Green Credit, TFP Heterogeneity and Allocation Efficiency

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This Version: June, 2024

Abstract

China implemented its "Green Credit Policy" in 2007. This paper investigates how the green credit policy affects bank loan allocation efficiency across and within green and brown firms. By using firm-level data from China, we provide the stylized facts that the Total Factor Productivity (TFP) of green firms exhibits stronger heterogeneity than that of brown firms, and TFP is negatively correlated with firm-level emission. Utilizing these two facts, we develop a model based on Dong and Xu (2020) to investigate the efficiency of credit allocation under the green credit policy. The model shows that green loan expansion makes credit allocated to firms with less productivity and the average productivity decreases for green firms. On the other hand, implementing a green interest subsidy combined with penalties for brown firms can play a positive role. The model provides a number of predictions that we validate empirically. Specifically, we show that TFPs of green firms fall sharply compared to those of brown firms after the implementation of the policy in DID tests. We also find that credit is less concentrated in high-TFP green firms, while it is the opposite for brown firms. The resulting transition matrix indicates that the policy incentivizes brown firms more effectively than green firms.

Keywords: Green Credit, TFP Heterogeneity, Allocation Efficiency.

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I Introduction

Over the past decade, regulators and other stakeholders have increasingly recognized climate change as a significant risk and have demanded that firms accelerate investment in sustainability to mitigate their negative impact on the environment. Alexander (2014) suggests that financial intermediaries play a significant role in realizing a green economy. Following the Paris Agreement in 2016, legislators have highlighted the crucial stewardship role of banks in enhancing social and economic welfare through financing green investments and guiding the transition to a carbon-neutral economy.

Green credit was first introduced in China through the "Directives on Implementing Environmental Protection Policies and Regulations and Managing Credit Risks", jointly issued by the Environmental Protection Administration, the People's Bank of China, and the China Banking Regulatory Commission on July 12, 2007. The primary goal of this document is to use financial mechanisms to bolster environmental protection initiatives. Specifically, it mandates commercial banks to channel funds into industries and firms that prioritize environmental sustainability and foster sustainable development. In accordance with this policy, commercial banks must factor in firms' compliance with environmental protection regulations as a prerequisite for loan approval. Additionally, they are urged to apply credit control to projects that violate industrial policies or commit environmental infringements. Financial institutions are explicitly barred from providing credit support to projects that fail environmental audits. This green credit policy framework is designed to encourage environmentally responsible practices and deter activities posing environmental risks, by integrating environmental considerations into banks' strategic and risk management processes. Consequently, the environmental risk of firms, gauged by their environmental performance and compliance with laws and regulations, becomes a pivotal factor in securing bank loans[1].

This paper investigates how the green credit policy affects bank loan allocation efficiency across and within green and brown firms, by using firm-level data from China. This study is particularly meaningful, because as the largest manufacturing country in the world, China's transition to a greener economy is crucial for slowing global climate change, and the launch of the "green credit policy" in China provides us with a quasi-natural experiment to test the

[1] According to news, in 2007, five large state-owned commercial banks (Industrial and Commercial Bank of China, Agricultural Bank of China, China Construction Bank, Bank of China and Bank of Communications) issued loans of 106.334 billion RMB to support key projects of energy conservation and emission reduction. Industrial and Commercial Bank of China, in 2007, took the lead in formulating green credit policies among domestic peers, and comprehensively promoted the construction of green credit. It not only formulated a systematic green credit policy, but also set a strict environmental protection standard and implemented the "one-vote veto system for environmental protection".

effects of this policy on the economic and environmental performance of firms and assess the allocation efficiency of financial resources under this policy.

We first present evidence regarding the Total Factor Productivity (TFP) of firms in China, including the distribution of TFP and its heterogeneity among green and brown firms. We categorize firms into quintiles based on their emission intensity (COD and SO_2), with those in quintiles smaller than 33.3% and larger than 66.7% representing green and brown firms, respectively. By calculating the TFP of manufacturing firms using the OLS method and the Olley and Pakes (1996) method separately, we find that green firms exhibit greater heterogeneity in TFP compared to brown firms. This is evidenced by the sub-sample of green firms having a wider TFP distribution than that of the brown firms. We also show that there exist negative correlations between TFP and emission intensity. Higher TFP is associated with higher production efficiency and resource utilization ability, thus lower emissions.

In order to explore how financial markets internalize credit allocation among green and brown firms, we develop a model based on Dong and Xu (2020) to examine the impact of the green credit policy, investigate the credit allocation process, and evaluate its effect on social welfare. The model yields the following intuition about the credit misallocation mechanism: credit expansion reduces the marginal capital return of high-quality projects, while inefficient projects may get too many loans, and it provides a good framework to investigate the credit reallocation process under the green credit policy.

There are two sectors in the model: the production sector and the frictional banking sector. The production sector is composed of green firms and brown firms. Given the empirical findings that green firms exhibit greater TFP heterogeneity compared to brown firms, we model green firms as heterogeneous in productivity, whereas brown firms are homogeneous in productivity. This productivity heterogeneity allows for an analysis of credit allocation among green firms with varying production efficiencies.

Firms rent physical capital and hire labor to produce final goods. The production produces externalities to the environment. The total supply of labor is fixed at one unit. The economy has a unit measure of banks that invest in firms in the production sector or in other banks in the interbank market. Under a green credit policy, banks are not allowed to invest in brown firms and can only invest in green firms. However, due to moral hazard problems, they may divert loans to invest in brown firms, if it offers a better return. Each individual bank meets one green firm and one brown firm and decides whether to provide a loan or not, depending on the return for each choice. If the bank does not invest, they lend their money to another bank that decides to invest. The borrowing banks then invest the loan amount plus their own capital, and they may divert a portion of interbank loans, along with their endowed capital, to brown firms.

We assume this diverting behavior may be observed by regulators afterward, and the offending banks will be punished. The punishment value is positively correlated with the emission volume of the brown firms that receive loans. In the end, no brown firms obtain bank loans in the model, only green firms receive funding from banks.

Each bank must decide whether to borrow and invest in a green firm or to lend its endowment to other banks. If borrowing, they must decide the amount of leverage to take on. With this setting, we examine the effects of green loan expansion, green interest subsidies, and brown investment penalties, respectively, on credit allocation and on economic and environmental outcome.

The model implies that green loan expansion reduces the capital return for banks that lend to green firms, making investments in green firms less attractive. As the credit demand of high-TFP green firms decreases, surplus credit resources flow to firms with lower productivity. On the other hand, green interest subsidies and brown punishments affect the profitability of green and brown investments, respectively, improving the credit demand from green firms. Our model further explores how these policies impact total output and emission. Green credit expansion lowers overall output while increasing emission due to a reduction in the average TFP among productive firms. However, green subsidies and brown penalties may enhance total output and reduce emission.

We also examine the welfare implications of green credit policies by incorporating a household sector, with polluting emission negatively affecting welfare. Households consume a final good and deposit funds with banks. To quantify welfare effects and allocation efficiency, we calculate welfare along transition paths post-shock by determining the consumption equivalent for a representative household relative to the steady state. The results show that the green credit expansion shock results in a welfare loss of -0.094% of steady-state consumption, while the green subsidy shock and brown penalty shock lead to a welfare loss of -0.667% and a welfare gain of 0.485% of steady-state consumption, respectively.

Based on the model's implications, green credit expansion implies that credit moves to projects with lower productivity. Consequently, the average productivity of firms receiving loans decreases. This misallocation process leads to increased emissions. We use the launch of the "green credit policy" in China as a quasi-natural shock to test the economic and environmental impacts of this policy, which in our data period mainly focused on green credit expansion. We examine the changes in total factor productivity (TFP) after the shock using Difference-in-Difference (DID) tests, and investigate the credit reallocation among firms. We also evaluate changes in emissions. We find a significant treatment effect of the green credit policy, indicated by a substantial decrease in the TFP of green firms compared to brown firms after the policy's introduction in 2007.

Regarding bank loans, data shows that post-shock, green firms receive more loans, while brown firms receive less. This is consistent with the finding of Guo and Fang (2024) that the green credit policy effectively curbs debt financing for high-pollution firms. In addition, the concentration of bank loans in green firms with high TFP decreases, opposite to the trend observed for brown firms. Emission data indicates that the policy incentivizes brown firms more effectively than green firms, corroborating with the evidence in Guo and Fang (2022). The transition matrix shows that brown firms become greener more significantly, while green firms have a checked pattern in their green rankings.

This paper contributes to the growing body of literature on green or climate finance, which has gained significant attention as sustainable practice becomes more widely recognized. The integration of environmental, social, and governance (ESG) factors into investment decisions has been a focal point for both academic research and industry practice. For example, firms are generally willing to engage in beneficial environmental activities, but they also care about effectiveness and worry about the associated costs and risks (Bauer and Hann, 2010). Similarly, Wu et al. (2024) argue that the endogeneity of green investment is a key issue, as firms seek to understand whether such investments can provide additional benefits beyond compliance and reputation management.

The criteria and targets for ESG investments, as well as their real impact, have been studied by Heinkel et al. (2001), Hong et al. (2020), Chava (2014), and Keller and Levinson (2002). These studies aim to provide a clearer understanding of what drives ESG investment decisions and the potential outcome for both environmental and financial performance of firms. Empirical research on the information content of firms' environmental indicators has been conducted by Hong et al. (2019), who examine how well environmental metrics reflect the actual sustainability performance of companies. This research is crucial for investors seeking to make informed decisions based on ESG factors.

From the perspective of households, Tang and Zhang (2020) and Riedl and Smeets (2017) explore whether individual investors can benefit from ESG investments and whether there are welfare gains or specific benefits associated with ESG products. Chay and Greenstone (2005) delve into the costs that firms may incur when they adopt environmentally friendly practices, questioning whether the benefits outweigh the expenses. The pricing of ESG products has also been a subject of interest, with Baker et al. (2018) examining bonds, Sharfman and Fernando (2008) and Hong and Kacperczyk (2009) focusing on stocks, Riedl and Smeets (2017) looking at funds, and Goss and Roberts (2011) at bank loans. These studies aim to understand how the market values ESG considerations and whether there is a premium or discount associated with sustainable financial products.

More related to this paper, the impact of green policies on the macro economy has been discussed by Wang et al. (2019) and Annicchiarico and Di Dio (2015). Annicchiarico and Di Dio (2015) proposes incorporating green financial factors into traditional macroeconomic models to create a dynamic stochastic general equilibrium (DSGE) model that can study the intersection of the economy, finance, and the environment. Wang et al. (2019) simulate the effects of various green credit policies within a DSGE framework, demonstrating the positive impact of green credit incentives on the real economy. Recently, Hartzmark and Shue (2022) find that sustainable investing may be counterproductive, as their evidence shows that green firms experience minimal improvement when their cost of capital is reduced, while increasing the cost of capital for brown firms leads to a significantly negative impact on their environmental performance. Li et al. (2024) investigate the allocative efficiency of green finance instruments. In their model, ex-ante instruments, such as green credit schemes, are more allocatively efficient. These instruments effectively guide financially constrained firms towards adopting cleaner technologies by lowering the upfront financial burden, while ex-post instruments like carbon taxes tend to be less allocatively efficient, as they often shift dirty capital towards financially constrained firms, which tend to use their capital more intensively and thus produce higher emissions.

Our research differs from these studies in several ways. First, we categorize all firms into green and brown based on their emissions and measure their respective productivity using the total factor productivity (TFP), which provides a comprehensive metric. Using firm-level data, we provide microscopic evidence that green firms exhibit stronger heterogeneity in their TFP distribution. Second, we consider the enactment of a rigorously enforced green credit policy in China as an exogenous shock to analyze the impact of the policy on firm productivity, economic growth, and the environment. Third, we provide a theoretical model to rationalize our empirical findings and extend the model into a dynamic framework to analyze the effect on resource allocation, environmental performance and social wealfare, considering the higher productivity heterogeneity in green firms. This is the first time the green credit policy has been analyzed systematically within a framework of firms with heterogeneous productivity.

The structure of the rest of this paper is as follows: Section II provides stylized facts about TFP distribution and the relationship between TFP and emissions. Section III describes the basic model setting and analyzes its partial equilibrium properties. Section IV presents an analysis of the model dynamics. Section V sets up a general equilibrium model by adding a household sector and performs a welfare analysis. Section VI presents empirical evidence on TFP, bank loans, and emissions to validate the model's implications. Section VII concludes.

II Stylized Facts

In this section, we present stylized facts regarding the TFP of firms in China. This includes the distribution of TFP and its heterogeneity among green and brown firms. Additionally, we examine the relationship between TFP and emissions.

II.1 Sample and Data

Our firm-level production and financial accounting information is based on the Annual Survey of Industrial Firms (ASIF) from 2000 to 2013. The ASIF dataset is widely used by empirical researchers, and the detailed production information allows us to measure firm-level productivity for the entire Chinese manufacturing sector[2].

We follow standard procedures utilized in the literature, such as He et al. (2020), to clean the data. First, we drop observations with missing key financial indicators or with negative values for items such as value-added, employment, and capital stock. Next, we drop observations that violate accounting principles: liquid assets, such as fixed assets, or net fixed assets that are larger than total assets, or current depreciation larger than cumulative depreciation. Finally, we trim the data by dropping observations with values of key variables outside the range between 0.5th to 99.5th percentiles.

We collect firm-level emission data and resource consumption data from the Green Development (GD) database, managed by the Ministry of Environmental Protection (MEP). The GD database provides the most comprehensive environmental data in China, monitoring polluting activities, including resource consumption, pollution discharge, and pollution treatment.

II.2 Variable Definition

II.2.1 TFP

While there are various approaches to measuring TFP, it has been documented in the literature that these measures are generally highly correlated with each other (Syverson, 2011). In this paper, we rely on an OLS estimation and a semi-parametric estimator suggested by Olley and Pakes (1996) to construct our baseline TFP measures separately. There is a common argument (Van Beveren, 2012) about the method of calculating the total production rate of enterprises. It is generally recognized that OLS is not enough to solve endogenous

[2] The ASIF data include private industrial enterprises with annual sales exceeding 5 million RMB and all the state-owned industrial enterprises (SOEs). The data are collected and maintained by the National Bureau of Statistics (NBS) and contain a rich set of information obtained from the accounting books of these firms, such as inputs, outputs, sales, taxes, and profits.

problems and will lose effective information. The latter approach addresses the simultaneity and selection biases in estimating the labor and capital coefficients and has been the most widely used method for investigating Chinese firms' productivity (e.g., Brandt et al. (2012); Yang (2015)). Using the Olley-Pakes approach ensures that our findings can be benchmarked against existing estimates in the literature (He et al., 2020).

To reflect the technical level of enterprises as accurately as possible, we assume that the production models of enterprises in the same industry are similar. The capital and labor coefficients are estimated by each industry, and year fixed effects are included in every regression to control for the industry-year level production dynamics. Additionally, whether a firm is classified as a green firm is included as a state variable to account for the possibility that green firms might be forced to install more abatement facilities by the government.

The procedures for constructing our key variables and performing OLS and Olley-Pakes estimations are discussed in more detail in Appendix A. The estimated labor and capital coefficients for each industry are reported in Table 3. Figure 14 plots the density lines of OLS TFP and OP TFP, showing that TFP estimated by these two methods has a similar distribution. This indicates that our results are robust and consistent.

II.2.2 Green or Brown

To compare the cross-sectional differences between green firms and brown firms, we need to establish criteria to distinguish them. Some papers, such as He et al. (2020), use a DID framework to test the effects of water quality monitoring on TFP for polluting and non-polluting industries, borrowing official definitions from the Ministry of Environmental Protection (MEP). According to the MEP, ASIF firms can be categorized into polluting and non-polluting industries. However, using whether a firm belongs to a polluting or non-polluting industry to distinguish green or brown firms is not suitable for us because this classification does not consider heterogeneity between firms in the same industry. Additionally, a firm belonging to a polluting industry does not necessarily mean it does not have environmental improvement behavior.

The core difference between green firms and brown firms lies in the difference of their environmental externalities. Hence, we distinguish a firm as green or brown according to its pollution emission volume, using the same approach as in Hartzmark and Shue (2022). For every firm included in the GD dataset, total output value, as well as pollutant emissions of various types, are recorded. Among the different types of pollutants measured for each GD firm, chemical oxygen demand (COD) and sulfur dioxide (SO_2) are the most relevant subjects for this study. COD measures the amount of oxygen required to oxidize soluble and particulate organic matter in water and is widely used as an omnibus indicator for water pollution [3], while SO_2 is a dominant air pollutant.

We define variable $COD = \frac{COD \text{ emission}}{\text{Gross revenue}}$ and $SO_2 = \frac{SO_2 \text{ emission}}{\text{Gross revenue}}$ and sort all firms in one industry into three groups—low, middle, and high—by COD and SO_2 according to their 33.3% quantile and 66.6% quantile. A firm belongs to the green category when its COD or SO_2 is in the low tercile group, while it is classified as brown if it is in the high tercile group of either. We implement this grouping standard industry by industry. Finally, we combine all the low groups from all industries to form a subsample of GREEN firms, while combining all the high groups from all industries to form a subsample of BROWN firms.

II.3 TFP Distribution of Green Firms and Brown Firms

In this section, we compare the distribution differences between the two sub-samples: green firms and brown firms. As mentioned in Section II.2.1, we calculated TFP using both the OLS method and the Olley and Pakes (1996) method (OP method) separately.

