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Environmental regulation and financial stability: Evidence from Chinese manufacturing firms

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ABSTRACT

This paper evaluates the short-run economic and financial implications of tightening the environmental regulations. We build an Environmental Dynamic Stochastic General Equilibrium (E-DSGE) model that combines green policies aiming to reduce firms' emission together with financial frictions and endogenous default. The simulation results show that tightening environmental policies dampens the positive impact of expansionary shocks, compromises the firms' ability to repay loans, and consequently poses risks to the financial stability. For the empirical analysis, we examine the effect of environmental regulations tightened by the Chinese 11th Five-Year Plan on manufacturing firms' productivity and its implications for the financial sector. Using the difference-in-difference approach, we find that the manufacturing firms' productivity deteriorated due to the enhanced environmental regulation stringency, making the profitability and total output decline accordingly. As a result, firms located in the cities with higher emission reduction targets were more likely to default, threatening the financial stability.

"Too rapid a move towards a low-carbon economy could materially damage financial stability. A wholesale reassessment of prospects could destabilise markets, spark a pro-cyclical crystallisation of losses and lead to a persistent tightening of financial conditions: a climate Minsky moment." Mark Carney, Governor of Bank of England (2016).[1]

1. Introduction

During the last decade, policy makers around the world have put an increasing effort in coupling the economic growth with environmental policies that aim at reducing pollution and greenhouse gas emissions. As of February 2020, 188 states and the EU, representing more than 87% of global greenhouse gas emissions, have ratified or acceded to the Paris Agreement which intends to keep the increase in global average temperature to well below 2ºC. To achieve the emission abatement target, tightening the environmental regulations is unavoidable.

Take China, the second largest economy as an example. As shown in Fig. 1, sulphur dioxide emissions, for which China had been ranked as the top global emitters, have been decreasing since 2006 when the 11th Five-Year Plan came into force. A more remarkable decline has been witnessed since 2016.[2] Accompanying the rapid emission abatement, the stringency of environmental policies has been rising remarkably.[3] The regulation tools, either the price instruments like carbon tax or the quantity instruments like intensity target or cap-and-trade, are imperative to reduce the emission. Yet, our knowledge about the impact of these policy tools on firms' productivity and financial stability is still limited.

Against this backdrop, this paper evaluates the short-run economic and financial implications of the environmental policies, with a specific focus on China. In particular, the Chinese government set the aim of reducing total SO_2 emissions by 10 percent under the 11th Five-Year Plan. This transition increased production costs for industries with heavy pollutant emissions, such as coal burning and industry processes. Extra costs, expressed in terms of higher external financing cost for firms, can also arise as commer-

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[1] See Carney (2016).

[2] A similar pattern is found for the US. See Appendix A for details.

[3] The OECD Environmental Policy Stringency Index (EPS) is a country-specific and internationally-comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour.

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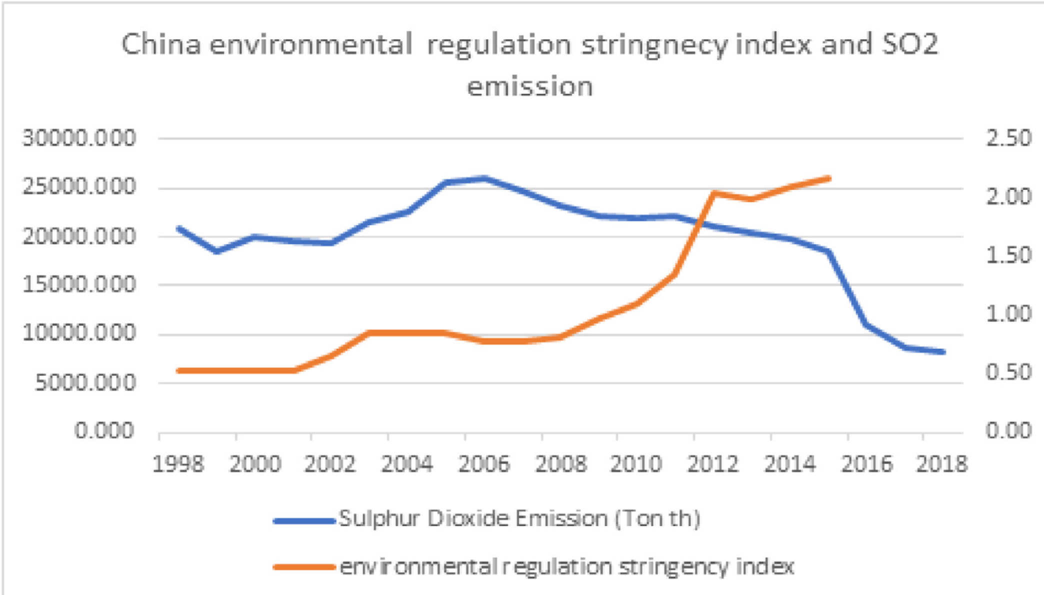

Fig. 1. China - China Sulphur Dioxide Emission and Environmental Policy Stringency Index. *Source*: Data for sulphur dioxide emission is from CEIC China Premium Database. Data for environmental regulation stringency is from OECD.

cial banks factored in possible forgone profits that such industries would gain in the absence of environmental policy when setting the lending rate. We investigate such banking channel in this paper, showing how it threatens the financial instability.

To engineer a transition away from unsustainable growth to eventual low-emission and sustainable development requires a massive reallocation of capital and adoption of clean production technology, which is likely to generate significant and systematic impacts on financial stability and macroeconomic conditions. The higher risk can arise from reduced corporate earnings and business disruption during the transition phase. This could leave entrepreneurs unable to repay outstanding loans or reduce the value of the company. Although a bank often has secured claim in the form of capital collateral of the borrowing firms, only a limited portion of losses could be recovered through corporate insolvency procedures.[4] Recognizing the potential shocks to the financial sector in the coming years, more and more central banks are considering the introduction of climate-related risks in their assessment of the financial system (Weidmann (2019) and NGFS (2019)). Indeed, emission abatement policy has important implications for the monetary policy as tighter carbon constraints, or any related climate change mitigation policy, can push up the production cost of carbon-intensive goods, and consequently spur inflation, other things equal. Under such circumstance, the central banks have to raise interest rates to stabilize inflation, which would hurt employment and economic growth. Thus, climate change policies can become a source of macroeconomic shocks and central banks should consider how to meet their mandate of maintaining price stability.[5]

To understand the impact of environmental policy shocks on macroeconomic fluctuations and financial instability, we first construct an environmental dynamic stochastic general equilibrium (E-DSGE) model which integrates the environmental policies into a framework that explicitly considers borrowing constraints and endogenous default. The inclusion of financial frictions in credit markets is crucial for understanding business cycle in that entrepreneurs are able to access credit with better conditions to finance new production during credit boom (Aivazian et al. (2015)). Given that gas emissions are proportional to total output, this also implies the comovement of emissions with credit expansion. Fig. 2, which plots the growth of greenhouse gas emissions against the growth of GDP and commercial loans respectively for China, confirms the positive association of emissions with both business cycle and credit boom. In the other words, economic expansions are followed by large and significant increase in emissions. Moreover, given that accelerated emissions growth is often associated with credit expansions, the positive correlation between emission and financial cycle tends to be more pronounced. These stylized facts indicate when entrepreneurs are able to finance new project with favourable conditions during credit boom, emissions would increase accordingly as a result of more intensive use of pollution inputs for the production process.

The inclusion of financial frictions in credit markets is also imperative for modelling the endogenous default mechanism that arises when the repayment of the loan used to finance new projects become larger than the rate of return of the underline project, leaving entrepreneurs underwater. The model characterizes entrepreneurs who use capital as collateral to obtain funds to finance the production process. Entrepreneurs can decide whether to repay the loans based on a cut-off value that determines their probability of defaults, which occurs when the debt repayment is larger than the value of the collateral they have pledged.

Overall, the E-DSGE analysis identifies the two channels through which environmental policy affects the financial stability. On one hand, the environmental policy moderates the en-

[4] Fossil fuel industry is directly exposed to the environmental risks, but other sectors, such as real estate, energy facility, transport and the financial firms that serve them, are indirectly exposed to the same risk. For instance Cahen-Fourot et al. (2021) show that fossil industry can generate significant and stranding cascades affecting downstream sectors and the economic system as a whole, while Battiston et al. (2017) adopt a network approach to financial dependencies to study how climate policy risk might propagate through the financial system.

[5] Further, environmental damage (e.g. flood and drought) can affect price stability by changing food and energy prices, and consequently having a negative impact on production. Such environmental risk, and the implementation of policies that try to limit such risk, can lead to market distortion and losses for financial institutions when providing credit.

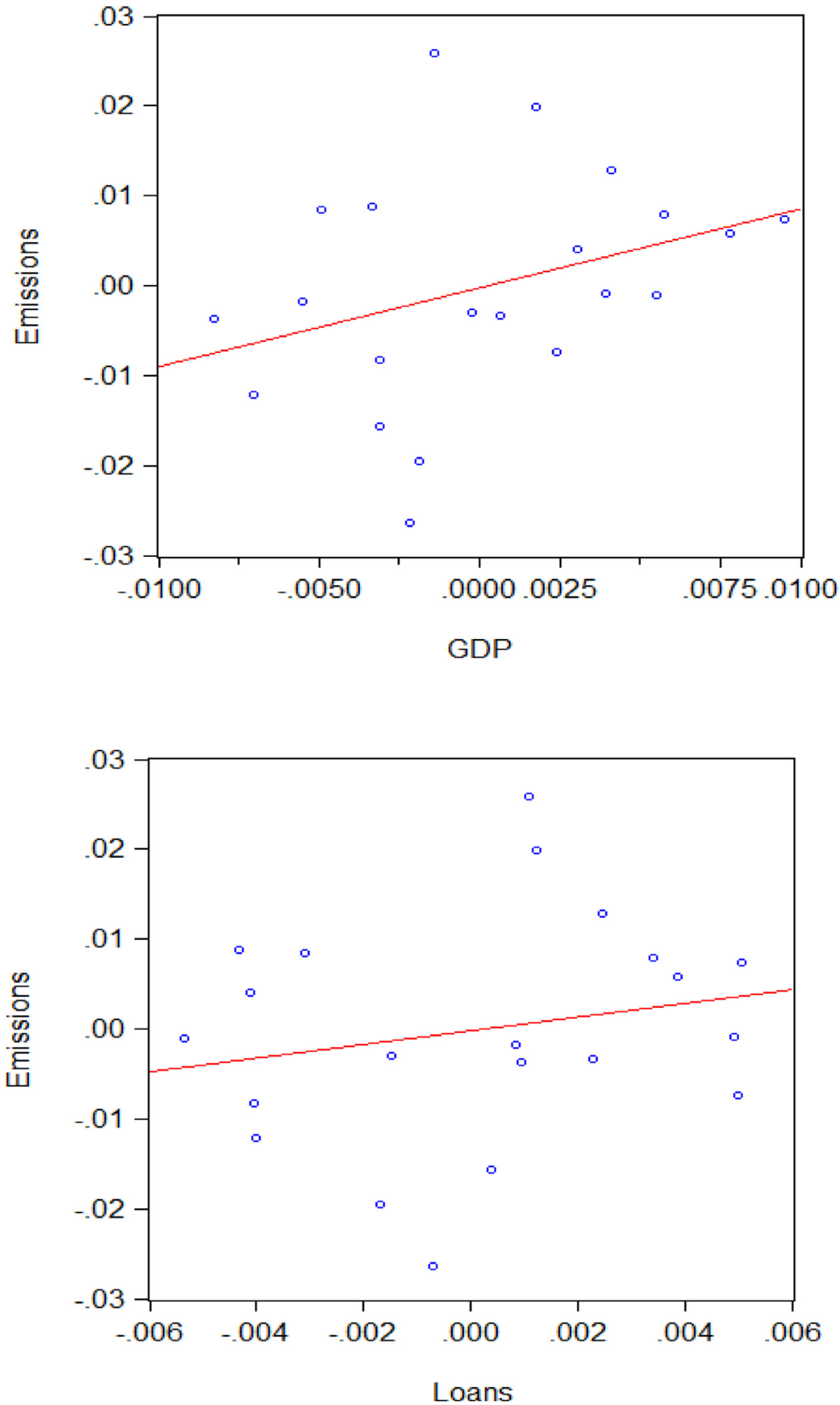

Fig. 2. Relationship of emissions with GDP and Commercial Loans. *Note*: All series are detrended using HP-Filter. *Sources*: GDP: Billions of RMB, Seasonally Adjusted (The People's Bank of China). Loans: Commercial and Industrial Loans, All Commercial Banks - Billions of RMB, Seasonally Adjusted (The People's Bank of China). Emissions: Chinese Greenhouse Gas Emissions by Gas (World Bank).

trepreneurs' profitability and compromises firms' liquidity; on the other hand, banks price environmental risk by charging higher lending rates, implying an increase in the threshold value of default.[6] Moreover, the model simulations show that environmental policies reduce the positive effect that a technological shock would normally yield. This deceleration in economic expansion is due to three main factors. First, the environmental policy reduces the usage of pollutant inputs below the desired level in the production process, forcing firms to cut the production below the optimal level. Second, the environmental policy blocks the inflation from falling as it would do in the absence of policy, enforcing central banks to adjust the policy rate. As a result, new investments and credit demand will change accordingly. Third, although the fi-

[6] Similar mechanism is described in Huang et al. (2021).

nancial frictions allow entrepreneurs to finance more projects with external funds, the higher loan rates, imposed by the commercial banks to internalize the environmental risk, restrict entrepreneurs from financing the desired new projects. The model augments two types of entrepreneurs, who differ in terms of the emission intensity of their production process, to reveal a spillover effect from the non-green to the green sector through bank capital and bank funding channels. The banks charge higher lending rates to all sectors in order to restore the balance sheet due to the foregone loans, leading to lower demand and supply of funds.

