, $c^j_{e,t}$, to pay wages to workers, $w^j_t L^j_t$, and to acquire extra inputs, $X = E, M$. Moreover, each period, entrepreneurs borrow, $b^j_{e,t}$, from banks to finance the acquisition of new capital for new projects, $q^j_t I^j_{e,t} = q^j_t(k^j_{e,t} - (1-\delta_k)k^j_{e,t-1})$. Each project financed is subject to individual contract where the financial institution charges an interest rate equal to $R^j_{z,t}$.[8] Entrepreneurs also rent capital and R^k_t is the rental rate they pay on capital service. Green sector uses clean and renewable energy, E, while the non-green sector uses polluting inputs, M. As in

[7] $\sigma_g + \sigma_{ng} = 1$.

[8] Loan rate $R^j_{z,t+1}$ is determined at time t, after the realization of the shocks.

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.[9]

The production function of intermediate goods is given by:

$$Y_{e,t}^{j} = A_t (k_{e,t-1}^{j})^{\alpha} (L_t^{j})^{1-\alpha-\gamma_j} X_t^{\gamma_j}, \tag{2.7}$$

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 $\varepsilon_{M,t} = \rho_{\varepsilon} \varepsilon_{M,t-1} + \epsilon_{\varepsilon,t}$.[10]

Similar to Fischer and Springborn (2011), the government imposes a reduction of polluting emissions in a fixed amount $\bar{M}$.[11] As a result, $\Omega_t^{ng} = \bar{M}$ and the above emission constraint becomes:

$$M_t \leq \bar{M} - \varepsilon_{M,t}. \tag{2.8}$$

Financial frictions are introduced in Eq. 2.5. Entrepreneurs borrow from the banking sector funds 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 define the repayment ability of the loan, as described in Eq. 2.2.

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

$$Z_{e,t}^{j} = F_{j,t}(\bar{\omega}_t^{j}) R_{z,t}^{j} b_{e,t-1}^{j} - q_t^{j,k} (1-\delta_k) k_{e,t-1}^{j} G_t^{j}(\bar{\omega}_t^{j}), \tag{2.9}$$

where $F_{j,t}(\bar{\omega}_t^{j})$ is the share of entrepreneurs who default their debt to the bank, while $G_t^{j}(\bar{\omega}_t^{j})$ is the fraction of capital stock seized by the bank in case of default.[12] $m_{e,t}^{j}$ is the loan-to-value ratio and it is equal to $\left[\Gamma_{t+1}(\bar{\omega}_{bj,t+1}) - \mu_{ej} G_{t+1}(\bar{\omega}_{bj,t+1})\right]$, and μ_j is the fraction of the capital value that banks pay to monitor and seize the collateral in case of default.

[9] We assume the price of intermediate inputs to be equal to 1 ($P^X = 1$).

[10] ρ_{ε} is the persistence parameter and $\epsilon_{\varepsilon,t}$ is a i.i.d. white noise process with mean zero and variance σ_{ε}^2.

[11] 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.

[12] As in Bernanke, Gertler, and Gilchrist (1999) and Forlati and Lambertini (2011), the seized housing stock is destroyed during the foreclosure process.

Finally, the entrepreneur's maximization problem is subject to a bank participation constraint described in Eq. 2.6, 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.

2.2 Banking Sector

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

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

subject to the flow of funds

$$c_{b,t} + \frac{R_{t-1}}{\pi_t} d_{t-1} + b_t + \Theta(d_t, b_t) = d_t + \frac{R_t^L}{\pi_t} b_{t-1} - Z_{e,t}^j$$

and

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

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 $x_t = (1 - \rho_b) b_t - d_t$. See Table 1.

In Eq. 2.2, we follow Kollmann, Enders, and Müller (2011) and Kollmann (2013) in assuming that the banking sector faces a capital requirement such that the capital to asset ratio should be larger than the fraction 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, Θ_t, which is a function of bank's excess capital, $\Theta_t = \Theta(x_t)$.[13]

The flow of fund described in Eq. 2.2 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 conditions, 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. 2.9.

[13] Θ_t 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.

The *optimal contract* is defined as a one-period loan contract which guarantees a risk neutral banks to obtain a predetermined rate of return on their 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:

$$R_t^L b_{e,t}^j = \left\{ (1-\mu^j) \int_0^{\bar{\omega}_{j,t+1}} \omega_{j,t+1}^i (1-\delta_h) q_{t+1}^{j,k} \pi_{t+1} k_{e,t+1}^j f_{t+1}(\omega_j^i) d\omega_j^i \right\} + \left\{ \int_{\bar{\omega}_{j,t+1}}^{\infty} R_{Z,t+1}^j b_{e,t}^j f_{t+1}(\omega_j^i) d\omega_j^i \right\}, \tag{2.10}$$

where $f(\omega_j^i)$ is the probability density function of ω_j^i, $G_{t+1}(\bar{\omega}_{bj,t+1}) \equiv \int_0^{\bar{\omega}_{t+1}^j} \omega_{bj,t+1}^i f_{t+1}(\omega_{bj}^i) d\omega_{bj}^i$ is the expected value of the idiosyncratic shock for the case $(\omega_{t+1}^j)^i \in \left[0, \bar{\omega}_{t+1}^j\right]$ multiplied by the probability of default, while $\Gamma_{t+1}(\bar{\omega}_{t+1}^j) \equiv \bar{\omega}_{t+1}^j \int_{\bar{\omega}_{t+1}^j}^{\infty} f_{t+1}(\omega_j^i)\omega_j^i + G_{t+1}(\bar{\omega}_{t+1}^j)$ is the expected share of capital stock, gross of monitoring costs that goes to lenders in case of default, μ^j. Equation 2.10 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 $\bar{\omega}_{t+1}^j$ and the state-contingent mortgage rate $R_{Z,t+1}^j$ are determined, to fulfill the above participation constraint.

2.3 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:

$$\max E_0 \sum_{t=0}^{\infty} (\beta)^t \left[\frac{c_t^{1-\sigma_c}}{1-\sigma_c} - \frac{\upsilon_L}{\eta} (L_t)^{\eta} \right], \tag{2.11}$$

subject to the following budget constraint:

$$c_t + d_t \leq w_t L_t + \frac{R_{t-1}}{\pi_t} d_{t-1} + F_t. \tag{2.12}$$

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.

2.4 Retailers

The model assumes there is a continuum of retailers 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:

$$Y_t = \left[\int_0^1 Y_t(n)^{\frac{\xi-1}{\xi}} dn\right]^{\frac{\xi}{\xi-1}}, \tag{2.13}$$

Retailers aggregate intermediate goods from both green and non-green firms:[14]

$$Y_t(n) = \sigma_g Y_{e,t}^g + \sigma_{ng} Y_{e,t}^g \tag{2.14}$$

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:

$$Y_t\left(n\right) = \left(\frac{P_t\left(n\right)}{P_t}\right)^{-\xi} Y_t, \tag{2.15}$$

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

$$P_t = \left[\int_0^1 P_t(n)^{1-\xi} dn\right]^{\frac{1}{1-\xi}}. \tag{2.16}$$

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:

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

where $Y_{t+k}^*\left(i\right) = \left(\frac{P_t^*(i)}{P_{t+k}}\right)^{-\xi} Y_{t+k}$. 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:

$$P_t = \left[\theta P_{t-1}^{\xi} + (1-\theta)(P_t^*)^(1-\xi)\right]^{\frac{\xi}{\xi-1}}. \tag{2.17}$$

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

$$\hat{\pi}_t = \beta_s E_t \hat{\pi_{t+1}} - \kappa \hat{X}_t, \tag{2.18}$$

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

[14]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.

2.5 Capital Producers

Capital producers combine a fraction of the final goods purchased from retailers as investment goods, $i_{k,t}$, to combine it with the existing capital stock, $k_t = \sum_j \sigma_j k^j_{e,t}$, 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

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

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

$$q^k_t = \left[1 + \psi_k\left(\frac{i_{k,t}}{k_{t-1}} - \delta_k\right)\right], \tag{2.19}$$

where q^k_t is the relative price of capital. In the absence of investment adjustment costs, q^k_t, is constant and equal to one. The usual capital accumulation equation defines aggregate capital investment:

$$i_{k,t} = k_t - (1 - \delta_k)\, k_{t-1}. \tag{2.20}$$

2.6 Monetary Policy

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

$$\frac{R_t}{\bar{R}} = \left(\frac{R_{t-1}}{\bar{R}}\right)^{\phi_R}\left(\frac{\pi_t}{\bar{\pi}}\right)^{\phi_\pi(1-\phi_R)}\left(\frac{Y_t}{y}\right)^{\phi_Y(1-\phi_R)} \tag{2.21}$$

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.

2.7 Market Clearing

$$Y_t = C_t + i_{k,t} + E_t + M_t + \Sigma_j \mu^j G_{t+1}(\bar{\omega}_{j,t+1}) q^{j,k}_{t+1}(1 - \delta_k) k^j_{e,t}) \tag{2.22}$$

$$C_t = c_t + \sigma_g c^g_{e,t} + \sigma_{ng} c^{ng}_{e,t} + c_{b,t} \tag{2.23}$$

$$k_t = \sum_j \sigma_j k^j_{e,t} \tag{2.24}$$

$$L_t = \sum_j \sigma_j L_t^j \tag{2.25}$$

$$b_t = \sum_j \sigma_j b_{e,t}^j \tag{2.26}$$

$$q_t^k = \sum_j \sigma_j q_t^{j,k} \tag{2.27}$$

2.8 Parameterization

The time unit is measured in quarters. The parametrization follows standard values used in the real business cycle literature and they are reported in Table 2.[15] The discount factor $\beta = \beta_b$ is set to 0.99 to target the annual nominal free-risk interest rate of 4%. Similar to Iacoviello (2015), entrepreneurs face a lower discount factor and $\beta^e = 0.94$. The price elasticity ξ is set equal to 6 and the Calvo probability to adjust prices, θ, is set equal to 0.67. Similar to Justiniano, Primiceri, and Tambalotti (2015), the coefficient for the interest rate inertia, ρ_R, equal to 0.8, the reaction to the output gap, $\rho_Y = 0.125$, and the reaction to inflation of $\rho_\pi = 1.5$. The production function follows a constant returns to scale with a Cobb-Douglas specification, and the capital return to scale α is set equal to 0.35. The capital depreciation rate δ_k is set at 0.025, while the adjustment cost parameter on investments is equal to 5. The share of clean energy and pollution emission in the production function, γ_j is equal to 0.099 to imply an averaged energy expenditures as a share of GDP of 9.9%. The intensity target coefficient, ϑ, is set equal to 0.05, a value smaller than γ_j, as in Fischer and Springborn (2011). In order to achieve a 20% decrease in the emissions, the persistence of the environmental policy shock is set equal to 0.97 and the standard deviation is set to 0.01. The size of green firms is set equal to 0.3. As in Christiano, Motto, and Rostagno (2014), the monitor cost is set to 0.21, and it is the same for both entrepreneurs, and the average probability of default, $F_j(\bar{\omega}^j)$ is set to be equal to 0.007. Similar to Kollmann, Enders, and Müller (2011), the required bank capital ratio equal to 0.08, the bank cost parameter for deviating from capital requirements is set equal to 0.25.