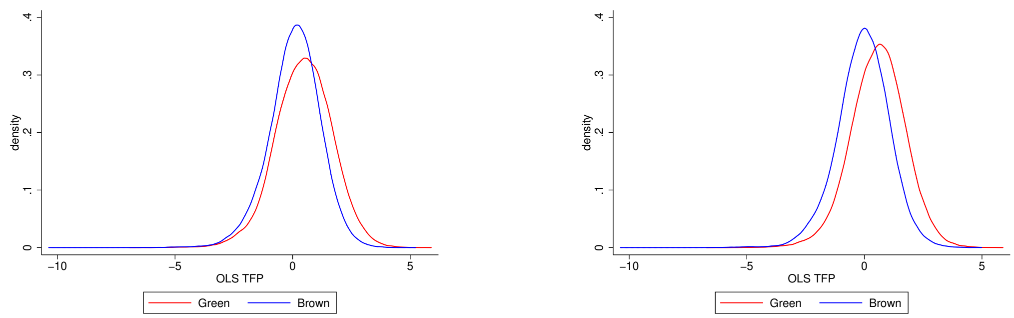
Figure 1 shows the TFP density distribution function where TFP is calculated using the OLS method. The two panels illustrate the TFP distribution heterogeneity between the two types of firms, categorized by COD and SO_2 separately. The red line represents the green firms, while the blue line represents the brown firms. The figure reveals one key fact about the TFP distribution: The TFP distribution of green firms is wider than that of brown firms. For robustness, we also plot the TFP density distribution function in Figure 15, where TFP is calculated using the OP method. Figure 15 shows similar results to Figure 1, confirming the robustness of our findings.

To formally test the mean and variance differences shown in Figures 1 and 15, we perform mean comparison tests (T-test) and equal variance tests (F-test). The results are shown in Table 6. First, the difference in TFP levels between green firms and brown firms is positive. The T-test indicates that these differences are significant. Second, the ratio of the standard deviation of TFP between green firms and brown firms is greater than 1. The F-test shows that these differences are significant. This indicates that green firms has a wider TFP distribution compared to brown firms.

Stylized fact 1. *Green firms' TFP shows stronger heterogeneity compared to brown firms. This is indicated by the green firm sub-sample having a wider TFP distribution compared to the brown firm sub-sample.*

[3] A higher COD level indicates a greater amount of oxidizable organic material in the sample, which reduces dissolved oxygen levels. A reduction in dissolved oxygen can lead to anaerobic conditions, which are deleterious to higher aquatic life forms. COD is also the "target pollutant" in China's surface water quality standards: the central government explicitly set a 10% abatement target for COD emissions in the 10th and 11th Five-Year Plans (2001–2005 and 2006–2010).

Figure 1. **OLS-TFP heterogeneity in green firms and brown firms**



Panel A. COD Panel B. SO_2

Notes: This figure reports the OLS-TFP density distribution of green firms and brown firms, categorized by COD and SO_2 separately. We divide the total sample into three sub-samples based on the 33.3% and 66.7% quantiles of the sample. The red line corresponds to green firms, while the blue line represents brown firms.

II.4 TFP and Emission

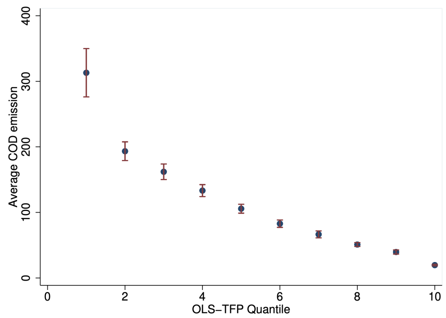
In this section, we investigate the relationship between TFP and firm-level emissions. Intuitively, higher production efficiency should lead to stronger resource utilization capabilities, resulting in lower pollution emissions. We divide the entire sample into ten deciles based on the TFP levels of companies, with the first decile having the lowest TFP and the tenth decile the highest. We then calculate the average pollution emission levels for each decile. The results are reported in Figure 2. Here, TFP is measured using the OLS method, and we use COD and SO_2 (scaled by gross revenue) to proxy emission levels. The figure also shows the 95% confidence interval. It is straightforward to see that there is a negative relationship between TFP and emissions. We also use OP-TFP for a robustness test, which gives us a similar result shown in Figure 16.

Figure 2 shows the negative correlation between a firm's TFP and its emissions. Specifically, higher production efficiency is associated with lower pollution emissions. This is intuitive, as higher TFP helps reduce emissions. Although this result is unlikely to suffer from causal inversion, there is a possibility of missing variables. Therefore, we construct a formal regression (Equation 1) to test this relationship.

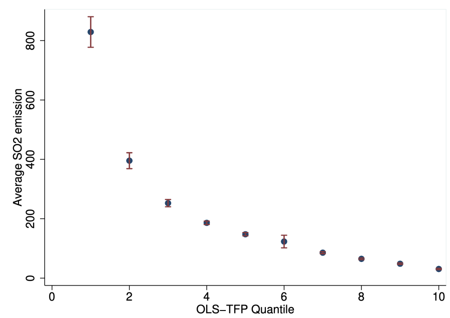
$$Emission_{ijt} = \alpha_0 + \alpha_1 TFP_{ijt} + \gamma Z_{ijt} + u_j + v_t + \varepsilon_{ijt} \tag{1}$$

where $Emission_{ijt}$ is the COD or SO_2 emission of firm i in industry j in year t. We measure firm's emission intensity here by its absolute value and its scaled value with respect to revenue, respectively. TFP_{ijt} is the OLS TFP or the OP TFP of firm i in industry j

Figure 2. **OLS-TFP and Emission**



Panel A. COD



Panel B. SO_2

Notes: This figure reports the relationship between the OLS-TFP and emission level, which is categorized by COD and SO_2 separately. We divide the total sample into ten subsamples according to the their OLS-TFP. We also shows the 95% confidence interval in the figure. The figure shows that the pollution emissions of firms are smaller with higher levels of TFP.

in year t. Z indicates the vector of control variables. Here, we control firms' size, bank loan level, ROA and SOE. To account for the industry- and year-specific emission and TFP determinants in the non-parametric estimations, we control for industry- and year-fixed effects u_j and v_t in the model. We use robust standard errors in the regression.

The regression results are reported in Table 7. Panel A shows the regression results using COD emission as the dependent variable. Columns (1-2) use the log value of the absolute COD, and columns (3-4) use COD scaled by revenue. Panel B shows the regression results using SO_2 emission as the dependent variable. Columns (1-2) use the log value of the absolute SO_2, and columns (3-4) use SO_2 scaled by revenue. All the TFP coefficients are negative and significant. These results are consistent with Figure 2 and support the idea that TFP helps reduce emissions. This insight will be used when we construct a model in the next section.

Stylized fact 2. *There is a negative correlation between TFP and emissions per unit. Higher TFP indicates higher production efficiency and resource utilization ability, leading to lower emissions.*

III The Model

In the previous section, we provided evidence of structural differences in the TFP distribution between green firms and brown firms. Specifically, the dispersion of TFPs for green firms is higher than that for brown firms.

This difference may be related to the various ways green firms achieve emission reductions. Some firms reduce emissions per unit of output by improving production technologies and their efficiency, while others achieve reduction by purchasing abatement equipment, even if their inherent production efficiency is poor.

We further tested the relationship between TFP and emissions and found a negative correlation, indicating that higher TFP is associated with higher production efficiency and thus lower emissions per unit of production.

Based on these two stylized facts, we construct a model to analyze the impact of green credit policies on credit allocation and evaluate their performance in both economic and environmental aspects. The model we build is based on Dong and Xu (2020) who offer a dynamic model in which excessive credit creation by the frictional banking sector may lead to over-investment and subsequent endogenous boom-bust cycles. We introduce green policies into the model and study the credit allocation process of banks. Our model also build in an environmental dimension to exam the implications for environmental outcome. In addition, We construct a general equilibrium by introducing a household sector and assuming that polluting emissions from the production sector damage household welfare.

Specifically, we consider a discrete-time production economy with an infinite horizon. We label each period by $t = 0, 1, 2, \cdots$. The model economy has a production sector and a banking sector. Firms in the production sector are classified into green firms and brown firms. Considering the empirical fact that TFP heterogeneity of green firms is stronger than that of brown firms, we set the production sector to include a continuum of green firms with heterogeneous productivity and a continuum of brown firms with homogeneous productivity, respectively. They rent physical capital and hire labor to produce final goods. The production of firms will produce externalities to the environment. The total supply of labor is fixed with one unit.

The economy has a unit measure of banks. Each bank is endowed with ω units of capital and the quantity of capital that the bank can employ is $\xi\omega$. They make loans to firms or to other banks in the interbank market. Under the green credit policy, the banks are not allowed to invest in brown firms and could only invest in green firms. The parameter ξ reflects the tightness of the green loan credit and $\xi \in (0, 1)$. However, because of the presence of moral hazard problems, banks may divert loans and invest in brown firms. Each individual bank meets one green firm and one brown firm and decides whether to provide a loan or not, which depends on the return for each choice. If the bank does not invest in a firm, it lends its funds to another bank that decides to invest in a firm, and the borrowing bank will invest with the loan amount equal to the borrowed capital plus their own capital.

a priori, a borrowing bank may divert θ ($\theta \in (0,1)$) portion of the interbank loan, together with their own endowed capital, to lend to a brown firm. We assume this diverting behavior could be observed by the regulator afterward, and these offending banks will be punished and the punishment value is positively correlated with the brown firms' emission volume.

III.1 The Production Sector

The production sector consists of green firms and brown firms. Each firm corresponds to a project, which combines physical capital k and labor n to produce final goods. We assume that a firm's physical capital is fully financed by a bank if the bank decides to invest (i.e., provide loans) in this firm. Following Coimbra and Rey (2017), we assume that there is no asymmetric information or agency problem between the bank and the firm so that the bank takes all the capital income from the firm as the payment to the loan.

III.1.1 Green Firms

A typical green firm with idiosyncratic productivity z uses capital k_g and labor n_g to produce goods according to the Cobb-Douglas production technology

$$y_g = A_g \left(zk_g\right)^{\alpha} n_g^{1-\alpha} \tag{2}$$

where $\alpha \in (0,1)$ and A_g denotes the aggregate productivity of green firms. Green firms are heterogeneous in the sense that each firm has an idiosyncratic productivity z. We assume $z \in [\underline{z}, \bar{z}]$ and the distribution follows a cumulative distribution function $F(z)$, with $E(z) = 1$. As for emission, we set that each green firm has an emission function

$$e_g = [1 - \chi(z)]\tau k_g \tag{3}$$

where $\tau > 0$ denotes emission per unit of used capital without pollution abatement, and $\chi(z)$ denotes the pollution governance or environment-friendly measures. We specify $\chi(z) = \kappa z^{\rho}$. The idiosyncratic productivity z is assumed to be negatively related to the firm's emission, which is based on the stylized fact that higher z means higher capital utilization efficiency, thus lower emission level. Note that banks in our model are indeed heterogeneous because of the productivity heterogeneity of green firms. The capital k_g is fully financed from the bank loan. To incentivize green firms, we assume that the government only penalizes the pollution emissions of brown firms. Therefore, green firms do not have to consider pollution emissions when making decisions to maximize profits. The optimal labor decision for a green firm:

$$\pi(z) = \max_{n_g \geq 0} A_g \left(zk_g\right)^{\alpha} n_g^{1-\alpha} - W n_g \tag{4}$$

where W is the wage rate. The first-order condition implies that the labor demand satisfies:

$$n_g(z) = \left[\frac{(1-\alpha)A_g}{W}\right]^{\frac{1}{\alpha}} zk_g \tag{5}$$

Then, capital return is linear in k_g, i.e.,

$$R_g^K k_g = A_g \left(zk_g\right)^{\alpha} n_g^{1-\alpha} - W n_g \tag{6}$$

R_g^K can be easily derived as $r_g^K z$, where $r_g^K = \alpha A_g^{\frac{1}{\alpha}} \left(\frac{1-\alpha}{W}\right)^{\frac{1-\alpha}{\alpha}}$. For simplicity, we assume that households inelastically provide one unit of labor.

III.1.2 Brown Firms

For brown firms, we assume that they are homogeneous in their productivity and produce the final goods by only using capital. The production technology follows a linear form

$$y_b = A_b k_b \tag{7}$$

where A_b is brown firms' productivity. Thus, marginal capital return from investing in a brown firms is simply a constant A_b. Each brown firm has an emission function

$$e_b = \tau k_b \tag{8}$$

We assume that brown firms' capital does not have characteristics for pollution governance with the absence of χ.

Considering the heterogeneity in green productivity, we further assume that a fraction of green firms are more productive than brown firms while the remaining green firms are less productive. Given the capital stock ω, the marginal product of capital for the green firm with the highest productivity is greater than that for brown firms. That is:

$$\alpha A_g \bar{z}^{\alpha} \omega^{\alpha-1} > A_b \tag{9}$$

Besides, we also have

$$\alpha A_g \underline{z}^{\alpha} \omega^{\alpha-1} < A_b \tag{10}$$

Under this assumption, a socially optimal allocation without capacity constraints implies that all capital should be allocated to the most productive green firms.

III.2 The Bank Sector

An individual bank meets a green firm with idiosyncratic productivity z and one brown firm. There is an interbank market from which the bank can supply or obtain a loan. We denote R^f as the competitive interest rate prevalent in the interbank market. Given $\xi\omega$ units of capital available, we denote the ratio of interbank loans to the bank's endowed capital as λ. Then, $\lambda\xi\omega$ is the amount of loan the bank borrows from the interbank market so that the overall capital available is $(1+\lambda)\xi\omega$. $\lambda = 0$ implies the bank does not borrow from the interbank market and use its own endowed capital.

In order to introduce a green credit policy into the model, we assume that a bank can receive an interest subsidy from the central bank if the bank decides to invest in green firms. The rate of subsidy is the γ fraction of R^f. On the other hand, an emission punishment is incurred if a bank diverts capital into a brown firm. We assume that the punishment function takes a linear form of the total emission, i.e., $g(e) = \psi e$, where $\psi > 0$.

An individual bank that meets a green firm with idiosyncratic productivity z can choose to (i) lend to other banks in the interbank market with the interest rate R^f or (ii) borrow from the interbank market with R^f and provide loans to the green firm with the rate of return $r_g^K z$. The return is $(r_g^K z + S)(1+\lambda) - R^f\lambda$, where S denotes the green interest subsidy rate and we set $S = \gamma R^f$. However, the presence of financial frictions, such as moral hazard problems, may distort credit trade in the interbank market. In particular, following Boissay et al. (2016), we assume that the borrowing bank has a choice to (iii) divert $\theta \in (0,1)$ portion of the interbank loans to the brown firm, with a return of $(A_b - \psi\tau)(1+\theta\lambda)$.

III.2.1 Bank's Investment Strategies

Each bank has to decide whether it borrows and invests in a green firm or just lends its endowed capital to other banks. Further, for a borrowing bank, it has to decide how much leverage to take on.

For a borrowing bank, the payoff from investing in a green firm is positively related to the idiosyncratic productivity z. When a bank meets a high-productivity green firm, it tends to borrow to make the loan because higher z improves the payoff. When a bank meets a low-productivity green firm, it tends to lend to other banks. There exists a threshold z^*. If $z < z^*$, investing in green firms is less profitable than lending to the interbank market. The threshold can be obtained by equalizing the payoff from either case ($i = ii$):

$$(r_g^K z + \gamma R^f)(1 + \lambda) - R^f \lambda = R^f \tag{11}$$

where r_g^K can be expressed as a function of (ω, z), which will be shown later. Equation (11) defines an implicit function of the threshold $z^* = Function(R^f, \omega)$.

Due to the prohibition of making loans to brown firms by the green credit policy, the brown payoff should be smaller than the green payoff in equilibrium. Specifically, if a bank decides to lend and not invest in a green firm (individual rationality condition 1 (IR1): $i > ii$), then it needs also to make sure (incentive compatibility condition 1 (IC1): $i > iii$) that it does not have the incentive to divert the interbank loans into brown firms. On the other hand, if the bank decides to invest in the green firm (IR2: $ii > i$), then it needs to make sure (IC2: $ii > iii$) so that the bank does not have the incentive to divert the interbank loans into brown firms. In sum, there exists a one-and-only incentive compatibility (IC) condition:

$$(A_b - \psi\tau)(1 + \theta\lambda) \leq R^f \tag{12}$$

And we can derive λ as:

$$\lambda \leqslant \frac{R^f - A_b + \psi\tau}{(A_b - \psi\tau)\,\theta} \tag{13}$$

The inequality (13) puts a limit on the leverage level a borrowing bank can take on such that it will not have incentives to divert loans to brown firms.

Proposition 1. *Whenever a bank decides to make loans to green firms, it will take leverage level up to its IC constraint.*

Proposition 1 states that the incentive compatibility (IC) condition (13) holds with equality at the optimum (The proof can be seen in Appendix B). Proposition 2 below characterizes the leverage ratio λ.

Proposition 2. *The loan-to-equity ratio λ increases with the interest rate R^f, the punishment measure ψ, and decreases with the productivity of brown firms A_b, and the severity of the moral hazard problem θ. That is $\frac{\partial\lambda}{\partial R^f} > 0$, $\frac{\partial\lambda}{\partial\psi} > 0$, $\frac{\partial\lambda}{\partial A_b} < 0$, $\frac{\partial\lambda}{\partial\theta} < 0$.*

When θ is zero, i.e., there is no moral hazard, then λ is unbounded from above. Otherwise, when R^f rises, only those banks with efficient projects (z is high, Equation (11)) intend to borrow, which in turn mitigates the moral hazard problem and therefore induces a higher λ. As for the negative relationship between λ and ψ, a stronger punishment mitigates the moral hazard directly, thus inducing a higher λ. Oppositely, a higher A_b or θ will induce a stronger incentive for diverting behavior, so the supply in the interbank market decreases.

