Bank deregulation and corporate environmental performance

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Bank Deregulation and Corporate Environmental Performance*

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Keywords: Environmental performance, Firm emission, Bank deregulation, Credit conditions.
JEL Classification: Q53, Q55, G21

Abstract

In this study, we provide one of the first evidence on the effects of bank deregulation on corporate environmental performance. We use a unique dataset that contains rich information on firms' toxic emissions and exploit bank branching deregulation in China. We find that the bank deregulation significantly improve firms' environmental performances, as measured by lower chemical oxygen demand (COD) emission intensity after deregulation. We further demonstrate that these firms' production efficiency increases and the ratio of tangible assets to total assets decreases, which suggests that upgrading technology and asset mix are the main channels. To improve the efficiency of the banking system, many developing countries are undergoing or moving toward liberalizing it. By focusing on firm environmental performance,

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1. Introduction

Banks play an important role in real economic activities by allocating and investing a society's savings. The literature offers ample evidence that a country's banking sector has significant effects on credit availability to firms, the operations of nonfinancial industries, and economy-wide growth.[1] Some studies have expanded the research agenda by including analysis of the banking sector's socioeconomic impacts. Beck, Levine, and Levkov (2010) find that bank deregulation alleviates income inequality by boosting incomes in the lower part of the income distribution. Célerier and Matray (2019) document the bank deregulation in US promotes financial inclusion for low-income populations and thus improve household wealth accumulation and financial security.

Environmental deterioration caused by pollution can have both economic and social consequences. Recently there is growing interest in delineating the role banks play in the environment. Some practitioners and policymakers point to banking sectors as a potential solution to environmental degradation and argue that banks could contribute to better environmental conditions by allocating resources to "green sectors." A key example is the burgeoning concept of green finance. A large number of banks, which account for about 80% of global lending volume, have adopted the Equator Principles and agreed to improve the environment by considering environmental issues in lending decisions (Chava, 2014). Others, however, assert that banks should be blamed for environmental problems. De Haas and Popov (2019) state that banks may fear that "funding new (and possibly cleaner) technologies erodes

[1] See, for example, reviews by Berger et al. (2004); Levine (2005); and Popov (2018).

the value of the collateral that underlies existing loans," and thus, in previous centuries, have financed the growth of less carbon-efficient industries.

Whereas an extensive body of research examines the impact of lowering regulatory barriers to bank competition with respect to how banks function and the overall economy, there is scarce evidence on how bank deregulation affects firms' environmental performance. This paper fills this gap by employing a unique dataset that contains rich information on firms' toxic pollutant emissions and exploiting a quasi-natural experiment—bank branching deregulation—in China, which is the largest bank loan market worldwide (Gao et al., 2019). China has undergone rapid and large-scale economic expansion in the wake of economic reforms. However, its economic growth has also rendered it the largest polluter in the world (Jiang, Lin, and Lin, 2014). This offers an opportunity to examine how the banking sector affects firm environmental performance in developing countries that are undergoing banking liberalization.

Prior theoretical and empirical literature suggests that bank deregulation can improve corporate credit conditions. Better credit conditions, in turn, could lead to less toxic discharge by firms through at least three channels. First, improved credit conditions would increase firms' investment in pollution abatement activities and therefore reduce toxic emissions (Xu and Kim, 2021). Second, loosened credit conditions would increase the probability of firms' upgrading their technology and raising production efficiency (Andersen, 2016), and the reduction of toxic emissions is a byproduct of such technological changes (Gutiérrez and Teshima, 2018). Third, improved credit conditions would lead to the use of less tangible assets as loan collateral, which would result in less firm pollution (Andersen, 2017).

To investigate how bank deregulation affects corporate environmental performance, we use China's 2009 deregulation policy on bank branching, which significantly and suddenly lowers barriers to competition. Before 2009, joint-equity banks in China were not allowed to freely establish branches, while the five state-owned banks faced no such restrictions. The 2009 deregulation removed the restriction whereby joint-equity banks could not establish new branches in cities in which they didn't already have branches. The deregulation increased competition between joint-equity banks and state-owned banks and increased lending to corporate borrowers (Gao et al., 2019). Cities with greater numbers of branches concentrated in state-owned banks ex ante have greater exposure to the shocks, and such cross-city variation in exposure to the deregulation shock allows us to identify the causal effects of bank deregulation on corporate environmental performance.

We find that the bank deregulation significant improve firms' environmental performances, that is, firms that are more exposed to the banking deregulation reduce their emission intensity more significantly after the shock than firms with lower exposure, and the observed pattern is consistent with various robustness tests. These results suggest a potential and unanticipated benefit of bank deregulation from the perspective of firms' environmental performance. We further investigate the channels through which bank deregulation would affect firms' environmental performance. First, we investigate firms' investment in pollution abatement activities. We find that in our sample of Chinese firms, firms have not significantly increased their abatement expenditure. Second, we examine how firms' production technologies change after bank deregulation. We find that treated firms experience an increase in production efficiency and a higher level of innovation. As Gutiérrez and Teshima (2018)

demonstrate, upgrading technology can simultaneously trigger a decrease in abatement expenditure and less pollutant discharge in Mexico after trade liberalization. Finally, we test the asset mix channel proposed by Andersen (2017). Consistent with his theoretical model and empirical evidence, we find that firms more exposed to the shock reduce their tangible assets ratio, which is considered to be the main contributor to firm pollution. Our results suggest that the asset mix channel contributes to the relation between bank deregulation and firm environmental performance in China.

Our study mainly contributes to the small and growing literature that examines the effect of firm financial status on firms' environmental performances. The evidence is limited with mixed conclusions. Xu and Kim (2021) find that relaxing financial constraints reduces U.S. public firms' toxic releases; Levine et al. (2019) uses plant level data from the Toxic Release Inventory dataset in the US and demonstrate that the positive shock to credit availability arising from the discovery of shale gas reduces firms' toxic emissions. Akey and Appel (2021) show that stronger liability protection for parents leads to lower investment in abatement technologies, and thus a 5% to 9% increase in toxic emissions by subsidiaries. Andersen (2017) develops a theoretical model and provides empirical evidence that credit constraints can have an impact on firms' toxic emissions through overinvestment in fixed assets.

Our study differentiates from the literature in three ways: First, while most studies focus on firms in the US, our study contributes to the literature by providing one of the first evidence about financial status and environmental performance in developing economies in which the finance and legal institutions are substantially different from developed economies. Second, taking advantage of the comprehensive and unique information from the firm level pollution

dataset, we provide novel and comprehensive evidence about the mechanism through which financial conditions play roles. Third, we use a bank deregulation reform in China as an exogenous shock to firms' credit constraints, so that we can have an identification to document a causal relationship between firm financial constraints and environmental performance. In addition, given that many developing economies are undergoing or moving toward banking liberalizing, our study also provides policy implications for those reforms from the perspective of environmental performance.

More broadly, our study is related to the literature on the consequences of bank deregulation that triggers greater bank competition. Prior studies demonstrate that bank deregulation has effects not only on the banking industry itself, but on economy-wide growth. It could affect the economy by altering firm credit conditions (Berger et al., 2004; Levine, 2005; Popov, 2018), the ability to conduct innovation (Chava et al., 2013; Hombert and Matray, 2017) and many other channels. There is also growing interest to investigate the effect of banking on social economic consequences. For example, the recent study by Fonseca and Matray (2021) shows that banking deregulation in developing countries like Brazil fosters firm creation and firm expansion, leading to increasing labor demand and higher wages. We contribute to the literature by providing new evidence that the bank competition caused by bank deregulation would help firms invest in upgrading technology and holding a lower level of tangible assets, actions that can improve corporate environmental performance. In addition, to our knowledge, ours is one of the first studies to demonstrate the benefits of bank deregulation in China and provide an opportunity to evaluate liberalization of the banking sector in a more holistic way by considering its socioeconomic consequences.

The rest of the paper is organized as follows. In Section 2, we review the literature and develop our hypotheses. In Section 3, we briefly describe China's banking system and our identification based on the banking deregulation policy. In Section 4, we present variable construction, data sources, and summary statistics. In Section 5, we provide the main regression results, and in Section 6 we test for potential mechanisms. We conduct robustness tests in Section 7 and conclude in Section 8.

2. Hypothesis development

Bank deregulation could increase bank competition and improve borrowers' credit conditions, which could lead to a reduction of corporate toxic discharges through at least three channels. First, the loosened credit conditions caused by bank deregulation could induce firms' investment in pollution abatement, and therefore reduce toxic emissions. Xu and Kim (2021) exploit three quasi-natural experiments that reduce firms' financing cost, and find that relaxing financial constraints reduces U.S. public firms' pollutant discharge by lowering the marginal cost of environmental abatement. Goetz (2019) exploit heterogeneity in US firms' exposure to the Federal Reserve's maturity extension program (MEP), which lowers the cost of long-term debt financing, and find that firms with higher exposure to the MEP shock boost their investment in emission reduction activities, especially capital–intensive pollution control activities.