3 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 in the form of tightening the pollution constraint, i.e. $\bar{M}$ should decrease by

[15] 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.

20%. The impulse responses show a percentage deviation from the initial steady state over a 20-quarter period under the environmental policy scenario.

Fig. 1 shows that such policy enforcement produces the effect of reducing the productivity of non-green sector by around 2%, as firms have to use a lower input in the production process and the cap prevents additional output from being used as more of the intermediate good. Consequently, entrepreneurs in non-green sector decrease their investments and the price of capital drops down. Less investments leads to lower rental return on capital, as the demand for renting capital decreases.

The decrease in the collateral value of non-green entrepreneurs, bring them to decrease their demand for funds. The change on the price of capital, capital stock and borrowing level affects the entrepreneurs' return on capital and the cut-off value, $\bar{\omega^{ng}}$, that endogenously determines the entrepreneurs' failure to repay outstanding loans due to the rising costs of complying with environmental protection policies. Fig. 2 shows that the cut-off value increases for both types of entrepreneurs, with higher impact on the non-green sector, as the regulatory environmental standards target exactly this sector in the economy (See solid line). This increase in the cut-off value reflects the movement in $\bar{\omega}$ as described in Fig. 3. The left side corresponds to the distribution of default for the non-green sector, while the right side refers to the green sector. Fig. 3 shows that when the governments tights the environmental standards in order to improve air quality, the default increases due a movement to the right of the $\bar{\omega}$, thus 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 Fig. 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 Fig. 3. Indeed, the default rate for the green sector is described by the diagonal lines area minus the shaded area. As a result, default rates in the non-green sector increase by around 0.75%. 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%.

Through a banking capital channel, banks reduce the supply of loans as they face a reduction in bank capital due to higher default rates and due to a lower price of capital. As a result, banks deleverage because they keep in their balance sheet assets with lower value. This mechanism is reinforced by a banking funding channel, in which banks charge higher lending rates also to green entrepreneurs in order to recover from the losses from higher monitoring costs and the forgone loan repayments. Higher borrowing cost leads green entrepreneurs to lower their demand for external funds, and production and investment in the green sector slow down because of less financing available. Also clean energy inputs decrease as green entrepreneurs produce less. Ultimately, some green entrepreneurs can experience a lower return on new projects, affecting their ability to repay their debt. Indeed, even if in smaller value, default rates in the green sector increase as well. This result is in line from the findings of the European Banking

Federation (EBF) which shows that Industrial and Commercial Bank of China tend to have lower default rates to loans to green businesses relative to those in the non-green loans.[16]

To sum up, the main findings reveal that an environmental policy that aims at reducing pollution in the non-green sector spillovers to the green sector.

4 Background: Clean Air Action and the banking industry in China

To provide further supporting evidences to the theoretical implications of the E-DSGE model, we employ the Clean Air Action that the Chinese government launched in 2013 as a quasi-natural experiment to examine the financial impacts of tightening environmental regulations in the short term. This section provides background information on the Clean Air Action and banking industry in China.

4.1 Clean Air Action

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

Despite the phenomenal economic growth that China achieved in recent decades, environmental degradation such as deteriorating water quality, land deforestation and pollution, frequent haze plague attracts a great deal of attention 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, 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 $\mu g/m3$ 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, who eventually turning to be the "PM2.5 crisis."

Eight months after the widely-reported air pollution episode, on 12 September 2013, the China's State Council released the Action Plan for Air Pollution Prevention and Control.[17] As a crucial step forward in fighting against air pollution, the Clean Air

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

[17]For the details of the plan, please refer to http://www.cleanairchina.org/product/6349.html

Action 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 PM10 should decline by at least 10% 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%, 20%, and 15% respectively, for the three key regions. For Beijing, the annual average concentration of PM2.5 should remain at the 60 $ug/m3$ level. This is 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. 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 Action 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 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. It usually divided the responsibilities for achieving the targets and implementing the measures effectively among governmental departments. Manufacturing sectors were among the foci of the Action. Industrial upgrading and restructuring are necessary for high polluting industries with high energy consumption and with backward productivity or excess capacity. The strategies and measures targeting manufacturing sectors mainly include end-of-pipe measures, 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_x, 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%. 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_x, 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 Action 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.

4.2 Banking Industry in China

Banks play a very important role in the Chinese economy as most Chinese firms largely rely on debt financing. The total assets of the Chinese banking system amounts 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, Peoples 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 the economic reform, 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 the role of a central bank.

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 Chinas banking system, controlling for approximately 45% 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 cooperation, finance company, 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 reform, the proportion of assets of state-owned commercial banks decreased from 58.03% in 2003 to 37.29% in 2016, while the assets of joint-stock commercial banks increased from 10.70% in 2003 to 18.72% in 2016. According to the newest statistics released by China Banking and Insurance Regulatory Commission (CBIRC), which replaced the CBRC in April 2018, there are 4588 financial institutes by the end of 2018, including 134 city commercial banks, 1427 rural commercial banks, 1616 village banks, 812 rural credit cooperative, 115 foreign banks, among others.[18]

5 Data and Empirical Strategy

5.1 Data source and summary statistics

Our data come from a corporate credit database that the CBIRC Jiangsu Office established. With a population of 80.4 million in 2018 and an area of 102,600 km2, Jiangsu is one of the most densely populated provinces in China. Thanks to its large and well-developed manufacturing sector, it is one of Chinas fastest developing provinces over recent decades. As of 2018, Jiangsu had a GDP of US$1.377 trillion (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% 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 industrial SO2 and COD emissions per unit of land area are 8.48 and 19.51 tons per square kilometer, respectively.[19]

This dataset contains around 1.3 million commercial loans that all banks operating in six prefectures within this 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. Moreover, this coastal province offers an ideal setting in which 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, the GDP per capita of the six prefectures varies widely between USD 7,000 and 20,000, representing different levels of economic development. On the other hand, various types of banks such as the Big Five state-owned commercial banks, joint-equity commercial banks, foreign banks, city commercial banks, rural commercial banks, rural credit cooperative,. According to the newest statistics released by CBIRC, the total asset of commercial banks in Jiangsu

[18]The figures used in the paragraph come from China Banking Regulatory Commission Annual Reports published in various years.

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

Province amounts to RMB 16781.52 billion yuan (around US$2,494 billion), accounting for 8% of the whole commercial banking industry in the country as of 2018.[20]

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 targets. Besides the comprehensive coverage, the dataset provides 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, loan maturity, credit guarantee, issuing date, maturity date, and loan delinquency status). The banks update the loan 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 one of our main outcome variables. Following the existing literature, we measure the spread of each loan by the percentage deviation of its lending rate 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 domestic commercial banks shall 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. Table 3 provides the summary statistics of our main variables for the period of 1 January 2013 to 31 December 2014. 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 379,130 loans to 59,094 firms during this period of time. The mean borrowing rate is 7.4%, 23.5% higher than the benchmark rate of 6%. The average amount of borrowing is RMB8.06 million. In terms of maturity, 93.6% of loans are short term borrowing. There are various types of loans, among which 45% are secured loans with collateral and around 40% are loans with a guarantee. With an average age of 10.6 years, 84.5% of borrowers are micro and small firms, 12.2% are medium-sized firms and 3.3% are big firms.[21] The Big Five and rural commercial banks are the major lenders, accounting for 34.3% and 38.5% of loans respectively.

5.2 Empirical Strategy

This paper employs the Clean Air Action that Jiangsu province implemented in January 2014 as a quasi-experiment to evaluate the financial risks posed by the transition toward

[20]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 (yrl-http://www.cbrc.gov.cn/jiangsu/docPcjgView/8AB96DDF7DDF487C95D1D4D4FB8FC0E1/600811.html)

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

low emission economy. In particular, 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 industry defined by the Clean Air Action (Jiangsu version) as our treatment group,[22] while the rest as the control group. 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 unexposed (or less exposed) to the policy shock, allows us to capture this trend and thus better estimate a counterfactual.

Table 4 compares the descriptive statistics between the control and treatment groups. The 52 commercial banks grant 294, 664 loans to the low polluting firms and 84,466 loans to the highly polluting firms respectively. The lending cost is similar across two groups while the default rate of highly polluting firms is slightly higher than that of low polluting firms. However, the average loan amount borrowed by the low polluting firms is twice as large as that by highly polluting firms. The term of maturity and loan type are also similar between the treatment and control groups. Regarding the firm size, big firms account for 3.7% of low polluting borrowers and 2% of high polluting borrowers. In terms of lenders' structure, local banks including the city commercial banks and rural commercial banks grant 57.9% of loans to highly polluting firms while only 50.7% of loans to low polluting firms.

Overall, we find that the treatment and control groups are comparable in loan characteristics. 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 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. This comparison, considers the loans granted to the high-polluting firms as the treatment group and the loans granted to the low-polluting firms as the control group. We obtain our DID estimators measuring the effect of the environmental policy shock on the financial stability using the following model:

$$\begin{aligned} y_{lbft} = \beta_0 + \beta_1 Action_t + \beta_2 Action_t * Treat_i + \beta_3 Treated_i \\ + \beta_4 L_{it} + \beta_5 F_{ft} + u_{lbft} \end{aligned} \tag{5.1}$$

One of our main outcome variables is the repayment of loan l that bank b grants to f at time t. It equals 1 if default, 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

[22]The high polluting industries targeting by the Clean Air Action (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.

loan spread is indeed induced by the Clean Air Action. We divide our sample into three subperiods. We define the time between 1 January 2013 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, 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, $Action_t$, takes the value of 1 if a bank loan is 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 other dummy variable, *Treat*, takes the value of 1 if a bank grants a loan to a high-polluting firm, 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 Clean Air Action. 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-year characteristics respectively that might affect the cost of loans. At the loan level, we control for the borrowing 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. At the prefecture-level, we control for regional macroeconomic variables, including the share of the secondary and tertiary industry in GDP, and real per capita GDP of the prefecture where a borrowing firm is located.

