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Green light for green credit? Evidence from its impact on bank efficiency

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Abstract

We assess, for the first time in the literature, the impact of green credit on bank efficiency. We find that green credit has a negative impact on bank efficiency. However, the effect is heterogeneous among different types of banks. While small and low capitalized banks are more affected, the impact is lower in banks with higher levels of risk. On the other hand, we find that highly capitalized banks can offset the negative effects of green credit, while large banks and those highly involved in green credit, benefit from this activity.

KEYWORDS

bank efficiency, bank risk, financial stability, green credit, stochastic frontier models

1 | INTRODUCTION

In the upcoming years, the transformation process towards a green economy will consolidate. These new projects will demand large amounts of bank credit, while loans to contaminating companies and projects will be penalized, changing the structure of the banks' loans portfolio. This process will have implications for the banking sector and financial stability given the uncertainty on the success and profitability of green projects, which in many cases are still dependent on public funding. In particular, characteristics of green credit related to higher risk and lower profitability than conventional loans are behind the creation of specific public institutions with the purpose of granting credit to green projects in some countries.[1] In this context, the impact that this change has on bank performance will determine bank strategies, public policies and banking regulation. Against this background, in this study we identify the impact of green credit on bank efficiency.

Certainly, if higher risk is a characteristic of green projects, then green credit would have a negative impact on bank efficiency via higher costs derived from using more screening and monitoring resources in the short run when compared to traditional loans. However, if regulation effectively incentivises this type of credit, and competition for this market segment consolidates, then its effect on bank efficiency can turn positive (Schaeck & Cihak, 2014). The position of banks in terms of capitalisation may also play an important role on the impact of green credit on banks performance. While the higher resilience of more capitalized banks may allow them to engage on green credit, a more costly funding structure may have mixed effects depending on the relationship between capital and risk. The relationship between green credit and banks' capitalisation is of great importance in terms of policy due to the impact of capital-based regulation on the incentives to grant more green loans. In this context, the aim of our study is to identify the association between the provision of green loans and banks' cost and profit efficiency by analysing potential heterogeneous effects on banks with different characteristics. This allows us to analyse the way regulation should be designed in the upcoming years in order to incentivize bank green credit while preserving financial stability.

For this purpose, we study a broad sample of Chinese banks over the period 2007–2017. The Chinese banking sector is a very interesting case for studying these effects for several reasons. China is one of the countries that has been in the focus of the international discussion on sustainable economy and green finance given its position as the country with the highest pollution emissions in the world.[2] This has motivated the issuance of green policies in the financial sector during the last decade.[3] In 2007 the China Banking Regulatory Commission (CBRC), the People's Bank of China and the State Environmental Protection Administration issued a policy entitled “opinion on implementing environmental regulations and managing credit risk” (Aizawa & Yang, 2010; CBRC, 2012). This policy required and encouraged Chinese commercial banks to allocate credit to environment friendly companies and projects as well as to reduce credit allocation to highly environment polluted projects and companies. In 2009, the China Banking Association issued a guideline on corporate social responsibility that encouraged banks to increase their allocation of credit to support environmental projects. Later on, in 2012, a formal policy was issued by the CBRC entitled the Green Credit Guideline, in which commercial banks were required to focus on granting green credit, reducing the environmental risk and further to facilitate the transformation towards a sustainable economy. More recently, in 2016 the green credit policy has been further expanded by the Chinese government aiming to build a green financial system in China. All these policies have incentivized Chinese banks to increase the share of credit granted to green projects and have required banks to classify these loans under a specific and well-defined category. The guidelines for the classification of loans as green credit are included in the final report of the Green Finance Task Force published by The Peoples' Bank of China, and facilitates that all Chinese banks follow the same definitions.[4] These characteristics make the Chinese banking sector an interesting case for studying the relationship between green credit and efficiency.

We assess the effects of green credit on bank efficiency using a dynamic stochastic frontier model with inefficiency heterogeneity (Tsionas, 2006; Galán et al., 2015). This method is able to recognize the presence of adjustment costs in the bank production process, which have not been explicitly modelled before in the Chinese banking sector and allows us to identify the relationship between green credit and inefficiency persistence. In particular, we propose an extension that includes bank fixed effects in the frontier and the inefficiency specification, which allows to capture sources of bank-specific unobserved heterogeneity in both components.