Second, firms with improved financial conditions could reduce emissions as a byproduct of upgrading technologies. Andersen (2016) provides cross-country-level evidence that credit constraints and technology upgrading interact and affect pollution levels. Gutiérrez and

Teshima (2018) argue that technology upgrading can indirectly affect firms' environmental performance. They provide evidence that the increasing import competition in Mexico leads to technological changes, which cause local firms to increase energy efficiency and reduce toxic emissions. They emphasize that when evaluating the effect of policies on the environment, it is important to investigate abatement expenditure and pollutant discharges simultaneously. In their setting, they find that the import competition triggered by free trade agreements leads to lower abatement expenditure but less toxic emissions. If only abatement expenditure had been examined, one would have been tempted to conclude that import competition affects the environment negatively. Levinson (2009) and Fan et al. (2019) also provide empirical evidence that technology upgrading contributes to lower pollutant discharge and thus a cleaner environment in US and China, respectively.

Third, improved financing conditions after bank deregulation could reduce firm toxic emissions through the asset mix channel, as proposed by Andersen (2017). He develops a theoretical model and empirically shows that credit constraints distort firms' asset composition toward overinvestment in tangible assets that can be pledged as collateral. Because pollutant emissions are positively related to the share of tangible assets, Andersen shows that a tangible assets-oriented asset mix would lead to a higher level of pollutant emissions.

Collectively, the pollution abatement investment channel, the upgrading technologies channel and the asset mix channel suggest that bank deregulation would lead to better corporate performance:

Hypothesis: Bank deregulation leads to a lower intensity of pollutant discharge.

3. Institutional Background

3.1. China's banking system

Before the 1978 economic reforms, the People's Bank of China (PBOC) was the only bank in China. It functioned as both the central bank and a commercial bank. After the economic reform, the PBOC began to concentrate on its central banking role, and four large commercial banks—the Agriculture Bank of China (ABC), People's Construction Bank of China (PCBC), Bank of China (BOC), and Industrial and Commercial Bank of China (ICBC)—started to take over the PBOC's commercial banking business. In 1986, another major state-owned bank, the Bank of Communications (BOCOM), was established, thus transforming the "Big Four" into the "Big Five." Following Gao et al. (2019) and Zhu and Yang (2016), we classify these banks as the Big Five commercial banks in China that are directly controlled by the state. The Big Five are the first-tier banks in China's banking industry, and owned almost 45% of banking assets in 2013[2].

Between 1988 and 2005, twelve nationwide joint-equity banks were established. They are owned jointly by the government, the private sector, and foreign investors. Different from the Big Five, these 12 joint-equity banks are controlled by state-owned enterprises (SOEs) rather than being directly controlled by the central government. In addition, they operate on a smaller scale and usually focus on local businesses, in constrast to the Big Five. These joint-equity banks constitute the second tier in China's banking system, and owned almost 18% of banking assets in 2013.

[2] The share of banking assets is collected and reported by the China Banking and Insurance Regulatory Commission (CBIRC), and similarly hereinafter.
http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=28621&itemId=954&generaltype=0

A number of smaller banks in urban areas, known as city commercial banks, started to develop in late 1980. They mainly provide commercial banking services to local small and medium-sized enterprises. Most were restructured from urban credit cooperatives, and are controlled by provincial or city-level governments and local SOEs. They account for approximately 10% of total markets.[3] City commercial banks and other types of banks (e.g., solely foreign banks and rural banks) constitute third-tier banks and accounted for less than 40% of all markets in 2013.

3.2. China Banking and Insurance Regulatory Commission regulation of bank branches

Since we exploit the China Banking and Insurance Regulatory Commission's (CBRC) 2009 deregulation of new branches for joint-equity banks as a quasi-experimental shock to firms' credit conditions, in this section we briefly describe the policy's background. Before 2009, bank branching was heavily regulated. Although not prohibited, joint-equity banks and city banks faced great regulatory costs to establish branches in cities in which they did not already have branches. The turnaround time for each application was 1 year or even longer (Gao et al., 2019), and a bank can only apply for one branch at a time. In contrast, the Big Five faced no such restrictions. In April 2009, the CBRC introduced Action Order [143], "Adjustment comment on the market access policy of setting up branches for small- and medium-sized commercial banks," which removed the restriction on setting up new branches in new cities for joint-equity banks. This has two main effects. First, joint-equity banks can freely open branches in a city in which they already have branches. Second, joint-equity banks are permitted to freely enter all cities in a province in which they have branches in the capital city of

[3] As we will explain in Section 4.2., our sample firms are from Annual Surveys of Industrial Firms (ASIF), which contain firms with annual sales above 5 million CYN. They are relatively large and are target clients of joint-equity banks rather than city commercial banks.

the province.

Similar to the deregulation of interstate banking and interstate branching in the US, the removal of branching prohibitions increases competition between banks. Joint-equity banks expanded rapidly, while the Big Five banks' market share declined across the nation. Figure 1 shows the heat map of Big Five bank concentration (*BIG5%*) across prefecture-level cities. *BIG5%* is measured by the proportion of outstanding branch number of Big Five state-owned commercial banks in each city. As can be seen in Figure 1, the concentration of Big Five branches decreases sharply after the shock.

3.3. Identification strategy

The bank deregulation increases competition between state-owned and joint-equity banks. Fiercer market competition results in an increase in the supply of bank credit, and thus eases credit conditions for corporate borrowers. Gao et al. (2019) document empirical evidence that this deregulation policy leads to an increase of 31.2% in lending by joint-equity banks. Although it is a one-time shock, we attempt to exploit city-level heterogeneous exposure to the deregulation. Because the deregulation allows joint-equity banks to establish branches as freely as state-owned banks, the effect of deregulation on banks and firms would be more prominent in cities more dominated by state-owned banks before the shock.

One concern that may weaken our identification strategy is cross-regional bank lending—i.e., firms can borrow from banks outside the cities in which they operate. However, cross-regional bank lending is uncommon in China. The cross-regional flow of bank credit resources is strictly prohibited owing to the administrative barriers of China's jurisdictions and the branch

system for commercial banks in China. Firms' regional location is still one of the most important factors in determining credit availability.

We employ a difference-in-differences (DID) setting to exploit the effects of bank deregulation on firms' environmental performance.[4] We construct a continuous city-level treatment variable, *Exposure*, in two steps. First, we search for all cities not affected by the deregulation. According to the details of Action Order [143], if any of the 12 joint-equity banks already had branches in a city, or had branches in the capital of the province in which the city was located before the shock, then the city is treated as a deregulated city—that is, affected by the shock. The remaining cities are therefore unaffected. Based on information on the 12 joint-equity banks' branches established before April 16, 2009, only four provinces (Guizhou, Ningxia, Qinghai, and Tibet) did not have a joint-equity bank in their capital city and were still highly restricted at the end of the sample period, which can also be seen in Figure 1. Firms in these cities have *Exposure* equal to 0, indicating that they are fully isolated by deregulation.

Second, we exploit cross-city variation in the branching deregulation as a positive shock to bank competition. For deregulated cities, we measure their heterogeneous exposure to the deregulation by using the shares of state-owned banks before the shock. Since the removal of the bank branching restriction intensifies competition between joint-equity banks and state-owned banks, exposure to the deregulation would be higher for cities with higher market shares of state-owned banks ex ante. Gao et al. (2019) explore the heterogeneity across cities and document that the effect of deregulation on bank lending and firm access to capital is stronger in cities with less banking competition ex ante. Based on information on all bank branches

[4] We are not the first to exploit this policy shock; Gao et al. (2019) document increasing bank sector competition and corporate lending after the shock.

established just before implementation of the policy (i.e., April 16, 2009), we construct the variable *BIG5%*—i.e., the concentration ratio of the Big Five state-owned commercial banks. This is measured by the proportion of branches of Big Five banks in each city. A higher value of *BIG5%* indicates greater exposure to the policy shock. To conclude, the variable *Exposure* equals *BIG5%* for all deregulated cities, and zero for all unaffected cities.

3.4. Regression model

We apply a DID regression specification:

(1)

where *i*, *c*, *t* denote firm *i*, prefecture-level city *c*, and year *t*, respectively. is firms' toxic emission intensity. *Exposure* is the city-level continuous treatment variable. As discussed in Section 3.3, this equals the market share of Big Five banks in affected cities and zero for unaffected cities. takes a value of one for year 2009 and subsequent years and zero otherwise.

We control for standard firm and city characteristics () and a set of fixed effects. represents firm fixed effects, which capture all firm-specific and time-invariant characteristics; represents year fixed effects, which control for all nationwide shocks common to cities in a given year. The normally distributed error term is denoted by . Standard errors are robust and clustered at city-by-year level to allow for an arbitrary variance-covariance matrix within a city in a given year.

The interaction term is the variable of interest. Its coefficient β_1 captures the change in the toxic emission intensity of firms after 2009 in cities with higher exposure to the branching deregulation relative to firms in cities with lower exposure. A negative value of β_1 indicates relatively lower toxic emission intensity after the deregulation for treated firms.

4. Data and variables

4.1. Variable construction

We measure corporate environmental performance by using the emission intensity of water pollutants, which is measured by the chemical oxygen demand (COD) emissions per unit of output value at constant price. COD is a commonly used and representative measurement of water pollution in environmental chemistry that measures the oxygen required to oxidize soluble and particulate organic matter in water (Kahn, Li, and Zhao, 2015). As reported by Zhang, Chen, and Guo (2018), compared with other indicators of firm pollution, COD emitted by most industrial firms has become a key indicator under routine monitoring in China. The data quality of COD emissions is guaranteed by the central supervision and strict regulation by the government during our sample period. Therefore, COD emissions is a relatively good measure for corporate environmental performance for our sample firms. We follow prior literature and use COD to measure firm toxic pollution (Zhang, Chen, and Guo, 2018; He, Wang, and Zhang, 2020).