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, 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. Considering demand-side potential omitted variables, the usual time-varying firm-specific characteristics mitigate such 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.

In this DID estimation, we first compare, in the pre- and post- Clean Air Action periods, the loan spread and default of loans to high-polluting firms with those of low-polluting firms based on their exposure to environmental regulation. As implied by our E-DSGE model, the tightening environmental regulation, which internalizes the cost of pollution, leads entrepreneurs to endogenously default on the outstanding value of their debt. That is, high-polluting firms with a higher than average exposure to environmental-policy stringency face a higher risk of default. Hence, we should observe higher default rate of high-polluting firms after the implementation of Clean Air Action, i.e. $\beta_2 > 0$.. At the same time, if the financial intermediaries factor in the environmental risk after 2014, firms with higher than average exposure to environment policy should face a higher cost of borrowing.

6 Empirical Results

6.1 Baseline analysis

To understand whether the risks of lending to high polluting industries 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. The results are reported in Table 6.

All the specifications control for the loan and borrowing firms' characteristics, the regional macroeconomic factors, the benchmark interest rate and the different types of fixed effects. We control for the year, bank and prefecture fixed effects in specification (1); the bank fixed effect and *prefecture*year* effect in specification (2); and the prefecture fixed effect and *bank*year* effect in specification (3). All the specifications show very similar estimates. The results are consistent across different specifications. Higher default is associated with loans with shorter terms of maturity, or loans granted to private or small and micro enterprises. 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 0.5 percentage points after the policy implementation. Comparing with the mean default rate of 1% for the whole sample, this is equivalent to a 50% increase in the default rate.

With such a considerable increase in the probability of default, it is naturally for banks to charge higher risk premiums on the firms heavily exposed to the Clean Air Action. To understand whether the banks are aware of the transition risks, we then report the baseline DID estimation results on the lending spread relative to the benchmark rate in Table 5. The model specifications are similar to those in Table 6. We control for the loan and borrowers characteristics, the regional macroeconomic factors, benchmark interest rate and different types of fixed effects, including bank, city and year fixed effects, the interaction of bank and year fixed effects, and the interaction of city and year 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 makes the lending spread to polluting firms significantly increase by 1.3 percentage points, which is equivalent to 5.5% 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 is not sufficient. 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 likelihood. Borrowers who are young, private or small in size are more likely to pay higher borrowing rate.

6.2 Cross-sectional Variations

The baseline results show the average effect of the Clean Air Action on the lending spread and default. The escalated environmental risk may change 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 Tables 5 and 6 varies cross-sectionally along certain observable dimensions.

6.2.1 Firm size

It seems plausible that the effect of the Clean Air Action 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 target. 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 in which the original DID term interacts with firm size dummies. Table 7 reports the coefficient estimates that we obtained from a DDD specification that controls for bank, year, and city fixed effects, and their interactions. Consistent with the view that the impacts of environmental regulation are stronger in smaller firms, the DDD estimates for both lending spread and the default rate show the largest treatment effects for the small and micro enterprises.

6.2.2 Bank Size

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 five biggest state-owned commercial banks, 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. 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, which make their lending rates higher than the big banks. 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. The results that Table 8 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.

6.2.3 City heterogeneity

Although the Clean Air Action was a nationwide policy, the regionally-decomposed target 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 and Zhou (2019) 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 then interact it with the DID term. The DDD estimation results that Table 9 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.

6.3 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-period 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 (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 19-month window, spanning from 7 months before the Clean Air Action was implemented until 12 months after it was enforced. Fig. 4 plots the estimation results that account for year, bank and prefecture effect, and the 95% confidence intervals. The estimates show 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 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 0.015 on the first month after the policys implementation.

6.4 Robustness Check

In this subsection, we further conduct various robustness tests on our baseline results. Regarding the loan spread and default rate as possibly being correlated for firms within the same industry, we first cluster the standard error at the industry level and report the results in Table 10. Moreover, loans that the same bank issues might also correlate with each other. We re-estimate the baseline DID analysis and cluster the standard errors at the bank level. Table 11 presents the results for loan spread and default. All the estimates are in line with the baseline results. The default rates for the loans granted during the post-treatment period increased. At the same time, the loan spread for the high-polluting firms rose significantly following the implementation of Clean Air Action, indicating that the banks to some degree priced the risks arising from the transition to a low emission economy.

Considering that a bank may have negotiated the loan contract before the enactment of the Clean Air Action, we lag the policy implementation time by 30 and 60 days[23] to determine whether the policy influenced the default and loan spread immediately. We report the results in Table 12 and 13 respectively. 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.

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, 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 January 2013 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, $Action1_t$, which takes the value of 1 if a bank grants a loan during the interim period, and 0 otherwise. Its in-

[23]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.

teraction with *Treat* measures the policy effects over different periods of time. Table 14 reports the estimation results. The coefficient for the interaction term between $Action1_t$ and *Treat* is insignificant for the loan spread, indicating that the banks operating in Jiangsu province did not adjust its pricing strategy until the local government enforced its own version of Clean Air Action. This is consistent with the reality that the Clean Air Action 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. 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 15 and 16 respectively, present 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 and default rate decreases.

7 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 to improve the air quality, affects the macroeconomy and financial sector. In this paper 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 that the Chinese government launched in September 2013 as a quasi-experiment to investigate the impact of transition on the banking sector. We use a unique micro-level big dataset that covers 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 Action targets dramatically increase by 50%. At the same time, loan spreads of these lending also rise, but to a much smaller degree, indicating that the commercial banks have not sufficiently priced the transition risk. Our empirical evidences are 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 suggests that transition towards low emission economy is one source of structural change which significantly affects all economic sectors and the financial stability. While urgent action is desirable for environmental improvement, an orderly and smooth transition providing adequate time for technological progress could minimize these risks. In addition, financial institutions shall 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-related financial risks into the prudential supervision to ensure the resilience of the financial system to the potential risks.

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Fig. 1: Environmental Shock to Decrease Pollution Emissions