This approach allows us to contribute to the literature by investigating directly the effects of green credit on bank efficiency, while accounting for the adjustment costs of the transition to this activity and its interaction with bank characteristics associated to size, risk and capitalisation. Certainly, most of previous studies addressing the implications of green credit have focused on its effects on certain characteristics of banks, mainly those associated to risk and profitability. Recently, Yin et al. (2021) investigates the inter-relationships among green credit, bank performance and bank risk, finding that green lending increases risk but also bank profitability. Lian and Gao (2022) identify that green credit improves financial performance indicators such as the Return on Assets (ROA) and the Net Interest Margin (NIM). Zhou et al. (2022) investigates the association between green lending and bank risk, finding that it depends on the size and the structure of ownership. Finally, Del Gaudio et al. (2022) find that a higher propensity to green lending leads to lower profitability and higher default risk. In general, green credit has been found to affect negatively risk and ambiguous effects have been identified on profitability. However, none of these studies have assessed the effects on cost and profit efficiency, which would be affected though the costs associated to the higher risk of this activity, the expected returns of these projects, and the way banks with different characteristics handle with the features of this type of credit. Against this background, our study constitutes the first piece of research in the literature of banking and green finance that explicitly assesses the impact of green credit on bank cost and profit efficiency, and that identifies how key bank characteristics associated to size, credit risk and capitalisation affect the relationship between green credit and efficiency.

In general, we identify a negative impact of green credit on bank efficiency, mainly related to the costs associated to the higher credit risk of this type of loans and the difficulty to assess the funded projects. However, we identify that banks that have adapted their business models towards a loan portfolio highly composed of green loans benefit from this type of credit in terms of cost efficiency. We also identify that large banks are able to obtain benefits from green loans on efficiency due to their larger scale of operation and diversification. Also, highly capitalized banks are able to offset the negative impact of involving in green credit. In terms of profits, we find a similar negative impact of green credit on efficiency, suggesting that revenues obtained by these loans do not compensate the higher costs, which is possibly attributable to the long-term characteristics of green projects. A key challenge for managers and policymakers is to reduce the high adjustment costs identified in the sector, which may pre-empt banks from involving more actively in allocating green credit to the economy. In this context, policies that facilitate the adaptation of banks business models and strategies towards a green loan portfolio will benefit banks performance. In this regard, we also find that regulation on green finance should focus the design of incentives in banks of small and medium size and banks relatively low capitalized. Overall, our analysis provides useful insights for the formulation of banking regulation and other policies that guarantee that the transition towards sustainable finance preserves financial stability.

The rest of the document is organized as follows: In Section 2, we present a brief literature review on the risk of green projects, and the role of green credit in banking. In Sections 3 and 4, we describe the methodology and the data. In Section 5, we present the results of the main estimations of cost efficiency, a more detailed analysis of the effects across heterogeneous banks and an extension to the analysis of profit efficiency. Finally, we present the main conclusions and policy implications in Section 6.

2 | LITERATURE REVIEW

2.1 | The risk of green projects

The higher risk associated to green projects has been documented in recent empirical literature (Hwang et al., 2017; Zhao et al., 2016). In this regard, most of previous studies have focused on the difference in the pricing between green and conventional bonds. In general, green bonds have been identified to be issued and traded at a premium with respect to conventional bonds (Baker et al., 2018; Nanayakkara & Colombage, 2019; Partridge & Medda, 2020). The reasons behind the risk premium charged to green bonds include not only characteristics of the market such as lower levels of liquidity (Bachelet et al., 2019) and higher levels of volatility (Pham, 2016) than the conventional bond market, but also characteristics of the issuers and the projects financed by corporate green bonds (Fatica et al., 2021). In this regard, some studies identify that issuers of corporate green bonds tend to present lower credit ratings (Zerbib, 2019) and present higher default risk (Demary & Neligan, 2018). This can be related to the fact that many corporate green bond issuers are either new companies experimenting with unconsolidated projects, which have a higher uncertainty of success and of their expected returns, or large companies involved in projects focused on accomplishing environmental regulation but with no expectations of obtaining high returns from these projects in the mid-term. This implies that these projects have a lower level of expected return on net assets than projects financed by conventional bonds, which translates into a risk premium (Wang, Zhou, et al., 2019). Moreover, given these characteristics many of these bond issuances are not backed by physical collateral, which also lead to lower demand of these types of bonds and a higher risk premium required by investors (Chiesa & Barua, 2019). Expectations on the success of these projects would also play a role. Agliardi and Agliardi (2019) argue that investors are more cautious when investing in green bonds because they perceive green projects as riskier regardless of their type of collateral and issuer. These specificities of the green bonds market, which reflect the characteristics of green projects would also affect green loans and thereby bank performance.