To validate the theoretical predictions of the E-DSGE model, we empirically assess the impact of environmental regulation tightened by the Chinese 11th Five-Year Plan (2006–2010) on manufacturing firms' profitability and productivity, and its implications for the financial stability. Under this Plan, the central government allocated the mandatory national emission reduction targets to all levels of local governments. In 2010, the binding targets set for the National 11th Five-Year Plan were largely met, and the environmental quality has improved significantly. Using the Annual Survey of Industrial Firms (ASIF), the most comprehensive Chinese firm-level datasets, we implement the difference-in-difference (DID) estimation and find that with the advent of tighter environmental regulations, the total factor productivity (TFP) of those firms located in cities with higher emission reduction target declined significantly compared with those located in cities where the emission reduction target is lower. As TFP which represents the technological progress and production efficiency declines, a firm's ROA and total output fall accordingly. These findings are consistent with Fan et al. (2019) who conclude that stricter environmental regulations lower firms' profits, capital, and labor. We further extend the research by investigating the impact on the banking sector. We find credits to the industrial firms located in the cities with higher emission reduction targets not only fall but also become more costly. Moreover, those firms having higher exposure to the regulation are more likely to default, threatening the financial stability.

Our research has strong theoretical and policy implications. We first shed light on the macroeconomic fluctuations and financial instability arising from the transition to low emission economy. In particular, the risk is induced by the imposition of policy tools like carbon pricing or tightening of emission standards. The transition through these policy tools is meant to bring overall benefits in the long term, but the costs to society, especially in the short term, cannot be ignored. We innovatively link environmental policy to the deterioration of firms' credit positions and consequently higher probability of default, which pose substantial threats to financial stability and economic growth. We complement the theoretical implications by empirically examining the impact of tightened environmental regulation on the manufacturing firms' productivity and loan performance. We show that environmental regulation depresses the improvement of TFP which in turn impairs firms' output and ROA, leading to higher probability of default.

The rest of the paper is organized as follows. Section two highlights the contribution of this research to the main literature. Section three presents the theoretical model in one-sector version. Section four reports the simulated impulse responses function to a technology shock. Section five estimates the impact of the Chinese 11th Five-Year Plan on manufacturing firms' productivity, and its implications for the financial stability. Section six concludes the paper.

2. Contribution to literature

This paper contributes to the existing literature in several ways. First, it develops an E-DSGE model with credit frictions and endogenous default. We extend the financial accelerator mechanism developed by Bernanke and Gertler (1989) and Christiano et al. (2014) by including an environmental policy that aims at reducing productive firms' emissions. This paper is closely related to Comerford and Spiganti (2017) who develop a model a l*à Kiyotaki and Moore* (1997) and find that a carbon bubble would generate a fire-sale as investors rush in selling assets from polluting industries, generating a large and persistent fall in output and investment.[7] However, our model differs from theirs in three ways. First of all, the specification of the environmental policy is introduced under a different setup. While Comerford and Spiganti (2017) impose a carbon tax to high-carbon firms and offer subsides to low-carbon firms, we follow Fischer and Springborn (2011)'s approach by imposing a constraint on the quantity of polluting inputs that can be used by the production sector. Second, we extend Comerford and Spiganti (2017)'s model by setting an endogenous cut-off value to reflect the likelihood of default. Our model predicts entrepreneurs would choose to default when the value of loan repayment exceeds the value of capital that entrepreneurs used as collateral to access external funds. Third, this model contains a banking sector, which creates an equilibrium spread between the loan rate and the deposit rate as banks price loans by taking into account entrepreneurs' default risks. Consequentially, facing higher cost of borrowing, entrepreneurs choose to reduce their demand for credit and cut investment, resulting in a further increase in the excess premium.

Regarding financial frictions, this paper is also related to Carattini et al. (2021) who study the effect of carbon tax by implementing an E-DSGE model with a specification for a pollution market. Further, they finds that macroprudential policy alone, without a carbon tax, is not very effective at addressing the pollution externality. Similarly, Diluiso et al. (2020) discuss climate policy under a DSGE model with financial frictions to assess the risks that the transition to a low-carbon economy pose to financial stability. They also explore possible instruments central banks could use to reduce these risks. In the context of credit frictions and endogenous default, the paper is related to Huang et al. (2021) who find that tightening environmental regulation enforces firms to internalize the pollution costs, which consequentially deteriorates firms' balance sheets and escalates the risks facing the financial system in the short term. While Huang et al. (2021) assess the impact of environmental policy shock on the real and financial sectors, this paper investigates the productivity channel through which the shocks of environmental policies are transmitted to the financial sector. Further, our empirical strategy is different from Huang et al. (2021) who employ the Chinese Clean Air Action Plan launched in 2013 as a quasi-natural experiment to directly evaluate its impact on the financial sector, in particular the probability of loan default and the banks' pricing strategy. In this paper, we estimate the short term impact of the Chinese 11th Five-Year Plan, under which the central government allocated the mandatory national emission reduction targets to all levels of local governments, on manufacturing firms' productivity, through which the financial sector was affected.

An increasing number of researchers have augmented the dynamic stochastic general equilibrium models to study the emission mitigation policies. Angelopoulos et al. (2010) analyze the impact of alternative environmental policy tools in a real business cycle model under the assumptions that pollution occurs as a by-product of output produced. Fischer and Springborn (2011) evaluate volatility and welfare costs by comparing cap-and-trade, carbon tax and the intensity target in a dynamic stochastic general equilibrium model with one polluting intermediate input. Using a dynamic stochastic general equilibrium model that includes a pollu-

[7] See Kiyotaki and Moore (1997) for details.

tion externality, Heutel (2012) proposes an optimal emissions policy during phases of expansions or recessions. Annicchiarico and Di Dio (2015) analyze different environmental policy regimes in a new Keynesian model with nominal rigidities and the presence of a monetary authority. Similar to our research, they find that macroeconomic fluctuations of shocks are dampened if a climate change policy is in place. All these papers abstract from the macro financial inter-linkage, which is a fundamental feature to explain business cycle fluctuations.[8] Following Annicchiarico and Di Dio (2015)'s setting, we introduce the credit cycle as a driving force of economic expansion, allowing entrepreneurs to access external funds to enhance production capacity. This setting implies the co-movement of emission with business cycle, i.e. larger emission during economic booms. However, when environmental policies are in place, larger emissions mean higher abatement costs for polluting firms, leading to fluctuations in firms' profitability and default probability.

This paper is also close to Dafermos et al. (2018) who find that climate change is likely to reduce firms' productivity and thereby gradually deteriorate the liquidity of firms, leading to a higher rate of default. Dafermos et al. (2018)'s approach is based on a stock-flow-fund ecological macroeconomic model and focuses on the long-run trends in the interactions between the financial system and climate change, assuming that global warming will damage capital and firms' profitability. Our research, instead, focuses on the short-run fluctuations in business and financial cycles through the lens of a DSGE model with nominal rigidities, and with an explicit role for monetary policy.

Finally, we contribute to the emerging literature highlighting the financial risks of transition to low emission economy. In this direction, Semieniuk et al. (2021) survey the literature studying the possible threats imposed by a low-carbon transition to the stability of financial system as a whole. Indeed, they point the fact that transition costs arising from enforcement of environmental regulation could lead to higher ratio non-performing loans, which could in turn reduce the profitability of lending banks, and even leading to bank run and bankruptcy (Anglii (2017), Dafermos and Nikolaidi (2019) and Bolton et al. (2020)). However, the impact is amplified with a larger banking exposure to industries triggered by the transition process (Vermeulen et al. (2019)). Different from existing literature, we highlight the role of the banking channel in which credit rationing arises from the increase in non-performing loans of commercial banks. Even if the shock originates from the highly carbon-intensive sectors, credit rationing could affect all sectors irrespective of their carbon intensity. This important spillover effect engineered by the banking sector would translate into higher lending rates, which would consequently lead to a drop in investment and return on projects of all productive sectors. Dafermos and Nikolaidi (2021) and Lamperti et al. (2021) also show how climate risks affect both the real economy and the financial system by increasing loan defaults. Using a stock-flow consistent model and an agent-based macro financial model, respectively, they analyze the implications of green capital requirements in reducing the risks arising from transition toward a greener economy. Dafermos and Nikolaidi (2021) run their model for a long horizon that starts in 2018 and ends in 2100 to examine both the short-run effects (transition risks) and the long-run effects (physical risks) of green differentiated capital requirements on climate change, and they find that the short-run effects can be both positive and negative. Different from their, our model focuses on short-run effects of tightened environmental policy in the presence of positive supply shocks. While Lamperti et al. (2021) enrich the ecological macroeconomic literature by showing that carbon-adjustments in credit supply reduce emissions and physical risks, but they can also increase the probability of default, our model contributes to the literature by applying the dynamic general equilibrium models to investigate the economic impact of environmental transition.

[8] See among others Kiyotaki and Moore (1997), Bernanke and Gertler (1989), Bernanke et al. (1999), Christiano et al. (2014), Jermann and Quadrini (2012), Campbell and Hercowitz (2009), Gerali et al. (2010), Iacoviello (2005), Iacoviello and Neri (2010), Iacoviello (2015), Justiniano et al. (2015), Lambertini et al. (2013), Mendicino and Punzi (2014), Punzi and Rabitsch (2015), Kollmann et al. (2011), Rabitsch and Punzi (2017).

3. Model

We develop a dynamic stochastic general equilibrium (DSGE) model in the spirit of Bernanke and Gertler (1989) and Christiano et al. (2014). Our model extends those mentioned by accounting for pollutant emissions and by analysing the effects of financial intermediation on the energy-economy system. The model includes six economic agents: (i) households who consume final goods, supply labor to firms and save in the form of bank deposits; (ii) two types of entrepreneurs, one in the green sector and one the other in the brown sector, that rent capital and labor from households, and combine them with green energy or polluting inputs to produce differentiated intermediate goods; (iii) perfectly competitive firms that produce a final consumption good by combining intermediate goods supplied by monopolistically competitive firms from the brown and green sector; (iv) a capital producer that rents capital from households and produces new capital from the existing capital stock; (v) a banking sector that collects deposits from households and uses them to supply loans to entrepreneurs; banks also seize part of the capital stock in case of entrepreneur default; (vi) a monetary authority that sets nominal interest rates by following a standard Taylor rule.

3.1. Households

A representative household who consumes good, c_t, and supplies labor, L_t, and saves bank deposits, d_t, in order to solve the following life time utility:

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

subject to the following budget constraint:

$$c_t + d_t \leq w_t L_t + \frac{R_{t-1}}{\pi_t} d_{t-1} + F_t. \tag{2}$$

E is the expectation operator and β is the discounting factor. w_t indicates the real wage, η is the inverse of the Frisch elasticity of work effort and ν_L represents the weight of the disutility from working. R_t is the free-risk nominal interest rate received on deposits and $\pi_t = P_t/P_{t-1}$ is the inflation rate. Households also receive real dividends from firms, F_t.