III.3 Partial Equilibrium

III.3.1 Financial Market Clearing

Now, we solve the partial equilibrium by financial market clearing. The interbank capital market clearing condition implies that loan demand equals loan supply, which can be expressed as

$$\int_{z^*}^{\bar{z}} \lambda \xi \omega \mathrm{d}\mathbf{F}(z) = \int_{\underline{z}}^{z^*} \xi \omega \mathrm{d}\mathbf{F}(z) \tag{14}$$

which can be reduced as

$$[1 - \mathbf{F}(z^*)]\, \lambda = \mathbf{F}(z^*) \tag{15}$$

The RHS of the above equation indicates that the supply of loans depends only on $\mathbf{F}(z^*)$, which monotonically increases with the cutoff value z^*, whereas the LHS of the equation shows that the aggregate demand for loans consists of $1 - \mathbf{F}(z^*)$ and the leverage λ.

We now specify the r_g^K by solving the aggreate labor N. From the individual labor demand (5), the aggregate labor N is given by

$$N = \int_{z \geq z^*} n_g(z) \mathrm{d}\mathbf{F}(z) = \left[\frac{(1-\alpha)A_g}{W}\right]^{\frac{1}{\alpha}} [1 - F(z^*)]\,(1+\lambda)\xi\omega \mathbf{E}(z \mid z \geqslant z^*) \tag{16}$$

where $\mathbf{E}(z \mid z \geqslant z^*)$ denotes the average productivity of the firms who get loans and $[1 - F(z^*)]\,(1+\lambda)\xi\omega\mathbf{E}(z \mid z \geqslant z^*)$ is the effective capital used by green firms. Consistent with Dong and Xu (2020), we assume that the productivity z conforms to a Pareto distribution with CDF $F(z) = 1 - (\frac{z}{\underline{z}})^{-\eta}$ and $\eta > 2$. We set $\underline{z} = 1 - 1/\eta$ so that $E(z) = 1$.

With the inelastic labor supply, that is $N = 1$, plus the financial market clearing condition (15), r_g^K could be written as

$$r_g^K = \alpha A_g \left[\xi \omega \mathbf{E}(z \mid z \geqslant z^*)\right]^{\alpha - 1} \tag{17}$$

Plugging equation (17) into equation (11), the equilibrium interest rate satisfies:

$$R^f = \frac{\alpha A_g \left[\xi \omega \mathbf{E}(z \mid z \geqslant z^*)\right]^{\alpha-1} z^*}{1-\gamma} \tag{18}$$

The equilibrium interest rate equation (18) means the interbank interest rate R^f is a function of cut-off z^* and capital ω as $R^f = Function(z^*, \omega)$. Notice that with the Pareto distribution, we have $\mathbf{E}(z \mid z \geqslant z^*) = \frac{z^*}{\underline{z}}$. For the above implicit function, by taking derivatives of R^f to z, it is straightforward to show that the equilibrium interest rate R^f strictly increases with z^*. From the binding incentive compatibility constraint (13), λ increases with R^f, implying that the leverage increases with z^* as well. Therefore, the relationship between the aggregate demand for loans and the cutoff value z^* could be nonmonotonic. A rise in the cutoff z^* would raise the borrowing capacity of banks; meanwhile, it reduces the number of firms that choose to borrow and produce.

The equilibrium interest rate equation (18), together with the credit market clearing condition (15) pin down the interest rate R^f and the marginal levered bank z^* for a given ω. The equilibrium solution can be found in Appendix C. Due to the nonmonotonic charater of credit demand, there may exist multiple equilibria. In our subsequent analysis, we consider only the equilibrium that results in higher overall welfare, where the value of z^* reflects the efficiency of credit allocation.

III.3.2 Partial Equilibrium Analysis

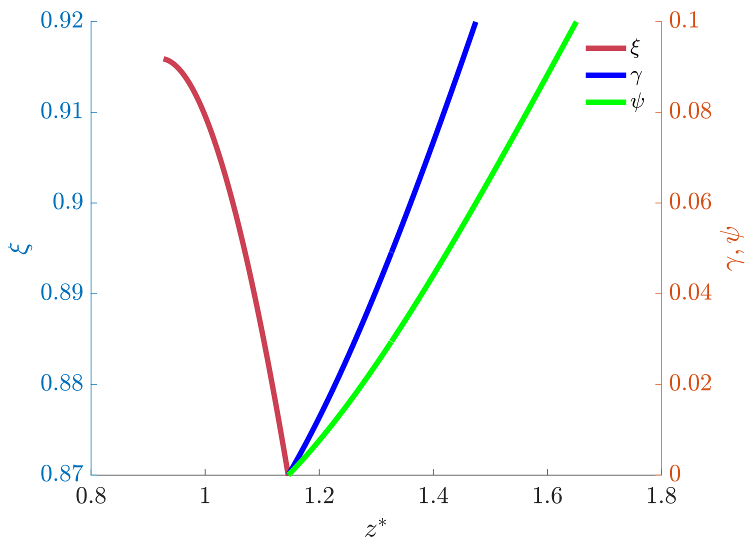
We first focus on the credit amount parameter ξ and set $\gamma = \psi = 0$. The movement pattern of z^* is shown by red line in Figure 3. It could be found that z^* decreases with the green loan amount parameter ξ. Figure 23 in Appendix D illustrates what happens when ξ changes. With a higher ξ, increasing aggregate capital ω results in the decline of capital returns, causing the investment in green firms less profitable overall, which in turn induces reduction in R^f and leverage λ. This leads to the excess supply of credit, with extra credit resources moving to firms with lower productivity (z^* decreases). As more low productivity firms enter into the credit market, the aggregate productivity measured by $\mathbf{E}(z \mid z \geq z^*)$ decreases.

We now illustrate how the movement of γ and ψ influences the system given the credit amount parameter ξ. A rise in γ makes investing in green firms more profitable, which increases the credit demand, while brown penalty ψ restricts the profit of diverting credit resources and increasing λ too. In both cases, the cutoff z^* increases and the aggregate productivity in the market $\mathbf{E}(z \mid z \geq z^*)$ also increases, hence the aggregate production efficiency in the economy improves. The blue line and green line in Figure 3 shows how cutoff z^* moves with γ and ψ.

III.3.3 Aggregate Output and Emission

Now we consider the real economy and the environment. In our model, because brown firms are prevented from obtaining credit, only green firms exist. For the aggregate output and

Figure 3. **Cut-off level z^***



the aggregate emission, we have:

$$Y_g = \int_{z \geq z^*} y_g(z)\mathrm{d}\mathbf{F}(z) = A_g \left[\xi\omega\mathbf{E}\left(z \mid z \geq z^*\right)\right]^\alpha \tag{19}$$

$$E_g = \int_{z \geq z^*} e_g(z)\mathrm{d}\mathbf{F}(z) = \tau\xi\omega\left[1 - \kappa\mathbf{E}\left(z^\rho \mid z \geqslant z^*\right)\right] \tag{20}$$

Figure 4. **Aggregate output and emission under ξ**

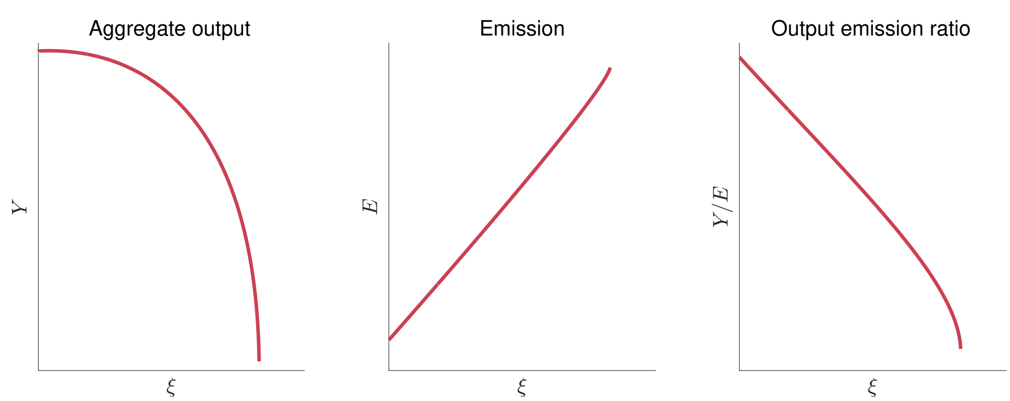


Figure 4 plots the static analysis of aggregate output and emission with ξ. In the left subplot, it is worth noting that the aggregate output is nonmonotonous. As equation (19) shows, ξ has two offsetting effects on the output: On one hand, it directly raises the total capital used for production, i.e., $\xi\omega$ increases. On the other hand, it induces banks to finance more less-efficient projects and thus reduces the average productivity $\mathbf{E}(z \mid z \geqslant z^*)$. As a result, the output level increases first and then decreases. For the emission level, it increases all the time due to the fall of average emission treatment efficiency $\mathbf{E}(z^\rho \mid z \geqslant z^*)$ [4]. Moreover, TFP not only measures firms' productivity but also reflects their environmental governance ability. Lower TFP means worse resource utility efficiency and emission governance ability.

Figure 5. **Aggregate output and emission under γ and ψ**

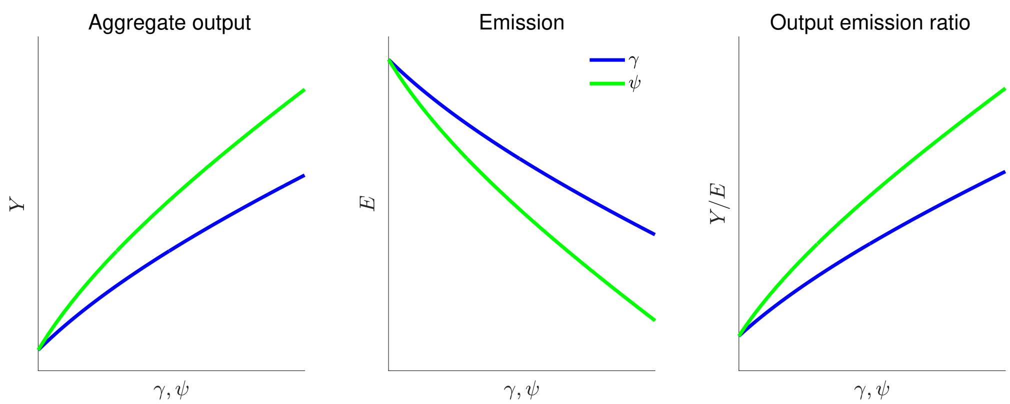


Figure 5 illustrates a static analysis of aggregate output and emission with γ, ψ. It can be seen that both γ and ψ rise with aggregate output and decrease in emission. The reason is opposite to ξ. Here, rising γ, ψ affects cutoff z^* such that the total capital is concentrated in firms with higher productivity.

IV Dynamics

In the previous section, we discuss the impact of the green credit policy on the real economy through a steady-state perspective. In this section, we aim to study the aggregate dynamics in response to the green credit policy.

IV.1 Calibration

We first calibrate the model as follows. We divide the parameters to be calibrated into three subsets. The first subset of parameters includes the capital share in production function α and the discount factor β. According to the empirical evidence for the Chinese manufacturing industries in Brandt et al. (2008), Song et al. (2011), and Zhu (2012), we set the capital income share α to be 0.5 and β to be 0.96.

[4] $\mathbf{E}(z^\rho \mid z \geqslant z^*) = \frac{\eta}{\eta-\rho} z^{*\rho}$.

The second subset of parameters is model specific, including the sectoral productivity A_g and A_b, the shape parameter in Pareto distribution η, the moral hazard parameter θ, emission per unit of used capital without pollution abatement τ, the production technology's efficiency and elasticity κ, ρ. We first calibrate $A_b = 1.03$ by making its log value equal to the average OP-log(TFP) in brown firms. Then, we set aggregate productivity for green firms A_g as 1.51 by making its log value equal to the average OP-log(TFP) of green firms. For the distribution shape parameter η, we calibrate it as 2.35 so that the standard deviation of OP-log(TFP) distribution is equal to 1.24[5]. As for the moral hazard parameter θ, we directly follow Boissay et al. (2016) and set it to 0.08. As for emission per unit parameter τ, we set it to 0.1 according to our sample. For emission reduction parameters, we set $\kappa = 0.1$ and $\rho = 0.5$.

The third subset of parameters contains three policy parameters including green loan amount parameter ξ, green interest subsidy rate γ, and brown punishment parameter ψ. We set ξ transits from 0.75 to 0.9 following an AR(1) process to fit the fact that the average reserve ratio between 2000-2013 in China is 13%. For green credit policy parameters γ, ψ, we follow Wang et al. (2019) and make them transit from 0 to 0.1, again following AR(1) processes, to match the transition dynamic path of the system.

Table 1 summarizes the calibration of parameters.

Table 1. **Parameter Calibration**

Parameter	Value	Description
α	0.5	capital share of output
β	0.96	discount factor
η	2.35	shape parameter in the Pareto distribution
θ	0.08	moral hazard parameter
τ	0.1	emission per unit of used capital without pollution abatement
κ	0.1	the efficiency of technology on reducing emissions
ρ	0.5	the elasticity of technology on reducing emissions
A_b	1.03	aggregate productivity for brown firms
A_g	1.51	aggregate productivity for green firms
ξ	transits from 0.75 to 0.9 following AR(1)	green loan amount
γ	transits from 0 to 0.1 following AR(1)	green interest subsidy rate
ψ	transits from 0 to 0.1 following AR(1)	punishment per unit emission incurred for a bank providing a loan to a brown firm

[5]The variance of log value of a random variable X which follows Pareto distribution is $\frac{1}{(\eta-1)^2(\eta-2)}$.

IV.2 Dynamic Impacts of Green Credit Policies

In this section, we simulate the effects of three credit policies, i.e., green loan expansion, green credit subsidy, and brown punishment for brown loans, on the real economy and the environment.

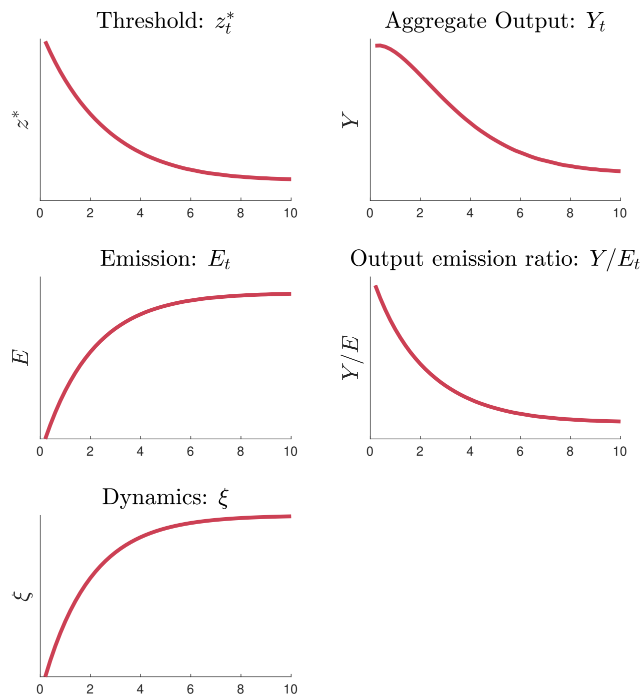
Figure 6 plots the transition dynamics when the green loan amount parameter ξ changes from 0.75 to 0.9 with an AR(1) process as shown in the last panel. The upper-left panel shows that in the baseline calibrated model, the green loan expansion reduces the cutoff z^*, leading to more low-productivity firms getting financing. Thus, direct green loan expansion reduces the efficiency in the real economy. As for aggregate output Y, the upper-right panel shows the output falls due to the average productivity decreases. The emission panel displays that the emission E actually increases with the green loan expansion. This is also due to the average productivity decreases and the emission is negatively correlated with productivity. This result is counter-intuitive that the policy failed to achieve the goal of reducing emissions. Similarly, Hartzmark and Shue (2022) also finds directing capital away from brown firms and towards green firms does not significantly improve the greenness of green firms. We also plots output emission ratio panel here. Actually, this is straightforward to see that output emission ratio decreases due to the increasing of emission and decreasing of output.

Figure 7 plots the transition dynamics when the green subsidy and brown punishment parameters permanently increase from 0 to 0.1 with an AR(1) process, respectively. Here, we set $\xi = 0.87$. The blue line is for green credit subsidy γ and the green line is for the brown punishment ψ. The upper-left panel shows that in the baseline calibrated model, increasing green credit subsidy and penalty for providing brown loans both improve the cutoff z^*, leaving more low-productivity firms without financing. For the output and environmental aspects, increasing green credit subsidy and penalty for providing brown loans both will increase the aggregate output and decrease the total emission.

V General Equilibrium

In order to proceed with an analysis of welfare implications and allocation efficiency, we now introduce the households sector and solve the model in general equilibrium by joining the household and banking problems. We consider that banks raise deposits D_t from households to generate their own initial capital ω_t. The households make their consumption and saving decisions to maximize their welfare.

Figure 6. **Dynamic path of ξ**



V.1 Household Sector

We assume there is one representative household, which has an infinite horizon and makes a consumption-saving decision. The household consumes the final good C_t and provides deposit supply to banks, while it has a fixed labor supply, normalized to $N = 1$, and finances its purchases using labor and investment income.