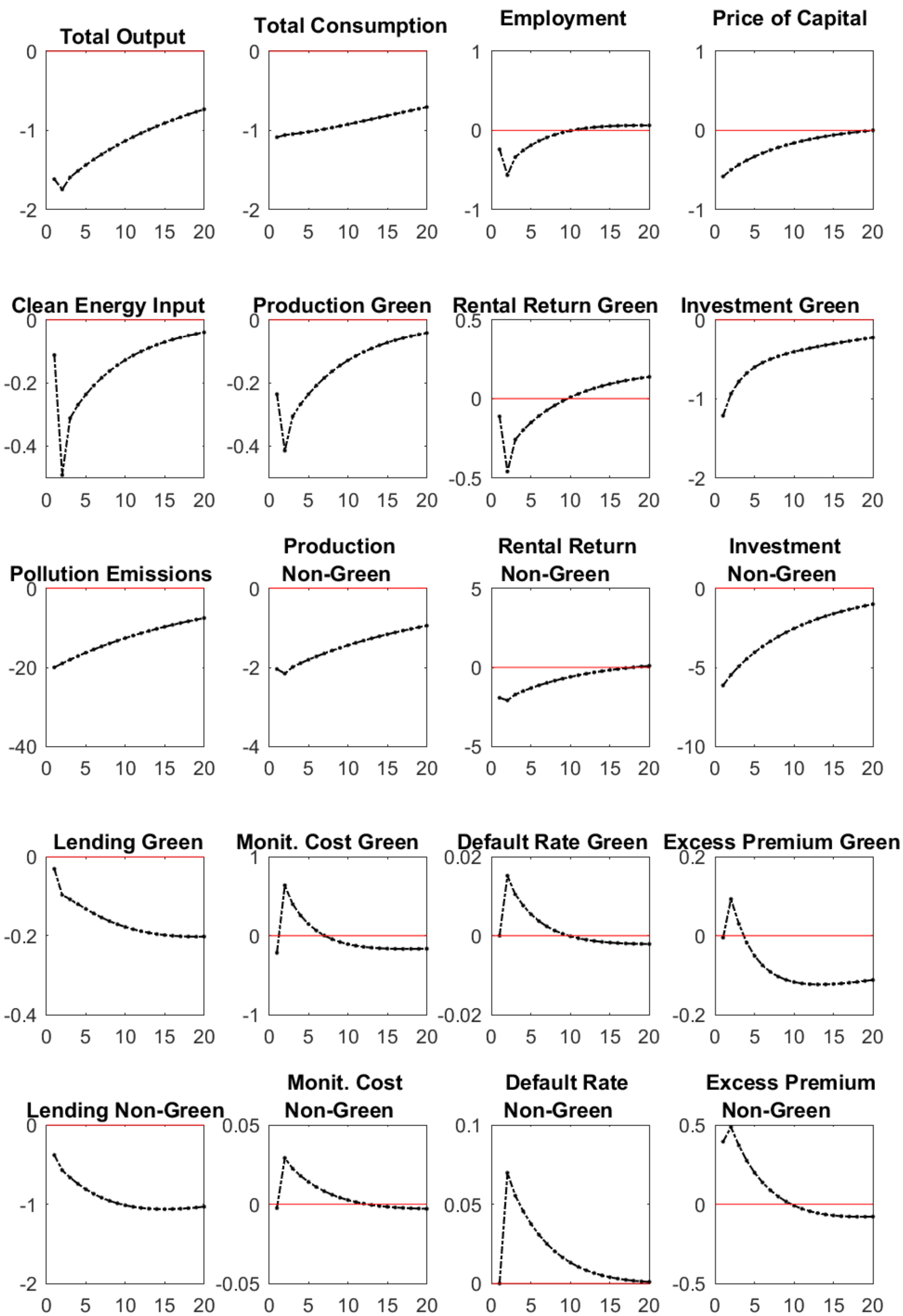

Fig. 2: Change in $\bar{\omega}$ due to Tightness of Environmental Standards

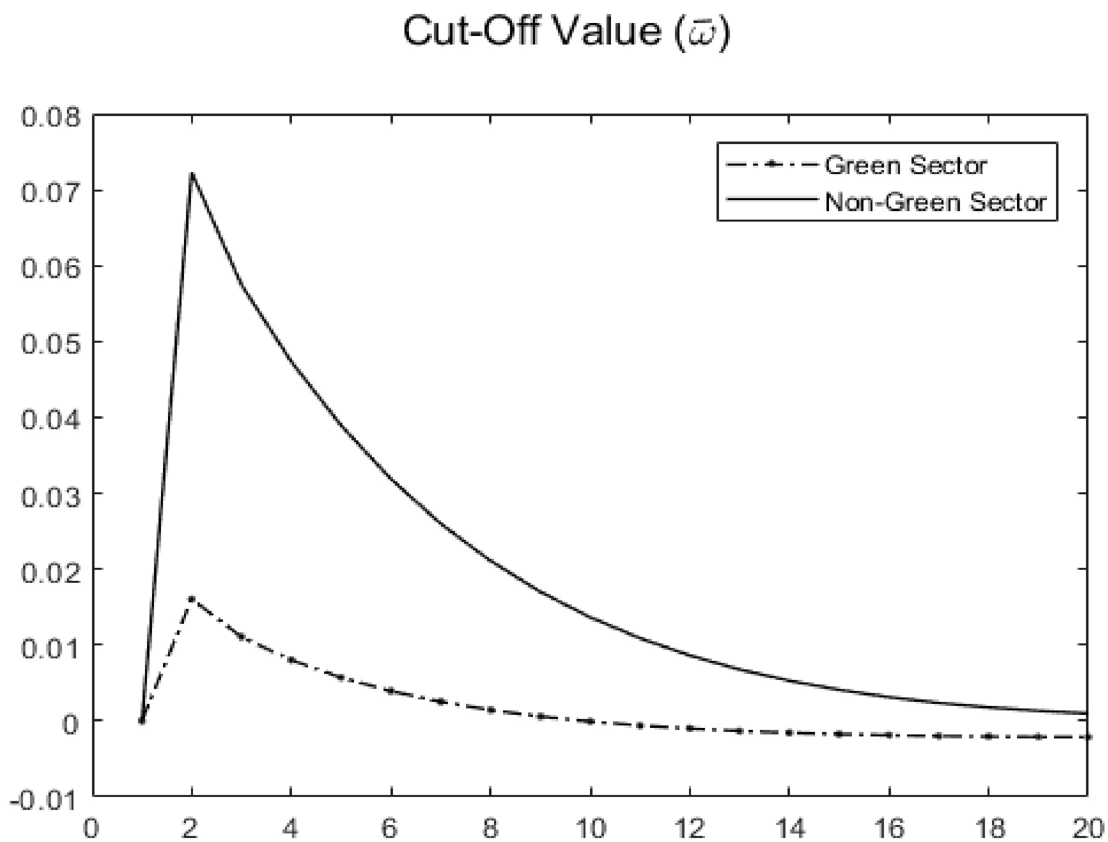

Fig. 3: Distribution of Default ($F(\omega_j^i)$) and Tightness of Environmental Standards: Non-Green Sector (Left side); Green Sector (Right side).

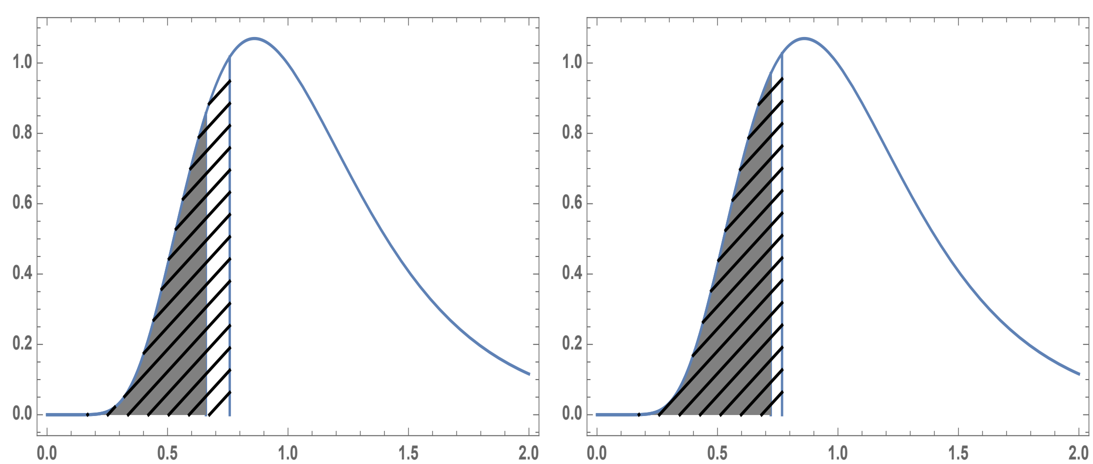

Fig. 4: The dynamic impact of the Clean Air Action on default.

The figure plots the impact of the Clean Air Action on default. We consider a 19-month window, spanning from 7 months before the Clean Air Action was implemented until 12 months after it was enforced. We control year, bank and prefecture fixed effect.

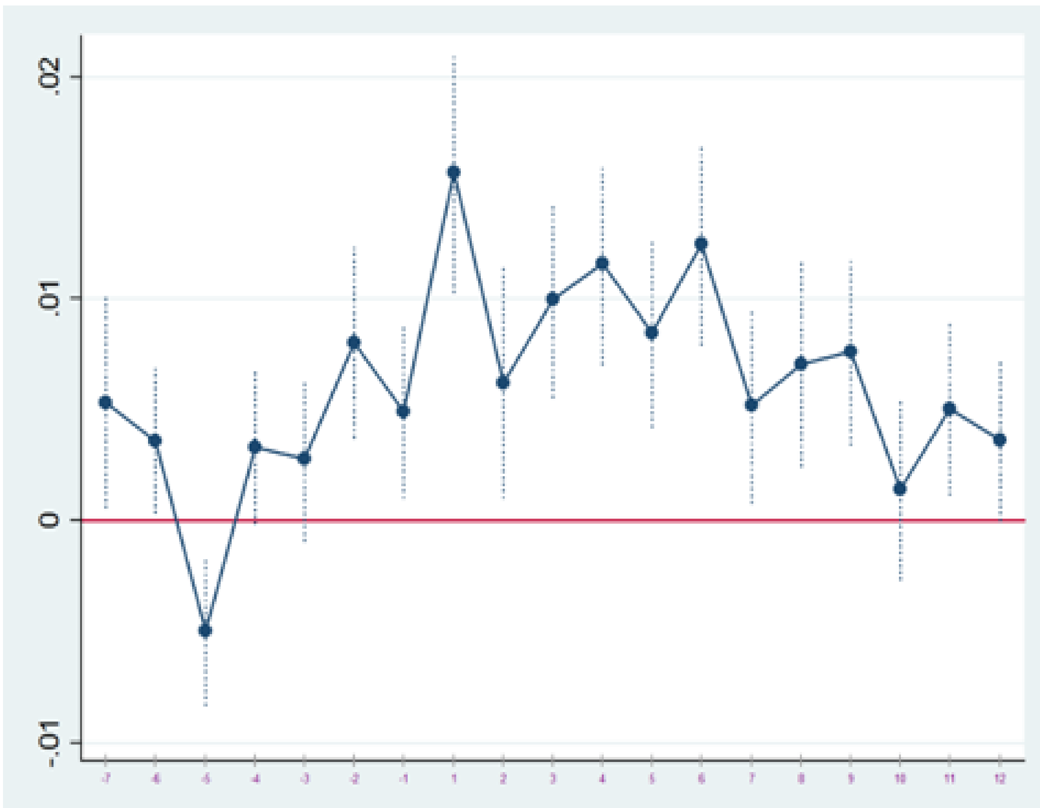

Table 1: Bank Balance Sheet

Assets	Liabilities
Green Firms ($b^g_{e,t+1}$)	Domestic Deposits (d_t)
Non-Green Firms ($b^{ng}_{e,t+1}$)	Bank Capital (x_t)

Table 2: Parameters' Values

Parameter	Description	Value
β	Households Discount factor	0.99
β^e	Entrepreneurs Discount factor	0.94
σ_c	Elasticity of substitution for consumption	1.01
ν_L	Labor disutility parameter	1
η	Labor supply aversion	1.01
δ_k	Capital depreciation parameter	0.025
ψ_k	Capital adjustment cost	5
α	Capital Share	0.35
γ_g	Energy Inputs Share	0.099
γ_{ng}	Pollution Inputs Share	0.09
ϑ	Intensity Target coefficient	0.05
$F_j(\bar{\omega}^j)$	Probability of default	0.007
ξ	Price Elasticity of Demand for Good n	6
θ	Calvo's Price Parameter for Nominal Rigidities	0.67
ρ_R	Monetary Policy Inertia	0.8
ρ_Y	Monetary Policy Reaction to Y	0.125
ρ_π	Monetary Policy Reaction to π	1.005
β_b	Banks Discount factor	0.99
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

Table 3: Summary Statistics

This table presents the summary statistics of the key variables for the sample period running from Jan 2013 to Dec 2014. We report the summary statistics for the main outcome variable the lending spread – the percentage deviation of its lending rate from the benchmark rate; the loan-level characteristics including loan amount, maturity, and credit guarantee; the firm-level fundamentals of age and size; types and ownership of banks; and local economic structure and GDP per capita.

Variable	Obs	Mean	Std. Dev.	Min	Max
Lending spread	379130	0.235	0.269	-0.4	2
Lending rate	379130	0.074	0.016	0.034	0.191
Benchmark interest rate	379130	0.060	0.227	5.6	6.55
Loan amount (CNY 10 thousand)	379130	806	2440	5	210000
Maturity					
Short term loan	379130	0.936	0.245	0	1
Mid-term loan	379130	0.05	0.217	0	1
Long-term loan	379130	0.015	0.123	0	1
Loan type					
Secured loan	379130	0.446	0.497	0	1
Fiduciary loan	379130	0.028	0.164	0	1
Loan on guarantee	379130	0.397	0.489	0	1
Pledged loan	379130	0.078	0.268	0	1
Discount loan	379130	0.052	0.222	0	1
Firm size					
Micro and Small firms	379130	0.845	0.362	0	1
Medium firms	379130	0.122	0.327	0	1
Big firms	379130	0.033	0.179	0	1
Company age (Year)	379130	10.6	5.73	1	60
Bank type					
Big five	379130	0.343	0.475	0	1
Joint-stock commercial banks	379130	0.134	0.341	0	1
City commercial banks	379130	0.138	0.345	0	1
Rural banks	379130	0.385	0.487	0	1
Local Economic structure					
Share of secondary industry	379130	0.505	0.018	0.442	0.526
Share of tertiary industry	379130	0.455	0.028	0.384	0.484
GDP per capita (CNT Yuan)	379130	101248.9	29247.46	35484	129926

Table 4: Summary statistics, low polluting versus highly polluting Industries

This table compares the summary statistics of the key variables between low polluting and highly polluting industries for the sample period between Jan 2013 and Dec 2014. We report the summary statistics for the main outcome variable the lending spread – the percentage deviation of its lending rate from the benchmark rate; the loan-level characteristics including loan amount, maturity, and credit guarantee; the firm-level fundamentals of age and size; types and ownership of banks; and local economic structure and GDP per capita.