3.2. Production sector

3.2.1. Final good production

We assume that final consumption good, Y_t, is produced by perfectly competitive firms, which combine a bundle of differentiated intermediate goods $Y_t(n)$, with $n \in [0, 1]$, according to a constant elasticity of substitution technology:

$$Y_t = \left[\int_0^1 Y_t(n)^{\frac{\xi-1}{\xi}} dn \right]^{\frac{\xi}{\xi-1}}, \tag{3}$$

where $\xi > 1$ governs the degree of substitutability between differentiated intermediate goods.

The final-good-producing firms operate under perfect competition, therefore the final good price P_t and the intermediate goods prices $P_t(n)$ are given. In order to maximize profits, final-good-producing firms choose the quantities of intermediate goods $Y_t(n)$, as follows:

$$Max\left[P_tY_t - \int_0^1 P_t(n)Y_t(n)dn\right]. \tag{4}$$

The optimal solution to (4) is given by the first order condition which results in the following input demand for the intermediate good n:

$$Y_t(n) = \left(\frac{P_t(n)}{P_t}\right)^{-\xi} Y_t, \tag{5}$$

where P_t is the CES-based final (consumption) price index[9] given by

$$P_t = \left[\int_0^1 P_t(n)^{1-\xi} dn\right]^{\frac{1}{1-\xi}}. \tag{6}$$

3.2.2. Intermediate goods production

This subsection describes the intermediate goods sector which introduces price stickiness into the model.[10]

A continuum of monopolistically competitive firms that produce intermediate goods $Y_t(n)$ and sell to the final goods producer at price $P_t(n)$. The intermediate goods sector aggregates intermediate goods from both green and non-green firms. Thus, there are two types of entrepreneurs (superscript by j). They differ in terms of their friendly environmental production process: green (g) versus non-green (ng).[11]

The final good sector assembles the sold output of the green and non-green sectors according to the following function:

$$Y_t(n) = [\sigma_g^{1/\zeta}(Y_{e,t}^g(n))^{\frac{\zeta-1}{\zeta}} + \sigma_{ng}^{1/\xi_H}(Y_{e,t}^{ng}(n))^{\frac{\zeta-1}{\zeta}}]^{\frac{\zeta}{\zeta-1}}, \tag{7}$$

where σ_g and σ_{ng} represents the market share of green and non-green firms, respectively, and ζ is the elasticity of substitution between the two sectors.

The price index of the core consumption bundle is defined as: $P_t(n) = [\sigma_g(P_{e,t}^g(n))^{1-\zeta} + \sigma_{ng}(P_{e,t}^{ng}(n))^{1-\zeta}]^{\frac{1}{1-\zeta}}$.

The intermediate goods sector, composed by green and non-green firms, produces intermediate goods n with the following production function:

$$Y_{e,t}^j(n) = A_t(k_{e,t-1}^j)^{\alpha}(L_t^j)^{1-\alpha-\gamma_j}H_t^{\gamma_j}. \tag{8}$$

where A is aggregate technological progress, L is labor, and k is capital. $H = \{E, M\}$ is the intermediate input where E represents clean and renewable energy, while M is the polluting input. γ_j is the elasticity of output with respect to clean energy and polluting inputs.[12] Following Fischer and Springborn (2011), we assume that emissions are proportional to the use of the polluting inputs, therefore the unit of emission are equal to the quantity of emissions M.

Price rigidities are introduced by relating to the standard Calvo price-setting mechanism in which firms producing intermediate goods firms adjust each period their prices with a probability of $(1-\theta)$. See Calvo (1983). $(P_t)^*(n)$ is the price that intermediate firms are able to adjust. Thus, intermediate goods firms maximize the following expected profit:

$$\max E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,t+k}\left[\frac{P_t^*(n)}{P_{t+k}}]P_t(n) - \frac{X}{X_{t+k}}\right]Y_{t+k}^*(n). \tag{9}$$

where $Y_{t+k}^*(n) = \left(\frac{P_t^*(n)}{P_{t+k}}\right)^{-\xi} Y_{t+k}$. Recall that, households are the owners of the intermediate sector, therefore $\Lambda_{t,t+k} = \beta^{t+k}\frac{U_{C_{t+k}}}{U_{C_t}}\frac{P_t}{P_{t+k}}$ represents the households' stochastic discount factor, where β^t is the households' discount factor and U_{C_t} is the household marginal utility. X_t is the markup of final over intermediate goods and the steady state is $X = \xi/(\xi-1)$.

The Calvo price evolves according to the following:

$$P_t = \left[\theta P_{t-1}^{\xi} + (1-\theta)(P_t^*)^(1-\xi)\right]^{\frac{\xi}{\xi-1}}. \tag{10}$$

Combining these two last equations, (9) and (10), and after log-linearizing, we can obtain the following expression for the Phillips curve:

$$\hat{\pi}_t = \beta_s E_t \hat{\pi_{t+1}} - \kappa \hat{X}_t, \tag{11}$$

where π represents the inflation rate and $\kappa = \frac{(1-\theta)(1-\beta)\theta}{\theta}$.

3.2.3. Entrepreneurs

Entrepreneurs in green and non-green sectors operate in the continuum of monopolistically competitive firms that produce differentiated intermediate goods by choosing the quantity of capital to be invested next period, which can be financed by borrowing from the banking sector. Entrepreneurs use capital to pledge against borrowing. The model allows the possibility for entrepreneurs to endogenously default by introducing a threshold value that defines the repayment ability of the loan.

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

$$\max E_0 \sum_{t=0}^{\infty} (\beta^e)^t \left[ln(c_{e,t}^j)\right] \tag{12}$$

subject to:

$$\begin{aligned} cc_{e,t}^j &+ q_t^{j,k}(k_t^j - (1-\delta_k)k_{t-1}^j) + w_t^j L_t^j + R_t^K k_t^j \\ &+ \frac{R_{t-1}^L}{\pi_t} b_{t-1}^j - Z_t^j = Y_t^j + b_t^j, \end{aligned} \tag{13}$$

and

$$b_t^j \le m_t^j\, E_t \frac{(q_{t+1}^{j,k}\pi_{t+1}(1-\delta_k)k_t^j)}{R_t^L}. \tag{14}$$

β^e is the entrepreneur's discount factor and $c_{e,t}^j$ is the entrepreneur's consumption. $q_t^{j,k}$ is the real price of physical capital k that entrepreneurs own, δ_k is the depreciation rate of capital stock. Entrepreneurs also rent capital and R_t^k is the rental rate they pay on capital service. w_t^j is the real wage that entrepreneurs in each sector pay to households in exchange of the labor they supply. Y_t^j represents the aggregate production of intermediate goods as defined in eq. (8), $Y_t^j(n) = A_t(k_{t-1}^j)^{\alpha}(L_t^j)^{1-\alpha-\gamma}M_t^{\gamma}$. Similar to Fischer and Springborn (2011), the government can impose an emission cap to reduce emissions from the polluting input in the form of emission cap, i.e. a fixed amount of $\bar{M}$.[13] Therefore, for the non-green sector, which uses polluting inputs for production, the above

[9] The CES-based final (consumption) price index, P_t, is obtained by combining equations (3) and (5).

[10] See Iacoviello (2005).

[11] Throughout the paper, we use the terms "non-green" and "brown" interchangeably to identify the polluting sector.

[12] Many low-polluting firms do not use only non-polluting inputs as assumed in the model, but a combination of polluting and non-polluting inputs. However, the theoretical model abstracts from considering this set of firms.

[13] Alternatively, Heutel (2012), Annicchiarico and Di Dio (2015), and Chan (2019) assume that emissions are proportional to output and environmental policies and abatement measures limit the environmental impact of production activities. Moreover, their models specify for a damage function with the aim of captur-

maximization problem is also subject to the following input constraint:

$$M_t \leq \bar{M} \tag{15}$$

We assume that the emission constraint on cap is always binding, and the shadow price of permits (i.e. the lagrangian multiplier of the emission constraint) adjusts to clear the market for permits.[14]

Entrepreneurs finance capital for new projects by obtaining loans, b_t^j, from commercials banks, and they agree to repay back $R_t^L b_{t-1}^j$, where R_t^L is the gross nominal interest rate on one-period loans. Entrepreneurs can use capital as a collateral to raise funds to finance new projects, as defined in eq. (14), where m_t^j is the endogenous loan-to-value ratio, which will be defined later in Section 2.4.

Entrepreneurs and banks do not have access to the same information, and entrepreneurs can decide to default if the return on new projects does not cover the borrowing cost. Thus, entrepreneurs can decide to pay back less than their initial contractual obligations, Z_t, in which case the banking sector can size a fraction of the capital during the foreclosure process. Therefore, the amount of loans that entrepreneurs default is given by the amount of missed loan repayments minus the sized capital stock: $Z_t^j = [F_t^j(\bar{\omega}_t^j) R_{z,t} b_{t-1}^j - q_t^{j,k}(1-\delta_k) k_{t-1}^j G_t^j(\bar{\omega}_t^j)]$, where $F_t(\bar{\omega}_t)$ is the share of entrepreneurs who default their debt to the bank, while $G_t(\bar{\omega}_t)$ is the fraction of capital stock seized by the bank in case of default.[15]

In order to define the endogenous default decision, we assume that there is a representative entrepreneur which consists of many members, indexed by i. The entrepreneur assigns equal resources to each member i to purchase capital $(k_t)^i$, where $\int_i (k_t)^i di = k_t$. Each member i experiences an idiosyncratic shock ω_{t+1}^i such that the ex-post value of the capital is $\omega_{t+1}^i q_{t+1}^k (k_{t+1})^i$. The entrepreneur defaults when the value of the capital is lower than the loan repayment. The defaulting decision is based on a cut-off value, $\bar{\omega}_{t+1}$, defined as follows:

$$\bar{\omega}_{t+1}^j = \frac{b_t^j R_{z,t+1}^j}{(q_{t+1}^{j,k} \pi_{t+1}(1-\delta_k) k_t^j)} \tag{16}$$

$R_{z,t+1}^j$ represents the gross contractual state-contingent loan rate paid to the bank by non-defaulting entrepreneurs.[16] Notice that $R_{z,t}^j$ differs from R_t^L. The latter is the lending rate charged by banks to satisfy the bank participation constraint, which is defined later in details.

If $(\bar{\omega}_{t+1})^i \in [\bar{\omega}_{t+1}, \infty]$, entrepreneurs are solvent and repay the loan to the bank; while for loans with low realizations, $(\bar{\omega}_{t+1})^i \in [0, \bar{\omega}_{t+1}]$, entrepreneurs declare bankruptcy and defaulting members loose their capital.[17]

ing the reduction in productivity due to pollution. In contrast, we do not model the damages explicitly as in our model the damages arise from the stock of emissions, which present a very slow rate of decay. See also Fischer and Springborn (2011) and Dissou and Karnizova (2016).

[14] The KuhnTucker orthogonality conditions requires $[\mu_t^M (M_t - \bar{M})] = 0$, which implies $\mu_t^M > 0$ all the time when the cap is always binding.

[15] As in Bernanke et al. (1999), Forlati and Lambertini (2011) and Punzi and Rabitsch (2018), the seized capital stock is destroyed during the foreclosure process.

[16] Loan rate $R_{z,t+1}$ is determined at time t, after the realization of the shocks.

[17] The random variable $(\omega_{t+1})^i$ is an i.i.d. idiosyncratic shock which is log-normally distributed with cumulative distribution $F_t[(\omega_{t+1})^i)]$. We allow for idiosyncratic risk, such that $E_t[(\omega_{t+1})^i] = 1$. This implies that $\log[(\omega_t)^i] \sim N(-\frac{\sigma_{\omega_t^2}}{2}, \sigma_{\omega_t^2})$, where σ_{ω_t} is a time-varying standard deviation for each type of entrepreneurs, which follows an AR(1) process.

Table 1
Bank Balance Sheet.

Assets	Liabilities
Green Firms (b_{t+1}^g)	Domestic Deposits (d_t)
Non-Green Firms (b_{t+1}^{ng})	Bank Capital (e_t)

3.3. Capital producers

While the previous subsection identified the demand for capital, this subsection defines the supply side for capital, where capital goods producers produce investment goods subject to adjustment costs. This decentralized specification allows the model to have an explicit asset price variable. See Justiniano et al. (2011) and Justiniano et al. (2015).