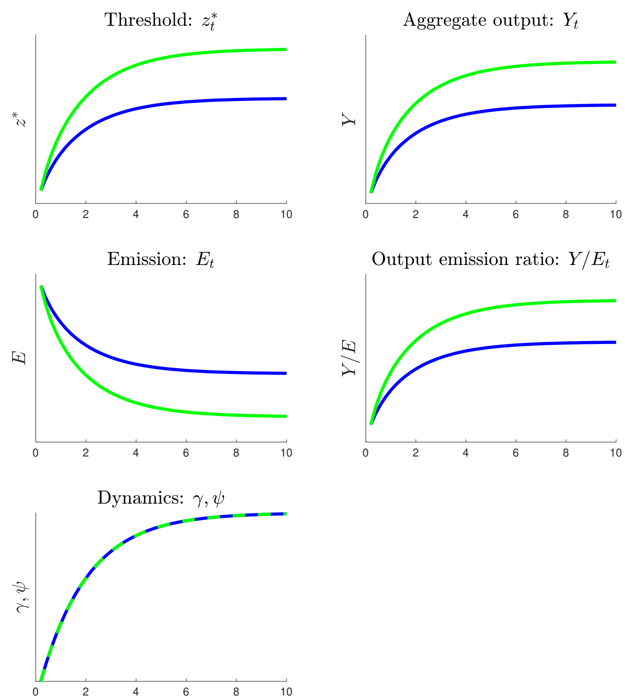
The representative household program may be written as follows:

$$\max_{\{C_t, D_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left[u\left(C_t\right) - v(E_t) \right] \qquad \text{s.t.} \tag{21}$$

$$C_t + D_t = R_{t-1}^f D_{t-1} + \int_{z_t^*}^{\bar{z}} W_t n_{g,t} \, \mathrm{d}\mathbf{F}(z) \quad \forall_t \tag{22}$$

where β is the subjective discount factor, C_t indicates consumption, D_t denotes deposit supply, and W_t is labor wage. R^f is the rate of return on deposits. We assume for simplicity that the deposit rate of return is equal to the rate of return in the interbank market. $u(\cdot)$ is the utility function. In our dynamic general equilibrium model, we assume a standard log utility form so that $u(\cdot) = \log C_t$. $v(E)$ is the negative utility brought by pollution. We

Figure 7. **Dynamic path of γ and ψ**



follow Zhang et al. (2020) and set $v(E) = hE$ and calibrate $h = 0.5$.

With the log utility and the specified dis-utility from pollution, the household problem becomes

$$\max_{\{C_t, D_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left[u\left(C_t\right) - v(E_t)\right]$$

subject to the budhet constraint (22). The solutions of this problem may be represented as

$$C_t = (1-\beta)\{R_{t-1}^f D_{t-1} + (1-\alpha) A_g [\xi \omega_t \mathbf{E}\left(z \mid z \geqslant z_t^*\right)]^{\alpha}\} \tag{23}$$

$$D_t = \beta\{R_{t-1}^f D_{t-1} + (1-\alpha) A_g [\xi \omega_t \mathbf{E}\left(z \mid z \geqslant z_t^*\right)]^{\alpha}\} \tag{24}$$

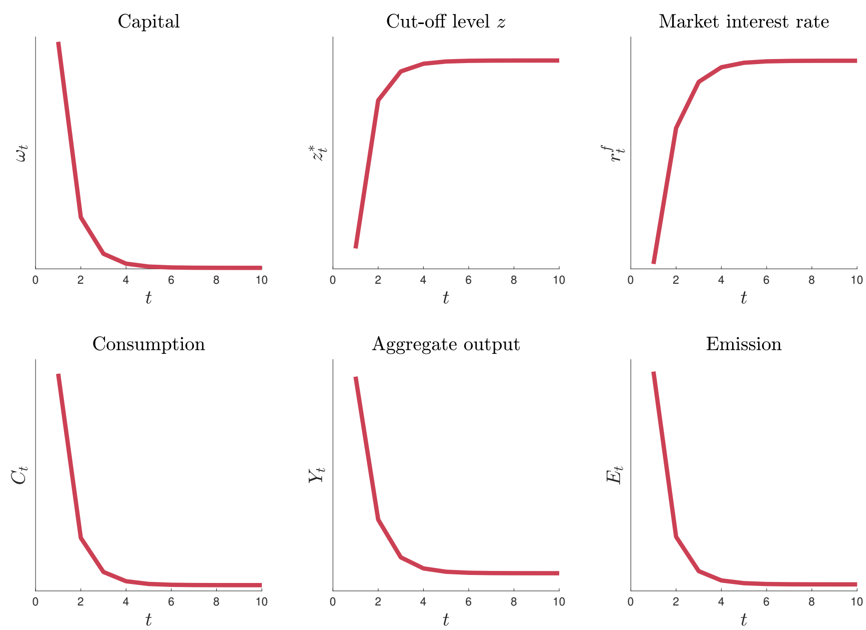
V.2 Financial Market Clearing

To close the financial market equilibrium, we need to use the market clearing condition. The aggregate capital stock of the economy is equal to the total saving of households.

$$D_t = \int_{\underline{z}}^{\bar{z}} \omega_t d\mathbf{F}\left(z\right) = \omega_t \tag{25}$$

The full system consists of equations (41) to (47) in Appendix E. Given the calibrated parameters, the full system gives us the solution of all endogenous variables. We assume $\xi = 0.75$, and begin to solve the system by setting $\omega_0 = 1$ and z_0^* equal to the value obtained in the partial equilibrium for given ξ and ω_0. To solve for the equilibrium of the whole dynamic system, we proceed by iterating on ω_t period by period, imposing the financial market clearing condition (25), until the system converges to a steady state. Figure 8 plots the movement paths of the key variables and illustrates how the system converges to a steady state under the general equilibrium conditions.

Figure 8. **Converge path of general equilibrium**

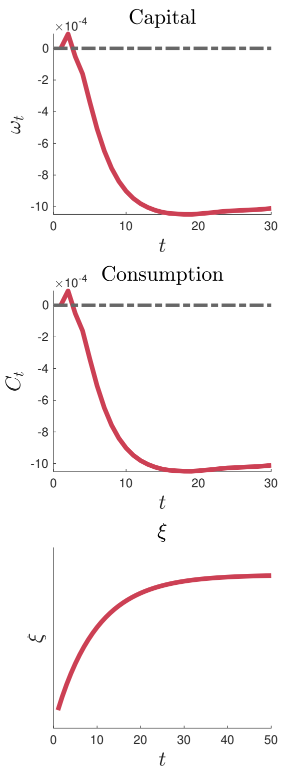


V.3 Transition Dynamics

In this section, we simulate the transition dynamics of the key macroeconomic variables for the model following shocks to green credit parameters $\{\xi, \gamma, \psi\}$. We focus on a perfect foresight equilibrium. In period 0, the economy stays in a steady state. In period 1, policy shocks hit the economy and there are no further shocks in subsequent periods. We begin with $D_0 = 1$ to solve for the new equilibrium in the dynamic system.

Figures 9 and 10 display the transition dynamics (or equivalently, impulse responses) of a few key macroeconomic variables in the model following three types of policy shocks, where ξ (red line), γ (blue line) and ψ (green line) all increase by 10%, respectively, from 0.75, 0.01 and 0.01. The shocks follow AR(1) processes. The vertical axes show percentage deviations

Figure 9. **Transition dynamics following ξ shock**



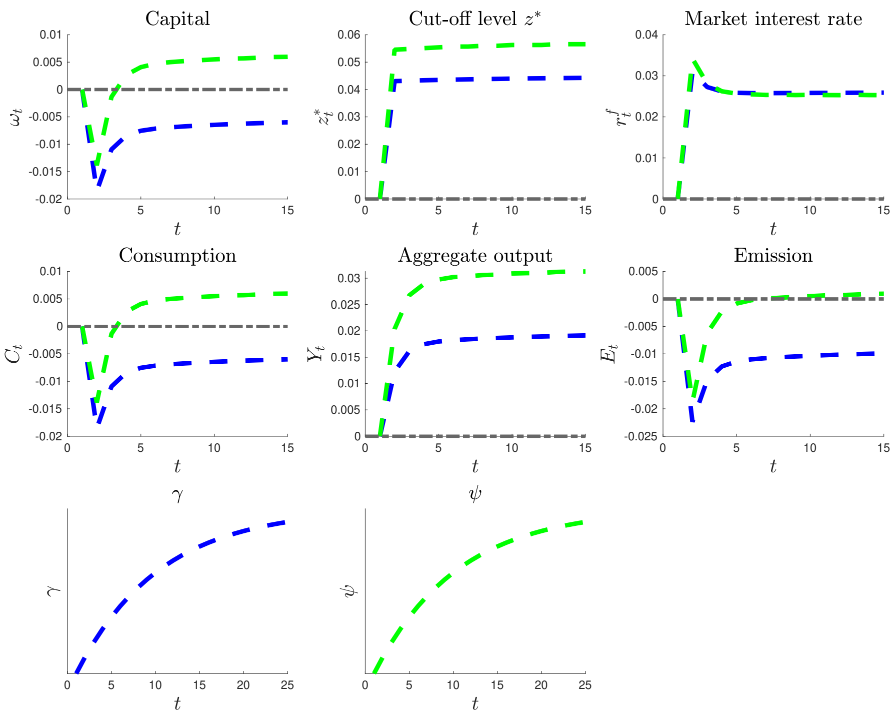
from the initial steady state (e.g., 0.01 corresponds to 1%). The horizontal axes show the periods after the shocks.

Consistent with the results in the partial equilibrium analysis, the positive shock to ξ decreases cutoff z^*, while the positive shocks of γ and ψ increase z^*. Besides, the production output and the emission also show similar patterns as in the partial equilibrium. For capital and consumption, increasing ξ induces decreasing of ω and C, while increasing γ and ψ make them fall first, and then rise again until reaching the new steady state.

V.4 Welfare Implications

As discussed before, cutoff z^* reflects the low threshold of productivity for firms to receive financing, and hence the expected productivity in the economy $\mathbf{E}(z \mid z \geq z^*)$ is strictly positively related to the cutoff z^*. A lower z^* indicates that more resources are allocated to the firms with lower productivity, and this implies an aggravating degree of resource misallocation. On the contrary, a higher z^* indicates that resource allocation is more efficient. According to Figure 9 and 10, green loan expansion ξ induces lower z^*s, thus aggravating

Figure 10. **Transition dynamics following γ and ψ shocks**



the resource misallocation, while positive shocks to green interest subsidy γ and brown punishment ψ induce higher z^*s, indicating a more efficient resource allocation.

To quantify the welfare effects and the extent of resource misallocation following a policy shock, we measure the welfare change along the transition path following a policy shock by computing the consumption equivalent for the representative household relative to the steady state (with no shocks). In particular, welfare change is measured as the fraction of steady-state consumption required for the household to stay indifferent between an economy with a green credit policy shock and one without. That is, we solve for the value of Φ such that

$$\sum_{t=1}^{\infty} \beta^t [\log C_t - hE_t] = \beta \frac{\log\left(C^{ss}(1+\Phi)\right) - hE^{ss}}{1-\beta} \tag{26}$$

where C^{ss}, E^{ss} are the steady-state consumption and emission.

We compare the welfare in the benchmark model with that in the dynamic models with shocks to calculate Φ. Our calculation shows that the expansionary monetary policy shock leads to a welfare loss of $\Phi = -0.094\%$ of steady-state consumption, while the green subsidy shock and brown addition cost shock lead to a welfare loss of $\Phi' = -0.667\%$ and a welfare gain of $\Phi'' = 0.485\%$, respectively.

VI Empirical Design and Results

In the previous section, the model suggests that increasing the amount of green loans makes investment in green projects less profitable. Bank loans are reallocated across green firms, with the cutoff productivity for firms receiving financing shifting to a lower level. As a result, the average productivity of firms receiving loans decreases, leading to increased total emissions.

In this section, we present empirical evidence supporting these economic and environmental predictions. The launch of the "green credit policy" in China provides us with a quasi-natural experiment to test the effects of this policy. We examine the change in TFPs after the policy shock and investigate credit allocation across firms. We also evaluate the change in emissions.

VI.1 Summary Statistics

In Table 4, we list the summary statistics of key variables in for green and brown firms, which are divided by the emission levels (COD or SO_2). These variables include capital, labor, gross revenue, emission, TFP, debt level, and asset level. In Table 5, we provide the cross-sectional summary statistics of key variables across industries. These variables include capital, labor, gross revenue, emission, and TFP.

VI.2 Green Credit Shock and Aggregate TFP

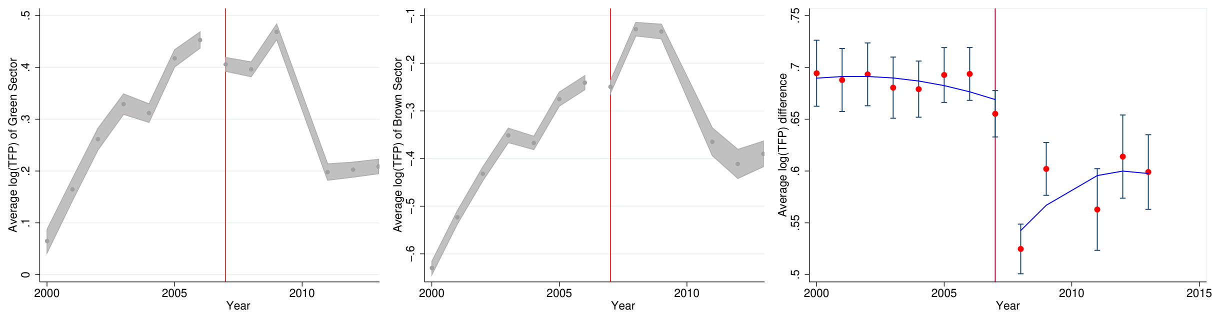
In this part, we provide evidence on how the aggregate TFP levels for green firms and brown firms change after the implement of the green credit policy in 2007. To this end, we carry out the regression (27) to investigate.

$$log(TFP)_{ijt} = \alpha_0 + \alpha_1 Green_{ijt} * Post + \alpha_2 Post + \alpha_3 Green_{ijt} + \gamma Z_{ijt} + u_j + v_t + \varepsilon_{ijt} \quad (27)$$

where $log(TFP)$ is the log value of total factor productivity of firm i in industry j in year t. $Green$ is an indicator variable that equals 1 if firm i (in industry j) is categorized as a green firm, and 0 otherwise. $Post$ is a dummy variable that measures the year of observation and equals 1 after 2007, and 0 before or in 2007. Z indicates the vector of control variables. To account for the industry- and year-specific determinants of TFP in non-parametric estimations, we control for industry and year-fixed effects u_j and v_t in the baseline model. We use robust standard errors in the regression.

Before presenting the specific regression results, we first show DID plots. Figure 11 plots the average OLS-log(TFP) of the green firms (treated group) and the brown firms (control group), and the difference between these sub-samples over time, using COD as the standard to distinguish between green and brown firms. Each dot represents the average log(TFP) difference between the two groups within a year, with 90% confidence intervals also presented. A fitted curve illustrates the discontinuity around the year 2007.

Figure 11. **DID plot: Effects of green credit policy on TFP**



Panel A. Average TFP-OLS of Green Firms | Panel B. Average TFP-OLS of Brown Firms | Panel C. Average TFP-OLS Difference

Notes: This figure plots the average log(TFP)s of green firms and brown firms, and their difference around the year 2007. The whole sample period is from 2000 to 2013. We use *COD* to categorize green firms and brown firms. Each dot in Panel A and Panel B indicates the average OLS log(TFP) of green firms and brown firms, respectively, while the shadow shows the confidential interval at the 90% level. The red vertical line denotes the cut-off year 2007. We plot the average log(TFP) difference between two types of firms in Panel C.

In Panel A, there is no overlap between the confidence intervals before and after 2007 for green firms. In contrast, Panel B shows no significant difference in the confidence intervals for brown firms before and after 2007. When we calculate the average TFP difference between these two types of firms, we observe a sharp fall in the TFP difference precisely in 2007. This indicates a treatment effect applied to green firms due to the green credit policy.

Using SO_2 emissions to distinguish between green and brown firms gives us similar results, shown in Figure 17. We also plot the OP-log(TFP) difference between the two sub-samples over time in Figures 18 and 19, which shows similar results.

From these observations, we conclude that there is a significant treatment effect of the green credit policy shock in 2007 on green firms, indicated by the decline in the aggregate TFP level. In regression (27), our primary focus is on α_1. This coefficient captures the treatment effect of the green credit policy in 2007. Based on the DID plots, we expect α_1 to be negative, indicating that TFP falls for green firms compared to brown firms after the policy shock.

Before running formal regressions, we need to ensure that sub-samples of green firms and brown firms have the same movement trend and avoid a self-selection bias. We follow Jacobson et al. (1993) and adopt the event-study method to perform a dynamic effects test.

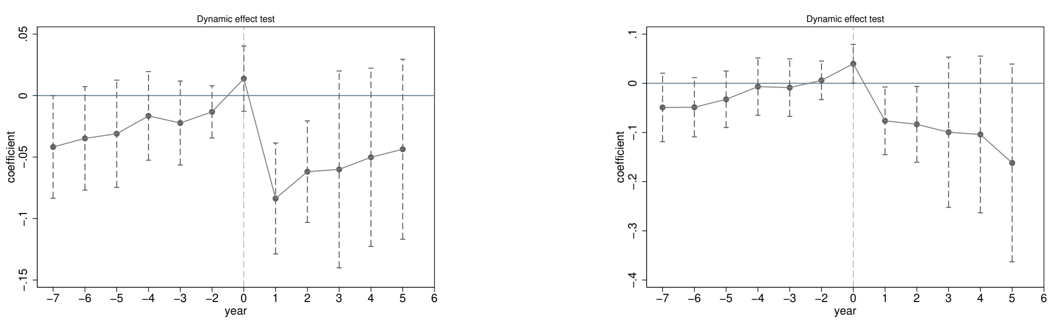
The dynamic effects test introduces a finite number of time dummy variables and multiplies them with the treatment variable to investigate the significance of the cross-product terms. This test not only examines the differences between groups before the event but also highlights the differences between groups after the event. Specifically, we use regression (28) to conduct the dynamic effects test.

$$log\,(TFP_{ijt}) = \alpha + \sum_{b=-7}^{6} \beta_b D_{t+b} * Green_{ijt} + \gamma Z_{ijt} + u_j + v_t + \varepsilon_{ijt} \tag{28}$$

where $D_{t-b} * Green$ is a dummy variable, which equals 1 if a firm is green in year $t - b$, otherwise, 0. We set year $t - 1$ as the benchmark time and drop it when running the regression to avoid multicollinearity. Z, u_j, and v_t indicate the vector of control variables, the industry fix effect, and the year fix effect, respectively.