2.2 | Green credit and bank performance

There are few studies investigating the issue of green credit in the banking industry. Using a sample of Chinese banks as the sample, Luo et al. (2021) investigate the impact of green credit on the core competence of commercial banks in China. The core competence is an index constructed by factor analysis using a number of different indicators reflecting different perspectives of banking operations, including profitability, liquidity, safety, growth, and competence. The study further investigates the impact of green credit on the core competence index using a difference-in-difference method. The findings show that green credit not only enhanced the core competence of urban and rural banks, but also that it promoted the core competence of banks with higher levels of risk.

Another piece of study by Zhou et al. (2021) examine the impact of corporate social responsibility on bank performance and the mediating role played by green credit in the relationship. Facilitated by the principal component analysis, the study chose four different performance factors including the growth capacity factor, the profitability factor, the earning quality factor and the risk control factor. The finding suggests that corporate social responsibility has a negative impact on bank performance in the short-run, while the impact turns to positive in the long run. Finally, it shows that green credit could significantly alleviate the negative relationship between bank social responsibility and growth ability and risk control.

Instead of investigating the one-way impact of green credit on bank performance, Yin et al. (2021) investigates the inter-relationships among green credit, bank performance and bank risk in the Chinese banking industry under a simultaneous system of equations estimated by the generalized method of moments estimator. The bank performance is proxied by the financial indicator return on equity. The results show that green lending increases bank profitability in China.

Using a sample of Chinese commercial banks between 2007 and 2018, Lian and Gao (2022) investigate the impact of green credit on financial performance. Two profitability indicators are used including ROA and NIM. The results from fixed effect model show that green credits improve bank performance. In comparison, rather than investigating banks' financial performance, Zhou et al. (2022) evaluate the relationship between bank green lending and credit risk using a sample of Chinese banks between 2007 and 2018. The results derived from the regression analysis with year fixed effect suggest that the association between green lending and bank risk depends on the size and structure of state ownership. Del Gaudio et al. (2022) use a sample of 217 green facilities financing syndication worldwide to assess the relationship between green lending and lead bank performance. Three different models are proposed with each of them focusing on different aspects of bank performance, reflected by different dependent variables, including ROA, credit risk, and default risk. The results from the ordinary least square estimator indicate that a higher propensity to green lending leads to lower profitability and credit risk, but higher default risk. Finally, the closest study to our analysis is the one by Fukuyama and Tan (2020), who propose a three-stage network Data Envelopment Analysis model to estimate efficiency in the Chinese banking industry and further examine the impact of green credit on bank efficiency. However, the aim of that study is more related to the impact of loan loss provisions and market power on efficiency, while green credit is included as a control for corporate social responsibility. Thus, there is no policy guidance regarding the treatment of green credit nor further analysis on how bank characteristics affect the relationship between green credit and bank efficiency. In summary, as we can see that there is a level of exploration in terms of the impact of green credit on bank performance, in particular, during the recent couple of years. However, the limitation of the existing studies in the related research topic lies to the fact that no attempt has yet been made to examine the impact of green credit on bank performance from the efficiency perspective.

3 | METHODOLOGY

3.1 | A dynamic stochastic cost frontier model

We propose to estimate the effect of green credit on cost efficiency using stochastic frontier analysis (SFA), which is a parametric method introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977) and has several advantages in comparison to non-parametric methods. In particular, SFA allows inferring on the parameters, considering idiosyncratic errors, dealing easily with panel data structures and modelling the evolution of efficiency over time. The latter characteristic is of great importance given that it allows capturing the dynamic behaviour of inefficiency.