Capital producers combine a fraction of the final goods purchased from retailers as investment goods, $I_{k,t}$, to combine it with the existing capital stock, k_t, in order to produce new capital. Existing capital is subject to an adjustment cost specified as $\frac{\psi_k}{2}\left(\frac{I_{k,t}}{k_{t-1}} - \delta_k\right)^2 k_{t-1}$, where ψ_k governs the slope of the capital producers adjustment cost function. Capital producers choose the level of $I_{k,t}$ that maximizes their profits

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

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

$$q_t^k = \left[1 + \psi_k \left(\frac{I_{k,t}}{k_{t-1}} - \delta_k \right) \right], \tag{17}$$

where q_t^k is the relative price of capital. In the absence of investment adjustment costs, q_t^k, is constant and equal to one.

Eq. 17 is similar to the Tobin's q relationship for investment in which the marginal cost of a unit of capital is related the marginal cost of adjusting the capital stock. The usual capital accumulation equation defines aggregate capital investment:

$$I_{k,t} = k_t - (1-\delta_k) k_{t-1}, \tag{18}$$

where k_t is the capital used by the green and non-green sector. Thus, $k_t = \sum_j k_t^j$.

3.4. Banking sector

The model assumes the banking sector receives at time t deposits from households, d_t, and make loans to entrepreneurs, $b_t = \sum_j b_t^j$. This setup is similar to Kollmann et al. (2011), Kollmann (2013) and Rabitsch and Punzi (2017).

The banking sector extends loans to both entrepreneurs, as described in Table 1.

Thus, the banking sector maximizes

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

subject to the flow of funds

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

and

$$\frac{e_t}{d_t + e_t} \geq \Theta, \tag{19}$$

where $c_{b,t}$ denotes the banker's consumption (dividends) and β_b is its discount factor; e_t is the bank' equity $(= b_t - d_t)$ and $\Gamma > 0$

indicates a real marginal cost that banks pay during banking operations of collecting deposits and extending loans. The banking sector faces a capital requirement, described in eq. 19, where bank's leverage ratio, i.e. capital-asset ratio, can not be smaller than a fraction Θ.

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

$$R_t^L b_{e,t}^j = \left\{ (1-\mu^j) \int_0^{\bar{\omega}_{j,t+1}} \omega_{j,t+1}^i (1-\delta_h)_{t+1}^{j,k} \pi_{t+1} k_{e,t+1}^j f_{t+1}(\omega_j^i) d\omega_j^i \right\} + \left\{ \int_{\bar{\omega}_{j,t+1}}^{\infty} R_{Z,t+1}^j b_{e,t}^j f_{t+1}(\omega_j^i) d\omega_j^i \right\}, \tag{20}$$

where $f(\omega^i)$ is the probability density function of ω^i, μ is the fraction of the capital value that banks pay to monitor and seize the collateral in case of default, and $R_{z,t+1}$ is the gross contractual state-contingent loan rate paid to the bank by each individual non-defaulting entrepreneur.[18] The participation constraint in (20) states that the return on total loans the banking sector expects to obtain comes from the value of the capital stock, net of monitoring costs and depreciation, of the defaulting entrepreneurs (the first term on the right hand side); and, from the repayment by the non-defaulting entrepreneurs (the second term on the right hand side). Once the idiosyncratic and environmental policy shocks hit the economy, the threshold values $\bar{\omega}_{t+1}$ and the state-contingent mortgage rate $R_{Z,t+1}$ are determined, to fulfill the above participation constraint.

Combining the participation constraint (20) and the borrowing constraint (14), we can define the endogenous loan-to-value ratio, m_t^j, equal to $\left[\Gamma_{t+1}^j(\bar{\omega}_{b,t+1}^j) - \mu^j G_{t+1}^j(\bar{\omega}_{b,t+1}^j)\right]$, where $G_{t+1}(\bar{\omega}_{b,t+1}) \equiv \int_0^{\bar{\omega}_{t+1}} \omega_{b,t+1}^i f_{t+1}(\omega_b^i) d\omega_b^i$ is the expected value of the idiosyncratic shock for the case $(\omega_{t+1})^i \in [0, \bar{\omega}_{t+1}]$ multiplied by the probability of default, while $\Gamma_{t+1}(\bar{\omega}_{t+1}) \equiv \bar{\omega}_{t+1} \int_{\bar{\omega}_{t+1}}^{\infty} f_{t+1}(\omega_j^i)\omega^i + G_{t+1}(\bar{\omega}_{t+1})$ is the expected share of capital stock, gross of monitoring costs that goes to lenders in case of default, μ. Thus, the participation constraint in eq. (20) can be rewritten as:[19]

$$b_{e,t}^j = \left[\Gamma_{t+1}^j(\bar{\omega}_{b,t+1}^j) - \mu^j G_{t+1}^j(\bar{\omega}_{b,t+1}^j)\right] E_t \frac{(q_{t+1}^k \pi_{t+1}(1-\delta_k)k_t^j)}{R_t^L}. \tag{21}$$

3.5. Monetary policy

The central bank follows a Taylor-type rule that reacts to deviations of the nominal interest rate, total output, and inflation from their steady-state values:

$$\frac{R_t}{\bar{R}} = \left(\frac{R_{t-1}}{\bar{R}}\right)^{\phi_R} \left(\frac{\pi_t}{\bar{\pi}}\right)^{\phi_\pi(1-\phi_R)} \left(\frac{Y_t}{\bar{Y}}\right)^{\phi_Y(1-\phi_R)} \varepsilon_{R,t} \tag{22}$$

where ϕ_π is the coefficient on inflation in the feedback rule, ϕ_Y is the coefficient on output, and ϕ_R determines the degree of interest rate smoothing.[20]

3.6. Aggregate equilibrium

Final GDP is defined as:

$$Y_t = C_t + I_t + E_t + M_t + \Sigma_j \mu^j G_{t+1}(\bar{\omega}_{j,t+1}) q_{t+1}^{j,k} (1-\delta_k) k_{e,t}^j) \tag{23}$$

where

$$C_t = c_t + \sigma_g c_{e,t}^g + \sigma_{ng} c_{e,t}^{ng} + c_{b,t}, \tag{24}$$

and

$$q_{t+1}^k = \sum_j \sigma_{gj} q_{t+1}^{j,k}. \tag{25}$$

3.7. Exogenous factors

We assume the aggregate productivity shock that follow an AR(1) process:

$$\ln A_t = \rho_A \ln A_{t-1} + \varepsilon_{A,t},$$

where ρ_A is the persistence parameter and $\varepsilon_{A,t}$ is a i.i.d. white noise process with mean zero and variance σ_A^2.

3.8. Parametrization

The model is parameterized at a quarterly frequency, aimed at capturing key features of long term statistics for the Chinese economy, as in Huang (2005), Liu (2008), Chang et al. (2015), Zhao et al. (2016) and Punzi (2019). Some parameters are set by largely referring to the standard real business cycle literature. See Table 2. The discount factor for households and bankers $\beta = \beta_b$ is set as in Zhao et al. (2016) and Punzi (2019), and equal to 0.985 per quarter to target the annual nominal free-risk interest rate of around 4%. Similar to Iacoviello (2015), entrepreneurs face a lower discount factor and $\beta^e = 0.94$. The price elasticity ξ is set equal to 6 and the Calvo probability to adjust prices, θ, is set equal to 0.85. See Zhao et al. (2016). The coefficient of the monetary policy role is set as in Zhao et al. (2016) and Punzi (2019), thus the coefficient for the interest rate inertia, ρ_R, the reaction to the output gap, ρ_Y, and the reaction to inflation of ρ_π is equal to 0.9, 0.159 and 1.14, respectively. Justiniano et al. (2015) use similar values: $\rho_R = 0.8$, $\rho_Y = 0.125$, $\rho_\pi = 1.5$, with slightly lower weight to the reaction of

Table 2
Parameters' Values.

Parameter	Description	Value
β	Households Discount factor	0.99
β^e	Entrepreneurs Discount factor	0.94
σ_c	Elasticity of substitution for consumption	1.01
ν_L	Labor disutility parameter	1
η	Labor supply aversion	1.01
ς	Elasticity of substitution between sectors.	2
δ_k	Capital depreciation parameter	0.035
ψ_k	Capital adjustment cost	5
α	Capital Share	0.35
γ_g	Energy Inputs Share	0.09
γ_{ng}	Pollution Inputs Share	0.09
$F_j(\bar{\omega}^j)$	Probability of default	0.007
ξ	Price Elasticity of Demand for Good n	6
θ	Calvo's Price Parameter for Nominal Rigidities	0.85
ρ_R	Monetary Policy Inertia	0.9
ρ_Y	Monetary Policy Reaction to Y	0.159
ρ_π	Monetary Policy Reaction to π	0.14
β_b	Banks Discount factor	0.99
ρ_b	Banks Capital ratio	0.08
Γ	Banks Operating Costs	0.0018
μ_j	Monitoring Cost	0.12
σ_g	Size of Green Firms	0.75
ρ_A	Persistency of Technology shock	0.95
σ_A	Standard deviation on Technology shock	0.00173

[18] Loan rate $R_{z,t+1}$ is determined at time t, after the realization of the shocks.

[19] For similar specification see Forlati and Lambertini (2011) and Lambertini et al. (2017).

[20] For similar specification, see Iacoviello (2005), Iacoviello and Neri (2010), Annicchiarico and Di Dio (2015), Zhao et al. (2016) and Chan (2019).

inflation, but higher to the reaction of output gap. The production function follows a constant returns to scale with a Cobb-Douglas specification, and the capital return to scale α is set equal to 0.35. As in Huang (2005), the capital depreciation rate δ_k is set at 0.035, while the adjustment cost parameter on investments is equal to 5 to match the share of investment to GDP of 0.394, the average value that China achieved during the period of 19902013.[21] The share of clean energy and pollution emission in the production function, Y, is equal to 0.099 so that the energy usage would account for 2.8% of GDP, the value that China had in 2005.[22] The inverse elasticity of consumption and labor supply is set equal to 1.01, similar to Liu (2008). We assume that the two sectors are perfect substitute as intermediate goods can be produced in one or both sectors, thus the elasticity of substitution between the two sectors in the intermediate goods production is set equal to 2.[23]

For the banking sector, we follow Christiano et al. (2014) to set the monitor cost as 0.21, and the average probability of default, $F_j(\bar{\omega}^j)$, is equal to 0.009. Moreover, the persistency of the risk shock is set equal to 0.48 with a standard deviation of 0.0010 to obtain a steady state value of entrepreneurs' probability of default of 3.78% and an excess risk premium of 4.49%. Similar to Kollmann et al. (2011), the bank operating cost coefficient is set equal to 0.0018, and the required bank capital ratio equal to 0.08. This value reflects the rules defined under Basel II, which requires that the total risk-weighted capital ratio, which is defined as total (Tier 1 and Tier 2) capital divided by total risk-weighted assets, to be at least 8%. Moreover, the persistency and standard deviation of the technology shock are defined as in Kollmann et al. (2011). Finally, the share of green firms, σ_g, is set to 0.75 to reflect the number of low- and high-polluting firms in the Annual Survey of Industrial Firms.[24]

4. Theoretical impulse responses

This Section presents results on simulated impulse responses to a positive productivity shock. Fig. 3 shows a percentage deviation from the initial steady state over a 20-quarter period of the difference between two scenarios: a model that includes the environmental policy of tightening the pollution inputs and the baseline model without environmental policy.

Similar to Fischer and Springborn (2011), Annicchiarico and Di Dio (2015) and Annicchiarico and Di Dio (2017), an environmental policy that aims at reducing the use of polluting inputs moderates the positive impact that technological progress would bring to the economy, making the response of production, consumption and investment smaller relative to the responses of a model abstracting climate change regulations. The dotted line in Fig. 3 indicates that the difference across the two model versions of the responses of the main macroeconomic variables is negative as the expansionary effect of the positive technology shock is less pronounced after introducing environmental policies to reduce pollution emissions.[25] The technological progress allows entrepreneurs in the green sector to use larger input of clean energy, which leads to a slightly higher production relative to the non-green sector, which on the contrary shows a decrease in production due to the limited use of resources in the production process. As a result, the environmental policy tends to dampen macroeconomic fluctuations, due to the fact that the cap prevents additional output from being used to produce more of the intermediate goods.[26] In the model, the polluting constraint is always binding, and the shadow price, i.e. the lagrangian multiplier, is always positive, implying larger marginal costs for polluting firms.[27] The shadow permit price in Fig. 3 indicates the positive reaction of the lagrangian multiplier when the positive technology shock hits the economy, suggesting that the non-green sector is paying an implicit higher cost for polluting in order to take advantage of the better technology.