We include two sets of control variables that prior literature identifies as important determinants of firm toxic emissions. Our first set of control variables includes measures of firm characteristics (Pargal and Wheeler, 1996; Cole, Elliott, and Shimamoto, 2005; Jiang, Lin, and Lin, 2014) that could influence firms' credit conditions and environmental performance at the same time. These include firms' age (*Age, Age^2*), an indicator for state-owned firms (*SOE*, equal to one for state-owned firms and zero otherwise), and an indicator for abatement equipment (*Equipment*, equal to one if the firm possesses at least one piece of equipment to

abate wastewater and zero otherwise). Our second group of controls contains some predetermined controls—the interactions between some city-specific characteristics in 2008 and the post-2009 dummy—to alleviate confounding effects owing to other city-specific characteristics. The ex ante characteristics of prefecture-level cities in 2008 (i.e., 1 year before the shock) mainly capture local economic and financial developments and include the city's GDP in 2008 (*Citygdp2008*, measured in 10,000 CHY), population density in 2008 (*Citypopdensity2008*, persons to the unit square kilometer), and the loan balance and deposit balance of financial institutions at the end of 2008 (*Cityloan2008* and *Citysaving2008*).

4.2. Data sources

4.2.1. Toxic emissions data

Firm-level pollution information comes from the proprietary Environmental Survey and Reporting (ESR) database[5], which is administered annually by the Ministry of Environmental Protection (MEP). It is recognized as the most extensive nationwide micro-dataset in China's environmental economy. All ESR data are self-reported by firms and compiled by the MEP.[6] The data's reliability is guaranteed by the MEP's strict data quality standards; in particular, the local (usually county-level) environmental protection bureau ensures data quality by conducting monitoring activities and unannounced field inspections. The ESR collects annual data for 39 two-digit NSIC industries, and primarily contains information on each firm's name, location, production, usage of energy and resources, emissions, and abatement of major toxic pollutants (e.g., COD, NH_3-N and SO_2). We concentrate on the manufacturing sector in our

[5] Some recent studies have started to use this dataset (He, Wang, and Zhang, 2020; Liu et al., 2021; Zhang, Chen, and Guo, 2018). He, Wang, and Zhang (2020) argue that firms in the ESR database have little incentive to misreport their emission records.

[6] All firms within each county are first ordered from highest to lowest according to their annual discharge of COD and NH_3; also, those that account for 85% of the annual county-level emissions of at least one pollutant are included in the ESR.

analysis, and mainly use information from this dataset on the emissions, yield, and removal of COD (measured in kilograms); output value; number and capacity of wastewater abatement equipment; emissions of other pollutants; ownership type; district code; industry classification; and so forth.

4.2.2. Firm characteristics

Information on firm-level characteristics comes from the Annual Surveys of Industrial Firms (ASIF) conducted by the National Bureau of Statistics of China (NBS). This is a comprehensive database of industrial production widely used by China's microeconomics researchers (He, Wang, and Zhang, 2020). This annual survey covers all industrial firms in China with annual sales above 5 million CYN (about $714,000 USD). The surveys cover more than 40 two-digit NSIC industries. The database contains rich information (with more than 100 variables) on firms' basic characteristics, production, and finances, mainly from firms' balance sheets, income statements, and cash-flow statements. From this database, we extract the birth year, ownership category, industry classification, total assets, total debts, interest expense, etc. In addition, we delete observations with extreme values for output, total assets, total debt, age, or employment.[7] To create the panel data, we match the database from the ESR and the ASIF via a firm's Chinese name and numerical ID, and 48.4% of observations in the ESR from 2004 to 2013 are successfully matched.

4.2.3. Bank branch information

To identify the cities affected by the bank branching deregulation and the extent to which they are exposed to the deregulation, we collect information on bank branches. We obtain

[7] We delete observations with output measured by present price above 5 billion RMB, total assets below zero or above 5 billion RMB, total debts below zero or above 3 billion RMB, age below zero or above 100, and employment below 1 or above 5,000.

financial licensing information on all bank branches in China from the CBRC.[8] The dataset contains branch-level information including agency code, full name, and exact approval date of establishment. According to the coding rule, we can learn about the organization type and the prefecture-level city in which the branch is located from the agency code, and further calculate the outstanding branch number for each bank for each city in each year. Taking into account the special nature of corporate loans from some types of financial institutions—such as policy banks, rural cooperative banks, and credit cooperative banks—we only retain a sample of bank branches of commercial banks in the analysis.

4.3. Summary statistics

After winsorizing all continuous variables at the 1% level in both tails, our final sample consists of 179,367 firm-year observations over the period 2004-2013, with 41,838 unique firms. Table 1 presents summary statistics for the main pollution variables (firms' emissions, yields, removals and emission intensity of COD), the regressor of interest (interaction between city's exposure to the deregulation and the post-2009 dummy), and a set of control variables and other variables used in mechanism analysis and robustness tests.

The mean value of firms' COD emission intensity after log transformation is -0.2645, which amounts to 0.7676 kilograms of COD emissions per 1,000 CHY of output value. The mean of firms' COD emissions after log transformation is 8.4524, which amounts to 4,686.31 kilograms. The mean value of *BIG5%* is 0.4840. Put differently, the Big Five state-owned commercial banks account for nearly half the total, on average, in our sample. The minimum *BIG5%* is 0.1235 (Ankang, Shaanxi province) and the maximum is 0.8386 (Zhongshan,

[8] The raw data in this dataset can be retrieved from http://xukezheng.cbrc.gov.cn/ilicence.

Guangdong province).[9] Only 911 firm-year observations are totally unexposed to the deregulation, and the rest—178,456 observations—have been affected to various degrees. The mean value of the treatment variable *Exposure* and the interaction term are 0.4814 and 0.2490, respectively.

5. Regression results

5.1. Main results

5.1.1. Baseline estimate

Table 2 reports estimates of the interactive term between the city's degree of exposure to the shock and the post-2009 dummy of Equation (1). All specifications include firm fixed effects, year fixed effects, and predetermined controls.[10] Column 2 adds firm-level control variables, as detailed above. Column 3 further controls for 2-digit industry by year fixed effects to address the concern about unobservable industrial differences in a particular year that may be correlated with the potential degree of exposure to the shock; for example, variations in industrial price.

The coefficient of interest, β_1 (i.e., the coefficient on the interaction between cities' degree of exposure to the shock and the post-2009 dummy) is negative and significant across the three regressions. This suggests that compared with their counterparts, firms located in cities with higher exposure to the banking deregulation tend to reduce COD emission intensity more after the policy.

[9] Of all prefecture-level cities in China, the one with the largest BIG5% is the Naqu region, Tibet province, whose BIG5% is 0.9740. However, our sample does not include firms located in Tibet province.
[10] We exclude firms that moved to a different prefecture-level city during sample period, and they make up only 0.16% (287 out of 179,654) of the total sample.

5.1.2. Economic magnitude

To gain a more intuitive understanding of the magnitude of emission intensity reduction that resulted from banking deregulation, we use the estimated coefficients to interpret this effect. Using the estimates in column 3 of Table 2 (-0.4075) to calculate the economic magnitude, we find that an additional 10-percentage-point increase in exposure to the policy shock decreases firms' annual emission intensity of COD by 4.075% following banking deregulation. Considering that the average annual COD emission intensity of sample firms before the shock is 30.50 kilograms per 1,000 CHY, this magnitude would imply a decrease of roughly 1.24 kilograms per 1,000 CHY of output value.

After introduction of the bank deregulation policy, firms in the city with the maximum exposure to the shock (Zhongshan, Guangdong province) experienced a 29.14% (-0.4075*(0.8386-0.1235)) higher rate of decline in average COD emissions compared with that of firms in the city with the minimum exposure (Ankang, Shaanxi province).

To summarize, these regression results suggest that the banking deregulation helps to improve firms' environmental performance significantly, and the magnitude of the reduction in emission intensity is substantial.

5.2. Pre-trend tests

The validity of the DID estimation depends on the following parallel trends assumption: In the absence of the deregulation shock, treated firms' pollutant discharge would have evolved in a manner similar to that of control firms. This assumption requires that pollutant discharge exhibit a similar trend for firms with different degree of exposure to the shock during the pre-treatment period. Following the method of Hong and Kacperczyk (2010), we present results

from examination of the pre-treatment trend in Figure 2. Specifically, we estimate the following regression:

(2)

The parameter identifies the differences between firms located in cities with different degrees of exposure to the shock in year *t*. This allows us to detect the preexisting trend and examine the evolving pattern of differences in emissions across cities year by year relative to 2008, the year just before the shock.

Figure 2 reports the results. We observe that the coefficients on variables from *exposure* × *year2004* to *exposure* × *year2007* are close to zero and not statistically significant. This suggests that the parallel trends assumption of the DID approach is not violated. The impact starts to show up from the deregulation year and continues to the following years: The coefficients on *exposure* × *year2009* to *exposure* × *year2013* variables become significantly negative. Overall, Figure 2 shows that firms with different exposure share a similar trend in pollutant discharge prior to the impact of branching deregulation, and thereby support the parallel trends assumption associated with the DID estimation.

6. Mechanism

In this section, we first document evidence that the bank deregulation shock truly improves firms' credit conditions. We then investigate the three channels we describe in Section 2.