First, we use COD emission as the gauge to categorize green or brown firms and plot the regression coefficients and their 95% confidence intervals in Figure 12. Panel A shows the dynamic effect test using the OLS method to calculate TFP, while Panel B uses the OP method.

Figure 12. **Dynamic effect test**



Panel A. OLS-TFP, COD Panel B. OP-TFP, COD

Notes: This figure shows the dynamic effects test result based on regression (28). Each dot represents the regression coefficient of $D_{t-b} * Green$ and we show the 95% confidence interval of each estimate. For this graph, we use COD emission as the gauge to categorize green or brown firms. Panel A shows the result using the OLS method to obtain TFP, while Panel B uses the OP method.

Both panels show that coefficients of $D_{t-b} * Green$ ($\beta_{(-7)}$ - $\beta_{(-2)}$) are not statistically significantly different from 0. This indicates that there is no significant difference between the treatment group and the control group before the policy shock, supporting the parallel trend hypothesis. This means the treatment group and the control group are comparable before the green credit policy. After 2007, $\beta_{(1)}$ and $\beta_{(2)}$ are significantly smaller than 0, which indicates the green credit policy incurs a negative effect on TFP. This finding confirms the result in Figure 11. We further use SO_2 emission as the gauge to categorize green or brown firms and plot the result of the dynamic effect test in Figure 20, which shows a similar pattern to Figure 12.

We first use regression (27) to test the green credit policy's treatment effect on the aggregate productivity. The regression results are reported in Table 8. In this regression, we use TFP calculated by the OLS method as the dependent variable, and then we change to the OP method in a robustness check. Columns (1-2) report the OLS TFP results, and columns (3-4) report the OP TFP results. Columns (2) and (4) include year fixed effects and industry fixed effects, while columns (1) and (3) do not.

In Panel A, we use COD emissions to distinguish green firms from brown firms. In Panel B, we use SO_2 emissions for this distinction. All four columns show a significant and negative coefficient for the interaction term α_1, indicating a strong negative treatment effect of the green credit policy on green firms' productivity. This evidence is consistent with our model, which implies that green loan expansion shifts the cutoff productivity to the left, resulting in a decrease in the average productivity of green firms.

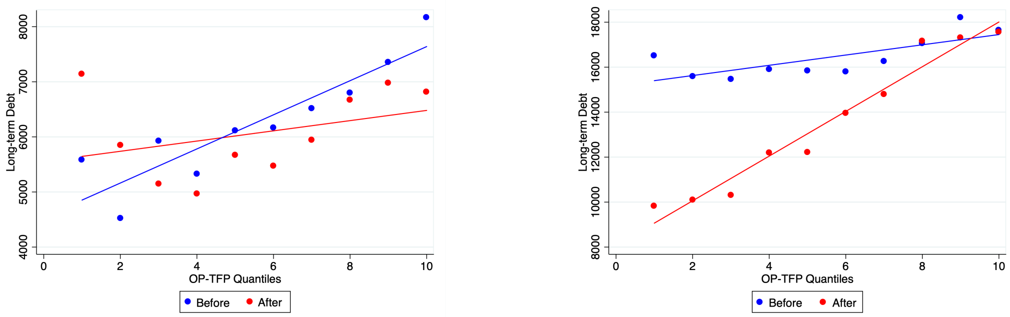
VI.3 TFP and Bank Loan

Before the implementation of the green credit policy, the lending standard for commercial banks was to increase the profitability of loans within an acceptable risk range. Therefore, it is reasonable to assume that banks would provide more loans to enterprises with higher TFP. However, after the introduction of the green credit policy, banks are required to allocate more credit resources to green enterprises according to regulations. This part of our study examines the reallocation process of these credit resources.

We first divide the entire samples of green and brown firms into ten groups based on firms' TFP levels, with the first group having the lowest TFP and the tenth group having the highest TFP. Figure 13 shows the relationship between the average bank loan amount for each sub-TFP group before 2007 and after 2007 for green firms and brown firms, respectively. We use long-term debt to proxy for bank loans obtained by firms and COD as the emission gauge to classify green or brown firms. The corresponding figure using SO_2 as the gauge to classify green or brown firms is shown in Figure 21.

From this figure, we find three significant results. First, there is a positive correlation between bank loans and TFP in both green firms and brown firms. This is expected as

Figure 13. **TFP and Bank Loan (Green or Brown: by COD emission)**



Panel A. Green Firms   Panel B. Brown Firms

Notes: This figure shows scatter plots of the average long-term debt amount for each sub-TFP group before and after 2007, for green firms and brown firms, respectively. Here, we use COD emission as the gauge to classify green or brown firms. We also plot the fitted value in the figure. The blue points are corresponding to the values before 2007, while the red points are corresponding to the values after 2007.

banks pursue profits. Second, divergence between green and brown firms occurs after the green credit policy shock. Specifically, for green firms, compared to the credit distribution across sub-TFP groups before 2007, credits are less concentrated in the high-TFP firms after 2007. In contrast, for brown firms, after the green credit policy shock, credits are more concentrated in high-TFP firms. Third, it is clear that bank loans obtained by brown firms decrease significantly after the policy shock.

Now, we construct a regression model to test these results.

$$Loan_{ijt} = \alpha_0 + \alpha_1 TFP_{ijt} * Post + \alpha_2 Post + \alpha_3 TFP_{ijt} + \gamma Z_{ijt} + u_j + v_t + \varepsilon_{ijt} \tag{29}$$

where $Loan_{ijt}$ is the log value of long-term debt of firm i in industry j in year t. $Post$ is a dummy variable that measures the year of observation and equals 1 after 2007, and 0 before or in 2007. Z indicates the vector of control variables. Following Laeven and Levine (2009), we control for size, earning performance (ROA), current ratio (Liquidity), debt level (L.T. debt), leverage ratio (Lev), state-owned enterprises or private enterprises (SOE) and profitability for the firms. Table 2 shows the variable definition. To account for the industry- and year-specific bank loan and TFP determinants in the non-parametric estimations, we control for industry- and year-fixed effects u_j and v_t in the model. We use robust standard errors in the regression.

We run the regression (29) for green firms and brown firms, respectively. The results are reported in Table 9. Columns (1)-(2) report the results where we use COD to divide green firms and brown firms. Columns (3)-(4) report the results where we use SO_2 to divide green firms and brown firms. The coefficients are suggestive. First, all of the coefficients α_3 of TFP are positive, which is intuitive as banks lend to productive firms. Second, the coefficients α_1 for the interaction item $TFP * Post$ are negative for green firms and are positive for brown firms. These are consistent with Figure 13, where the slope for green firms in Panel A decreases after the shock, while the slope for brown firms in Panel B increases after the shock. This finding reflects that credit resources are less concentrated among green firms, while the circumstance is reversed among brown firms. Third, the coefficients α_2 of $Post$ are positive for green firms and negative for brown firms, capturing the change in the availability of funds to these two types of firms.

The contrasting results of α_1 and α_2 for green firms and brown firms indicate that credit resources are indeed reallocated across firms. Green firms receive more credit resources, but the allocation efficiency among green deteriorates. This is evident in the decreased concentration of credit resources in green firms with high TFP, while the opposite situation occurs for brown firms.

These findings support our model's implications. Our model suggests that green loan expansion reduces the average capital return of green projects, as more loans being allocated to less productive green firms. Consequently, the concentration of credits in highly productive green firms decreases.

VI.4 To be Greener or Browner: Transition Matrix

In the previous section, we found that the green credit policy shock causes a sharp decline in the average TFP for green firms. We are interested in its effect on emissions. As shown earlier, higher TFPs are associated with lower emissions. Given the drop in the average TFP, we anticipate that total emissions may increase.

Beyond the aggregate emission level, we are also interested in the cross-sectional differences between green firms and brown firms. We calculate the transition matrix to capture the movement of green and brown firms, focusing on their tendency to become greener or browner. Table 10 shows the transition matrix. We divide firms into deciles by their emissions (COD and SO_2, respectively) intensity (the non-scaled value) before and after the shock, with deciles 1 and 10 representing the most green and the most brown firms, respectively. We track each firm's emissions before and after the shock, and count the number of firms that change the deciles of emissions they belong in.

Panel A shows the transition matrix using COD emissions to form deciles, and Panel B shows the transition matrix using SO_2 emissions. The number in each cell represents the number of firms belonging to this combination. For example, the number 993 in the cell of the first row and the first column in Panel A represents 993 firms that were in decile 1 before the shock and remain in decile 1 after the shock. The diagonal cells contain firms whose decile numbers do not change. We use a heat map to represent the relatively size of these numbers in different cells. The darker the color, the greater the number of firms in that cell. From this heat map, we see significantly more dark cells on the right side of the diagonal than on the left side, indicating that after the implementation of green policies, more firms have become (relatively) browner. For each row, we calculate the proportion of firms that have shifted to browner cells (browning ratio) and the proportion of firms that have moved to greener cells (greening ratio) after the policy shock, which are calculated by dividing the number of firms on the right or left of the diagonal by the total number of firms in that row, respectively.

Further, we also show the emission matrix before and after the green credit policy shock in Table 11, in the similar construction of Table 10. We calculate the average change in emissions value for each cell in the matrix.

Panel A shows the emission matrix using COD emissions to form deciles, and Panel B shows the emission matrix using SO_2 emissions. The number in each cell represents the average emission change, i.e., post-shock emission volume minus pre-shock emission volume. The diagonal cells represent the emission changes for firms whose decile numbers do not change. Greener cells indicate a greater reduction in emissions, while redder cells indicate a greater increase in emissions. From this heat map, we can see that the numbers in each column gradually fall, i.e., browner firms show more significant emission reductions. This means the green credit policy shock incentivizes brown firms more than green firms to reduce their emissions. Besides, by adding the change of emission number for each cell times the number of firms in that cell in transition matrix in one row, we could get the total emission changes for each before-shock decile. It is obvious to find that the total emission increases for firms who are relatively green, such as firms in row 1 (the greenest firms that belong to decile 1 before the shock). This result is consistent with our model's implication that the decrease in average productivity of green firms caused by green loan expansion leads to an overall increase in aggregate emissions by these firms.

In sum, we evaluate the impact of the green credit policy shock in 2007 on firms' TFP, the loans firms obtained from banks, and their emissions. We find that green firms obtain more loans, while brown firms obtain fewer loans. This indicates that the green credit policy has played a role in reallocating credit across different types of firms, bring more credit to green firms. However, when we evaluate the policy's effect on productivity, we find that it causes productivity for green firms to fall significantly. Meanwhile, credit is more concentrated in high-TFP firms for brown firms, while it is less concentrated in more productive green firms.

In terms of emissions, the emission matrix shows that the policy has a greater incentive effect on brown firms than on green firms. As a result, brown firms become greener, while green firms become less green.

VII Conclusion

China's green credit policy, introduced in 2007, mandates that commercial banks direct funds toward industries and firms prioritizing environmental sustainability. This policy aims to promote environmentally responsible practices and deter activities posing environmental risks by integrating environmental considerations into banks' strategic and risk management processes.

Our study aims to provide a comprehensive assessment on the effectiveness of China's green credit policy, using both a theoretical approach and an empirical examination of firm-level data to evaluate its impact on economic output and total emissions. We first document that green firms exhibit greater heterogeneity in TFP compared to brown firms. We also demonstrate a negative correlation between productivity and emission intensity.

In order to explore how financial markets internalize credit allocation among green and brown firms with the policy shock, we develop a model to examine the impact of the green credit policy, investigate the credit allocation process, and evaluate its effect on social welfare. Our theoretical model simulates three types of green credit policies and investigates the credit reallocation process and social welfare impact.

The model reveals that green loan expansion can reduce the marginal capital return of green firms, as less productive green firms may receive financing. On the other hand, policies with green interest subsidies or brown penalties may yield opposite results. Simulation results indicate that green loan expansion can lower overall output while increasing emissions due to a reduction in the average TFP among green firms. In contrast, green subsidies and brown penalties can enhance total output and reduce emissions, demonstrating the differential effects of different policy approaches. The welfare implications of these policies are also significant, with green credit expansion and green interest subsidy resulting in a welfare loss, while brown penalties yield a positive welfare outcome.

Our model implies that green credit expansion make credit to move to projects with lower productivity. Consequently, the average productivity of firms receiving loans decreases. This misallocation process leads to increased emissions. We use the launch of the "green credit policy" in China as a quasi-natural shock to test the economic impact of the policy, which in our data period mainly focuses on green credit expansion. The empirical evidence shows that the policy leads to a significant decline in TFP for green firms relative to brown firms.

In terms of bank loans, the policy results in increased loans for green firms and reduced loans for brown firms. Additionally, the concentration of bank loans in firms with high TFP decreases for green firms, contrary to the trend observed for brown firms. Emission data indicate that the policy incentivizes brown firms more effectively than green firms, as evidenced by the transition matrix showing that brown firms become greener while green firms become browner.

In conclusion, our research contributes to the growing body of literature on climate and environmental finance, providing empirical and theoretical insights into the effects of policy initiatives, using China's green credit policy as a test case. By highlighting the heterogeneity in firm productivity and the differential impact of green credit policies, our study underscores the importance of tailored financial mechanisms to achieve sustainable economic and environmental outcome. These findings should be informative in helping shape policies that promote both economic growth and environmental sustainability.

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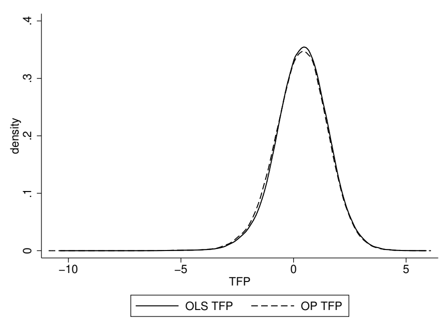
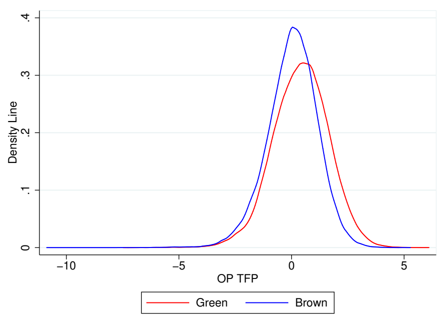
Figures

Figure 14. **OLS TFP and OP TFP distribution**

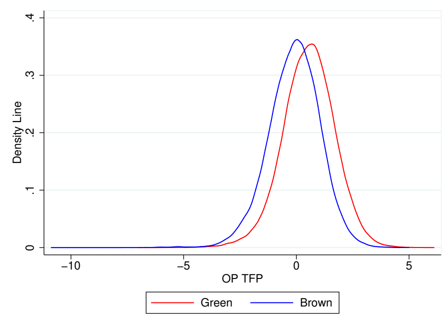


Notes: This figure plots the density line of OLS TFP (solid line) and OP TFP (dashed line). The figure shows TFP estimated by OLS method and OP method has similar distribution and the results are robust and consistent. Later, we use TFP estimated by OLS method in the baseline regression, and use OP-TFP as the robustness test.

Figure 15. **OP-TFP heterogeneity in green firms and brown firms**



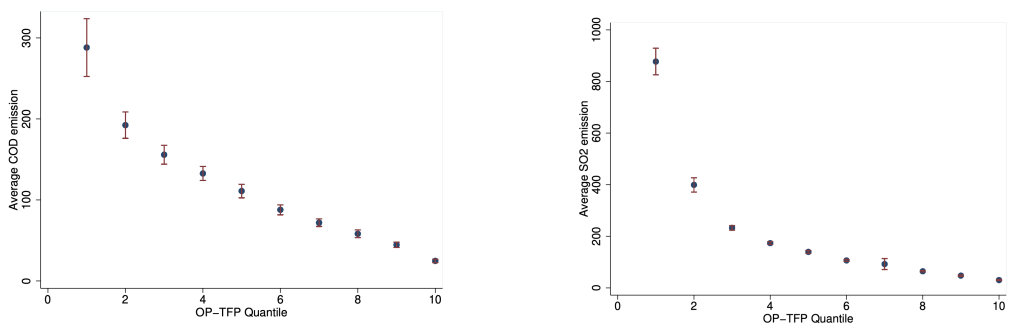
Panel A. COD



Panel B. SO_2

Notes: This figure is the robustness check of stylized fact 1, where we use Olley and Pakes (1996) method rather than OLS method to calculate the TFP. The red line is corresponding to the green firms, while the blue line is for the brown firms. To be the same as figure 1, the figure gives us two consistent results. First, the green firms have a higher average TFP compared to the brown firms. Second, the green firms' TFP distribution is squatter compared to the brown firms, which indicates the green firms' TFP shows a stronger heterogeneity.