Due to the presence of financial frictions, i.e. the ability for entrepreneurs to borrow against the value of their capital, lending increases due to higher value of asset prices during such phase of economic expansion, but the positive impact is dampened by the presence of active climate change policies. Therefore, the difference of impulse responses between the two models for lending is negative for both sectors. Lending shows a less amplified positive effect for both green and non-green sectors as the increase of asset price increase is less pronounced. Indeed, the financial accelerator mechanism prevents borrowing from increasing further as it does in the baseline model, and consequently, less funds are available for new investments. Eq. 16 defines the threshold value, $\bar{\omega}_{t+1}$, as a function of the loan amount, b_t, the contractual loan rate, $R_{z,t+1}$, the asset value, q^k_{t+1}, the inflation rate, π_{t+1}, and the holding of capital stock, k_t. Any movement in one of these variable implies a fluctuation in $\bar{\omega}_{t+1}$. If $(\bar{\omega}_{t+1})^i \in [\bar{\omega}_{t+1}, \infty]$, entrepreneurs are solvent and repay the loan to the bank; while for loans with low realizations, $(\bar{\omega}_{t+1})^i \in [0, \bar{\omega}_{t+1}]$, entrepreneurs declare bankruptcy. In general, given favourable economic conditions due to a technological progress, banks would pay lower costs to monitor entrepreneurs and would charge lower interest rates, therefore default rates would decrease. However, when climate change regulations are in place, default rates decrease by less in the non-green sector, resulting in a positive spread between the two models version. This occurs because the restrictions on the use of polluting inputs, or the acquisition of polluting permits, have the effect to increase firms' costs, thus compromising firms' profitability and the ability to repay outstanding loans. In general, the positive technology shock would decreases the probability of default as $\bar{\omega}$ becomes smaller and the non-defaulting interval $[\bar{\omega}_{t+1}, \infty]$ becomes larger. However, when the expansionary shock is combined with a restrictive environmental policy, the model replicates a shrinking negative impact on default rates. This can be seen in Fig. 3, which shows a positive increase in the difference of responses of default rates for a model with environmental policy and the baseline model.[28] Moreover, the model simulations show that the such difference is more pronounced for the non-green sector. Indeed, it is important to highlight the spillover effect from the non-green

[21] Source: National Bureau of Statistics of China.

[22] See https://yearbook.enerdata.net/total-energy/world-energy-production.html for details.

[23] Acemoglu et al. (2012) and Papageorgiou et al. (2017) find evidence that the elasticity of substitution between clean and dirty energy significantly exceeds unity.

[24] The high polluting industries refer to those industries whose COD emission account for more than 4% of total emissions by all industries in 2005, including paper making and paper products, agricultural and sideline food processing, manufacture of raw chemical materials and chemical products, manufacture of textile, manufacture of beverages, and smelting and pressing of ferrous metals. These 6 industries together account for 76.33% of total emission, 27.3% of total output and 26.9% of total sample. In the calibration, energy is linked to Scope 2 emissions.

[25] Although not reported in the paper, different policy tools can be considered. For instance, a carbon tax policy would generate similar responses as the cap policy. This part of analysis is definitely available to the readers upon request.

[26] Similar to Fischer and Springborn (2011) and Annicchiarico and Di Dio (2015), the price of emissions permits is determined by the market and it raises on impact to maintain the cap. Indeed, given the highest technology, firms demand for more permits in order to produce more during economic booms, which translates into higher marginal costs for the firms.

[27] Eq. 15 implies that $\mu^M_t(M_t \leq \bar{M}) = 0$, thus $\mu^M_t > 0$ and $M_t = \bar{M}$. The intuition is that, during favourable economic conditions, firms tend to maximize, up to the limit allowed, the use of polluting inputs.

[28] It is important to note that our model simulation replicates a temporary shock arising from environmental policy, which allows the default rate for non-green firms to return to its initial value. It is worthwhile to investigate a permanent negative effect of environmental policy on emission-intensive sectors. We leave this interesting extension to further research.

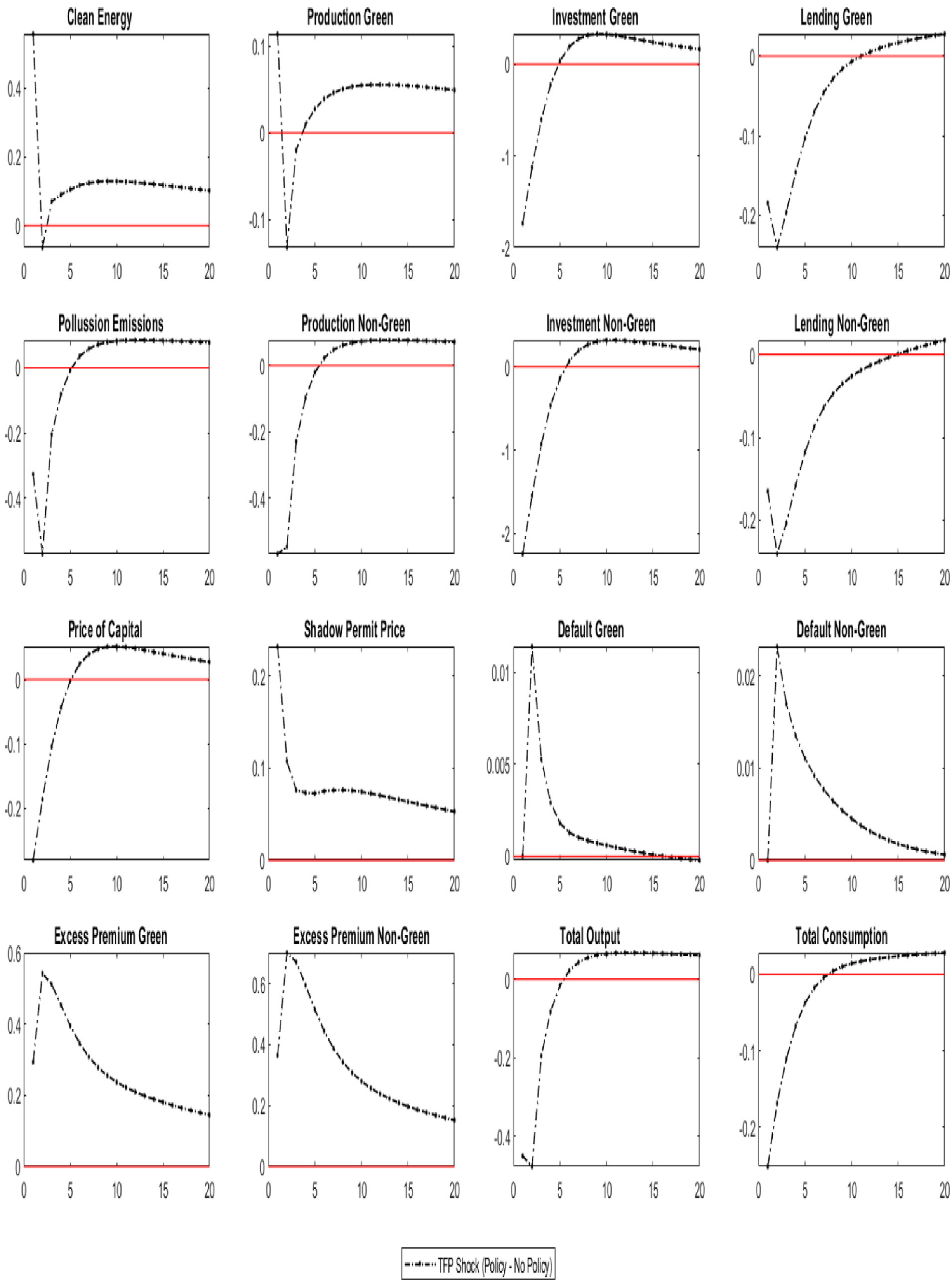

Fig. 3. Impulse Responses Functions to a Positive Technology Shock. *Note*: All variables are expressed as percentage deviations from steady state. All variables are expressed as % difference of simulations of a model with and without environmental policy.

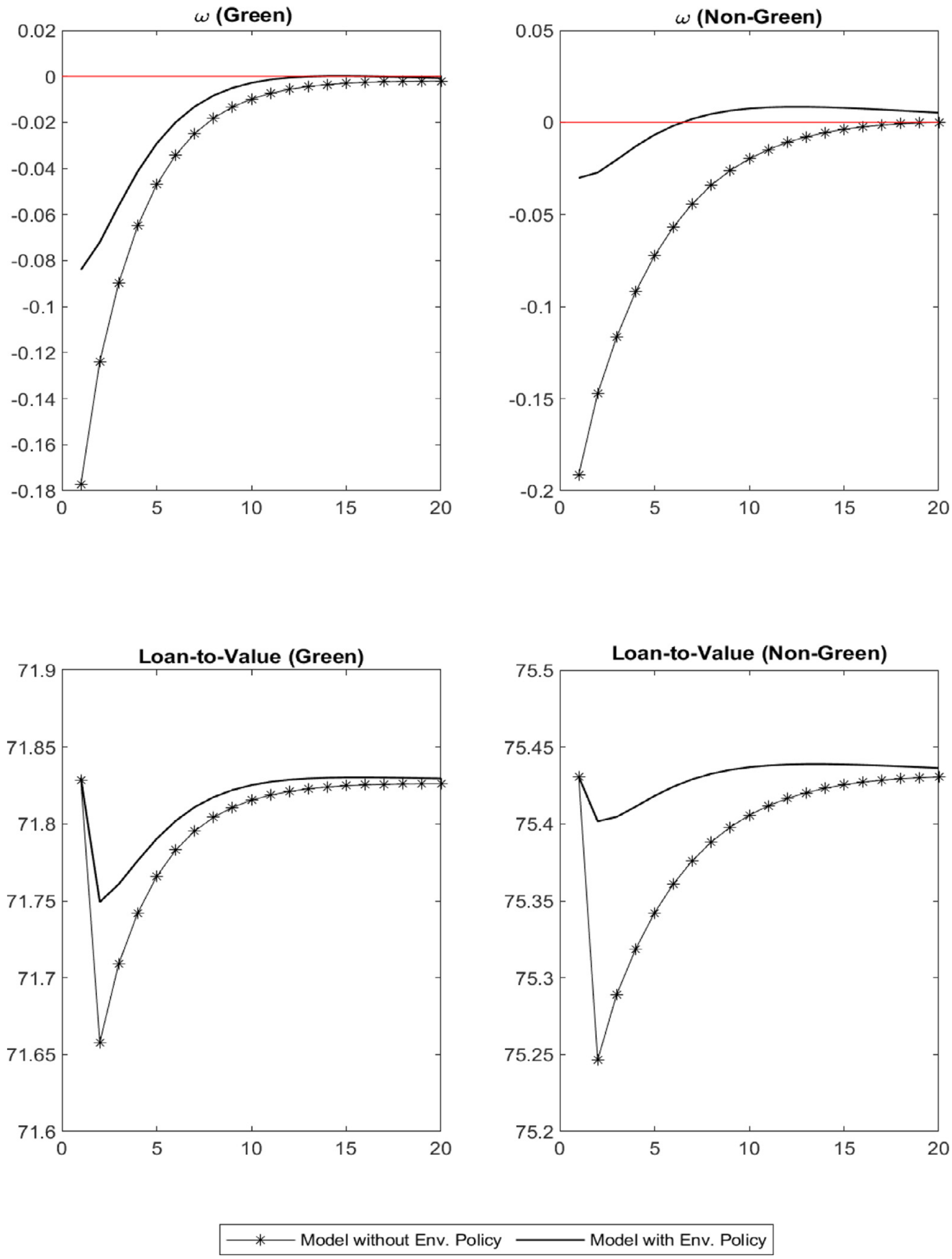

Fig. 4. Default and Loan-to-Value Responses to a Positive Technology Shock. *Note*: Loan-to-Value ratios are expressed in levels.