6.1. The effects of deregulation on firms' credit conditions

Our argument is based on the premise that the bank deregulation increases bank competition and thus eases borrowers' credit constraints, and we directly examine this issue in

three steps. First, we show that the outstanding branch number of joint-equity banks increases more after the deregulation shock in the cities with higher degree of exposure. It provides direct evidence that the regulation change reshapes the competitive environment between joint-equity and state-owned banks. Second, we explore whether firms more exposed to the shock experience larger decreases in financing cost after the shock compared with less-exposed firms. Finally, we use a difference-in-difference-in-difference (DDD) setting to investigate whether firms facing more stringent credit constraints before the shock respond more strongly to the bank deregulation.

6.1.1. The bank deregulation and the expansion of joint-equity banks

Since the bank deregulation is intended to loosen restrictions on opening branches for joint-equity banks, we would expect that the number of branches of joint-equity banks would increase more after the shock in policy-affected cities. Table 3 reports the results. In column 1, the dependent variable is the number of branches of joint-equity banks per capita (*no. joint equity banks per capita*), which is measured by the total number of branches for 12 joint-equity banks scaled by the corresponding city-level population in each year. It shows that the coefficient of the interaction term *Exposure* × *Post2009* is positive and significant, which indicates a boom in establishing branches by joint-equity banks after the deregulation shock.

In column 2 we investigate the change in the number of branches of the Big Five state-owned banks. We find that the coefficient of the interaction term *Exposure* × *Post2009* is not significant, which implies that the number of branches of these banks (*no. big5 banks per capita*) barely changes. In column 3, we change the dependent variable to the number of all other banks per capita (*no. all other banks per capita*). We can observe that the coefficient of

the interaction term *Exposure* × *Post2009* is still insignificant. Collectively, the results show that the joint-equity banks grow faster than state-owned banks and other types of banks after the deregulation.

6.1.2. The effects of deregulation on firms' financing cost

We then explore whether firms more exposed to the shock experience a deeper drop in financing cost.

Based on our sample of firms, we employ two measures to examine the general effects of deregulation on firms' credit conditions. Following Gao et al. (2019), we construct the first variable, *Ln credit cost*, which is calculated as the logarithm of firm interest expense scaled by total debts. This is used to measure firms' average cost of credit. The second measure is the proxy for firm financial expense, *Ln financial expense rate*. This is calculated as the logarithm of the ratio of firm financial expenses to its prime operating revenues—a commonly used index in China to analyze the financial burden of a firm.

According to the results reported in columns 4 and 5 of Table 3, the coefficients of the interaction term *Exposure* × *Post2009* are significantly negative, which indicates lower average cost of credit and less interest expense for firms more exposed to the shock. This provides evidence of improved credit conditions after banking deregulation. These results are in line with those of Gao et al. (2019), who find that the bank deregulation leads to the expansion of joint-equity banks and improvement in firm credit conditions.[11]

6.1.3. Cross-sectional variation in firm credit conditions

[11] Using propriety data on bank loans, Gao et al. (2019) measure firm credit conditions by using the amount of loans in addition to the interest rate, and find that the quantity of loans also increases after the shock.

If changes in credit conditions indeed affect firms' toxic emissions, then the impact of deregulation would be relatively greater for firms with lower borrowing ability and more financial dependence before the shock. Therefore, in this section we exploit the cross-sectional variation in firms' borrowing ability and financial dependence, respectively, by conducting a DDD analysis.

We first use the cost of credit (measured by *Interest expense/Total debts*) in the year before the shock to proxy for firms' borrowing ability. We construct a dummy variable, *Highcost*, which equals one if the firm's average cost of credit is above the sample median before the shock and zero otherwise.

We then use the measure for industrial external financial dependence. Industries with higher levels of dependence on external sources of financing should be more responsive to the change in the banking system (Kroszner, Laeven, and Klingebiel, 2007). We construct a dummy variable, *Highdependence*, which takes the value of one if a firm is classified in an industry with external financial dependence above the sample median and zero otherwise. Following Rajan and Zingales (1998), industrial external financing dependence is calculated as the fraction of capital expenditures not financed by cash flows from operations. [12]

Next, we introduce a triple interactive term by interacting the two dummy variables with *Exposure* × *Post2009* (i.e., *Exposure* × *Post2009* × *Highcost, Exposure* × *Post2009* × *Highdependence*) and examine the heterogeneous effects of COD emissions.

Table 4 reports the results. The dependent variables in columns 1 and 2 are the intensity of COD emissions. In columns 1 and 2, the triple interaction term (*Exposure* × *Post2009* ×

[12] This measure has been widely used in the literature; for example, by Kroszner, Laeven, and Klingebiel (2007) and Claessens and Laeven (2002). Rajan and Zingales (1998) construct this measure using 3-digit ISIC sector codes, whereas we use Chinese NSIC sector codes correspondingly.

Highcost, Exposure × *Post2009* × *Highdependence*) is negative and significant. This implies that firms with lower borrowing ability before the shock and firms in industries with stronger dependence on external financing are more responsive to the bank deregulation in terms of greater reduction of pollutant discharge compared with other firms sharing the same degree of exposure to the shock. The results are also economically significant. In column 1, the coefficients of *Exposure* × *Post2009* and *Exposure* × *Post2009* × *Highcost* imply that an additional 10-percentage-point increase in exposure to the policy shock enables firms with stronger borrowing ability before the shock to reduce COD emission intensity by 2.58%, whereas firms with lower borrowing ability ex ante reduce COD emission intensity by 5.37%.

Overall, the results suggest that firms with lower borrowing ability and higher industrial external financial dependence ex ante are more affected by the shock, which confirms our argument that the bank deregulation contributes to emissions reduction by improving borrowers' credit conditions.

6.2. Pollution abatement investment

Goetz (2019) and Xu and Kim (2021) find that US firms cut pollutant discharge after shocks that ease financial conditions by increasing their investment in pollution abatement. In this section, we use three measures to investigate firms' pollution abatement activities. The first measure is the capacity of the firm's equipment to abate wastewater (*Ln abatement capacity*), which proxies for firms' investment in the fixed costs of pollution abatement. The second is COD removals (*Ln COD removals*), which reflects the variable costs of pollution abatement. The third measure is the ratio of the removal amount to the yield amount of COD (*COD remove*

ratio, i.e., *COD Removals/COD Yields*), which reflects the average efficiency of pollution abatement.[13]

Table 5 reports the results. In columns 1 and 2, the coefficients of the interaction term *Exposure* × *Post2009* are both positive, which indicates that treated firms' investment in the fixed and variable costs of pollution abatement might increase slightly after the shock, but neither is statistically significant. In column 3, we use *COD remove ratio* as the dependent variable and the coefficient of the interaction term is negative and insignificant. The results suggest that the average effectiveness of pollution abatement do not improve after the bank deregulation.

Taken together, none of the three measures provide convincing evidence that firms more exposed to the deregulation shock invest more in pollutant abatement when facing loosened credit conditions. Thus the results in this section suggest that the pollution abatement investment channel may not apply to Chinese firms.

6.3. Technology upgrading

In this section, we investigate the channel of technology upgrading proposed by Andersen (2016) and Gutiérrez and Teshima (2018); the latter find that in Mexico, as a result of improved technology after the free trade zone policy, there is a simultaneous decrease in abatement expenditure and pollutant discharge.

We construct three groups of measures to investigate the effect of technological changes in the production process. The first two are firms' usage of water resources: *Ln water*

[13] We can decompose *COD emission* into two components, *COD yields* and *COD removals* (Zhang, Chen, and Guo, 2018). *COD yields* indicate firms' annual yields of COD during production but before the abatement process for pollutants; *COD removals* indicate firms' annual removals of COD during end-of-pipe abatement of pollutants after production. Since the following equation holds, *Emissions = Yields – Removals*, reductions in COD emissions can be achieved by either reducing yields or increasing removals. Investment in pollution abatement has a direct effect on the removals.

consumption, which is the natural logarithm of total water usage during production, and *Ln unit water consumption*, which is the natural logarithm of water usage per output value; lower levels indicate higher production efficiency. These two measures are also used by Gutiérrez and Teshima (2018). The results are reported in columns 1 and 2 of Table 6. The coefficients of the interaction term are both significantly negative, suggesting a decrease in industrial water consumption by treated firms. The results thus show an increase in production efficiency.

Next, we examine whether there was a decline in COD yields during firms' regular production but before their abatement process for pollutants. As revealed in columns 3 and 4 of Table 6, both the absolute yields (*Ln COD yields*) and the yield intensity of COD (*Ln COD yield intensity*) decrease, which provides support for improvement of the production process.

Third, we directly test innovation-driven development. We use the city-industry-level innovation index during our sample period (*Innovation index*) as the dependent variable. The innovation index is a patent value-adjusted index on stock at city and 4-digit industry level, as measured by Kou and Liu (2017).[14] Column 5 of Table 6 reports the results. Estimates of the interactive term between the city's degree of exposure to the shock and the post-2009 dummy is positive and significant at the 1% level, which suggests enhanced capacity for innovation.