In this context, recognizing that efficiency evolves dynamically over time also implies recognizing that banks face rigidities related to regulation and quasi-fixed inputs, as well as transaction, information and other adjustment costs. These factors prevent banks from making free and instant adjustments towards optimal conditions, which leads inefficiency to become persistent over time. The first model recognizing the dynamics of the inefficiency under an adjustment costs framework in the banking sector was introduced by Tsionas (2006), who finds high inefficiency persistence in U.S. banks. Extending this idea, Galán et al. (2015) propose a model able to separate persistent from non-persistent effects on the inefficiency. The authors also identify high inefficiency persistence in an application of an input-distance function to Colombian banks. In the current study, we propose to use a dynamic SFA model for the estimation of cost and profit efficiency in the Chinese banking sector.

In particular, we propose an extension of these models that is able to account for unobserved heterogeneity not only in in the frontier but also in the inefficiency distribution.[5] Previously Galán and Pollitt (2014) had presented an extension of a dynamic SFA model that incorporates firm fixed effects in the frontier. Thus, in this application we propose to add a bank-specific parameter also in the inefficiency specification. The proposed dynamic cost efficiency SFA model is the following:

$$c_{it} = \alpha_i + \boldsymbol{x}_{it}\beta + v_{it} + u_{it}; v_{it} \sim N\left(0, \sigma_v^2\right) \tag{1}$$

$$ln\, u_{it} = \omega_i + \boldsymbol{z}_{it}\gamma + \rho\, ln\, u_{it-1} + \varepsilon_{it}; \varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right); t = 2 \ldots T \tag{2}$$

$$ln\, u_{i1} = \frac{\omega_i + \boldsymbol{z}_{it}\gamma}{1-\rho} + \varepsilon_{i1}; \varepsilon_{it} \sim N\left(0, \frac{\sigma_\varepsilon^2}{1-\rho^2}\right); \mathrm{t} = 1. \tag{3}$$

The cost frontier is represented by Equation (1), where c_{it} represents the cost for bank i at time t, α_i is a bank-specific parameter capturing unobserved sources of heterogeneity affecting the cost frontier, $\boldsymbol{x}_{it}$ is a row vector containing the cost frontier drivers, $\boldsymbol{\beta}$ is a vector of parameters, v_{it} is the two-sided idiosyncratic error term, and u_{it} is the inefficiency component, which captures how far is a bank from its minimum cost feasible frontier. As implied by the SFA methodology, this inefficiency component must be non-negative in order to assure that all observations are enveloped by the cost frontier and to properly identify it from the idiosyncratic component. In this case, we assume that u_{it} follows a log-normal distribution, as in the seminal proposals by Tsionas (2006) and Galán et al. (2015), where observed covariates can be included and may explain persistent effects of heterogeneity in the inefficiency. Thus, the dynamic specification for u_{it} is represented by Equation (2), where ω_i represents time-invariant bank characteristics, $\boldsymbol{z}_{it}$ is a row vector of time-varying bank-specific characteristics affecting the inefficiency, γ is the associated vector of parameters, ρ is the inefficiency persistence parameter, and ε_{it} is a white noise process with constant variance σ_ε^2. The inefficiency persistence is a key parameter under this dynamic setting since it captures the portion of inefficiency that is transmitted to the next periods, by recognizing the presence of adjustment costs in the short-run. The dynamic process assumed for the inefficiency is required to be stationary, which would ensure that the dynamics of the log-inefficiency do not diverge to negative or positive infinity. If this condition is not imposed, efficiency scores could be equal to one or zero in the long-run. Therefore, we restrict the persistence parameter to satisfy $|\rho|<1$ and specify Equation (3) in order to initialize the stationary dynamic process for each bank. In particular, a value close to 1 for the inefficiency parameter implies a high persistence of the inefficiency component and a slow adjustment of banks towards optimal conditions.

3.2 | Bayesian inference

Following the approaches implemented in the previous studies applying a dynamic SFA model in banking (Tsionas, 2006; Galán et al., 2015), the inference of our models is carried out through Bayesian methods. Bayesian inference in stochastic frontier models was introduced by van den Broeck et al. (1994) and has the advantage of providing posterior distributions of inefficiencies for every observation as well as formally incorporating parameter uncertainty in the estimations. This approach also facilitates the inference in dynamic specifications.