	Low polluting industry					Highly polluting industry				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Lending spread	294664	0.232	0.276	-0.4	2	84466	0.244	0.242	-0.4	2
Lending rate	294664	0.074	0.017	0.034	0.191	84466	0.074	0.015	0.034	0.18
Benchmark int. rate	294664	0.06	0.002	0.056	0.0655	84466	0.06	0.002	0.056	0.066
Default	283011	0.009	0.094	0	1	83660	0.011	0.107	0	1
Loan amount (CNY 10 thousand)	294664	901	2690	5	210000	84466	475	1160	5	93500
Maturity										
Short term	294664	0.922	0.268	0	1	84466	0.983	0.129	0	1
Medium term	294664	0.06	0.237	0	1	84466	0.014	0.119	0	1
Long term	294664	0.019	0.136	0	1	84466	0.003	0.051	0	1
Loan type										
Secured loan	294664	0.446	0.497	0	1	84466	0.445	0.497	0	1
Fiduciary loan	294664	0.03	0.171	0	1	84466	0.018	0.134	0	1
loan on guarantee	294664	0.388	0.487	0	1	84466	0.426	0.495	0	1
Pledged loan	294664	0.079	0.27	0	1	84466	0.072	0.259	0	1
Discount loan	294664	0.056	0.23	0	1	84466	0.039	0.192	0	1
Firm size										
Micro and small firms	294664	0.833	0.373	0	1	84466	0.886	0.318	0	1
Medium firms	294664	0.13	0.337	0	1	84466	0.094	0.292	0	1
Big firms	294664	0.037	0.189	0	1	84466	0.02	0.14	0	1
Company age (Years)	294664	10.42	5.94	1	60	84466	11.23	4.87	1	37
Bank type										
Big five	294664	0.356	0.479	0	1	84466	0.297	0.457	0	1
Joint-stock commercial banks	294664	0.137	0.344	0	1	84466	0.124	0.33	0	1
City commercial banks	294664	0.149	0.356	0	1	84466	0.1	0.3	0	1
Rural banks	294664	0.358	0.479	0	1	84466	0.479	0.5	0	1

Table 5: Clean Air Action and default

This table shows DID estimates of the effect of the Clean Air Action on the default of high polluting firms relative to low polluting firms. We trace the repayment status of loans granted during our post-treatment period up to March 2016. 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. *Action* is a dummy variable marking the post treatment period. All specifications contain loan, firm and macro-level controls. The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

VARIABLES	(1)	(2)	(3)
Action*	0.0026		
	(0.0024)		
Action*Treat	0.0052***	0.0053***	0.0058***
	(0.0008)	(0.0008)	(0.0008)
Treat	-0.0007	-0.0007	-0.0012**
	(0.0006)	(0.0006)	(0.0006)
Ln(Loan amount)	-0.0000	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0001)
Short-term loan	0.0099***	0.0098***	0.0046**
	(0.0020)	(0.0020)	(0.0020)
Medium-term loan	0.0076***	0.0076***	0.0047**
	(0.0021)	(0.0021)	(0.0021)
Fiduciary loan	0.0117***	0.0117***	0.0115***
	(0.0015)	(0.0015)	(0.0015)
Loan on guarantee	-0.0037***	-0.0038***	-0.0038***
	(0.0004)	(0.0004)	(0.0004)
Pledged loan	-0.0039***	-0.0039***	-0.0034***
	(0.0007)	(0.0007)	(0.0007)
Discount loan	-0.0061***	-0.0061***	-0.0059***
	(0.0008)	(0.0008)	(0.0008)
Small and Micro Enterprise	0.0060***	0.0060***	0.0059***
	(0.0008)	(0.0008)	(0.0008)
Medium-sized Enterprise	0.0018**	0.0017**	0.0018**
	(0.0008)	(0.0008)	(0.0008)
Firms age	-0.0008***	-0.0008***	-0.0008***
	(0.0001)	(0.0001)	(0.0001)
Firms age Sq.	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)
Collective Enterprise	0.0057***	0.0057***	0.0058***
	(0.0013)	(0.0013)	(0.0013)
Private Enterprise	0.0070***	0.0070***	0.0069***
	(0.0006)	(0.0006)	(0.0006)
Limited liability Enterprise	0.0112***	0.0112***	0.0110***
	(0.0005)	(0.0005)	(0.0005)
Incorporated Enterprise	0.0051***	0.0051***	0.0050***
	(0.0008)	(0.0008)	(0.0008)
Joint venture Enterprise	0.0110***	0.0111***	0.0108***
	(0.0010)	(0.0010)	(0.0010)
Foreign Enterprise	0.0094***	0.0094***	0.0091***
	(0.0009)	(0.0009)	(0.0009)
Other Enterprise	0.0042***	0.0043***	0.0042***
	(0.0009)	(0.0009)	(0.0009)
Share of secondary industry	0.8374***	-2.0556***	1.1906***
	(0.1619)	(0.5462)	(0.2242)
Share of tertiary industry	0.8766***	-2.6108***	1.2632***
	(0.1776)	(0.7212)	(0.2490)
Log(GDP per capita)	-0.0800***	0.2740***	-0.1161***
	(0.0172)	(0.0755)	(0.0241)
Benchmark interest rate	0.0033***	0.0033***	0.0032***
	(0.0008)	(0.0008)	(0.0008)
Year fixed effect	Y		
Bank fixed effect	Y		
Prefecture fixed effect	Y	Y	Y
Bank*year effect			Y
Prefecture∗year effect		Y	
Observations	366,671	366,671	366,671
R-squared	0.0136	0.0137	0.0156

Table 6: Clean Air Action and loan spread

This table shows DID estimates of the effect of the Clean Air Action on the loan spread of high polluting firms relative to low polluting firms. The dependent variable is loan spread. *Treat* is a dummy variable marking all firms belonging to the high-polluting industries targeted by the Clean Air Action. *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. The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* p < 0.10, ** p < 0.05, *** p < 0.01).

VARIABLES	(1)	(2)	(3)
Action	-0.1256***		
	(0.0047)		
Action*Treat	0.0127***	0.0123***	0.0115***
	(0.0014)	(0.0014)	(0.0014)
Treat	0.0007	0.0009	0.0010
	(0.0010)	(0.0010)	(0.0010)
Ln(Loan amount)	-0.0100***	-0.0100***	-0.0100***
	(0.0003)	(0.0003)	(0.0003)
Short-term loan	0.0470***	0.0468***	0.0403***
	(0.0040)	(0.0040)	(0.0040)
Medium-term loan	0.0071*	0.0070*	0.0034
	(0.0041)	(0.0041)	(0.0041)
Fiduciary loan	-0.0935***	-0.0936***	-0.0955***
	(0.0023)	(0.0023)	(0.0023)
Loan on guarantee	-0.0806***	-0.0806***	-0.0809***
	(0.0007)	(0.0007)	(0.0007)
Pledged loan	-0.1725***	-0.1724***	-0.1710***
	(0.0015)	(0.0015)	(0.0015)
Discount loan	-0.0961***	-0.0961***	-0.0960***
	(0.0020)	(0.0020)	(0.0020)
Small and Micro Enterprise	0.0707***	0.0707***	0.0709***
	(0.0022)	(0.0022)	(0.0021)
Medium-sized Enterprise	0.0111***	0.0111***	0.0124***
	(0.0022)	(0.0022)	(0.0022)
Enterprise age	-0.0004**	-0.0004**	-0.0004**
	(0.0002)	(0.0002)	(0.0002)
Enterprise age Sq.	-0.0000**	-0.0000**	-0.0000***
	(0.0000)	(0.0000)	(0.0000)
Collective Enterprise	0.0013	0.0014	0.0031
	(0.0046)	(0.0046)	(0.0046)
Private Enterprise	0.0139***	0.0139***	0.0153***
	(0.0033)	(0.0033)	(0.0033)
Limited liability Enterprise	0.0018	0.0018	0.0032
	(0.0032)	(0.0032)	(0.0032)
Incorporated Enterprise	-0.0311***	-0.0311***	-0.0294***
	(0.0039)	(0.0039)	(0.0039)
Joint venture Enterprise	-0.0305***	-0.0304***	-0.0297***
	(0.0036)	(0.0036)	(0.0036)
Foreign Enterprise	-0.0539***	-0.0539***	-0.0523***
	(0.0035)	(0.0035)	(0.0035)
Other Enterprise	0.0089**	0.0089**	0.0094**
	(0.0038)	(0.0037)	(0.0038)
Share of secondary industry	0.2416	-15.3263***	8.6960***
	(0.3888)	(1.1249)	(0.5721)
Share of tertiary industry	3.0117***	-18.4133***	9.8879***
	(0.4673)	(1.4604)	(0.6928)
Log(GDP per capita)	0.7656***	1.8804***	0.4334***
	(0.0334)	(0.1541)	(0.0484)
Benchmark interest rate	0.0306***	0.0305***	0.0303***
	(0.0017)	(0.0017)	(0.0017)
Year fixed effect	Y		
Bank fixed effect	Y	Y	
Prefecture fixed effect	Y		Y
Bank∗year effect			Y
Prefecture∗year effect		Y	
Observations	379,130	379,130	379,130
R-squared	0.4678	0.4679	0.4741

Table 7: Clean Air Action, default and loan spread by firm size

This table compares DID estimates of the Clean Air Action on the default and loan spread by the size of borrowing firms. The reference group is big firms. 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. *Action* is a dummy variable marking the post treatment period. We trace the repayment status of loans granted during our post-treatment period up to March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

		Default			Loan spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Action	0.0023			-0.1268***		
	(0.0024)			(0.0047)		
Treat	-0.0007	-0.0007	-0.0012**	0.0008	0.0010	0.0010
	(0.0006)	(0.0006)	(0.0006)	(0.001)	(0.001)	(0.001)
Action*Treat*Medium-sized Enterprise	0.0080***	0.0078***	0.0085***	0.0296***	0.0291***	0.0308***
	(0.0019)	(0.0019)	(0.0019)	(0.008)	(0.008)	(0.008)
Action*Treat*Small and Micro Enterprise	0.0132***	0.0130***	0.0150***	0.0495***	0.0493***	0.0536***
	(0.0015)	(0.0015)	(0.0015)	(0.0075)	(0.0075)	(0.0075)
Action*Treat	-0.0073***	-0.0070***	-0.0082***	-0.0338***	-0.0340***	-0.0387***
	(0.0015)	(0.0015)	(0.0015)	(0.0075)	(0.0075)	(0.0075)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	366,671	366,671	366,671	379,130	379,130	379,130
R^2	0.014	0.014	0.016	0.468	0.468	0.474
Adjusted R^2	0.013	0.014	0.015	0.468	0.468	0.474