Collectively, our results in this section suggest that technology upgrading is an important channel in explaining the effects of bank deregulation on firms' toxic emissions. After the credit-easing shock, firms increase their production efficiency by upgrading their technology and increasing related innovation activities. Therefore, we see a decrease in toxic emissions without a significant increase in abatement expenditure after the deregulation for firms more

[14] They measure intangible capital stock by the patent value, and distinguish the average value of patents of different ages by summing the value of all such patents. Details of the index can be found at http://kouzonglai.blog.caixin.com/archives/176063. Unfortunately, owing to the lack of firm-level data, we use the index at city-industry level to examine the policy effect.

exposed to the deregulation. Our results complement prior studies by showing that technology is an important channel that influences firm pollution—especially in developing countries, in which room for improved technology is more substantial.

6.4. The asset mix channel

Andersen (2017) examines the potential intermediate role played by the asset mix channel. He finds that in order to obtain bank loans, firms tend to overinvest in tangible assets, which can be pledged as collateral. The increasing proportion of tangible assets, in turn, is related to a higher level of pollutant emissions. Correspondingly, in the context of a relaxation of credit constraints, we sought to test whether firms in our sample reduce their investment in tangible assets and consequently improve their environmental performance.

We use two firm-level measures to detect changes in firms' collateral strategies. The first is the absolute value of a firm's major tangible assets, including plant, property, and equipment, with log transformation (*Ln tangible assets*). The second is the proportion of tangible assets to total assets (*Asset tangibility*), which is constructed by *Tangible assets/Total assets* following Andersen (2017).

To simultaneously test the intermediate role played by the tangible asset in pollutant discharge, we employ the 2SLS regression model. In the first stage, we investigate whether the policy shock affects firm tangible asset investment. In columns 1 and 2 of Table 7, we can see that the coefficients of the interaction term *Exposure* × *Post2009* are both significantly negative. These results suggest that both the absolute value and the proportion tangible assets of firms more exposed to the shock decrease significantly, indicating a lower tendency to overinvest in tangible assets.

We then test whether lower tangible assets caused by bank deregulation contribute to lower COD discharge. In the second stage, we use the predicted value of firms' tangible assets ratio (or the natural logarithm of tangible assets) from the first stage and adjust the standard errors of the coefficients accordingly. The results are reported in columns 3 and 4 of Table 7. We find that the coefficients of predicted *Ln tangible assets* and *Asset tangibility* are positive and significant. These results imply that bank deregulation reduces firms' investment in tangible assets, and thus help to improve their environmental performance.

Overall, the results in this section provide evidence that firms with higher exposure to the deregulation shock invest less in tangible assets and reduce their tangible asset allocations after the shock, which supports the asset mix channel proposed by Andersen (2017).

7. Robustness tests

7.1. Instrumental variable approach and the economic magnitude

In this section, we employ the method of instrumental variable (IV) to gain knowledge about the elasticity of firm pollutant discharge to firm credit constraint.

We first use the deregulation as the instrument for firm-level credit constraint variables: *Ln credit cost* and *Ln financial expense rate*, which we use in section 6.1. The results are reported in Panel A of Table 8. In columns 1 and 2, we present the results for the first stage. We can observe that the deregulation shock significantly reduces firm-level credit constraint, as measured by lower credit cost or financing expense rate. In columns 3 and 4, we report the results for the second stage, where we use the predicted value of firm credit conditions as the explanatory variables. We find that the coefficient of the predicted value of *Ln credit cost* and

Ln financial expense rate are both significant. The results in columns 3 imply that an additional one-percentage-point decrease in firm credit cost (the ratio of interest expense to total debt) translates into a decrease in firms' annual emission intensity of COD by 2.0% following banking deregulation.

We then use the deregulation as the instrument for city-level variable, number of joint equity branch scaled by city-level population. The results are reported in Panel B of Table 8. We continue to find consistent results that bank deregulation increase the number of joint equity banks, which leads to a significantly lower level of pollution. A one-standard-deviation increase in the number of joint equity banks per capita translates into a decrease in firm COD emission intensity by 9.035% (= 8.2434%*0.1096).

Therefore, all these results suggest that firm-level credit conditions and city-level development of joint-equity banks can significantly affect firm water pollutant discharge, which is economically meaningful.

7.2. Other robustness tests

7.2.1. Confounding policies and events

Concern could arise regarding whether our results may be contaminated by other contemporaneous policies. Our main results, to some extent, mitigate this concern because we explore the heterogeneity of the bank deregulation shock. Many contemporaneous events, such as the revision of Environmental Protection Law, were enforced at the country level and would not yield cross-regional results we documented above.

We attempt to further address this issue by examining the other two main ongoing environmental policies whose effect varied across different regions and are considered

important in the literature (Chen et al., 2018; Zhang, Chen, and Guo, 2018): the reduction mandate for COD during the Eleventh Five-Year Plan (FYP) and the National Specially Monitored Firms (NSMF) program.

The Eleventh FYP (2006-2010) specifically targeted a 10% reduction in COD emissions from 2005 levels and included province-level reduction mandates. To control for its impact, we construct two measures that capture the mandates' regulatory stringency. The first, at city-year level, is an interaction term (*Mandate* × *FYP11*). *Mandate* indicates the regulatory stringency of COD reduction mandates in a prefecture-level city, constructed following Chen et al. (2018).[15] *FYP11* is a dummy that denotes the Eleventh FYP period from 2006 to 2010. The other measure at province-year level (*Report ratio*) is the proportion of environmentally related text in each province's annual government work report, which is commonly used to measure local officials' actual effort to achieve the specific environmental target.[16]

The results are reported in column 1 of Table 9. We find that the coefficients of the interaction term are still negative and significant after controlling for the effect of the Eleventh FYP.

We further test the effect of the NSMF program, which the central government launched in 2007 to collect more reliable and accurate information on key industrial polluters' emissions through direct central supervision. This may change firm polluting behavior. The list of firms under monitoring is dynamically adjusted every year based on annual data on industrial firms

[15] COD reduction mandates can be found in the government document "The 11th Five-Year National Total Emissions Control Plan of Major Pollutants" (http://www.gov.cn/gongbao/content/2006/content_394866.htm).

[16] Government work reports are the most important official documents in China's political system. They summarize a government's achievements in the past year and lay out the work plan for the coming year. Following Chen et al. (2018), environmentally related text refers to sentences that contain the words environment, energy consumption, pollution, emission reduction, or environmental protection. Government work reports can be downloaded from http://data.people.com.cn/pd/gzbg/index.html.

from the ESR. To alleviate concern that firms under the monitoring program would bear a heavier burden of emission reduction, we identify all firms under monitoring in terms of sewage discharge by matching names in our sample. We add a time-varying dummy (*NSMF*) for each firm to indicate whether the firm is under monitoring or not.[17] The results in column 2 of Table 9 show that all estimates are similar to the baseline estimates.

7.2.2. Alternative measures of environmental performance

To gain a more comprehensive understanding of the effect on corporate environmental performance, we explore the emission intensity of other important pollutants in the dataset. For water pollution, we use an alternative measure NH_3-N (*Ln NH_3-N emission intensity*); for air pollution, we use SO_2 (*Ln SO_2 emission intensity*). As we explain in Section 4.1, these measures might not be as reliable as the COD measure we use in our main regression results. It can be observed that the number of firm-year observations with non-missing NH3-N or SO_2 is smaller than observations with non-missing COD. Regression results are reported in columns 3 and 4 of Table 9. All estimates are negative and significant, which is consistent with our main findings.

7.2.3. The role of exits and entrants

Concern would arise if most effects were driven by exits and entrants in our sample of firms instead of changes in those firms' behavior. To address this concern, we replicate the regressions by restricting our sample firms.

During the sample period, firms as entrants or quitters may perform quite differently in their investment and financing activities, and therefore in their emissions of industrial pollutants. To guarantee the consistency of the sample, we first focus on firms that appeared in the sample both before and after 2009 in column 5 of Table 9. Next, we exclude entrants in our

[17] The annual list of NSMF program firms can be found at http://www.mee.gov.cn/gkml/.

sample and replicate the regressions. Column 6 reports the results from a subsample that excludes entrant firms, which report a birth year at most 2 years prior to their first appearance in the sample, following the definition of Brandt, Van Biesebroeck, and Zhang (2012). As expected, the coefficients are still statistically significant.

7.2.4. Alternative event window

Given the increasing attention to environmental issues and tighter environmental regulations, especially after implementation of the Eleventh FYP, firms' emission behavior could be driven by many unobservable factors under the new circumstances. To mitigate these concerns, we use a shorter event window and restrict our sample period to the years between 2006 and 2011. The results reported in column 7 of Table 9 are smaller in magnitude, but still negative and significant.

7.2.5. Placebo test: Randomly assigning exposure

To further verify whether the identification is driven by any omitted variables, a placebo test is conducted by randomly assigning degree of exposure to the shock to different prefecture-level cities (referring to Chetty, Looney, and Kroft (2009); La Ferrara, Chong, and Duryea (2012); Li, Lu, and Wang (2016)). Using false degrees of exposure to the shock, a placebo estimation is implemented using the baseline setting in column 3 of Table 2. To increase the identification power of the placebo test, we repeat it 200 times.

Given the random data-generation process, the placebo tests should produce no significant estimate with a magnitude close to zero; otherwise, this would indicate a misspecification of the DID estimation. Distribution of the estimated coefficients in the placebo tests is depicted in

Figure 3. The estimated coefficients are centered on zero and differ significantly from the baseline estimation.

8. Conclusion

In this study, we use a unique dataset that contains rich information on firms' emissions and exploit bank branching deregulation in China to study the effects of bank deregulation on corporate environmental performance. We exploit the 2009 deregulation of bank branching, which removed the restriction on joint-equity banks' ability to establish new branches in cities in which they do not already have branches. The policy shock causes improvement in industrial firms' credit conditions.