We assume non-informative proper prior distributions for all the parameters. Regarding the frontier, in the case of the bank-specific parameters we define a hierarchical structure with $\alpha_i \sim N\left(\alpha, \lambda_{\alpha i}^{-1}\right)$, where $\alpha \sim N\left(0, \lambda_\alpha^{-1}\right)$, which allows estimating time-invariant unobserved effects under the Bayesian approach. The precision parameters $\lambda_{\alpha i}$ are set to 0.1 and the hyperparameter λ_α is set to 0.001, following the priors in Galán and Pollitt (2014). For the parameters in $\boldsymbol{\beta}$ we assume a normal prior distribution $\boldsymbol{\beta} \sim N\left(0, \boldsymbol{\Lambda}_\beta^{-1}\right)$, where $\boldsymbol{\Lambda}$ is a precision diagonal matrix with priors set to 0.001. The variance of the two-sided error component follows an inverse gamma distribution $\sigma_v^2 \sim IG(a,b)$, where a and b are the shape and scale parameters with priors set to 0.01 and 100.

Departing from Equations (2) and (3), the inefficiency component follows a log-normal distribution where $u_{it} \mid u_{it-1}, \omega_i, \boldsymbol{z}_{it}, \gamma, \rho, \sigma_\varepsilon^2 \sim LN\left(\omega_i + \boldsymbol{z}_{it}\gamma + \rho \ln u_{it-1}, \sigma_\varepsilon^2\right)$ for t greater or equal than 2, and $u_{i1} \mid \omega_i, \boldsymbol{z}_{it}, \gamma, \rho, \sigma_\varepsilon^2 \sim LN\left(\frac{\omega_i + \boldsymbol{z}_{it}\gamma}{1-\rho}, \frac{\sigma_\varepsilon^2}{1-\rho^2}\right)$ for t equal to 1. The bank-specific parameters in the inefficiency follows the same structure than those in the frontier. That is, a hierarchical structure where $\omega_i \sim N\left(\omega, \lambda_{\omega i}^{-1}\right)$ and $\omega \sim N\left(\mu_\omega, \lambda_\omega^{-1}\right)$. The priors for the precision parameters and hyperparameter are set to 0.1 and 1, respectively; while the prior for the mean hyperparameter is set to -1.5. This centres the efficiency prior distributions at 0.8, similar to other Bayesian applications of SFA models in banking. The distribution for the parameters of covariates are also normally distributed $\boldsymbol{\gamma} \sim N\left(0, \boldsymbol{\Lambda}_\tau^{-1}\right)$ where $\boldsymbol{\Lambda}_\tau^{-1}$ is a diagonal matrix of precisions with priors set to 0.1. In order to impose stationarity, the persistence parameter is defined as $\rho = 2k-1$, where k follows a beta distribution $k \sim (r,s)$ with priors set to 0.5 for shape parameters. Finally, for the variance of the inefficiency component an inverse gamma distribution is assumed $\sigma_\varepsilon^2 \sim IG(c,d)$ with priors set to 10 and 0.01 for the shape and scale parameters, respectively. These are the same priors used by Tsionas (2006) for the random shocks variance in the inefficiency equation.[6]

3.3 | Empirical specification

We follow a variable cost frontier approach (Berger & Mester, 1997). In this context, inefficiency is related to the excessive use of inputs and their inadequate allocation given the input prices and the output produced. Thus, the variable cost frontier is the following:

$$\boldsymbol{c}(\boldsymbol{y}, \boldsymbol{w}, k, \boldsymbol{r}, \boldsymbol{z}, t) = \min_x \left\{ \boldsymbol{wx} s.t. T(\boldsymbol{y}, \boldsymbol{x}, k, \boldsymbol{r}, \boldsymbol{z}, t) \leq 0, k = k^0 \right\} \tag{4}$$

where $\boldsymbol{y}$ is a vector of m outputs, $\boldsymbol{x}$ is a vector of n inputs, $\boldsymbol{w}$ is a vector of input prices, k represents equity capital included as a quasi-fixed input, $\boldsymbol{r}$ represents a vector of variables measuring risk, $\boldsymbol{z}$ is a vector of other bank characteristics affecting the inefficiency, and t is a time trend variable intended to capture technical change. We represent the cost frontier with a translog functional form (Mester, 1993). Thus, the dynamic stochastic cost frontier function is specified as follows:

$$\ln c_{it} = \alpha_i + \mathrm{TL}\left(\boldsymbol{y}_{it}, \frac{\boldsymbol{w}_{it}}{w_{Nit}}, k_{it}, \boldsymbol{r}_{it}, t; \boldsymbol{\beta}\right) + v_{it} + u_{it}; v_{it} \sim N\left(0, \sigma_v^2\right), \tag{5}$$