to the green sector when the environmental regulations are tightened. Even if regulations apply only to the non-green sector, default rates decrease by less also in the green sector. Fig. 4 shows that, without policies, default rates in the green sector would have dropped by 3%, while in the presence of environmental regulations, default rates drop by only 2%, meaning that this gap translates into a 1% increase in the default of green sector.[29] This is due to: (i) lower collateral value driven by a less amplified asset prices; (ii) higher lending rates charged by the banking sector wishing to restore the balance sheet from the missed loan repayments. Fig. 4 shows that the cut-off value in the green sector, $\bar{\omega}^g$, decreases by only 8% in the presence of environmental regulations, relative to a drop of almost 20% that would had occurred in absence of such policies. Fig. 4 also shows the behaviour of the loan-to-value ratio for both sector. First of all, it is important to notice that the model captures a different steady-state level for the loan-to-value ratio across sectors. Banks do not fully understand the technology behind the green firms and thus require a lower loan-to-value ratio. Second, the technological progress, and related economic boom, leads to a drop in the loan-to-value ratio, which is a function of the share of capital that goes to the bank in case of default. Although the drop in the loan-to-value ratio is marginal for both green and non-green sectors, this change reflects the fact that banks do price the environmental transition risks to the climate change policy. In particular, a less pronounced drop in the green loan-to-value ratio for the green sector implies spillover ef-

[29] See Fig. 3 in Appendix B.

fect from the non-green sector, as banks require larger share of capital to seize in case of default. The transmission mechanism works through three channels at work: a *banking capital channel* induces banks to supply less loans, as higher default rates reduce bank capital; a *banking funding channel* induces banks to charge higher lending rates in order to satisfy the participation constraint defined in Eq. 20, thus entrepreneurs will demand less loans as the cost of borrowing is higher; and an *income channel* which works through the effects of inflation on the real value of loan payments of outstanding debt. The banking channels are reflected by the amplified increase in the external finance premium, or excess premium, showed in Fig. 3, which represents the spread between the adjustable state-contingent loan rate paid by non-defaulting entrepreneurs and the policy rate.

To summarize the results, Fig. 3 reports the difference of the impulse responses of a technology shock when an environmental policy is in place relative to absence of policy. The Figure shows that under an active environmental policy, output, consumption, investment, lending and production are all lower relative to a model simulation that abstracts from environmental regulations. Moreover, default rates and lending rates are higher when the government targets polluting firms. The non-green sector experiences an increase of around 2% in loan defaults, while default in the green sector will be higher by only 1%. Also the excess premium charged on the non-green sector will become higher relative to the green sector.[30]

5. Empirical analysis

In the previous Section, the theoretical analysis indicates environmental policy that targets non-green firms by limiting the use of polluting inputs in their production process dampens the productivity growth, and lowers GDP growth, which in turn threatens financial stability because of the higher borrowing cost charged by banks, as well as the increasing default rates of the non-green sector due to lower than expected profitability.

To provide further evidences to validate the theoretical implications of the E-DSGE model, we empirically assess the impact of environmental regulation tightened by the Chinese 11th Five-Year Plan implemented during 2006 to2010 on manufacturing firms' profitability and productivity, and its implications for the financial stability. Under this Plan, the central government allocated the mandatory national emission reduction targets to all levels of local governments. At the same time, the enforcement of these targets became a meaningful component of local government officials' annual assessment. Such unprecedented change provides evidence of the central government's will and determination to abate emission. Moreover, given that it has been integrated into the political assessment of local officials, it has quickly started to take effect. In 2010, the binding targets set for the National 11th Five-Year Plan (20062010) were largely met, with great strides made in terms of both energy conservation and emissions reduction. Environmental quality has improved significantly: for example, the average sulfur dioxide (SO2) concentrations in the 113 key environmental protection (KEP) cities have decreased by 26.3% compared to 2005. The discharge of chemical oxygen demand (COD), the major regulated water pollutants, by the manufacturing sector, plunged by 23.1% during this period of time (Chen et al. (2020). The target of 10% reduction in these two pollutants were overwhelmingly achieved. Against this background, we utilize the variation of the emission reduction targets across cities to implement the difference-in-difference (DID) analysis to infer the causal impact of environmental regulation on manufacturing firms' performance and its impact on the financial sector.

5.1. Data source and summary statistics

We use the Annual Survey of Industrial Firms (ASIF), the most comprehensive Chinese firm-level dataset to assess how the firms' performance changes after the environmental regulation was tightened under the 11th Five-Year Plan. The survey has been conducted on all industrial firms whose annual sales is over RMB 5 million to collect a firm's information including name, identification, ownership, balance sheet, profit and loss, cash flow, among others. With around 400,000 firms being surveyed annually, we have more than 1 million observation for the years of 2001–2007. We measure a firm's performance by two indicators of return of asset (ROA) and total output. Regarding that technological shock is the key factor for our theoretical model, we follow Olley and Pakes (1996)'s approach to compute the total factor productivity (TFP) for each firm. However, the data needed to calculate TFP, in particular the value added, is available only up to 2007. Therefore, we report the main results estimated for the period of 2004–2007, two years before and after the 11th Five-Year Plan was implemented respectively. In the robustness check, we extend the estimation to the longer period of 2001 to 2007. The city-level data comes from China City Statistical Yearbooks. The summary statistics reported in Panel A of Table 3 indicate the Chinese manufacturing firms, with an asset of 574 million yuan, on average were able to achieve an ROA of 9.3%, an annual output of 667 million yuan and a TFP of 60.16 respectively, during this period of time.

Despite the wide coverage, ASIF doesn't contain the information of firms' borrowing. To assess the impact of environmental regulation on the financial sector, we first collect the aggregate amount of loans to the industrial sector for each city from CEIC database. However, the micro level bank loan data, whose information like interest rate, borrowing amount and default is essential for this research, is not publicly available in China. To investigate how the environmental regulation affects the financial stability by changing firms' productivity, we use the loans issued by a major state-owned bank's branch in Sichuang Province, and merge them with ASIF by firms' name and ID. As a result, we have a dataset containing 21,997 loans granted to 817 firms during our sample period of time. The summary statistics shown in Panel B of Table 3 indicate that the firms in Sichuang province on average borrowed from this bank for an amount of 2,560,000 yuan at a rate of 5.1% with 0.9% of probability of default and 12.7% probability of delinquency.[31]

5.2. Empirical specification and results

5.2.1. Environmental regulation and firm performance

Baseline Results

We first estimate how the performance of manufacturing firms varies across cities with different level of environmental regulation stringency after the 11th Five-Year Plan was implemented with the following specification:

$$y_{it} = \beta_0 + \beta_1 Post_t * Target_c + \beta_2 X_{ct} + \beta_3 Z_{it} + \varepsilon_i + \varepsilon_t + u_{it} \tag{26}$$

where y_{it}, the dependent variable measuring firm i's performance or productivity in year t; $Post_t$ is a dummy variable, taking value of 1 for years after 2006 and 0 otherwise; $Target_c$ is the city-level COD reduction target computed by Fan et al. (2019), reflecting city c's environmental regulation stringency mandated by the

[30] Appendix C reports difference in impulse responses for the other two expansionary shocks: (a) monetary policy, and (b) asset quality shock.

[31] Chinese banks classify the status of loan repayment into five categories of æNormal, Under attention, Subprime, Suspicious, and Loss. We define a loan as default if the loss is confirmed and as delinquent if it is in the status of Under attention, Subprime, Suspicious, or Loss.

Table 3
Summary Statistics.

	Obs	Mean	Std. Dev.	Min	Max
Panel A Annual Survey of Industrial Firms					
ROA	1114880	0.093	0.172	-0.216	0.895
Total Output (10000 yuan)	1114880	66670	144716	1	1008005
TFP	1114880	60.16	70.04	0.67	405.14
Total Asset (10000 yuan)	1114880	57350	151551	554	1145827
GDP per capita(10000 yuan)	1114880	30963	19045	2126	98398
Panel B Bank loans for firms in Sichuang Province					
Borrowing rate	21997	0.051	0.017	0.021	0.078
Loan amount (10,000 yuan)	21997	256	502	5	15000
Default	21997	0.009	0.095	0	1
Delinquent	21997	0.127	0.333	0	1
Panel C City-level Variables					
Growth of loans to industrial sector	2836	0.077	0.269	-0.445	0.680
Emission reduction target	2836	0.467	0.638	0	4.5
GDP	2836	680.1	1151.5	4.6	16190
GDP per capita(10000 yuan)	2836	3.10	1.91	0.213	9.84
Share of secondary industry	2836	0.454	0.126	0.161	0.807
Number of industrial firms	2836	864.3057	1575.079	3	19065

Note: This table presents the summary statistics of the key variables for the sample period running from 2004 to 2007. Annual Survey of Industrial Firms (ASIF) covers all industrial firms whose annual sales is over RMB 5 million. The data for bank loans is from a state-owned bank in Sichuang Province. We merge them with ASIF by firms' ID. The city-level data is from CEIC database.

Table 4
Environmental regulation and firm performance, unbalanced panel DID analysis.

	(1) ROA	(2) Ln(Total Output)	(3) TFP
Post*Target	-0.0077***	-0.0299***	-1.2853*
	(0.0022)	(0.0098)	(0.7186)
Ln(Total Asset)	-0.0336***	0.4342***	4.3552***
	(0.0038)	(0.0116)	(1.0473)
Ln(GDP per capita)	0.0758***	0.3651***	29.9626***
	(0.0175)	(0.0842)	(7.1002)
Firm fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
N	1114880	1114880	1114880
*R*2	0.037	0.331	0.077
adj. R^2	0.037	0.331	0.077

Note: This table shows DID estimates of the effect of the 11th Five-Year Plan on the performance and productivity of manufacturing firms located in cities with different targets of emission abatement for the years of 2004-2007. The dependent variables are ROA, logarithm of total output and TFP respectively. Target is the city-level COD reduction target, reflecting city c's environmental regulation stringency mandated by the 11th Five-Year Plan. Post is a dummy variable, taking value of 1 for years after 2006 and 0 for years before 2006. Standard errors are clustered at the city and year level and reported in parentheses (*p < 0.10, **p< 0.05, ***p < 0.01).

11th Five-Year Plan. We employ regional GDP per capita (X_{ct}) to reflect a city's characteristics, total asset (Z_{it}) to gauge a firm's size, firm fixed effects (ε_i) to account for the time-invariant but unobservable factors that may affect firms' emission, and year fixed effects (ε_t) to capture the common economic factors influencing all the cities. The interaction term between $Post_t$ and $Target_c$ is our main variable of interest. Its coefficient, β_1, measures the change of firm's performance in cities with tighter environmental regulations before and after the 11th Five-Year Plan was implemented in comparison with the equivalent changes in cities with laxer environmental regulations.

Table 4 summarizes the DID estimation result for an unbalanced panel for the years of 2004 to 2007. Column (1) and (2) present the estimated coefficients for the firms' performance measured by ROA and logarithm of total output respectively. All the coefficients on the interaction term between $Post_t$ and $Target_c$ are negatively significant at the 1% level. We perceive that ROA and total outputs of manufacturing firms registered in the cities setting higher pollution abatement commitment are 0.77% and 3% respectively lower than those of their counterparts operating in the cities with lower emission abatement commitment. These findings indicate that with the advent of tighter environmental regulations, the performance of those firms located in cities with higher emission reduction target is worse than those located in cities where the emission reduction target is lower. Given that the technological progress plays a critical role in our theoretical model, we compute the TFP for each firm in our sample and test how it varies across cities with different level of emission reduction target. The result reported in Column (3) of Table 4 shows that TFP of manufacturing firms in the cities with stringent environmental regulation declined by 1.3 after the 11th Five-Year Plan was enforced.

The above analysis shows TFP, which represents a firm's technological progress and production efficiency, declined by a remarkable degree once the environmental regulation was tightened. Given that TFP is the fundamental driver of firms' profitability, we further test its relationship with total output and ROA by implementing panel data analysis which controls firms' total asset, GDP per capita of the city that a firm is located, as well as year and firm fixed effects. The estimation results reported in Table 5 imply that TFP is an important driver of firms' performance. One unit increase in TFP is associated with 0.07% and 0.48% increase in ROA and output respectively. When TFP declines following the tightening of environmental regulation, ROA and total output will fall accordingly.