We find firms more exposed to the bank deregulation improve their environmental performance after the shock compared with firms with lower exposure, and the observed pattern is consistent with various robustness tests. This result suggests a potential and unanticipated benefit of the role of the banking sector from the perspective of firms' environmental performance. We further investigate the channels through which the bank deregulation would have effects on the emission intensity of firms' toxic discharge. We find that investment in the end-of-pipe abatement of pollutants after production hardly changes after the shock. However, we demonstrate that treated firms' production efficiency increases and the ratio of tangible assets to total assets decreases, which suggests that upgrading technology and asset mix are the main channels by which better credit conditions caused by bank deregulation reduce firms' toxic emissions.

The banking sector is the most important source of corporate financing in many developing countries. To improve the efficiency of allocating and investing a society's savings through the banking system, many of these countries are undergoing or moving toward liberalizing the banking industry. Our results highlight an important yet neglected aspect: the environmental ramifications of bank deregulation. The environmental benefits of bank deregulation in China offer an opportunity to reevaluate liberalization of the banking sector in a more holistic way, by taking its socioeconomic consequences into account.

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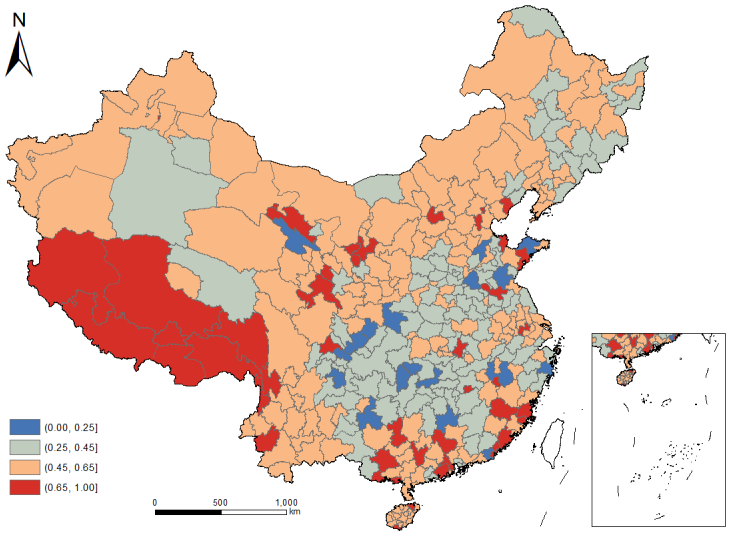
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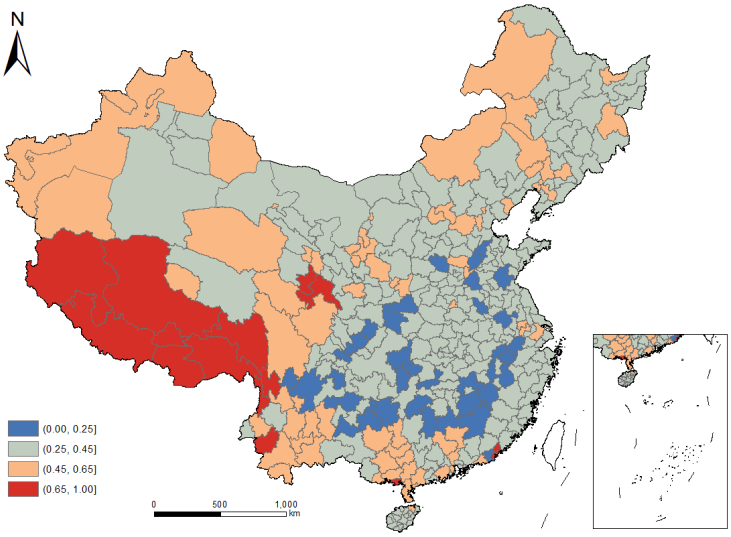
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Figure 1. Heat map of Big Five bank concentration (*BIG5%*) across prefecture-level cities, 2009/04/16 versus 2013/12/31.



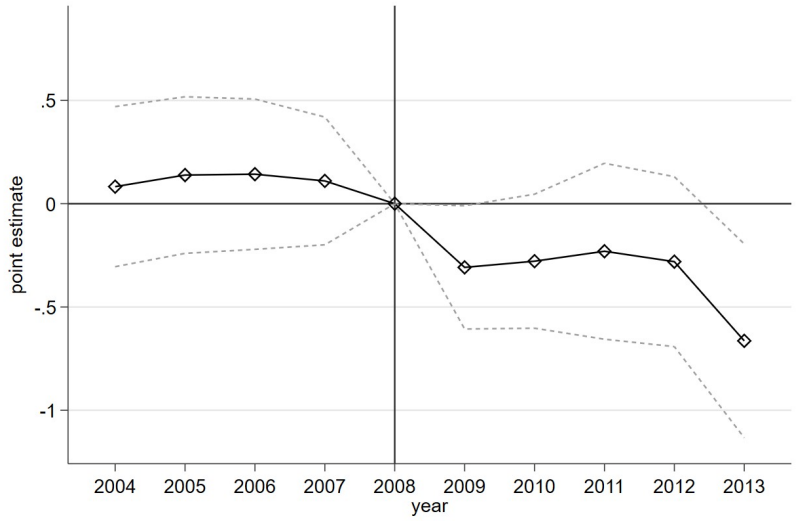
(a) By the Date of the Policy Shock (2009.04.16)



(b) By the End of the Sample Period (2013.12.31)

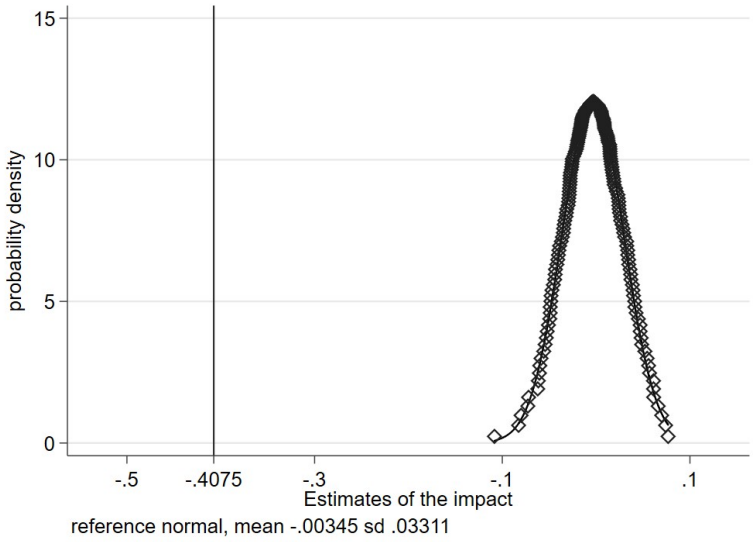
Note: This figure illustrates Big Five bank concentration (*BIG5%*) across all prefecture-level cities in China by the date of the policy shock (Panel a) and the end of 2013 (Panel b). *BIG5%* is measured by the proportion of outstanding branch number of Big Five state-owned commercial banks in each prefecture-level city. It covers 341 administrative regions in 31 provinces of China, including 4 centrally administrated cities (i.e., Beijing, Tianjin, Shanghai, and Chongqing), 333 prefecture-level divisions, and 4 provincially administrated counties.

Figure 2. Pre-trend test.



Note: This figure illustrates the dynamic impact of the deregulation of banks on firms' emission intensity of COD year by year, with year 2008 serving as the benchmark. Estimated coefficients are plotted at the 95% level.

Figure 3. Distribution of estimated coefficients in placebo tests.



Note: This figure shows the probability density distribution of the estimated coefficients from 200 simulations that random assign degree of exposure to the shock to different prefecture-level cities. The vertical line depicts the results in column 3 of Table 2.