Table 8: Clean Air Action, default and loan spread by bank size

This table compares DID estimates of the Clean Air Action on the loan spread and default by the ownership and size of lending banks. The reference group is small banks. 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. *Action* is a dummy variable marking the post treatment period. Big Five are the five largest state-owned commercial banks. JECBs refers to the joint equity commercial banks. We trace the repayment status of loans granted during our post-treatment period up to March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

		Default			Loan spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Action*Treat * Big Five	0.0045***	0.0045***	0.0022*	0.0162***	0.0161***	0.0111***
	(0.0013)	(0.0013)	(0.0013)	(0.0022)	(0.0022)	(0.0024)
Action*Treat * JECBs	0.0129***	0.0130***	0.0116***	0.0494***	0.0494***	0.0553***
	(0.0021)	(0.0021)	(0.0022)	(0.0029)	(0.0029)	(0.0031)
Action*Treat	0.0023***	0.0023***	0.0036***	0.0019	0.0016	0.0008
	(0.0008)	(0.0008)	(0.0009)	(0.0016)	(0.0016)	(0.0016)
Action	0.0024			-0.1263***		
	(0.0024)			(0.0047)		
Treat	-0.0008	-0.0009	-0.0012**	0.0003	0.0005	0.0011
	(0.0006)	(0.0006)	(0.0006)	(0.001)	(0.001)	(0.001)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	366,671	366,671	366,671	379,130	379,130	379,130
R^2	0.014	0.014	0.016	0.468	0.468	0.474
Adjusted R^2	0.014	0.014	0.015	0.468	0.468	0.474

Table 9: Clean Air Action, default and loan spread by local regulation stringency

This table compares DID estimates of the Clean Air Action 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 firms belonging to the high-polluting industries targeted by the Clean Air Action. *Action* is a dummy variable marking the post treatment period. We trace the repayment status of loans granted during our post-treatment period up to March 2016. The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

		Default			Loan spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Action*Treat*	0.001	0.0012	0.0006	0.0106**	0.0087**	0.0087**
high_regulated cities	(0.0017)	(0.0018)	(0.0017)	(0.0042)	(0.0043)	(0.0042)
ActionTreat	0.0043**	0.0042**	0.0053***	0.0032	0.0046	0.0038
	(0.0017)	(0.0017)	(0.0017)	(0.0042)	(0.0042)	(0.0042)
Action	0.0027			-0.1247***		
	(0.0024)			(0.0048)		
Treat	-0.0007	-0.0007	-0.0012**	0.0007	0.0009	0.001
	(0.0006)	(0.0006)	(0.0006)	(0.001)	(0.001)	(0.001)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	366,671	366,671	366,671	379,130	379,130	379,130
R^2	0.014	0.014	0.016	0.468	0.468	0.474
Adjusted R^2	0.013	0.014	0.015	0.468	0.468	0.474

Table 10: Clean Air Action, default and loan spread, cluster by industry

This table shows DID estimates of the effect of the Clean Air Action on the default and loan spread of high polluting firms relative to low polluting firms. 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. *Action* is a dummy variable marking the post treatment period (6 January 2014 and 31 December 2014). All specifications contain loan, firm and macro-level controls. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at bank level and reported in parentheses (* p < 0.10, ** p < 0.05, *** p < 0.01).

	Default			Loan spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Action * Treat	0.0052**	0.0053**	0.0058**	0.0127***	0.0123***	0.0115***
	(0.0025)	(0.0025)	(0.0024)	(0.0036)	(0.0038)	(0.0031)
Action	0.0026			-0.1256***		
	(0.0050)			(0.0137)		
Treat	-0.0007	-0.0007	-0.0012	0.0007	0.0009	0.001
	(0.0018)	(0.0018)	(0.0017)	(0.0032)	(0.0031)	(0.0033)
Ln (Loan amount)	-0.0000	-0.0001	-0.0000	-0.0100***	-0.0100***	-0.0100***
	(0.0005)	(0.0005)	(0.0005)	(0.0030)	(0.0030)	(0.0030)
Short-term loan	0.0099	0.0098	0.0046	0.0470***	0.0468***	0.0403**
	(0.0067)	(0.0067)	(0.0062)	(0.0162)	(0.0162)	(0.0174)
Medium-term loan	0.0076	0.0076	0.0047	0.0071	0.007	0.0034
	(0.0057)	(0.0057)	(0.0057)	(0.0171)	(0.0171)	(0.0174)
Fiduciary loan	0.0117**	0.0117**	0.0115**	-0.0935***	-0.0936***	-0.0955***
	(0.0046)	(0.0046)	(0.0045)	(0.0058)	(0.0058)	(0.0058)
Loan on guarantee	-0.0037***	-0.0038***	-0.0038***	-0.0806***	-0.0806***	-0.0809***
	(0.0010)	(0.0010)	(0.0010)	(0.0063)	(0.0063)	(0.0062)
Pledged loan	-0.0039***	-0.0039***	-0.0034***	-0.1725***	-0.1724***	-0.1710***
	(0.0012)	(0.0012)	(0.0012)	(0.0083)	(0.0084)	(0.0084)
Discount loan	-0.0061***	-0.0061***	-0.0059***	-0.0961***	-0.0961***	-0.0960***
	(0.0019)	(0.0019)	(0.0019)	(0.0075)	(0.0075)	(0.0075)
Small and micro enterprises	0.0060*	0.0060*	0.0059*	0.0707***	0.0707***	0.0709***
	(0.0032)	(0.0032)	(0.0031)	(0.0110)	(0.0110)	(0.0109)
Medium enterprises	0.0018	0.0017	0.0018	0.0111	0.0111	0.0124
	(0.0025)	(0.0025)	(0.0025)	(0.0084)	(0.0084)	(0.0084)
Firm age	-0.0008***	-0.0008***	-0.0008***	-0.0004	-0.0004	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0005)
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)
Collective enterprises	0.0057	0.0057	0.0058	0.0013	0.0014	0.0031
	(0.0037)	(0.0037)	(0.0038)	(0.0109)	(0.0108)	(0.0109)
Private enterprises	0.0070***	0.0070***	0.0069***	0.0139	0.0139	0.0153
	(0.0019)	(0.0019)	(0.0019)	(0.0121)	(0.0121)	(0.0122)
Limited liability enterprises	0.0112***	0.0112***	0.0110***	0.0018	0.0018	0.0032
	(0.0020)	(0.0020)	(0.0021)	(0.0112)	(0.0112)	(0.0112)
Incorporated enterprises	0.0051**	0.0051**	0.0050**	-0.0311**	-0.0311**	-0.0294**
	(0.0020)	(0.0020)	(0.0021)	(0.0144)	(0.0143)	(0.0142)
Joint venture enterprises	0.0110***	0.0111***	0.0108***	-0.0305**	-0.0304**	-0.0297**
	(0.0029)	(0.0029)	(0.0029)	(0.0133)	(0.0132)	(0.0133)
Foreign enterprises	0.0094***	0.0094***	0.0091***	-0.0539***	-0.0539***	-0.0523***
	(0.0027)	(0.0027)	(0.0026)	(0.0120)	(0.0120)	(0.0120)
Other enterprises	0.0042**	0.0043**	0.0042**	0.0089	0.0089	0.0094
	(0.0020)	(0.0020)	(0.0019)	(0.0124)	(0.0124)	(0.0124)
Share of secondary industry	0.8374***	-2.0556	1.1906***	0.2416	-15.3263***	8.6960***
	(0.2830)	(1.4850)	(0.4089)	(1.2182)	(3.3826)	(1.9008)
Share of tertiary industry	0.8766***	-2.6108	1.2632***	3.0117**	-18.4133***	9.8879***
	(0.3296)	(1.9881)	(0.4592)	(1.4335)	(4.5226)	(2.1944)
Ln (GDP per capita)	-0.0800*	0.274	-0.1161**	0.7656***	1.8804***	0.4334***
	(0.0441)	(0.2067)	(0.0494)	(0.0947)	(0.4769)	(0.1442)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	366671	366671	366671	379130	379130	379130
R^2	0.014	0.014	0.016	0.468	0.468	0.474
Adjusted R2	0.013	0.013	0.015	0.468	0.468	0.474

Table 11: Clean Air Action, default and loan spread, cluster by bank

This table shows DID estimates of the effect of the Clean Air Action on the default and loan spread of high polluting firms relative to low polluting firms. 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. *Action* is a dummy variable marking the post treatment period (6 January 2014 and 31 December 2014). All specifications contain loan, firm and macro-level controls. The lower part of the table denotes the type of fixed effects. Standard errors are clustered at bank level and reported in parentheses (* p < 0.10, ** p < 0.05, *** p < 0.01).