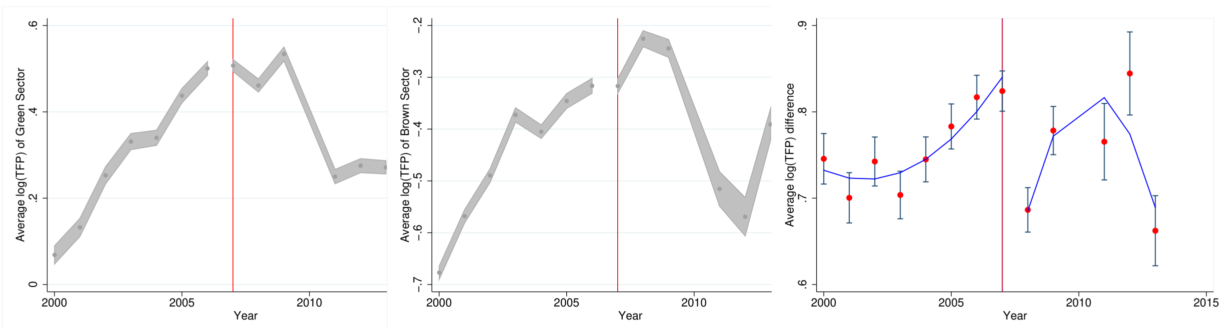
Figure 16. **OP-TFP and Emission**



Panel A. COD Panel B. SO_2

Notes: This figure reports the relationship between the OP-TFP and emission level, which is categorized by COD and SO_2 separately. We divide the total sample into ten subsamples according to the their OLS-TFP. We also shows the 95% confidence interval in the figure. The figure shows that the pollution emission of firms is smaller with the improvement of TFP.

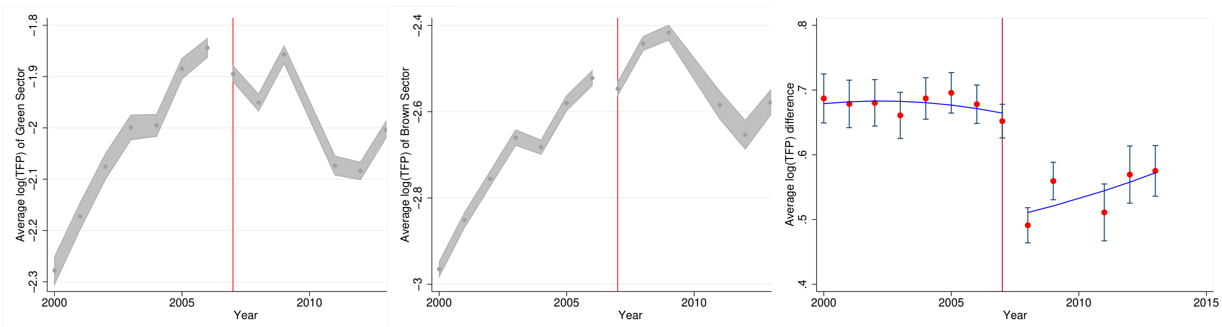
Figure 17. **Robustness test: DID plot: Effects of green credit policy on OLS-TFP**



Panel A. Average TFP-OLS of Green Firms | Panel B. Average TFP-OLS of Brown Firms | Panel C. Average TFP-OLS Difference

Notes: This figure is the robustness check of figure 11, where we use SO_2 to categorize the green firms and the brown firms. We plots the average OLS log(TFP) of green firms and brown firms, and their difference around the cut-off year 2007. The whole sample period is from 2000 to 2013. Each dot in Panel A and Panel B indicates the average log(TFP) of the green firms and the brown firms, respectively, while the shadow is the confidential interval at 90%. The place of red vertial line denotes the cut-off year 2007. We further plots the average log(TFP) difference between two sectors in Panel C. We can conclude that after 2007, there is a sharply fall on the green firms' TFP compared to the brown firms.

Figure 18. **Robustness test: DID plot: Effects of green credit policy on OP-TFP**



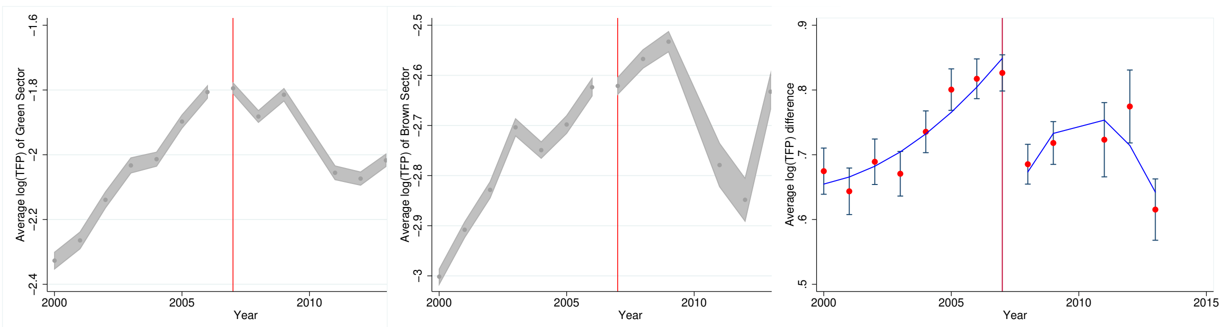
Panel A. Average TFP-OP of Green Firms

Panel B. Average TFP-OP of Brown Firms

Panel C. Average TFP-OP Difference

Notes: This figure is the robustness check of figure 11 and figure 17, where we use *COD* to categorize the green firms and the brown firms. We use Olley and Pakes (1996) method rather than OLS method to calculate TFP. We plots the average log(TFP) of green firms and brown firms, and their difference around the cut-off year 2007. The whole sample period is from 2000 to 2013. Each dot in Panel A and Panel B indicates the average log(TFP) of the green firms and the brown firms, respectively, while the shadow is the confidential interval at 90%. The place of red vertial line denotes the cut-off year 2007. We further plots the average log(TFP) difference between two sectors in Panel C. We can conclude that after 2007, there is a sharply fall on the green firms' TFP compared to the brown firms.

Figure 19. **Robustness test: DID plot: Effects of green credit policy on OP-TFP**



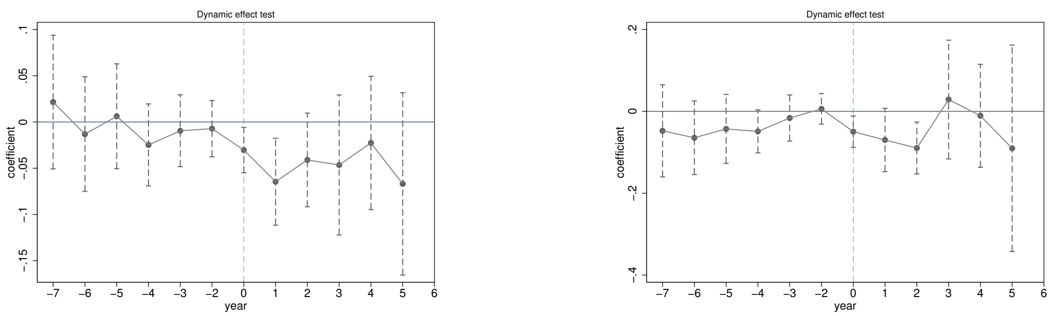
Panel A. Average TFP-OP of Green Firms

Panel B. Average TFP-OP of Brown Firms

Panel C. Average TFP-OP Difference

Notes: This figure is the robustness check of figure 11, figure 17 and 18, where we use SO_2 to categorize the green firms and the brown firms. We use Olley and Pakes (1996) method rather than OLS method to calculate TFP here. We plots the average log(TFP) of green firms and brown firms, and their difference around the cut-off year 2007. The whole sample period is from 2000 to 2013. Each dot in Panel A and Panel B indicates the average log(TFP) of the green firms and the brown firms, respectively, while the shadow is the confidential interval at 90%. The place of red vertial line denotes the cut-off year 2007. We further plots the average log(TFP) difference between two sectors in Panel C. We can conclude that after 2007, there is a sharply fall on the green firms' TFP compared to the brown firms.

Figure 20. **Dynamic effect test**

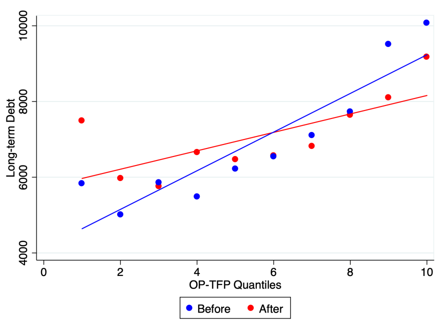


Panel A. OLS-TFP, SO_2

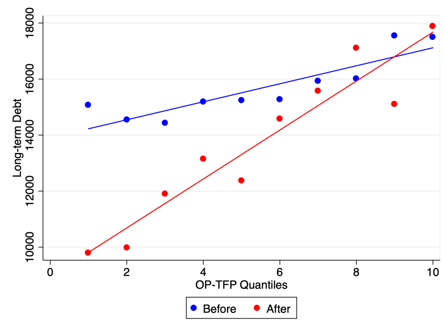
Panel B. OP-TFP, SO_2

Notes: This figure shows the robustness of dynamic effect test result. Here, we use SO_2 as the standard to categorize green or brown. Panel A shows the dynamic effect test, where use OLS method to get the TFP, while Panel B uses OP method. Both of panels in Figure 12 shows that coefficients of $D_{t-b} * Green$ ($\beta_{(-7)}$ - $\beta_{(-2)}$) are not significantly different from 0 statistically, while there is a fall trend after 2007.

Figure 21. **TFP and Bank Loan (Green or Brown: by SO_2 emission)**



Panel A. Green Firms



Panel B. Brown Firms

Notes: This figure plots the scatter plots between the average long-term debt amounts for each sub-TFP group before 2007 and after 2007 in green firms and brown firms, respectively. Here, we use SO_2 as the indicator to classify green or brown firms. We also plot the fitted value in the figure. The blue points are corresponding to the value before 2007, while the red points are corresponding to the value after 2007.

Tables

Table 2. **Variable definition**

This table shows the key variables and their defination in the empirical section. For the dependent variable in the regression, total productivity factor, bank loan and pollutant emission is used. For the independent variable, the treatment variable green or brown, and the treatment time cut-off is used. As for control variables, we control firm size, ROA, liduidity, profitability, debt level and shareholder nature in the regression.

Variables	Abbr	Definition
Dependent Variable		
Total productivity factor	TFP	The log value of TFP
Bank loan	Loan	Log-value of long-term debt
Pollution emission	Emission	COD or SO_2 emission
Independent Variable		
Green or brown	Green	If the firm is categorized as a green firm, then Green = 1, otherwise Green = 0.
time cut-off	Post	If the time after 2007, then Post = 1, otherwise Post = 0.
Control Variable		
Total asset	Size	Log-value of total asset
Return on asset	ROA	Earnings divided by total asset
Current ratio	Liquidity	Current asset divided by current liability
Debt level	L.T.debt	Long-term debt divided by total asset
Asset-liability ratio	Lev	Total liability divided by total asset
Shareholder nature	SOE	If the firm is state-owned, then SOE = 1, otherwise SOE = 0.
Operating profit over revenue	Profitable	Operating profit divided by revenue

Table 3. **Coefficients of labor and capital in TFP estimation**

This table reports the OLS TFP Coefficients and Olley-Pakes TFP Coefficients for Capital and Labor for different industries. Columns 1–2 report the industry and its code, columns 3-4 report the OLS-TFP coefficients of capital and labor, respectively. Columns 5-6 report the OP-TFP coefficients of capital and labor, respectively.

Code	Industry name	OLS		OP	
		Capital Coef.	Labor Coef.	Capital Coef.	Labor Coef.
06	Mining and Washing of Coal	0.368	0.293	0.386	0.259
08	Mining and Processing of Ferrous	0.229	0.572	0.242	0.570
09	Mining and Processing of Non-Ferrous Metal Ores	0.225	0.400	0.245	0.379
10	Mining and Processing of Non-Metallic Mineral	0.188	0.407	0.223	0.391
13	Agricultural and Sideline Food	0.263	0.604	0.298	0.595
14	Food Manufacturing	0.302	0.673	0.330	0.669
15	Beverage Manufacturing	0.344	0.596	0.364	0.593
16	Tobacco Manufacturing	0.664	0.656	0.777	0.510
17	Textile Mills	0.251	0.529	0.244	0.518
18	Wearing Apparel and Clothing Accessories Manufacturing	0.272	0.601	0.215	0.655
19	Leather, Fur and Related Products Manufacturing	0.253	0.493	0.254	0.481
20	Wood and Bamboo Products Manufacturing	0.251	0.572	0.251	0.516
21	Furniture Manufacturing	0.174	0.648	0.122	0.757
22	Paper Products Manufacturing	0.236	0.629	0.240	0.592
23	Printing and Reproduction of Recorded Media	0.480	0.354	0.533	0.298
24	Education and Entertainment Articles Manufacturing	0.220	0.631	0.209	0.634
25	Petrochemicals Manufacturing	0.326	0.635	0.331	0.617
26	Chemical Products Manufacturing	0.313	0.474	0.340	0.450
27	Medical Goods Manufacturing	0.241	0.694	0.273	0.670
28	Chemical Fibers Manufacturing	0.351	0.551	0.358	0.483
29	Rubber Products Manufacturing	0.402	0.529	0.417	0.575
30	Plastic Products Manufacturing	0.334	0.514	0.342	0.534
31	Non-Metallic Mineral Products Manufacturing	0.328	0.482	0.351	0.489
32	Basic Metal Processing	0.313	0.692	0.306	0.670
33	Non-Ferrous Metal Processing	0.313	0.476	0.314	0.462
34	Fabricated Metal Products Manufacturing	0.352	0.525	0.351	0.496
35	General Purpose Machinery Manufacturing	0.341	0.462	0.372	0.456
36	Special Purpose Machinery Manufacturing	0.433	0.469	0.404	0.437
37	Transport Equipment Manufacturing	0.355	0.563	0.373	0.526
39	Electrical Equipment Manufacturing	0.379	0.516	0.354	0.521
40	Computers and Electronic Products Manufacturing	0.353	0.673	0.341	0.669
41	General Instruments and Other Equipment Manufacturing	0.346	0.610	0.365	0.532
42	Craftworks Manufacturing	0.252	0.569	0.206	0.602
43	Waste Resources and Waste Materials Recycling Processing	0.323	0.194	0.288	0.259
44	Production and Supply of Electric Power and Heat	0.507	0.449	0.545	0.409
46	Water Production and Supply	0.541	0.347	0.568	0.337

Table 4. **Summary statistics by emission**

This table reports the cross-sectional summary statistics on the sector of green or brown. We divided the samples into three groups (Green, Middle, Brown) according to the 33.3% and 66.7% quantiles of emission for each industry. We use COD and SO_2 to measure emission respectively, where COD is calculated by COD emission over gross revenue and SO_2 is calculated by SO_2 emission over gross revenue. It is worth to note that since we classify firms based on pollution emissions within the industry, while the table here provides summary statistics for the entire sample, therefore, the pollution emissions listed in this table are not exclusively lower for the green firms than for the brown firms.

	3 quantiles of COD					**3 quantiles of SO2**				
	N	mean	sd	min	max	N	mean	sd	min	max
Green										
asset	168820	177118.61	568264.98	1.00	30382407.00	165647	218088.50	685142.43	1.00	33411214.00
employment	168821	402.03	654.67	9.00	8318.00	165648	428.05	682.07	9.00	8318.00
long term debt	146459	21394.21	179900.95	0.00	13236561.00	140473	27771.94	218007.32	0.00	16735203.00
gross revenue	168821	204063.41	512784.80	794.00	10975022.00	165648	233931.67	568344.92	770.00	13578747.00
capital	167793	41635.72	129375.76	31.74	2397514.50	164573	50861.80	151382.16	31.60	2397756.10
laber	168821	402.03	654.67	9.00	8318.00	165648	428.05	682.07	9.00	8318.00
COD/SO_2	168821	0.73	2.70	0.00	31.86	165648	7.28	44.51	-1.06	582.73
OLS TFP	167793	0.47	1.22	-6.92	5.89	164573	0.58	1.17	-6.72	5.89
OP TFP	167793	0.41	1.24	-7.48	6.11	164573	0.54	1.17	-7.02	6.11
Middle										
asset	125450	246332.05	722849.88	301.00	33411214.00	127840	222012.95	649170.43	63.00	29024236.00
employment	125451	499.98	785.66	9.00	8306.00	127840	485.28	767.21	9.00	8307.00
long term debt	107145	32457.67	219243.24	0.00	16735203.00	110421	29530.23	191535.48	0.00	7980130.00
gross revenue	125451	239226.26	554950.99	823.00	13578747.00	127840	222536.41	519699.41	809.00	13391368.00
capital	124675	58376.55	169689.52	31.94	2397918.00	127029	53544.24	158172.62	31.68	2397918.00
laber	125451	499.98	785.66	9.00	8306.00	127840	485.28	767.21	9.00	8307.00
COD/SO_2	125451	14.41	35.77	0.00	311.20	127840	74.26	187.39	0.00	1719.27
OLS TFP	124675	0.62	1.11	-6.64	5.67	127029	0.62	1.10	-7.06	5.65
OP TFP	124675	0.59	1.13	-6.87	5.71	127029	0.55	1.14	-7.48	5.71
Brown										
asset	147036	177072.49	565359.38	63.00	29064466.00	145866	153183.90	514093.13	134.00	29064466.00
employment	147037	476.78	779.47	9.00	8317.00	145868	455.89	767.96	9.00	8303.00
long term debt	131889	27065.38	163307.48	0.00	9296790.00	132890	24716.43	164998.36	0.00	10951568.00
gross revenue	147037	135546.54	405028.58	750.00	13391368.00	145868	114639.09	352218.04	750.00	10993291.00
capital	146058	51137.81	153773.89	31.60	2397756.10	144921	45376.04	145518.80	31.79	2397514.50
laber	147037	476.78	779.47	9.00	8317.00	145868	455.89	767.96	9.00	8303.00
COD/SO_2	147037	339.87	2579.95	0.54	425331.53	145868	587.67	3765.55	0.00	736560.06
OLS TFP	146058	0.08	1.11	-10.37	5.23	144921	-0.05	1.12	-10.37	4.99
OP TFP	146058	0.03	1.12	-10.88	5.28	144921	-0.10	1.15	-10.88	4.99

Table 5. **Summary statistics by industry**

This table reports the cross-sectional summary statistics for each industry. Here, COD is calculated by COD emission over gross revenue and SO_2 is calculated by SO_2 emission over gross revenue.