Table 1. Descriptive statistics

Variable	Obs.	Mean	S.D.	Min	Max
Pollution variables					
Ln COD emissions	179,367	8.4524	2.3327	-2.3026	14.5710
Ln COD emission intensity	179,367	-0.2645	2.4981	-13.1185	16.6594
Ln COD yields	179,367	9.7115	2.6542	-2.3026	19.4923
Ln COD yield intensity	179,367	0.9917	2.6411	-13.1185	16.6594
Ln COD removals	179,367	7.0965	5.0632	0	19.4503
Explanatory variables					
BIG5%	179,367	0.4840	0.1494	0.1235	0.8386
Deregu	179,367	0.9949	0.0711	0	1
Exposure	179,367	0.4814	0.1530	0	0.8386
Post2009	179,367	0.5140	0.4998	0	1
Exposure × Post2009	179,367	0.2490	0.2647	0	0.8386
Control variables					
Age	179,367	11.7184	11.4077	0	149
Age^2	179,367	267.4547	724.9931	0	22,200
SOE	179,367	0.1132	0.3168	0	1
Equipment	179,367	0.7370	0.4403	0	1
Citypopdensity2008	179,367	347.6182	453.6711	0	2,454.3101
Citygdp2008	179,367	1.46E+07	2.53E+07	0	1.37E+08
Cityloan2008	179,367	2.45E+07	5.85E+07	0	4.05E+08
Citysaving2008	179,367	1.69E+07	3.88E+07	0	2.42E+08
Other variables					
no. joint equity banks per capita	2,748	0.0332	0.1096	0	1.6532
no. big5 banks per capita	2,748	0.5385	0.3736	0.0652	2.9431
no. all other banks per capita	2,748	0.5887	0.4086	0	4.0551
Ln output	179,367	8.6407	1.6908	-2.3026	16.9510
Ln abatement capacity	179,367	4.4010	3.1041	0	14.6910
COD remove ratio	179,364	0.6893	0.5876	0	3.1649
Ln water consumption	179,328	11.3880	2.2716	-0.3567	20.9866
Ln unit water consumption	179,328	-0.1957	2.2110	-13.4252	10.7194
Innovation index	129,668	0.0382	0.1492	0	3.3374
Ln credit cost	131,891	-3.8620	1.3707	-13.0289	9.8535
Ln financial expense rate	136,361	-5.0892	1.5988	-15.425	0.0090
Ln tangible assets	179,356	9.8340	1.8474	0	15.6390
Asset tangibility	179,356	0.4610	0.8592	0	15.6759
Highcost	150,968	0.4111	0.4920	0	1
Highdependence	179,367	0.5157	0.4998	0	1
Mandates × FYP11	179,367	0.4881	0.8701	0	4.3091
Report ratio	179,367	0.0062	0.0021	0	0.0156
NSMF	179,367	0.0391	0.1938	0	1
Ln NH_3-N emission intensity	122,650	-2.8563	2.5617	-15.6734	10.6016
Ln SO_2 emission intensity	119,077	0.9038	2.3972	-12.9521	13.3927

Note: The sample consists of 179,367 firm-year observations, with 41,838 unique firms over the period 2004-2013. We clean the dataset in three main steps: (1) exclude firms with missing or zero values for COD emissions; (2) delete observations with output above 5 billion RMB, total assets below zero or above 5 billion RMB, total debts below zero or above 3 billion RMB, age below zero or above 100, and employment below 1 or above 5,000; (3) winsorize all continuous variables at the 1% level in both tails;

(4) exclude firms that moved to a different prefecture-level city during the sample period, which make up only 0.16% (287/179,654) of the total sample. Owing to the inherent limitations of our dataset, some dependent variables used in mechanism tests and control variables in robustness tests have fewer observations. Appendix 1 defines all variables.

Table 2. Main results: The effects of deregulation on firms' emission intensity of COD

Variables	Ln COD emission intensity		
	(1)	(2)	(3)
Exposure × *Post2009*	-0.3895***	-0.4142***	-0.4075***
	(0.1164)	(0.1195)	(0.1165)
Equipment		-0.2300***	-0.2329***
		(0.0284)	(0.0282)
SOE		-0.0142	-0.0109
		(0.0214)	(0.0212)
Age		0.0065***	0.0058***
		(0.0021)	(0.0021)
Age^2		-0.0001**	-0.0001**
		(0.0000)	(0.0000)
Citypopdensity2008 × *post2009*	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)
Citygdp2008 × *post2009*	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
Cityloan2008 × *post2009*	0.0000**	0.0000**	0.0000**
	(0.0000)	(0.0000)	(0.0000)
Citysaving2008 × *post2009*	-0.0000**	-0.0000**	-0.0000*
	(0.0000)	(0.0000)	(0.0000)
Observations	179,367	179,367	179,367
Adjusted R^2	0.7766	0.7770	0.7785
Predetermined controls	YES	YES	YES
Firm controls	NO	YES	YES
Year FE	YES	YES	na
City FE	YES	YES	YES
Firm FE	YES	YES	YES
Industry-year FE	NO	NO	YES

Note: The sample consists of 179,367 firm-year observations over the period 2004-2013. The dependent variable in each column is the emission intensity of chemical oxygen demand (COD, measured in kg) for firm in year with log transformation, which reflects sewage discharge at firm level. The main explanatory variable is the interactive term , in which indicates the potential degree of exposure to the shock in city ; equals 1 for observations in year 2009 or later years and 0 otherwise and denotes the post-shock period. The control variables and fixed effects adopted in column 3 are treated as baseline controls hereafter. Robust standard errors clustered at city by year level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Appendix 1 defines all variables.

Table 3. The effects of deregulation on credit conditions

Variables	(1)	(2)	(3)	(4)	(5)
	no. joint equity banks per capita	no. big5 banks per capita	no. all other banks per capita	Ln credit cost	Ln financial expense rate
Exposure × *Post2009*	0.0296***	-0.0155	0.0163	-0.2125***	-0.3601**
	(0.0100)	(0.0295)	(0.0821)	(0.0742)	(0.1605)
Observations	2,748	2,748	2,748	127,638	132,405
Adjusted R^2	0.9738	0.9708	0.8427	0.5627	0.6318
Predetermined controls	YES	YES	YES	YES	YES
Firm controls	na	na	na	YES	YES
City FE	YES	YES	YES	YES	YES
Firm FE	na	na	na	YES	YES
Year FE	YES	YES	YES	na	na
Industry-year FE	na	na	na	YES	YES

Note: The sample in columns 1-3 consists of 2,748 city-year observations. Columns 4 and 5 consist of 127,638 / 132,405 firm-year observations, respectively, over the period 2004-2013. The dependent variable is the number of branches of joint-equity banks / Big Five banks /all other banks per capita for city in year in columns 1/2/3, respectively. The dependent variable in column 4 is the cost of credit with log transformation for firm in year . The dependent variable in column 5 is financial expense rate, which is measured by the ratio of financial expenses to prime operating revenue, with log transformation for firm in year . The main explanatory variable is the interactive term , in which indicates the potential degree of exposure to the shock in city ; denotes the post-shock period. Robust standard errors clustered at city-by-year level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Appendix 1 defines all variables.

Table 4. Subsample tests

Variables	Ln COD emission intensity	
	(1)	(2)
Exposure × *Post2009* × *Highcost*	-0.2787**	
	(0.1301)	
Exposure × *Post2009* × *Highdependence*		-0.4366***
		(0.1247)
Exposure × *Post2009*	-0.2586**	-0.1924
	(0.1308)	(0.1232)
Observations	140,218	179,367
Adjusted R^2	0.7608	0.7785
Predetermined controls	YES	YES
Firm controls	YES	YES
City FE	YES	YES
Firm FE	YES	YES
Industry-year FE	YES	YES

Note: This table reports the results of DDD analysis. The sample consists of 140,218 firm-year observations over the period 2004-2013 (excluding observations with no records before 2009) in column 1 and 179,367 observations in column 2. The dependent variable is COD emission intensity for firm in year t with log transformation. The main explanatory variables are the interactive term , and , in which indicates the potential degree of exposure to the shock in city ; denotes the post-shock period; is an indicator whether firm suffered from average cost of credit above the sample median before the shock; is an indicator whether firm is classified in an industry with external financial dependence above median. Robust standard errors clustered at city-by-year level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Appendix 1 defines all variables.

Table 5. Pollution abatement investment and the effects of deregulation on firms' emission intensity of COD

Variables	(1) Ln abatement capacity	(2) Ln COD removals	(3) COD remove ratio
Exposure × *Post2009*	0.0432	0.1856	-0.0051
	(0.0953)	(0.4003)	(0.0426)
Observations	179,367	179,367	179,363
Adjusted R^2	0.9426	0.6751	0.7601
Predetermined controls	YES	YES	YES
Firm controls	YES	YES	YES
City FE	YES	YES	YES
Firm FE	YES	YES	YES
Industry-year FE	YES	YES	YES

Note: The sample consists of 179,367 firm-year observations over the period 2004-2013 (179,363 in column 3). The dependent variable is the abatement capacity of firm in year with log transformation in column 1, the removals of COD during abatement process of pollutants after production (measured in kilogram) with log transformation in column 2, and the remove ratio of COD in column 3. The main explanatory variable is the interactive term , in which indicates the potential degree of exposure to the shock in city ; denotes the post-shock period. Robust standard errors clustered at city by year level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Appendix 1 defines all variables.

Table 6. Technology upgrading and the effects of deregulation on firms' emission of COD

Variables	(1)	(2)	(3)	(4)	(5)
	Ln water consumption	Ln unit water consumption	Ln COD yields	Ln COD yield intensity	Innovation index
Exposure × *Post2009*	-0.3952***	-0.3953**	-0.3078***	-0.2731**	0.0173***
	(0.0919)	(0.1644)	(0.1136)	(0.1226)	(0.0053)
Observations	179,318	179,318	179,367	179,367	129,044
Adjusted R^2	0.8755	0.8294	0.8197	0.7813	0.8844
Predetermined controls	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES

Note: In columns 1 and 2, the sample consists of 179,318 firm-year observations over the period 2004-2013 (excluding observations with no consumption of water). The dependent variable in column 1 (2) is total (unit) consumption of water during production for firm in year with log transformation. In columns 3 and 4, the sample consists of 179,367 observations and the dependent variables are the absolute yields and yield intensity of COD with log transformation. In column 5, the dependent variable is a patent value-adjusted index of stock at city and 4-digit industry level with log transformation, and we have 129,044 observations. The main explanatory variable is the interactive term , in which indicates the potential degree of exposure to the shock in city ; denotes the post-shock period. Robust standard errors clustered at city-by-year level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Appendix 1 defines all variables.