	Default			Loan spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Action * Treat	0.0052***	0.0053***	0.0058***	0.0127**	0.0123**	0.0115**
	(0.0017)	(0.0017)	(0.0017)	(0.0049)	(0.0049)	(0.0043)
Action	0.0026			-0.1256***		
	(0.0045)			(0.0427)		
Treat	-0.0007	-0.0007	-0.0012	0.0007	0.0009	0.001
	(0.0016)	(0.0016)	(0.0015)	(0.0044)	(0.0043)	(0.0038)
Ln (Loan amount)	-0.0000	-0.0001	-0.0000	-0.0100*	-0.0100*	-0.0100*
	(0.0008)	(0.0008)	(0.0008)	(0.0051)	(0.0051)	(0.0051)
Short-term loan	0.0099	0.0098	0.0046	0.047	0.0468	0.0403
	(0.0125)	(0.0125)	(0.0103)	(0.0405)	(0.0405)	(0.0379)
Medium-term loan	0.0076	0.0076	0.0047	0.0071	0.007	0.0034
	(0.0074)	(0.0074)	(0.0067)	(0.0286)	(0.0286)	(0.0277)
Fiduciary loan	0.0117	0.0117	0.0115	-0.0935***	-0.0936***	-0.0955***
	(0.0082)	(0.0082)	(0.0080)	(0.0250)	(0.0251)	(0.0256)
Loan on guarantee	-0.0037**	-0.0038**	-0.0038**	-0.0806***	-0.0806***	-0.0809***
	(0.0018)	(0.0018)	(0.0017)	(0.0268)	(0.0268)	(0.0268)
Pledged loan	-0.0039	-0.0039	-0.0034	-0.1725***	-0.1724***	-0.1710***
	(0.0034)	(0.0034)	(0.0034)	(0.0438)	(0.0438)	(0.0445)
Discount loan	-0.0061	-0.0061	-0.0059	-0.0961***	-0.0961***	-0.0960***
	(0.0042)	(0.0043)	(0.0042)	(0.0318)	(0.0318)	(0.0324)
Small and micro enterprises	0.006	0.006	0.0059	0.0707***	0.0707***	0.0709***
	(0.0042)	(0.0042)	(0.0042)	(0.0103)	(0.0103)	(0.0105)
Medium enterprises	0.0018	0.0017	0.0018	0.0111**	0.0111**	0.0124**
	(0.0025)	(0.0024)	(0.0025)	(0.0050)	(0.0050)	(0.0053)
Firm age	-0.0008***	-0.0008***	-0.0008***	-0.0004	-0.0004	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0011)	(0.0011)	(0.0011)
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)
Collective enterprises	0.0057**	0.0057**	0.0058**	0.0013	0.0014	0.0031
	(0.0024)	(0.0024)	(0.0024)	(0.0105)	(0.0105)	(0.0106)
Private enterprises	0.0070***	0.0070***	0.0069***	0.0139	0.0139	0.0153
	(0.0021)	(0.0021)	(0.0020)	(0.0116)	(0.0116)	(0.0115)
Limited liability enterprises	0.0112***	0.0112***	0.0110***	0.0018	0.0018	0.0032
	(0.0022)	(0.0022)	(0.0021)	(0.0112)	(0.0112)	(0.0112)
Incorporated enterprises	0.0051**	0.0051**	0.0050**	-0.0311**	-0.0311**	-0.0294**
	(0.0022)	(0.0022)	(0.0023)	(0.0133)	(0.0133)	(0.0129)
Joint venture enterprises	0.0110***	0.0111***	0.0108***	-0.0305**	-0.0304**	-0.0297**
	(0.0026)	(0.0026)	(0.0025)	(0.0137)	(0.0138)	(0.0134)
Foreign enterprises	0.0094***	0.0094***	0.0091***	-0.0539***	-0.0539***	-0.0523***
	(0.0024)	(0.0024)	(0.0023)	(0.0124)	(0.0124)	(0.0120)
Other enterprises	0.0042*	0.0043*	0.0042*	0.0089	0.0089	0.0094
	(0.0023)	(0.0023)	(0.0022)	(0.0112)	(0.0113)	(0.0116)
Share of secondary industry	0.8374**	-2.0556	1.1906**	0.2416	-15.3263	8.696
	(0.3241)	(1.5747)	(0.5496)	(5.1644)	(13.1714)	(8.3422)
Share of tertiary industry	0.8766**	-2.6108	1.2632**	3.0117	-18.4133	9.8879
	(0.3499)	(2.1340)	(0.5752)	(6.3762)	(16.7827)	(9.8880)
Ln (GDP per capita)	-0.0800**	0.274	-0.1161**	0.7656*	1.8804	0.4334
	(0.0377)	(0.2262)	(0.0541)	(0.4263)	(1.7584)	(0.6816)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	366671	366671	366671	379130	379130	379130
R^2	0.014	0.014	0.016	0.468	0.468	0.474
Adjusted R^2	0.013	0.013	0.015	0.468	0.468	0.474

Table 12: Clean Air Action, default and loan spread, lagged by 30 days

This table reports DID estimates on the effect of the Clean Air Action on the default and loan spread where the implementation time of the Action is lagged by 60 days. 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. The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* p < 0.10, ** p < 0.05, *** p < 0.01).

		Default			Loan spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Action lag(30)*Treat	0.0048***	0.0049***	0.0054***	0.0121***	0.0116***	0.0111***
	(0.0008)	(0.0008)	(0.0008)	(0.0014)	(0.0015)	(0.0015)
Action lag(30)	0.0009			-0.1289***		
	(0.0024)			(0.0049)		
Treat	-0.0010*	-0.0010*	-0.0016***	0.0008	0.0011	0.0009
	(0.0005)	(0.0005)	(0.0006)	(0.0010)	(0.0010)	(0.0010)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	342,665	342,665	342,665	360,059	360,059	360,059
R^2	0.014	0.014	0.016	0.464	0.464	0.471
Adjusted R^2	0.014	0.014	0.015	0.464	0.464	0.471

Table 13: Clean Air Action, default and loan spread, lagged by 60 days

This table reports DID estimates on the effect of the Clean Air Action on the default and loan spread where the implementation time of the Action is lagged by 60 days. 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. The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* p < 0.10, ** p < 0.05, *** p < 0.01).

		Default			Loan spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Action lag(60)*Treat	0.0053***	0.0054***	0.0062***	0.0116***	0.0110***	0.0107***
	(0.0008)	(0.0008)	(0.0008)	(0.0015)	(0.0015)	(0.0015)
Action lag(60)	0.0015	0.066	0.0061	-0.1319***		
	(0.0024)	(0.0638)	(0.0040)	(0.0050)		
Treat	-0.0009*	-0.0010*	-0.0015***	0.0008	0.0011	0.0008
	(0.0005)	(0.0005)	(0.0006)	(0.0010)	(0.0010)	(0.0010)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	347,012	347,012	347,012	347,012	347,012	347,012
R^2	0.013	0.013	0.015	0.462	0.463	0.470
Adjusted R^2	0.013	0.013	0.014	0.462	0.463	0.470

Table 14: Clean Air Action, default and loan spread, multiple-period DID analysis

This table reports the multiple period DID estimates on the effect of the Clean Air Action on the default and loan spread. 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. *Action* is a dummy variable marking the post treatment period (6 Jan 2014 and 31 Dec 2014). $Action1_t$, 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 lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

		Default			Loan spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Action1*Treat	-0.0026**	-0.0029***	-0.0031***	0.0024	-0.0038**	-0.0011
	(0.0011)	(0.0011)	(0.0011)	(0.0019)	(0.0019)	(0.0019)
Action*Treat air	0.0057***	0.0060***	0.0063***	0.0046***	0.0113***	0.0089***
	(0.0008)	(0.0008)	(0.0008)	(0.0015)	(0.0015)	(0.0015)
Treat	-0.0012**	-0.0014**	-0.0016***	0.0115***	0.0081***	0.0082***
	(0.0006)	(0.0006)	(0.0006)	(0.0011)	(0.0011)	(0.0011)
Action	-0.0005	0.0031*	0.0031*	0.0159***	0.005	0.0051
	(0.0004)	(0.0019)	(0.0019)	(0.0007)	(0.0035)	(0.0036)
Action1	0.0025***	-0.0009	-0.0009	-0.0148***	-0.0042	-0.004
	(0.0005)	(0.0018)	(0.0018)	(0.0009)	(0.0035)	(0.0035)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	428,043	428,043	4280,43	450,13	450,138	450,138
R^2	0.012	0.012	0.014	0.421	0.424	0.428
Adjusted R^2	0.012	0.012	0.013	0.421	0.424	0.428

Table 15: Clean Air Action, default and loan spread, panel data analysis I

This table reports DID estimates on the effect of the Clean Air Action on the default and loan spread 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. *Action* is a dummy variable marking the post treatment period (6 January 2014 and 31 December 2014). The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

		Default			Loan spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Action*Treat	0.0020***	0.0021***	0.0032***	0.0081***	0.0075***	0.0069***
	(0.0007)	(0.0007)	(0.0007)	(0.0015)	(0.0015)	(0.0015)
Action	0.0165***			-0.1015***		
	(0.0022)			(0.0050)		
Treat	0.0018***	0.0017***	0.0009**	0.0044***		
	(0.0004)	(0.0004)	(0.0004)	(0.0010)		
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	325437	325437	325437	325437	325437	325437
R^2	0.016	0.016	0.019	0.464	0.464	0.471
Adjusted R^2	0.016	0.016	0.019	0.464	0.464	0.471

Table 16: Clean Air Action, default and loan spread, panel data analysis II

This table reports DID estimates on the effect of the Clean Air Action on the default and loan spread 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. *Action* is a dummy variable marking the post treatment period (6 January 2014 and 31 December 2014). The lower part of the table denotes the type of fixed effects. Standard errors are reported in parentheses (* p < 0.10, ** p < 0.05, *** p < 0.01).

		Default			Loan spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Action*Treat	0.0012*	0.0013**	0.0023***	0.0052***	0.0050***	0.0043***
	(0.0006)	(0.0006)	(0.0006)	(0.0015)	(0.0015)	(0.0015)
Action	0.0150***			-0.0839***		
	(0.0023)			(0.0052)		
Treat	0.0012***	0.0012***	0.0006*	0.0034***	0.0035***	0.0039***
	(0.0003)	(0.0003)	(0.0003)	(0.0011)	(0.0011)	(0.0011)
Year fixed effect	Y			Y		
Bank fixed effect	Y	Y		Y	Y	
Prefecture fixed effect	Y		Y	Y		Y
Bank∗year effect			Y			Y
Prefecture∗year effect		Y			Y	
Observations	273211	273211	273211	273211	273211	273211
R^2	0.012	0.013	0.016	0.517	0.517	0.525
Adjusted R^2	0.012	0.012	0.015	0.517	0.517	0.525

8 Appendix

8.1 Model Equations and First-Order Conditions

8.1.1 Households

$$\max E_0 \sum_{t=0}^{\infty} (\beta)^t \left[\frac{c_t^{1-\sigma_c}}{1-\sigma_c} - \frac{v_L}{\eta} (L_t)^{\eta} \right], \tag{8.1}$$

subject to the following budget constraint:

$$c_t + d_t \leq w_t L_t + \frac{R_{t-1}}{\pi_t} d_{t-1} + F_t. \tag{8.2}$$

The household optimality conditions yield the following first−order conditions:

$$\{c_t\} : \lambda_t = c_t^{-\sigma_c} \tag{8.3}$$

$$\{d_t\} : \lambda_t = \beta E_t \left[\frac{R_t}{\pi_{t+1}} \lambda_{t+1} \right] \tag{8.4}$$

$$\{L_t\} : v_L (L_t)^{\eta-1} = w_t \lambda_t \tag{8.5}$$

8.1.2 Entrepreneurs

Re-write the entrepreneurs maximization problem by starting from the bank participation constraint:

$$R_t^L b_{e,t}^j = \left\{ (1-\mu^j) \int_0^{\bar{\omega}_{j,t+1}} \omega_{j,t+1}^i (1-\delta_h) q_{t+1}^{j,k} \pi_{t+1} k_{e,t}^j f_{t+1}(\omega_j^i) d\omega_j^i \right\} + \left\{ \int_{\bar{\omega}_{j,t+1}}^{\infty} R_{z,t+1}^j b_{e,t}^j f_{t+1}(\omega_j^i) d\omega_j^i \right\}, \tag{8.6}$$