	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
ind	**06**		**08**		**09**		**10**		**13**		**14**	
capital	54428.33	178296.14	29079.55	77038.56	34077.97	92778.23	33534.98	90066.37	27018.58	61662.37	34883.93	85581.42
laber	636.99	996.76	313.05	551.34	419.57	644.25	411.73	816.88	312.14	503.28	361.52	548.06
gross revenue	165101.65	436801.78	166371.81	331452.19	107568.31	279685.96	80089.97	197491.97	199199.59	482272.61	156034.07	385154.72
COD	55.92	392.22	50.28	304.09	122.76	1296.77	73.40	412.80	75688.87	423900.58	50712.80	294722.47
SO_2	121.30	827.38	79.98	584.85	111.09	1191.77	273.45	2962.82	30616.61	136010.09	40300.16	168294.61
OLS TFP	0.64	1.07	0.79	0.99	1.31	0.97	1.79	0.96	0.70	1.07	-0.25	0.99
OP TFP	0.66	1.07	0.68	0.99	1.25	0.97	1.56	0.96	0.43	1.07	-0.49	0.99
ind	**15**		**16**		**17**		**18**		**19**		**20**	
capital	57819.68	113489.98	232374.11	281403.29	30004.67	59279.42	20999.68	44411.48	16112.79	28686.96	32364.76	66704.57
laber	428.62	595.92	1093.88	971.39	536.36	835.77	662.85	808.61	536.89	1006.23	292.03	401.92
gross revenue	176894.57	379076.81	930637.67	1341831.10	117474.86	238270.06	120799.36	251252.18	143517.54	245611.16	101669.25	180514.57
COD	97228.85	417358.61	33080.06	80947.47	48236.89	151121.22	14312.09	43555.14	49546.10	228949.96	16430.29	124438.63
SO_2	52022.78	141352.92	76272.29	120321.19	44767.19	166985.68	17905.52	60980.15	12280.24	45306.61	39107.18	94672.05
OLS TFP	-0.40	1.08	-4.15	1.02	0.88	0.89	0.17	0.90	1.52	0.98	0.77	0.93
OP TFP	-0.58	1.08	-4.52	1.03	0.99	0.89	0.36	0.90	1.57	0.98	1.07	0.93
ind	**21**		**22**		**23**		**24**		**25**		**26**	
capital	27387.08	51242.50	34789.34	134230.69	39946.31	60999.95	27511.79	49225.95	101925.43	238788.07	50144.84	164126.00
laber	576.74	779.10	287.00	452.14	385.88	451.91	765.44	1045.53	514.48	753.28	346.04	604.86
gross revenue	129492.63	210485.88	106082.64	281115.46	100871.41	183470.50	142850.95	330671.64	548202.01	1176663.60	190114.57	471718.57
COD	3226.55	11649.36	429040.01	1855704.60	4771.26	24408.44	4243.22	10978.59	41926.40	171133.71	61558.91	357436.86
SO_2	11245.84	63119.08	124031.93	509928.98	5689.47	17146.15	6841.15	17487.12	411918.88	1143958.80	132487.82	731190.53
OLS TFP	1.01	0.92	0.68	0.90	-0.59	1.02	0.45	0.87	-0.04	1.04	0.93	1.00
OP TFP	0.86	0.93	0.83	0.90	-0.81	1.02	0.54	0.87	0.02	1.04	0.81	1.00

Table 5. **Summary statistics by industry (continued)**

This table reports the cross-sectional summary statistics for each industry. Here, COD is calculated by COD emission over gross revenue and SO_2 is calculated by SO_2 emission over gross revenue.

	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
ind	**27**		**28**		**29**		**30**		**31**		**32**	
capital	34187.589	69266.53	165913.32	297817.63	65407.257	188633.68	46286.263	117170.57	37390.477	106596.24	63179.931	195429.1
laber	374.162	523.222	627.385	917.335	618.545	923.336	349.681	467.226	325.263	447.169	489.677	893.946
gross revenue	149125.84	324342.27	478961.06	897612.35	238459.08	599447.23	157249.27	304707.89	94017.787	231558.29	426543.91	945757.8
COD	44109.121	257699.25	228841.33	1395951.7	10711.767	48726.879	6087.638	33915.049	3982.587	31752.518	18671.307	130973.06
SO_2	31816.993	134251.82	192603.93	728184.22	63874.089	261570.82	47429.775	245865.07	141682.2	363277.38	230072.82	973335.52
OLS TFP	0.402	1.019	0.360	0.934	-0.435	0.920	0.485	0.922	0.205	0.992	0.127	1.013
OP TFP	0.227	1.019	0.687	0.936	-0.845	0.923	0.295	0.923	-0.045	0.993	0.313	1.014
ind	**33**		**34**		**35**		**36**		**37**		**39**	
capital	57937.061	164333.51	24075.936	69101.12	41318.588	99533.869	57507.607	119576.7	78482.054	163927.21	59472.265	131166.61
laber	444.353	827.837	345.568	571.923	516.689	735.901	718.58	967.992	837.412	1150.317	725.683	1061.386
gross revenue	356888.72	876359.15	132261.64	332668.71	182785.78	428632.88	230865.62	531829.52	340840.59	683034.87	369688.3	669563.21
COD	13893.249	98097.717	4598.201	24701.177	5062.767	34851.306	7424.792	44757.488	9765.574	63997.447	6654.505	32657.491
SO_2	201292.98	1311861.2	11009.372	51215.077	13188.502	59246.925	19036.515	149697.62	16702.699	88385.377	10855.567	59608.621
OLS TFP	1.039	1.115	0.133	0.948	0.540	1.059	-0.633	1.149	0.038	1.079	0.403	1.040
OP TFP	1.107	1.116	0.290	0.949	0.282	1.061	-0.160	1.151	0.085	1.080	0.621	1.041
ind	**40**		**41**		**42**		**43**		**44**		**46**	
capital	82249.668	176804.56	72051.043	191398.66	20808.451	66075.35	16449.724	67023.489	297009.99	511251.66	179755.22	385234.96
laber	866.265	1125.918	791.365	1053.923	521.318	757.966	361.534	518.687	517.246	651.092	577.684	997.42
gross revenue	329681.58	618194.2	227121.09	546577.97	118541.13	372118.8	92660.481	259605.89	454643.44	863806.43	111696.31	254016.36
COD	13110.19	42083.148	9666.689	54630.299	8555.809	125317.18	6261.282	79663.685	45157.859	226392.56	91608.761	248660.21
SO_2	7756.713	83766.321	9751.172	101066.11	8728.871	42	10856.499	135135.64	4297750.3	9671070	21881.004	149419.9
OLS TFP	-0.545	1.019	-0.630	1.102	0.426	1.031	1.838	1.164	-1.546	0.916	-2.091	0.794
OP TFP	-0.406	1.020	-0.347	1.107	0.643	1.033	1.793	1.166	-1.753	0.918	-2.326	0.794

Table 6. **T-test and F-test for TFP between green firms and brown firms**

This table presents the T-test and F-test for the mean and variance of the TFP distribution for green firms and brown firms. The TFP is estimated by two methods: OLS method and Olley and Pakes (1996) method. We distinguish the firms of green or brown by the emission of COD and SO_2, respectively. We calculate the difference between the mean of TFP in green firms and brown firms (for T-test), and the ratio between the standard deviation of TFP in green firms and brown firms (for F-test). $diff = mean(Green) - mean(Brown)$, $ratio = s.d.(Green)/s.d.(Brown)$.

		OLS		OP	
		COD	SO_2	COD	SO_2
F-test	s.d. (Green)	1.244	1.168	1.245	1.168
$H_0 : ratio = 1$	s.d. (Brown)	1.122	1.154	1.122	1.155
$Ha : ratio > 1$	ratio	1.109	1.012	1.109	1.012
	F	1.230	1.024	1.230	1.024
	$P - value$	0.000	0.000	0.000	0.000
T-test	mean (Green)	0.472	0.578	0.410	0.540
$H_0 : diff = 0$	mean (Brown)	0.080	-0.054	0.031	-0.101
$H_a : diff > 0$	diff	0.392	0.632	0.379	0.642
	T	93.787	153.037	89.109	153.388
	$P - value$	0.000	0.000	0.000	0.000

Table 7. **Emission regression**

This table presents the results of emission regression:

$$Emission_{ijt} = \alpha_0 + \alpha_1 TFP_{ijt} + \gamma Z_{ijt} + u_j + v_t + \varepsilon_{ijt}$$

This regression helps us to identify the relations between emission and TFP. *Emission* is the *COD* or SO_2 emission of firm i in industry j in year t. Panel A shows the regression results of *COD*, and Panel B shows the regression results of *COD*. We measure firm's emissions intensity here by its log absolute value and the value scaled by revenue, respectively. TFP is the OLS TFP or OP TFP of firm i in industry j in year t. Z indicates the vector of control variables. Here, we control firms' size, bank loan level, ROA and SOE. To account for the industry- and year-specific emission and TFP determinants in the non-parametric estimations, we control for industry- and year-fixed effects u_j and v_t in the model. The column (1)-(2) reports the regression results for using *COD* to seperate green and brown firms, and the column (3)-(4) reports the regression results for using SO_2 to seperate green and brown firms. We use robust standard error in the regression. * significant at 10% ** significant at 5% *** significant at 1%.

Panel A. COD

	COD		COD (scaled by revenue)	
	(1)	(2)	(3)	(4)
OLS TFP	-0.069***		-111.439***	
	(0.005)		(2.815)	
OP TFP		-0.065***		-109.925***
		(0.005)		(2.804)
Const.	2.824***	2.837***	81.406***	92.155***
	(0.042)	(0.042)	(25.022)	(24.971)
Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Ind FE	Y	Y	Y	Y
N	295216	295216	398124	398124
$adj.R^2$	0.268	0.268	0.029	0.029

Panel B. SO2

	SO2		SO2 (scaled by revenue)	
	(1)	(2)	(3)	(4)
OLS TFP	-0.011***		-129.606***	
	(0.004)		(4.224)	
OP TFP		-0.007*		-127.193***
		(0.004)		(4.208)
Const.	4.389***	4.399***	511.246***	525.202***
	(0.035)	(0.035)	(37.577)	(37.500)
Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Ind FE	Y	Y	Y	Y
N	319761	319761	395955	395955
$adj.R^2$	0.309	0.309	0.033	0.033

Table 8. **DID regression**

This table presents the results of DID regression:

$$log(TFP)_{ijt} = \alpha_0 + \alpha_1 Green_{ijt} * Post + \alpha_2 Post + \alpha_3 Green_{ijt} + \gamma Z_{ijt} + u_j + v_t + \varepsilon_{ijt}$$

This DID regression helps us to identify the treatment effect of green credit on the aggregate TFP change. Here, the TFP is estimated by OLS method and OP method at the firm-level. We divide all the firms into green firms and brown firms according to the emission of COD (Panel A) and SO_2 (Panel B), respectively. We control for industry and year-fixed effects u_j and v_t in the model. The robust standard errors are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Panel A. Distinguish green or brown by COD emission

	OLS TFP		OP TFP	
	(1)	(2)	(3)	(4)
Green * Post	-0.052***	-0.020***	-0.085***	-0.013**
	(0.006)	(0.006)	(0.007)	(0.006)
Green	0.245***	0.236***	0.234***	0.231***
	(0.003)	(0.003)	(0.004)	(0.003)
Post	0.100***	0.194***	0.136***	0.186***
	(0.004)	(0.009)	(0.005)	(0.009)
Const.	-0.200***	-0.505***	-2.377***	-1.222***
	(0.004)	(0.010)	(0.005)	(0.010)
Control	Y	Y	Y	Y
Year FE	N	Y	N	Y
Ind FE	N	Y	N	Y
N	385125	385125	385125	385125
$adj.R^2$	0.127	0.148	0.100	0.399

Panel B. Distinguish green or brown by SO2 emission

	OLS TFP		OP TFP	
	(1)	(2)	(3)	(4)
Green * Post	-0.081***	-0.034***	-0.080***	-0.032***
	(0.006)	(0.006)	(0.008)	(0.006)
Green	0.274***	0.254***	0.253***	0.253***
	(0.003)	(0.003)	(0.004)	(0.003)
Post	0.103***	0.209***	0.105***	0.205***
	(0.005)	(0.010)	(0.006)	(0.010)
Const.	-0.209***	-0.486***	-2.414***	-0.228***
	(0.004)	(0.010)	(0.006)	(0.010)
Control	Y	Y	Y	Y
Year FE	N	Y	N	Y
Ind FE	N	Y	N	Y
N	382999	382999	382999	382999
$adj.R^2$	0.13	0.148	0.094	0.473

Table 9. **Bank loan regression**

This table presents the results of bank loan regression:

$$Loan_{ijt} = \alpha_0 + \alpha_1 TFP_{ijt} * Post + \alpha_2 Post + \alpha_3 TFP_{ijt} + \gamma Z_{ijt} + u_j + v_t + \varepsilon_{ijt}$$

This regression helps us to identify the treatment effect of green credit on the bank loan allocation across green firms and brown firms. Here, the TFP is estimated by OP method at the firm-level. We divide all the firms into green firms and brown firms according to the emission of COD and SO_2, respectively. The column (1)-(2) reports the regression results for using COD to seperate green and brown firms, and the column (3)-(4) reports the regression results for using SO_2 to seperate green and brown firms. *Loan* is the log value of long-term debt off firm i in industry j in year t. *Post* is a dummy variable that measures the year of observation and equals 1 after 2007, and 0 before or in 2007. Z indicates the vector of control variables, including size, earning performance (ROA), current ratio (Liquidity), debt level (L.T. debt), leverage ratio (Lev), state-owned enterprises or private enterprises (SOE) and profitability for the firms. We control for industry and year-fixed effects u_j and v_t in the model. The robust standard errors are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

	COD		SO2	
	Green (1)	Brown (2)	Green (3)	Brown (4)
	Loan			
TFP*Post	-0.041**	0.191***	-0.126***	0.232***
	(0.018)	(0.023)	(0.019)	(0.024)
Post	0.847***	-0.357***	0.831***	-0.433***
	(0.025)	(0.026)	(0.025)	(0.027)
TFP	0.046***	0.051***	0.066***	0.037***
	(0.010)	(0.010)	(0.011)	(0.010)
Const.	7.802***	8.320***	8.007***	8.134***
	(0.012)	(0.012)	(0.013)	(0.012)
Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Ind FE	Y	Y	Y	Y
N	146179	123500	140335	123347
adj. R2	0.043	0.057	0.038	0.056

Table 10. **Transition Matrix**

This table shows the transition matrix of the green credit shock. We divide firms into deciles by their emissions (COD and SO_2) intensity (the absolute value, not scaled by revenue) before and after the treatment, respectively, with deciles 1 and 10 representing green and brown firms. We track each firm' emission before and after treatment, and count the number of firms in each cell. For each row, we calculated the proportion of firms that changed to browner (browning ratio) and the proportion of firms that changed to greener (greening ratio) after the treatment, which was calculated by dividing the number of firms on the right or left of the diagonal by the total number of firms in this row. Panel A shows the transition matrix when we use COD emission to divide deciles, and Panel B shows the transition matrix when we use SO_2 emission to divide deciles. The number in each cell represents the number of firms in that decile before shock and in the corresponding decile after shock. The diagonal cells represent that the firm's decile has not changed before and after treatment. We use a heat map to represent relatively size of the number in each cell. The darker the color, the greater the number of elements belonging to this group.

Panel A. Quantile by COD

Decile (before) \ Decile (after)	1	2	3	4	5	6	7	8	9	10	Browning Ratio	Greening Ratio
1	**993**	480	214	130	85	54	40	44	15	6	51.82%	0.00%
2	384	**549**	469	293	128	105	76	54	28	12	55.53%	18.30%
3	219	304	**441**	410	258	162	103	77	30	10	52.14%	25.97%
4	151	245	306	**367**	346	278	181	88	60	34	48.01%	34.14%
5	112	165	242	285	**363**	332	272	169	88	29	43.27%	39.09%
6	71	141	159	231	305	**341**	328	282	144	56	39.36%	44.07%
7	51	75	106	156	240	319	**373**	352	287	97	35.80%	46.06%
8	42	52	55	102	173	245	355	**402**	447	184	30.68%	49.78%
9	21	30	48	48	112	156	229	402	**551**	460	22.36%	50.85%
10	17	13	17	35	47	65	100	187	407	**1,169**	0.00%	43.17%

Panel B. Quantile by SO2

Decile (before) \ Decile (after)	1	2	3	4	5	6	7	8	9	10	Browning Ratio	Greening Ratio
1	**1,056**	521	220	109	72	55	19	14	11	4	49.26%	0.00%
2	353	**532**	462	315	190	89	44	24	22	3	56.49%	17.35%
3	201	343	**397**	381	301	234	117	47	29	7	54.25%	26.45%
4	123	225	298	**343**	357	298	244	116	46	7	51.92%	31.40%
5	96	169	271	300	**339**	316	267	194	77	28	42.88%	40.64%
6	81	122	181	228	269	**339**	341	291	173	32	40.69%	42.83%
7	64	73	100	175	262	316	**377**	352	278	60	33.54%	48.13%
8	49	41	70	127	169	239	328	**471**	405	158	27.37%	49.73%
9	20	24	45	60	77	135	243	383	**617**	453	22.02%	47.98%
10	15	7	13	19	21	36	77	165	399	**1,305**	0.00%	36.56%

Table 11. **Emission Matrix**

This table shows the emission matrix before and after green credit shock. We divide firms into deciles by their emissions (COD and SO_2) intensity (the absolute value, not scaled by revenue) before and after the treatment, respectively, with deciles 1 and 10 representing green and brown firms. We calculate average emission change value for each cell in the matrix. Panel A shows the emission matrix when we use COD emission to divide deciles, and Panel B shows the emission matrix when we use SO_2 emission to divide deciles. The number in each cell represents the average emission changes. We use a heat map to represent the emission changes of different cells. The greener indicates the emission reduces more, while the redder indicates the emission increases more.