Table 7. Asset mix and the effects of deregulation on firms' emission intensity of COD

Variables	2SLS (first stage)		2SLS (second stage)	
	(1)	(2)	(3)	(4)
	Ln tangible assets	Asset tangibility	Ln COD emission intensity	
Exposure × *Post2009*	-0.3730***	-0.0578**		
	(0.1028)	(0.0260)		
Ln tangible assets			1.1100**	
			(0.4598)	
Asset tangibility				7.1684*
				(3.9756)
Observations	174,701	174,701	174,701	174,701
SW F p-value	0.0003	0.0267		
Predetermined controls	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES

Note: This table reports the results of 2SLS estimation for the asset mix channel. The sample consists of 174,701 firm-year observations over the period 2004-2013, excluding those without records of fixed assets. The dependent variable in column 1 is the value of fixed assets (measured in 1,000 CHY) with log transformation for firm in year . The dependent variable in column 2 is the proportion of annual fixed assets in total assets for firm in year . The dependent variable in columns 3 and 4 is COD emission intensity for firm in year t with log transformation. The main explanatory variable is the interactive term , in which indicates the potential degree of exposure to the shock in city ; denotes the post-shock period. Robust standard errors clustered at city by year level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Appendix 1 defines all variables.

Table 8. Robustness tests: Instrumental variable approach

Panel A

Variables	2SLS (first stage)		2SLS (second stage)	
	(1)	(2)	(3)	(4)
	Ln credit cost	Ln financial expense rate	Ln COD emission intensity	
Exposure × Post2009	-0.2125***	-0.3601**		
	(0.0742)	(0.1605)		
Ln credit cost			1.9888**	
			(0.8532)	
Ln financial expense rate				1.1172*
				(0.6314)
Observations	127,638	132,405	127,638	132,405
SW F p-value	0.0042	0.0250		
Predetermined controls	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES

Panel B

Variables	2SLS (first stage)	2SLS (second stage)
	(1)	(2)
	no. joint equity banks per capita	Ln COD emission intensity
Exposure × Post2009	0.0296***	
	(0.0100)	
no. joint equity banks per capita		-8.2434***
		(2.8264)
Observations	2,748	179,367
SW F p-value	0.0000	
Pre-determined controls	YES	YES
Firm controls	na	YES
City FE	YES	YES
Firm FE	na	YES
Industry-year FE	YES	YES

Note: The sample in columns 1(3) / 2(4) of Panel A and column in Panel B consists of 127,638 / 132,405 firm-year observations, and column 1 of Panel B 2,748 city-year observations over the period 2004-2013. For the first stage, the dependent variable is the cost of credit with log transformation for firm in year in column 1 of Panel A, financial expense rate in column 2 of Panel A, and the number of branches of joint-equity banks per capita for city in year in column 1 of Panel B. For the second stage, the dependent variable is COD emission intensity for firm in year t with log transformation. The main explanatory variable is the interactive term , in which indicates the potential degree of exposure to the

shock in city ; denotes the post-shock period. Robust standard errors clustered at city-by-year level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Appendix 1 defines all variables.

Table 9. Other robustness tests

Variables	(1) Control for 11th Five-Year Plan	(2) Control for NSMF	(3) Ln NH_3-N emission intensity	(4) Ln SO_2 emission intensity	(5) Existing before and after 2009	(6) Excluding entrant firms	(7) Shorter window
Exposure × *Post2009*	-0.3960***	-0.4123***	-0.2446***	-0.1868***	-0.3945***	-0.4109***	-0.3314***
	(0.1156)	(0.1167)	(0.0912)	(0.0720)	(0.1167)	(0.1184)	(0.1208)
Mandates × *FYP11*	0.0017						
	(0.0149)						
Report ratio	-6.5247						
	(5.8072)						
NSMF		-0.1886***					
		(0.0297)					
Observations	179,367	179,367	118,780	116,963	162,416	162,610	111,837
Adjusted R^2	0.7785	0.7786	0.7357	0.8063	0.7778	0.7800	0.7837
Predetermined controls	YES	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES	YES

Note: The sample consists of 179,367 firm-year observations over the period 2004-2013 (118,780 / 116,963 / 162,416 / 162,610 / 111,837 observations in column 3/4/5/6/7, respectively, when applying sample restriction). The dependent variable is the emission intensity of COD for firm in year with log transformation, except in columns 3 and 4. The dependent variables in columns 3 and 4 are the emission intensity of NH_3-N and SO_2 with log transformation respectively. The main explanatory variable is the interactive term . indicates the potential degree of exposure to the shock in city ; denotes the post-shock period. Column 1 (2) adds controls for ongoing environmental regulation. Columns 5-7 report the results of three subsample regressions: column 5 uses a subsample of firms that appeared in the sample both before and after 2009; column 6 uses a subsample that excludes entrant firms; column 7 uses a subsample that restricts the event window to the period 2006-2011. Robust standard errors clustered at city-by-year level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Appendix 1 defines all variables.

Appendix

Variable	Definition	Source
Pollution variables		
Ln COD emissions	Emissions of chemical oxygen demand (COD, with log transformation), an important indicator of water pollution measured in kilograms	Environmental Survey and Reporting (ESR) database
Ln COD emission intensity	COD emissions per unit of output value (with log transformation), measured by *log(COD emissions/output value)*	ESR
Ln COD yields	Yields of COD during production measured in kilograms (with log transformation), and it holds that *Yields=Emissions+Removals*	ESR
Ln COD yield intensity	COD yields per unit of output value (log), measured by *log(COD yields/output value)*	ESR
Ln COD removals	Removals of COD during end-of-pipe abatement of pollutants after production (log)	ESR
Explanatory variables		
BIG5%	Ex ante concentration ratio of Big Five state-owned commercial banks, measured by the proportion of outstanding branch number of Big Five banks in each prefecture-level city	China Banking and Insurance Regulatory Commission (CBIRC)
Deregu	1 if a prefecture-level city is targeted by the deregulation policy (i.e., deregulated cities) and 0 otherwise (cities in Guizhou, Xizang, Qinghai, or Ningxia)	CBIRC
Exposure	Prefecture-level city's potential degree of exposure to the shock, measured by the interaction of *BIG5%* and D*eregu*	CBIRC
Post2009	1 if a year is 2009 (i.e., policy year) or later and 0 otherwise	
Control variables		
Age	Firm's age since its establishment	Annual Surveys of Industrial Firms (ASIF)
Age^2	The squared term of firm's age	ASIF
SOE	1 for state-owned firms and 0 otherwise	ASIF
Equipment	1 if possessing at least one piece of abatement equipment to remove wastewater	ASIF

	emissions and 0 otherwise

(continued)

Variable	Definition	Source
Citypopdensity2008	Prefecture-level city's annual population density (persons to the unit square kilometer)	China City Statistical Yearbooks
Citygdp2008	Prefecture-level city's annual GDP measured in 10,000 CHY	China City Statistical Yearbooks
Cityloan2008	Prefecture-level city's year-end loan balance of financial institutions	China City Statistical Yearbooks
Citysaving2008	Prefecture-level city's year-end deposit balance of financial institutions	China City Statistical Yearbooks
Other variables		
no. joint equity banks per capita	Number of branches of joint-equity banks per capita, measured by the total number of branches for 12 joint-equity banks scaled by the corresponding city-level population in each year	CBIRC, China City Statistical Yearbooks
no. big5 banks per capita	Number of branches of Big Five state-owned commercial banks per capita	
no. all other banks per capita	Number of branches of all other commercial banks (except joint-equity banks and Big Five banks) per capita	
Ln output	Output value at constant price in 1998 (1,000 CHY, with log transformation)	ESR
Ln abatement capacity	Capacity of firm's equipment to abate wastewater (with log transformation)	ESR
COD remove ratio	Ratio of the removal amount to the yield amount of COD (*COD Removals/COD Yields*)	ESR
Ln water consumption	Consumption of industrial water during production (with log transformation)	ESR
Ln unit water consumption	Industrial water consumption per unit of output value during production, measured by *log(industrial water consumption/output value)*	ESR
Innovation index	A patent value-adjusted index on stock at city and 4-digit industry level during the period from 2001 to 2016 (with log transformation)	FIND report on city and industrial innovation
Ln credit cost	Average cost of credit, measured by *log(Interest expense/Total debts)*	ASIF
Ln financial expense rate	Firm's financial burden, measured by *log(financial expenses/prime operating revenues)*	ASIF

Ln tangible assets	Value of major tangible assets, including plant, property, and equipment measured in 1,000 CHY (with log transformation)	ASIF

(continued)

Asset tangibility	Proportion of annual tangible assets in firm's total assets, measured by *Tangible assets/Total assets*	ASIF
Highcost	1 if a firm has the average cost of credit above median before the shock and 0 otherwise	ASIF
Highdependence	1 if a firm is in an industry with external financial dependence above median and 0 otherwise	Rajan and Zingales (1998)
Mandates × *FYP11*	An interaction denotes environmental regulation on COD during the 11th Five-Year Plan (FYP). *Mandates* indicates the regulation stringency of COD reduction mandates in a prefecture-level city. *FYP11* is a dummy of the 11th FYP period, from year 2006 to 2010	Total emissions control plan in the 11th FYP, ASIF
Report ratio	Indicator of environmental regulation during the 11th FYP measured by the environment-related text proportion of each province's annual government work report	Government work reports
NSMF	1 if a firm is listed as a National Specially Monitored Firm (NSMF) regarding sewage discharge in a specific year and 0 otherwise	NSMF lists