Define

$$\Gamma_{t+1}(\bar{\omega}_{t+1}^j) \equiv \bar{\omega}_{t+1}^j \int_{\bar{\omega}_{t+1}^j}^{\infty} f_{t+1}(\omega_j^i) \omega_j^i + G_{t+1}(\bar{\omega}_{t+1}^j), \tag{8.7}$$

$$G_{t+1}(\bar{\omega}_{bj,t+1}) \equiv \int_0^{\bar{\omega}_{t+1}^j} \omega_{bj,t+1}^i f_{t+1}(\omega_{bj}^i) d\omega_{bj}^i \tag{8.8}$$

and

$$\bar{\omega}_{t+1}^j = \frac{b_{e,t}^j R_{z,t}^j}{(q_{t+1}^{j,k} \pi_{t+1} (1-\delta_k) k_{e,t}^j)} \tag{8.9}$$

Use 8.7, 8.8 and 8.9 to solve the bank participation constraint:

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

$$R^L_t b^j_{e,t} = (1-\mu^j)(1-\delta_h) q^{j,k}_{t+1} k^j_{e,t} \pi_{t+1} \left\{ \int_0^{\bar{\omega}_{j,t+1}} \omega^i_{j,t+1} f_{t+1}(\omega^i_j) d\omega^i_j \right\}$$
$$+ \bar{\omega}^j_{t+1} q^{j,k}_{t+1} \pi_{t+1} (1-\delta_k) k^j_{e,t} \left\{ \int_{\bar{\omega}_{j,t+1}}^{\infty} f_{t+1}(\omega^i_j) d\omega^i_j \right\},$$

$$R^L_t b^j_{e,t} = (1-\mu^j)(1-\delta_h) q^{k}_{t+1} k^j_{e,t} \pi_{t+1} \left\{ \int_0^{\bar{\omega}_{j,t+1}} \omega^i_{j,t+1} f_{t+1}(\omega^i_j) d\omega^i_j \right\}$$
$$+ \bar{\omega}^j_{t+1} q^{j,k}_{t+1} \pi_{t+1} (1-\delta_k) k^j_{e,t} \left\{ \int_{\bar{\omega}_{j,t+1}}^{\infty} f_{t+1}(\omega^i_j) d\omega^i_j + G_{t+1}(\bar{\omega}_{bj,t+1}) - G_{t+1}(\bar{\omega}_{bj,t+1}) \right\},$$

$$R^L_t b^j_{e,t} = (1-\mu^j)(1-\delta_h) q^{j,k}_{t+1} k^j_{e,t} \pi_{t+1} G_{t+1}(\bar{\omega}_{bj,t+1}) + q^{j,k}_{t+1} \pi_{t+1} (1-\delta_k) k^j_{e,t} [\Gamma_{t+1}(\bar{\omega}^j_{t+1}) - G_{t+1}(\bar{\omega}_{bj,t+1})],$$

$$R^L_t b^j_{e,t} = (1-\delta_h) q^{j,k}_{t+1} k^j_{e,t} \pi_{t+1} [\Gamma_{t+1}(\bar{\omega}^j_{t+1}) - \mu^j G_{t+1}(\bar{\omega}_{bj,t+1})] \tag{8.10}$$

Re-call the budget constraint:

$$c^j_{e,t} + X_t + q^{j,k}_t (k^j_{e,t} - (1-\delta_k) k^j_{e,t-1}) + w^j_t L^j_t + R^K_t k^j_{e,t} + [1 - F_{j,t}(\bar{\omega}^j_t)] R^j_{z,t-1} b^j_{e,t-1}$$
$$= Y^j_{e,t} + b^j_{e,t} - q^{j,k}_t (1-\delta_k) k^j_{e,t-1} G^j_t(\bar{\omega}^j_t),$$

and substitute the threshold value:

$$c^j_{e,t} + X_t + q^{j,k}_t (k^j_{e,t} - (1-\delta_k) k^j_{e,t-1}) + w^j_t L^j_t + R^K_t k^j_{e,t} + [1 - F_{j,t}(\bar{\omega}^j_t)] \bar{\omega}^j_{t+1} q^{j,k}_{t+1} \pi_{t+1} (1-\delta_k) k^j_{e,t}$$
$$= Y^j_{e,t} + b^j_{e,t} - q^{j,k}_t (1-\delta_k) k^j_{e,t-1} G^j_t(\bar{\omega}^j_t),$$

Let's define $[1 - F_{j,t}(\bar{\omega}^j_t)]\bar{\omega}^j_{t+1} = [\Gamma_{t+1}(\bar{\omega}^j_{t+1}) - G_{t+1}(\bar{\omega}_{bj,t+1})]$, and substitute in the previous expression:

$$c^j_{e,t} + X_t + q^{j,k}_t (k^j_{e,t} - (1-\delta_k) k^j_{e,t-1}) + w^j_t L^j_t + R^K_t k^j_{e,t} + [\Gamma_{t+1}(\bar{\omega}^j_{t+1}) - G_{t+1}(\bar{\omega}_{bj,t+1})] q^{j,k}_{t+1} \pi_{t+1} (1-\delta_k) k^j_{e,t}$$
$$= Y^j_{e,t} + b^j_{e,t} - q^{j,k}_t (1-\delta_k) k^j_{e,t-1} G^j_t(\bar{\omega}^j_t),$$

$$c^j_{e,t} + X_t + q^{j,k}_t (k^j_{e,t} - (1-\delta_k) k^j_{e,t-1}) + w^j_t L^j_t + R^K_t k^j_{e,t} + [\Gamma_{t+1}(\bar{\omega}^j_{t+1}) - G_{t+1}(\bar{\omega}_{bj,t+1}) + \mu^j G_{t+1}(\bar{\omega}_{bj,t+1}) - \mu^j G$$
$$= Y^j_{e,t} + b^j_{e,t} - q^{j,k}_t (1-\delta_k) k^j_{e,t-1} G^j_t(\bar{\omega}^j_t),$$

Finally, we obtain:

$$c^j_{e,t} + X_t + q^{j,k}_t (k^j_{e,t} - (1-\delta_k) k^j_{e,t-1}) + w^j_t L^j_t + R^K_t k^j_{e,t} + R^L_t b^j_{e,t} = Y^j_{e,t} + b^j_{e,t} - \mu^j G^j_t(\bar{\omega}^j_t) q^{j,k}_t (1-\delta_k) k^j_{e,t-1},$$

Re-write the maximization problem as:

$$\max E_0 \sum_{t=0}^{\infty} (\beta^e)^t \left[ln(c^j_{e,t}) \right] \tag{8.11}$$

subject to:

$$c^j_{e,t}+X_t+q^{j,k}_t(k^j_{e,t}-(1-\delta_k)k^j_{e,t-1})+w^j_tL^j_t+R^{j,K}_tk^j_{e,t}+R^L_tb^j_{e,t} = Y^j_{e,t}+b^j_{e,t}-\mu^jG^j_t(\bar{\omega}^j_t)q^{j,k}_t(1-\delta_k)k^j_{e,t-1},$$

$$b^j_{e,t} \le m^j_{e,t}\ E_t\frac{(q^{j,k}_{t+1}\pi_{t+1}(1-\delta_k)k^j_{e,t})}{R^L_t}, \tag{8.12}$$

and

$$M_t \le \Omega_{ng,t} - \varepsilon_{M,t} \tag{8.13}$$

where

$$Y^j_{e,t} = A_t(k^j_{e,t-1})^{\alpha}(L^j_t)^{1-\alpha-\gamma_j}X_t^{\gamma_j}. \tag{8.14}$$

The entrepreneurs' optimality conditions yield the following first−order conditions:

$$\{c^j_{e,t}\} : \lambda^j_{e,t} = (c^j_{e,t})^{-\sigma_c} \tag{8.15}$$

$$\{L^j_t\} : w^j_t = (1-\alpha-\gamma)\frac{Y^j_{e,t}}{L^j_t} \tag{8.16}$$

$$\begin{aligned}\{k_{e,t}\} : q^{j,k}_t\lambda^j_{e,t} = \beta^eE_t(R^{j,K}_{t+1} + (1-\delta_k)q^{j,k}_{t+1}(1-\mu G^j_t(\bar{\omega}^j_t))\lambda^j_{e,t+1}))+ \\ E_t(\Lambda^j_{e,t+1}m^j_{e,t+1}\tfrac{(q^{j,k}_{t+1}\pi_{t+1}(1-\delta_k))}{(R^L_{t-1})})\end{aligned} \tag{8.17}$$

$$\{\bar{\omega}^j_{t+1}\} : \beta_e\Lambda^j_{e,t+1}\mu^j\frac{\partial G^j_{t+1}(\bar{\omega}^j_{t+1})}{\partial\bar{\omega}^j_{t+1}} = \lambda^j_{e,t+1}\pi_{t+1}\frac{\partial m^j_{e,t+1}}{\partial\bar{\omega}^j_{t+1}} \tag{8.18}$$

$$\{E^g_t\} : 1 = (\gamma_g)\frac{Y^j_{e,t}}{E_t} \tag{8.19}$$

$$\{M^{ng}_t\} : 1 = (\gamma_{ng})\frac{Y^j_{e,t}}{M_t} + \Phi_t \tag{8.20}$$

where $\lambda^j_{e,t}$ is the lagrangian multiplier on entrepreneurs budget constraint, $\Lambda^j_{e,t}$ is the lagrangian multiplier on the participation constraint and Φ_t is the lagrangian multiplier on the pollution constraint.

8.1.3 Banks

$$\{d_t :\} \quad \frac{1}{c_{b,t}}[1-\Gamma_d] = \beta_bE_t(\frac{R_t}{c_{b,t+1}\pi_{t+1}}) + \mu^b_t \tag{8.21}$$

$$\{b_t :\} \quad \frac{1}{c_{b,t}}[1 + \Gamma_b] = \beta_b E_t(\frac{R_t^L}{c_{b,t+1}\pi_{t+1}}) + (1-\gamma)\mu_t^b \tag{8.22}$$