Panel A. Quantile by COD

Decile (before) \ Decile (after)	1	2	3	4	5	6	7	8	9	10
1	-36	756	2268	4929	9659	18387	35204	68040	145586	1250373
2	-1025	-233	1278	3940	8670	17398	34215	67051	144597	1249384
3	-3144	-2352	-841	1821	6551	15279	32096	64932	142478	1247265
4	-7440	-6648	-5137	-2475	2255	10983	27800	60636	138182	1242969
5	-15299	-14507	-12996	-10334	-5604	3124	19941	52777	130323	1235110
6	-29709	-28917	-27406	-24744	-20014	-11286	5531	38367	115913	1220700
7	-58407	-57615	-56103	-53442	-48712	-39984	-23167	9669	87215	1192002
8	-120505	-119713	-118201	-115540	-110809	-102081	-85265	-52429	25117	1129905
9	-304314	-303522	-302010	-299349	-294619	-285891	-269074	-236238	-158692	946095
10	-3270602	-3269810	-3268298	-3265637	-3260906	-3252178	-3235362	-3202526	-3124980	-2020192

Panel B. Quantile by SO2

Decile (before) \ Decile (after)	1	2	3	4	5	6	7	8	9	10
1	-404	3321	9236	18104	30561	49768	83081	146910	310867	3387021
2	-5088	-1363	4552	13421	25877	45084	78398	142226	306184	3382337
3	-12773	-9048	-3134	5735	18191	37398	70712	134541	298498	3374652
4	-25097	-21372	-15457	-6588	5868	25075	58389	122217	286175	3362328
5	-45782	-42057	-36143	-27274	-14818	4390	37703	101532	265489	3341643
6	-78928	-75203	-69288	-60420	-47963	-28756	4557	68386	232343	3308497
7	-137924	-134199	-128285	-119416	-106960	-87752	-54439	9390	173347	3249501
8	-260034	-256309	-250395	-241526	-229070	-209863	-176549	-112720	51237	3127391
9	-576886	-573161	-567246	-558378	-545922	-526714	-493401	-429572	-265615	2810539
10	-10373726	-10370001	-10364087	-10355218	-10342762	-10323555	-10290241	-10226412	-10062455	-6986302

Appendix A. Estimation of TFP Using OLS Method and Olley-Pakes Method

The main TFP measure used in this paper is estimated following the control function approach developed by Olley and Pakes (1996). The dataset we use is based on the Annual Survey of Industrial Firms (ASIF) collected by the National Bureau of Statistics (NBS). We use data for all ASIF firms between 2000 and 2013. To assemble the ASIF as a panel dataset and construct the key variables for TFP estimation, we borrow heavily from the procedure elaborated in He et al. (2020), which refers to the main procedures in Brandt et al. (2012) and makes some minor adjustments in the construction and cleaning of key variables, following the suggestions of Yang (2015). In this appendix, we explain in detail the key steps in our TFP estimation.

Gross Output

We use gross revenue as the proxy variable of gross output. When constructing output deflators, we follow Yang (2015) by using output price indexes for every 2-digit industry in each year from the Wind database. Because those price indexes are linked across different years, we can use them to deflate yearly nominal value to real value in 2000.

Labor

The ASIF dataset contains information on the number of employees and the compensation for labor, including wages, employee supplementary benefits, and insurance. Brandt et al. (2012) sums up wages, benefits, and insurance as a proxy for total labor compensation. However, these variables were not provided in the sample between 2008 to 2010. Therefore, we use number of employees to proxy labor.

Capital Stock and Investment

In the ASIF dataset, firms report the value of their fixed capital stock at original purchase prices, as well as capital stock at the originally purchased prices less accumulated depreciation. Because these values are the sum of nominal values in all the past years, they cannot be taken directly to proxy for real capital stock. To back out the real capital stock and construct real investment from this variable, we follow the approach suggested by Yang (2015).

For observations in the first period of the panel, we assume that its real capital stock is equal to its capital stock at the originally purchased prices less accumulated depreciation. For each year after the first period, we first take the difference between "current capital stock" and "capital stock in the previous period", and then deflate it according to the previously calculated price indexes for this period. This step gives us real investment value for each year. We also deflate the depreciation value for each year. Note that the depreciation variable is omitted in ASIF database during 2008 to 2010. In this period, we set depreciation rate is 10%. Then, we are able to recover the real capital stock using the perpetual inventory system.

TFP Estimation

With the key variables constructed, we follow the literature and use the OLS approach and the Olley and Pakes (1996) approach to estimate the labor and capital coefficients for TFP calculation separately. The latter addresses both simultaneity and selection problems at the same time. For implementation, we use the Stata package provided by Yasar et al. (2008); please refer to their manual for the details of the estimation. The estimation is conducted separately for each industry. Year Fixed Effects are included as control variables, to take into account the dynamics of production choices in each industry. We add "investment" as a proxy variable of productivity in OP estimation. This method assumes that firms make investment decisions according to their current productivity, so the current investment of firms is used as the proxy variable of unobservable productivity shock, thus solving the problem of simultaneous deviation. The industry-specific capital and labor coefficients are reported in Table 3 and are in general comparable to that documented in the existing literature.

Appendix B. Proof of the Binding IC Condition

Given IR2, the optimization problem regarding λ is given by $\max\{(r_g^K z + S)(1+\lambda) - R^f\lambda\}$, subject to the IC constraint.

$$V = \max\{(r_g^K z + S)(1+\lambda) - R^f\lambda\} \tag{30}$$

$$\text{s.t. } \lambda = \frac{R^f - A_b + \psi\tau}{(A_b - \psi\tau)\,\theta} \tag{31}$$

The first order condition implies:

$$\frac{\partial V}{\partial \lambda} = (r_g^K z + S) - R^f \tag{32}$$

By IR2,

$$(r_g^K z + S)(1+\lambda) - R^f\lambda > R^f \tag{33}$$

Then, we have

$$r_g^K z + S > R^f \tag{34}$$

So the F.O.C. condition (32) is positive, which implies that the IC condition always binds at the optimum, i.e., the borrowers would always achieve the borrowing limit.

Appendix C. The Partial Equilibrium

By plugging the leverage λ determined by binding equation 13, capital return r_g^K 17 and threshold z^* determination equation 11 into interbank market clearing condition 15 and arranging all the parts containing z^* to one side, we obtain:

$$\frac{\alpha A_g(\xi\omega)^{\alpha-1}}{(A_b-\psi\tau)(1-\gamma)}=\frac{\theta\frac{\mathbf{F}(z^*)}{1-\mathbf{F}(z^*)}+1}{\left[\mathbf{E}\left(z\mid z\geq z^*\right)\right]^{\alpha-1}z^*} \tag{35}$$

The RHS of above equation is a function of z^*, and we define it as

$$\mathbb{F}\left(z^*\right)\equiv\frac{\theta\frac{\mathbf{F}(z^*)}{1-\mathbf{F}(z^*)}+1}{\left[\mathbf{E}\left(z\mid z\geq z^*\right)\right]^{\alpha-1}z^*} \tag{36}$$

We define the LHS of the equation 35 as $\mathbb{L}(\xi,\psi,\gamma)$. We have $\frac{\partial\mathbb{L}}{\partial\xi}<0$, $\frac{\partial\mathbb{L}}{\partial\psi}>0$ and $\frac{\partial\mathbb{L}}{\partial\gamma}>0$.

Now, we characterize the nature of function $\mathbb{F}(z)$. As z follows a Pareto distribution and $\mathbf{F}(z)=1-(\frac{z}{\underline{z}})^{-\eta}$ and a well-defined Pareto distribution with finite variance requires $\eta>2$. We have $\bar{z}=\infty$ and we set $\underline{z}=1-\frac{1}{\eta}$. Then we can prove $\mathbf{E}(z)=1$ and $\mathbf{E}\left(z\mid z\geq z^*\right)=\frac{z^*}{\underline{z}}$.

Then equation 36 can be rewritten as

$$\mathbb{F}\left(z^*\right)=\underline{z}^{\alpha-1}\left[\frac{\theta}{\underline{z}^{\eta}}\left(z^*\right)^{\eta-\alpha}+(1-\theta)\left(z^*\right)^{-\alpha}\right] \tag{37}$$

Furthermore, we can derive

$$\mathbb{F}'(z)=\underline{z}^{\alpha-1}\left[\frac{\theta}{\underline{z}^{\eta}}(\eta-\alpha)z^{\eta-\alpha-1}-\alpha(1-\theta)z^{-\alpha-1}\right] \tag{38}$$

$$\mathbb{F}''(z)=\underline{z}^{\alpha-1}\left[\frac{\theta}{\underline{z}^{\eta}}(\eta-\alpha)(\eta-\alpha-1)z^{\eta-\alpha-2}+\alpha(\alpha+1)(1-\theta)z^{-\alpha-2}\right] \tag{39}$$

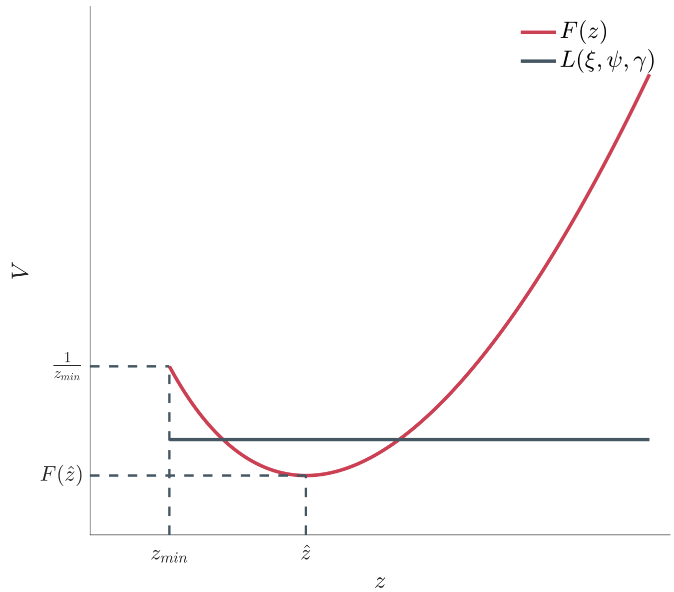
From equation 39, it can be shown $\mathbb{F}''(z)>0$ because $\eta>\alpha+1$ and $\eta>\alpha$, implying that $\mathbb{F}(z)$ is strictly convex in z. Thus, the minimum of $\mathbb{F}(z)$ is achieved under the first-order condition $\mathbb{F}'(z)=0$ and achieves $\mathbb{F}(z)$'s minimum at

$$\hat{z}=\left(1+\frac{\alpha/\theta-\eta}{\eta-\alpha}\right)^{\frac{1}{\eta}}\underline{z} \tag{40}$$

and $\hat{z}$ is an interior solution under the assumption $\eta<\frac{\alpha}{\theta}$, i.e., $\hat{z}\in(\underline{z},\bar{z})$.

We can also obtain that $\lim_{z\to\underline{z}}\mathbb{F}\left(z\right)=\frac{1}{\underline{z}}$ and $\lim_{z\to\bar{z}}\mathbb{F}\left(z\right)=\infty$. We draw the figure of functions of $\mathbb{F}$ and $\mathbb{L}$ to show the intuition.

Figure 22. $\mathbb{F}(z)$ **and** $\mathbb{L}(\xi, \psi, \tau)$



From Figure 22, $\mathbb{L}(\xi, \psi, \gamma)$ could has one intersection or two intersections with $\mathbb{F}$. In our model, we only consider the case with higher z, whose efficiency dominates the case with lower z.

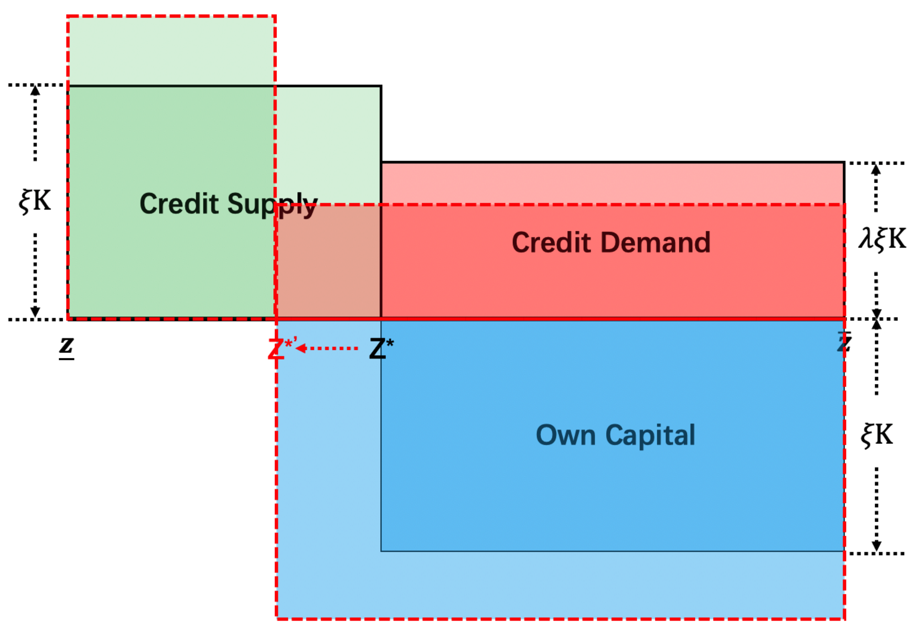
Appendix D. The Graphical Illustration of Partial Equilibrium

Figure 23 illustrates the intuition of credit reallocation process in Dong and Xu (2020)'s paper. Here, we use credit amount ξ as an example. The intuition behind γ and ψ follows the same principle as ξ.

Initially, the equilibrium interest rate equation 18 and credit market clearing equation 15 pin down an cutoff z^*. The banks meet the green firms with $z > z^*$ will borrow until IC constraint 13 binding. The borrowers will provide loans to the green firms using their own capital (blue part) plus the credit from lenders (red part). The banks meet the green firms with $z < z^*$ will lend (credit supply is shown by green part). Credit market clearing equation 15 means credit supply (green part) is equal to credit demand (red part).

As the increase of ξ, increasing aggregate capital K results in the capital return declines, so investing in the green firm is less profitable, which induces R^f decreases by equation 18. Then, lending banks need to limit the credit amount to other banks,thus leverage λ decreases. Existent financing firms' credit demand falls down, while credit supply increases, then extra credit resources will move to other firms with lower productivity (the cutoff z^* decreases). There are more low productivity firms enter into the credit market.

Figure 23. **Partial equilibrium**



Appendix E. The Dynamic System of General Equilibrium

In order to solve the dynamic system, we first list all the endogenous variables, and then we list all the relevant equations to solve these variables.

E.1. Summary of all the endogenous variables:

All the endogenous variables we need to solve can be summarized as $\{C_t, D_t, \omega_t, R_t^f, z_t^*, Y_{g,t}, E_{g,t}\}$.

E.2. Summary of the whole dynamic system of general equilibrium:

1. Partial equilibrium equation:

$$\frac{\alpha A_g(\xi\omega_t)^{\alpha-1}}{(A_b-\psi\tau)(1-\gamma)} = \frac{\theta\frac{\mathbf{F}(z_t^*)}{1-\mathbf{F}(z_t^*)}+1}{\left[\mathbf{E}\left(z \mid z \geq z_t^*\right)\right]^{\alpha-1} z_t^*} \tag{41}$$

2. Market interest rate:

$$R_t^f = \frac{\alpha A_g\left[\xi\omega_t\mathbf{E}\left(z \mid z \geqslant z_t^*\right)\right]^{\alpha-1} z_t^*}{1-\gamma} \tag{42}$$

3. Consumption decision for the household:

$$C_t = (1-\beta)\{R_{t-1}^f D_{t-1} + (1-\alpha)A_g[\xi\omega_t\mathbf{E}\left(z \mid z \geqslant z_t^*\right)]^\alpha\} \tag{43}$$

4. Saving decision for the household:

$$D_t = \beta\{R_{t-1}^f D_{t-1} + (1-\alpha)A_g[\xi\omega_t\mathbf{E}\left(z \mid z \geqslant z_t^*\right)]^\alpha\} \tag{44}$$

5. Deposit market clearing:

$$D_t = \omega_t \tag{45}$$

6. Aggregate output:

$$Y_{g,t} = A_g\left[\xi\omega_t\mathbf{E}\left(z \mid z \geq z_t^*\right)\right]^\alpha \tag{46}$$

7. Aggregate emission:

$$E_{g,t} = \tau\xi\omega_t\left[1-\kappa\mathbf{E}\left(z^\rho \mid z \geqslant z_t^*\right)\right] \tag{47}$$