$$\ln u_{it} = \omega_i + \delta_1 Green_{it-1} + \boldsymbol{z}_{it-1}\boldsymbol{\gamma} + \rho \ln u_{it-1} + \varepsilon_{it}; \varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right); t = 2 \ldots T \tag{6}$$

$$\ln u_{i1} = \frac{\omega_i + \delta_1 Green_{it-1} + \boldsymbol{z}_{it-1}\boldsymbol{\gamma}}{1-\rho} + \varepsilon_{i1}; \varepsilon_{it} \sim N\left(0, \frac{\sigma_\varepsilon^2}{1-\rho^2}\right); t = 1, \tag{7}$$

where α_i represent the bank-fixed effects, and $TL(.)$ represents the translog function that includes the vectors of outputs, normalized input prices and risk, as well as equity capital and a time trend. The normalization of total costs and input prices assures linear homogeneity of the cost function. Symmetry of cross-effects in the translog function is also assured. Equations (6) and (7) represent the dynamic specification for the inefficiency following the distributional assumptions detailed above, where the inefficiency component is allowed to be driven by both unobserved and observed bank-specific factors, including our main variable of interest regarding green credit. In this specification, the autoregressive term captures the portion of cost inefficiency that is transmitted from one period to the next, thereby recognizing the existence of adjustment costs in the production process of the banking industry.

4 | DATA

The sample is a balanced panel composed of 792 observations of 72 Chinese banks over the period 2007–2017. Our main data sources are FitchConnect and the annual bank financial statements.[7] In order to represent the production process, we follow the intermediation approach, where banks use inputs to produce outputs. We consider that banks use three different inputs, deposits (x_1), labour (x_2) and physical capital (x_3), to produce three types of outputs: loans (y_1), deposits (y_2) and other non-interest revenue (y_3). Regarding input prices, the price of deposits (w_1) is computed as interest expenses divided by total deposits, the price of labour (w_2) as personnel expenses divided by total staff, and the price of physical capital (w_3) is computed as the ratio of non-interest expenses-to-fixed assets. The latter is the chosen input used for the normalization of total costs and the other input prices. In addition to these inputs, equity capital (k) is included as a quasi-fixed input. As risk measures in vector $\boldsymbol{r}$, we include credit risk (*cred_risk*) and liquidity risk (*liq_ratio*), which are proxied by the ratio of loan loss provisions-to-total loans, and the ratio of liquid assets-to-total assets, respectively.

Green credit (*Green*) is included as computed as the ratio of total credit to green activities divided by total loans. Credit to green activities is defined as the credit granted for the specific purpose of environmental protection, which is specifically classified by Chinese commercial banks as pollution free loans and referred as green credit. In particular, it includes credit to fund projects for pollution control facilities, environmental protection and infrastructure, renewable energy, circular economy, and environment friendly agriculture (He & Zhang, 2007; Zhao & Xu, 2012). All Chinese banks follow the same classification which relies on the definitions in the final report of the Green Finance Task Force published by The Peoples' Bank of China.[8]

Additionally, in vector $\boldsymbol{z}$, we include other potential inefficiency determinants previously found to be relevant in the bank efficiency literature and that may interact with the effects of green credit. In particular, we include the size of banks (*Size*), which is measured by the log of total assets. Size has been previously identified as a very relevant determinant of cost efficiency and its omission has been found to bias the efficiency estimates, in particular, in dynamic specifications (see Galán et al., 2015; Tsionas, 2006). We also include credit risk, as defined above (Apergis, 2019), and banks capitalisation (Capital), measured as the ratio of total capital over total assets. All the inefficiency covariates are included lagged one period in the models. Table 1 presents a summary statistic of the variables.

The correlations between the variables included in the model is presented in Table 2. As it can be expected, operational costs are highly correlated with bank output, and consequently with size. Nonetheless, output level is negatively correlated with input prices suggesting scale economies in the banking sector. Output and size are also negatively correlated with the level of capitalisation, liquidity and exposures to green loans. Certainly, the share of green loans is relatively low for the largest banks, being mid-sized and small institutions those more involved in green credit (see Figure A1 in the Annex). This can be observed in Figure A1 in the Annex, where green credit is plotted against some bank characteristics. In this regard, although green credit is positively correlated with capital, liquidity and loan losses, this is not very evident from the graphical inspection, except for some institutions with both high loan losses and high share of green credit. Finally, the correlation of green credit with input prices is relatively low, suggesting that banks more specialized in green loans do not necessarily face higher input costs.