Industrial Heterogeneity

The emission intensity varies substantially across manufacturing industries in China. According to the Report of the First National Census Blueprint on Pollution Sources[32] released by the State Council in 2007, there are six heavily polluting manufacturing industries, including food manufacturing (14), textile (17), pa-

[32] The report is published at the website of China Bureau of Statistics and available at http://www.stats.gov.cn/tjsj/tjgb/qttjgb/qgqttjgb/201002/t20100211_30641.html.

Table 5
TFP, ROA and Total Output, unbalanced panel analysis.

	(1) ROA	(2) Ln(Total Output)
TFP	0.0007***	0.0048***
	(0.0000)	(0.0002)
Ln(Total Asset)	-0.0363***	0.4142***
	(0.0037)	(0.0091)
Ln(GDP per capita)	0.0653***	0.2566***
	(0.0141)	(0.0554)
Firm fixed effect	Y	Y
Year fixed effect	Y	Y
N	1114880	1114880
*R*2	0.110	0.495
adj. R^2	0.110	0.495

Note: This table shows the panel data fixed effect estimates of the effect of TFP on manufacturing firms' ROA and total output for the years of 2004-2007. Standard errors are clustered at the city and year level and reported in parentheses (*p < 0.10, **p< 0.05, ***p < 0.01).

Table 6
Environmental regulation and firm performance by industry, unbalanced panel analysis.

	(1) ROA	(2) Ln(Total Output)	(3) TFP
Post*Target* Emission	-0.0099**	-0.0332**	-2.4670**
	(0.0042)	(0.0147)	(1.2131)
Post*Target	-0.0072***	-0.0253***	-0.8462**
	(0.0014)	(0.0061)	(0.3625)
Post* Emission	0.0561***	0.0986***	13.3349***
	(0.0096)	(0.0309)	(2.1072)
Ln(Total Asset)	-0.0336***	0.4340***	3.0695***
	(0.0023)	(0.0080)	(0.3823)
Ln(GDP per capita)	0.0750***	0.3527***	20.0326***
	(0.0131)	(0.0636)	(3.7390)
Firm fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
N	1114880	1114880	1114880
R^2	0.037	0.331	0.102
adj. R^2	0.037	0.331	0.102

Note: This table compares DID estimates of the 11th Five-Year Plan on the performance and productivity of firms by the emission intensity of manufacturing industries for the years of 2004-2007. The dependent variables are ROA, logarithm of total output and TFP respectively. *Emission*, the pollution intensity of industry *s*, is measured by an industry's share of total COD emission in all industries in 2005. Target is the city-level COD reduction target, reflecting city c's environmental regulation stringency mandated by the 11th Five-Year Plan. Post is a dummy variable, taking value of 1 for years after 2006 and 0 for years before 2006. Standard errors are clustered at the city and year level and reported in parentheses (*p < 0.10, **p < 0.05, ***p < 0.01).

per making and paper products (22), petroleum processing, coking, and nuclear fuels (25), raw chemical materials and chemical products (26), and non-metal mineral products (31).[33] As shown in Appendix D, the emission intensity of COD by these six industries is much higher than that of other industries. The tightened environmental regulation shall disproportionately affect the firms in high polluting industries. We further investigate the variation of environmental policy effects across industries with different level of emission intensity by the following specification:

$$y_{it} = \beta_0 + \beta_1 Post_t * Target_c + \beta_2 Post_t * Target_c Emission_s + \beta_3 Post_t * Emission_s + \beta_4 X_{ct} + \beta_5 Z_{it} + \varepsilon_i + \varepsilon_t + u_{it} \quad (27)$$

where $Emission_s$, the pollution intensity of industry *s*, is measured by an industry's share of total COD emission in all industries in 2005. The data is from Fan et al. (2019). The definition of other variables remains the same as equation 5.1. The interaction term among $Post_t$, $Target_c$ and $Emission_s$ is our main variable of interest. Its coefficient, β_2, captures the heterogeneous effects of environmental regulation on firms' performance across high emission and low emission industries.

Table 6 reports the DDD estimation results. We find that those firms that are located in cities with higher emission reduction targets and belong to the industries with higher level of emission intensity cut down more productions, attain lower return of assets and achieve less improvement in TFP, compared with their intra-city counterparts in less-polluting industries.

5.2.2. Implications for financial sector

As the theoretical model predicts, the environmental regulation has important implications for the financial sector. On the one hand, the banks will cut the credit needed for the firms' production and capital investment; on the other hand, the probability of default will increase due to the deterioration of firms' economic performance.

To corroborate these predictions, we first assess how the 11th Five-Year Plan affected the aggregate amount of loans granted to the industrial sector by using city level data for the years of 2001–2009. The DID model can be specified as below:

$$y_{ct} = \beta_0 + \beta_1 Post_t * Target_c + \beta_2 X_{ct} + \varepsilon_c + \varepsilon_t + u_{it} \quad (28)$$

where the dependent variable is annual growth of loans granted by the banks to industrial sector for city c in year t, and the interaction term between $Post_t$ and $Target_c$ is the variable of our main interest. We employ regional GDP and its growth to gauge a city's economic development, the number of industrial firms (X_{ct}) to reflect a city's economic structure, city fixed effects (ε_c) to account for the time-invariant but unobservable factors that may affect a city's credit to industrial sector, and year fixed effects (ε_t) to capture the common economic factors influencing all the cities. The estimation results reported in column (1) of Table 7 suggest that the growth rate of loan to industrial sector declined by around 4% in cities with higher emission reduction targets compared to their peers with lower emission reduction targets. Concerning that higher credit growth might be simultaneously associated with higher economic growth, we lag the GDP by 1 and 5 years and present the estimation results in column (2) and (3) respectively. We also implement the generalized method of moment (GMM) developed by Arellano and Bond (1991) and report the result in column (4). The coefficients on the interaction term remain consistent across different estimations.

Further, we investigate how the environmental regulation affects the financial stability by changing firms' TFP. We employ the loan level data from one of Big Five state-owned bank's branch in Sichuang Province, whose information like interest rate, amount and default is essential for this research, and merge them with ASIF by firms' name and ID. We conduct the unbalanced panel data analysis with the following specification:

$$y_{it} = \beta_0 + \beta_1 TFP_{it} + \beta_2 X_{ct} + \beta_3 Z_{it} + \varepsilon_d + \varepsilon_c + \varepsilon_t + u_{it} \quad (29)$$

where y_{it} is the dependent variable measuring the amount of loan that firm *i's* borrowing amount and borrowing rate from this bank in year t and the chance of default. TFP is the main variable of interest in this analysis. We control firm i' total asset (Z_{it}), benchmark rate, GDP per capita of the city that a firm is located (X_{ct}), industry (ε_d), year (ε_t) and city (ε_c) fixed effects. Panel A of Table 8 reports the estimation results. Further, a firm that is able to borrow more or with favorable condition is more likely to use the debt-financed investment to boost its productivity. We employ the instrumental variable (IV) and GMM estimation to address the po-

[33] Appendix D lists the classification and two-digit code of each industry.

Table 7
Environmental regulation and lending to industrial sector.

	(1) Industrial loan growth	(2) Industrial loan growth	(3) Industrial loan growth	(4) Industrial loan growth
Post × Target	-0.0382***	-0.0364***	-0.0376***	-0.0313***
	(0.0103)	(0.0104)	(0.0134)	(0.0120)
Ln(number of industrial firms)	0.0030	0.0038	-0.0104	0.0373
	(0.0172)	(0.0167)	(0.0293)	(0.0090)
Share of secondary industry	0.2348**	0.2853**	0.5585***	0.2479
	(0.1166)	(0.1173)	(0.1989)	(0.0404)
Ln(GDP)	0.0156			-0.0190
	(0.0266)			(0.113)
Ln(GDP)_lag1		-0.0523**		
		(0.0253)		
Ln(GDP)_lag5			0.0024	
			(0.0515)	
Underidentification test statistic and p-value				2308.417
				(0.000)
N	2836	2836	1854	
*R*2	0.203	0.204	0.249	
adj. R^2	0.199	0.201	0.245	

Note: The first three columns of this table show DID estimates of the effect of the 11th Five-Year Plan on loans granted to the industrial sector for cities with different targets of emission abatement for the years of 2001-2009. Column (4) presents the GMM estimation. The dependent variable is the annual growth of loans granted by the banks to industrial sector for city c in year t. Target is the city-level COD reduction target, reflecting city c's environmental regulation stringency mandated by the 11th Five-Year Plan. Post is a dummy variable, taking value of 1 for years after 2006 and 0 for years before 2006. Standard errors are clustered at the city level and reported in parentheses (*p < 0.10, **p < 0.05, ***p < 0.01).

tential bias arising from the reverse causality. Regarding that a firm's productivity is related with its performance in the past, we construct a variable to show the quintile of TFP distribution that firm i belongs to in year *t-2*, and use it as an instrument for firm i's TFP measured in year *t*. This IV should only affect firm i's borrowing amount and borrowing rate from the bank in year t through this firm's TFP in the current year. Panel B of Table 8 presents the estimation results. The t-statistics indicate the IV we construct can significantly predict firm i's TFP in year t. Moreover, the F-statistic shown at the bottom of Panel B is much larger than the critical value of 16.98, excluding the concern of a weak instrument. Panel C of Table 8 shows the GMM estimation result where TFP in year *t-1* is employed as the instrument. In all the regressions, we note that firms with higher TFP are able to borrow more at lower rate. At the same time, they are less likely to default. These findings imply that when TFP declines due to the enhanced environmental regulation stringency, credit to the firms located in the cities with higher emission reduction targets tend to fall and become more costly. Moreover, they are more likely to default, threatening the financial stability.

In a word, both the DID analysis on the city-level aggregate data and the panel analysis on the micro-level loan data confirm the negative impact of environmental regulation on the financial sector, highlighting the necessity of adopting macroprudential policy to moderate the financial risks arising from the environmental transition.

5.2.3. Robustness check

Balanced panel data analysis

This paper employs DID analysis to infer the impact of the environmental regulation on manufacturing firms' performance. However, our estimation results might be susceptible to the endogeneity concern arising from unobservable factors and selection bias. For example, firms might change their production strategy to moderate their exposure to the environmental risk that the 11th Five-Year Plan has escalated. Some firms might not be able to meet the requirement set by new emission reduction target and bankrupted. To address these concerns, we identify the firms that are included in ASIF over the whole period of 2004 to 2007 to construct a firm level panel dataset. The results shown in Table E1, E2 and E3 in Appendix E are consistent with the results of unbalanced panel estimation presented in Table 4, 5 and 6 respectively, confirming that environmental regulation lowers the productivity of the firms located in cities with higher target of emission reduction, which in turn hurts firms' performance measured by ROA and total output. The effect is more remarkable for the firms with higher level of emission.

Dynamics of environmental regulation and firm performance

Our theoretical analysis indicates TFP is the key variable to explain the impact of environmental regulation on firms' performance and financial stability. An important assumption of our DID identification strategy is that the over time changes in firms' productivity at cities with different levels of environmental regulation stringency are solely caused by the laying out of reduction targets set in the 11th Five-Year Plan, rather than by any pre-existing differential time trends across firms. To test this assumption, we replace the interaction between environmental regulation stringency and the post dummy in Eq. 26 with the sum of the interaction terms between environmental regulation stringency and all the year dummies. We estimate the yearly effects of environmental regulation stringency on TFP for the extended period of 2001 to 2007. Fig. 5, which visualizes the estimation result, indicates that the 11th Five-Year Plan has no measurable impact on manufacturing firms' TFP until 2006.

Placebo test

We further perform the placebo tests aiming at validating the main result of 11th Five-Year Plan on the manufacturing firms' performance and productivity. In Table 9, we re-estimate the main specifications for the time period of 2001 to 2007, assuming that a change in environmental policy had taken place in 2004. The DID coefficients are not significant for ROA, total output and TFP, validating the conclusion of this research.

Extended sample period

Given that the Annual Survey of Industrial Firms (ASIF) only releases the data of value added, needed to calculate TFP, up to 2007, we report the main results on the manufacturing firms' per-

Table 8
TFP and Loan performance.

	(1) Borrowing rate	(2) Ln(Loan amount)	(3) Default	(4) Delinquent
Panel A Panel Data Estimation				
TFP	-0.0004***	0.1412***	-0.0032*	-0.0366***
	(0.0002)	(0.0453)	(0.0019)	(0.0082)
Ln(loan amount)	0.0005***		0.0022***	0.0131***
	(0.0001)		(0.0007)	(0.0044)
Ln(total asset)	-0.0006***	0.3375***	-0.0002	-0.0116*
	(0.0001)	(0.0213)	(0.0012)	(0.0067)
Ln(GDP per capita)	0.0001	0.1248	-0.0061	0.0395**
	(0.0004)	(0.0757)	(0.0065)	(0.0155)
Benchmark rate	1.2800***	59.1101***	0.4359**	7.3744***
	(0.0325)	(2.6924)	(0.1841)	(0.9517)
N	21997	21997	21997	21997
*R*2	0.921	0.421	0.037	0.183
adj. R^2	0.920	0.419	0.034	0.181
Panel B IV Estimation				
TFP	-0.0012***	0.1277*	0.0032	-0.0557***
	(0.0003)	(0.0673)	(0.0059)	(0.0194)
Ln(loan amount)	0.0005***		0.0016**	0.0143***
	(0.0001)		(0.0008)	(0.0051)
Ln(total asset)	-0.0007***	0.3358***	-0.0015	-0.0107
	(0.0001)	(0.0234)	(0.0015)	(0.0074)
Ln(GDP per capita)	-0.0000	0.1126	-0.0084	0.0211
	(0.0003)	(0.0908)	(0.0067)	(0.0182)
Benchmark rate	1.2746***	58.2550***	0.4662**	7.3992***
	(0.0335)	(2.6614)	(0.2089)	(0.9400)
N	18189	18189	18189	18189
R2	0.925	0.399	0.050	0.205
adj. R^2	0.924	0.397	0.047	0.202
1st stage regression T-statistics on IV F-statistics	88.66	88.86	88.66	88.66
	438.99	442.47	438.99	438.99
DWH test p-value	0.021	0.675	0.257	0.354
Panel C GMM Estimation				
TFP /100	-0.0006***	0.2203***	-0.0020	-0.0366***
	(0.0001)	(0.0184)	(0.0015)	(0.0052)
Ln(loan amount)	0.0005***		0.0021***	0.0143***
	(0.0000)		(0.0006)	(0.0020)
Ln(total asset)	-0.0007***	0.3318***	-0.0012*	-0.0139***
	(0.0000)	(0.0069)	(0.0006)	(0.0020)
Ln(GDP per capita)	0.0001	0.1488***	-	0.0310***
	(0.0001)	(0.0247)	0.0089***	(0.0069)
			(0.0021)	
Benchmark rate	1.2751***	59.0459***	0.4175***	7.2022***
	(0.0036)	(0.7262)	(0.0700)	(0.2354)
N	20222	20222	20222	20222
*R*2	0.922	0.407	0.040	0.190
adj. R^2	0.922	0.405	0.037	0.188
Underidentification test statistic and p-value	9588.868	9648.785	9588.868	
	(0.000)	(0.000)	(0.000)	
Industry fixed effect	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y

Note: This table shows the effect of TFP on manufacturing loan performance for the years of 2004-2007 estimated by the panel data fixed effect (Panel A), IV (Panel B) and GMM (Panel C) respectively. The dependent variables are borrowing rate, loan amount, default and delinquent respectively. TFP is normalized by 100. Standard errors are clustered at the city and year level and reported in parentheses (*p < 0.10, **p< 0.05, ***p < 0.01).

formance and productivity for the period of 2004–2007, two years before and after the 11th Five-Year Plan was implemented respectively. In this robustness check, we extend the estimation to the longer period of 2001 to 2007. The results reported in Table E4-6 in Appendix E are consistent with the baseline results.

6. Conclusion and policy implications

This paper evaluates the economic and financial implications of environmental policies that aim at reducing pollutant emissions. We first build an environmental stochastic general equilibrium (E-DSGE) model with financial frictions and endogenous default. The simulation results show that the environmental policies dampen the expansionary effect of a positive productivity shock, which in turn lowers firms' profitability, comprises firms' liquidity and a increases entrepreneurs' probability of default. The dampening effect on macroeconomic and financial variables occurs via banking capital and funding channels through which banks reduce the supply of credits and charge higher lending rates. The model assumes the coexistence of a representative entrepreneur in the green sector (using clean energy as input) and one in the non-green sector (using polluting inputs). The model shows a spillover

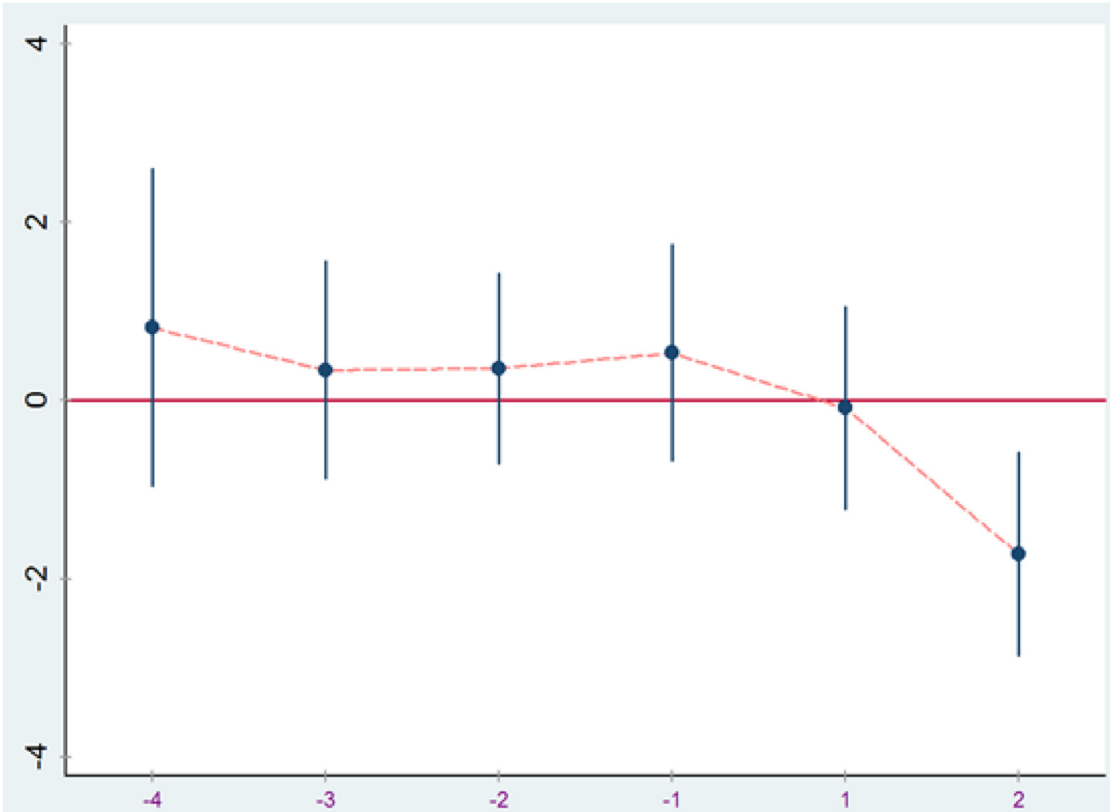

Fig. 5. The dynamic impact of the environmental regulation on TFP, 2001–2007. *Note*: The figure plots the impact of 11th Five-Year Plan on TFP. We consider a 6-year window, spanning from 4 years before the Plan was implemented until 2 years after it was implemented. We control year and firm fixed effect.

Table 9
Placebo Test.

	(1) ROA	(2) Ln(total output)	(3) TFP
Post*Target	0.0029	-0.0076 (0.0678)	-7.4652
	(0.0094)		(9.5616)
Ln(Total Asset)	-0.0347***	0.3820***	-0.2203
	(0.0033)	(0.0092)	0.6994)
Ln(GDP per capita)	0.0478***	0.2053***	13.0165***
	(0.0122)	(0.0522)	(2.6932)
N	519774	519774	519774
*R*2	0.025	0.207	0.031
adj. R^2	0.025	0.207	0.031

Note: This table shows placebo test results. We re-estimate the main specifications for ROA, total output and TFP, for the period of 2001-2007, assuming that a change in environmental policy had taken place in 2004. Target is the city-level COD reduction target, reflecting city c's environmental regulation stringency mandated by the 11th Five-Year Plan. Post is a dummy variable, taking value of 1 for years after 2004 and 0 for years before 2004. Standard errors are clustered at the city and year level and reported in parentheses (*p < 0.10, **p < 0.05, ***p < 0.01).

effect from the non-green sector to the green sector. When facing balance sheet distress for the missed repayments from the non-green sector, the banks would also apply higher lending rates to the non-green sector. Environmental policies are supposed to bring benefits in the long term by generating a clearer air and by reducing the occurrence of natural disasters. However, during the transition phase toward low-carbon emissions, these policies can generate higher costs for the society and threaten the financial stability. Therefore, this paper is a wake-up call for more policy interventions.

To verify the predictions of the E-DSGE model, we empirically examine the impact of environmental regulation tightened by the Chinese 11th Five-Year Plan (2006–2010) on manufacturing firms' profitability and productivity, and its implications for the financial sector. The difference-in-difference (DID) estimates on the Annual Survey of Industrial Firms (ASIF) find that those manufacturing firms located in cities with higher emission reduction targets and belong to the industries with higher level of emission intensity achieve less improvement in TFP, compared with their intra-city counterparts in less-polluting industries. Consequently, the credits to the industrial firms located in the cities with higher emission reduction targets not only fall but also become more costly. Moreover, the firms are more likely to default, threatening the financial stability.

To provide a clear guidance for the policymakers, it would be interesting to shed new light on the role of macroprudential policy in achieving financial stability when the economy is transiting toward low emission production. There is already an ongoing discussion on the potential role of monetary policy in reducing risks associated with climate change. See among others Murphy and Hines (2010), Anderson (2015), Campiglio (2016), Matikainen et al. (2017) and Monasterolo and Raberto (2018). A few central banks have already started implementing macroprudential policies with specific instruments to promote green financing. For example, the Bank of Lebanon has introduced differentiated reserve requirement ratios by reducing the commercial bank obligatory reserve requirements by an amount equal to 100–150% of the loan value for energy saving projects. See Campiglio (2016). The Bank of Bangladesh has been providing additional liquidity to commercial banks lending to the green sector, while the Reserve Bank of India has implemented a minimum proportion of bank lending to flow to green financing. The Central Bank of Brazil requires commercial banks to incorporate environmental and social risk in their governance framework and evaluate these risks in the calculation of their capital needs. See Volz (2017) and Punzi (2018). The question of the optimal monetary or macroprudential policies, or even the optimal interaction policy, is left for future research.

In addition, our theoretical model can be extended from several perspectives. First of all, the theoretical simulation of the technological shock replicates impulse response functions only over the short run. It is important to study the implications of environmental policy shocks over the long run. Second, the model assumes that firms use only polluting or non-polluting inputs, without any switching mechanism. It would be interesting to develop a model where the polluting firms can transform into non-polluting firms to avoid penalties due to the use of polluting input, by investing in green technology or using renewable energy. Such transition will reduce emissions and the default rate for both green and non-green sector. The shadow permit price will be lower than that in a model which abstracts from a switching mechanism, allowing banks to charge a lower excess premium on their lending activities, with a positive feedback to the real economy. However, non-polluting firms would face higher cost due to the new investments, thus in the short-run the output response to shocks would be the same as in a model without switching mechanism, while in the long-run a switching model will show a more positive response of output. Third, our model simulation replicates a temporary shock arising from environmental policy, which allows the default rate for non-green firms to return to its initial value. It is worthwhile to investigate a permanent negative effect of environmental policy on emission-intensive sectors. Fourth, the model uses the financial friction approach which is standard in the DSGE literature, but has been criticized for underestimating the impact of the financial sector on economic activity (see e.g. Jakab and Kumhof (2018)). This is because banks are portrayed as being financial intermediaries, rather than creating money endogenously as in reality (see McLeay et al. (2014)). Consequently, our model might potentially underestimate the impact of credit provision on the level of economic activity.

Last, our model analyzes a policy that restrains the use of polluting inputs in the production process. We assume that this constraint is always binding for positive shocks. It would be very interesting to study potential asymmetries arising from negative shocks and non-binding constraints. All these model features are recommended for future work.

CRediT authorship contribution statement

Bihong Huang: Conceptualization, Methodology, Writing review & editing. **Maria Teresa Punzi:** Conceptualization, Modeling, Calibration, Simulation, Writing. **Yu Wu:** Formal analysis.

Supplementary materials

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2021.106396.

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