TABLE 1 Summary statistics

Variable	Mean	Median	S.D.	Min.	Max.
Total loans	123,138,578	18,248,274	299,737,995	10,111	2,133,571,721
Total deposits	177,604,407	29,126,751	432,303,567	49,098	2,952,630,455
Non-interest income	1,170,670	198,799	2,222,337	305	14,388,832
Interest expenses	4,546,944	465,769	10,381,688	1177	98,133,987
Personnel expenses	806,528	226,850	1,721,285	1590	15,201,486
Overhead costs	3,390,018	658,910	6,988,511	12,951	39,269,262
Non-interest expenses	280,432	119,506	448,519	1078	5,515,091
Number of employees	36,785	7789	90,834	101	503,082
Fixed assets	2,329,888	345,050	5,736,235	1008	38,046,562
Total assets	254,211,475	49,351,231	572,588,764	92,009	4,006,241,520
Equity capital	17,907,986	4,011,943	41,147,179	42,371	328,806,429
Total Costs	9,023,922	1,681,429	18,016,349	40,110	100,849,752
Green loans	3,221,966	1,208,488	4,732,667	12,693	41,912,339
Loan losses	1,009,221	117,344	2,405,990	1008	19,057,681
Liquid assets	43,104,718	12,702,023	84,776,023	190,129	966,052,946

Note: Values expressed in 10,000 RMB.

TABLE 2 Correlation matrix between the main variables in the models

	Costs	Loans	Deposits	Non-interest income	Price of deposits	Price of fixed capital	Price of labour	Size	Capital ratio	Loss ratio	Liquidity ratio
Costs											
Loans	0.82										
Deposits	0.84	0.88									
Non-interest income	0.85	0.73	0.75								
Price of deposits	0.16	−0.10	−0.21	0.08							
Price of fixed capital	−0.05	−0.35	−0.37	−0.09	0.34						
Price of labour	−0.12	−0.25	−0.26	−0.21	0.18	0.25					
Size	0.93	0.91	0.92	0.82	0.01	−0.26	−0.24				
Capital ratio	−0.44	−0.63	−0.60	−0.41	0.11	0.48	0.17	−0.62			
Loss ratio	−0.12	−0.45	−0.18	−0.12	−0.02	0.23	0.06	−0.19	0.26		
Liquidity ratio	−0.45	−0.60	−0.58	−0.43	0.11	0.42	0.30	−0.63	0.62	0.34	
Green ratio	−0.54	−0.74	−0.62	−0.53	0.16	0.31	0.16	−0.63	0.55	0.46	0.55

5 | RESULTS

In a first stage, we estimate four models following the specification in Equations (5)–(7). We depart from a baseline model (model 1), where we only include our main variable of study (*Green*) as a covariate in the inefficiency component (i.e., $\gamma = 0$). Then, we add other potential inefficiency drivers regarding bank characteristics associated to their size, risk engagement and capitalisation (models 2 to 4).

The results of the posterior estimates show that all coefficients regarding output and input prices present the expected signs and their significance levels are stable across models (see Table A1 in the Appendix A). Regarding risk, we observe that while engaging on more credit risk increases bank costs due to the cost associated to higher loan loss provisions, facing lower liquidity risk increases costs, suggesting that holding more liquid assets is costly for banks. These results are consistent with previous findings on the effect of risk on bank costs (Castro & Galan, 2019; Hughes & Mester, 2013).

Table 3 presents the posterior mean estimates of the inefficiency parameters. Inefficiency persistence is found to be very high in Chinese banks, suggesting that this sector faces high adjustment costs. Posterior mean values of the persistence parameter are all above 0.87, which would mean that more than 87% of the inefficiency in 1 year is transmitted to the next. This is consistent with previous findings in other banking sectors. Using a very similar dynamic SFA model, which serves as the basis for our proposed model, Tsionas (2006) and Galán et al. (2015) find high inefficiency persistence in the United States and Colombian banking sectors, respectively.[9] This evidences the great importance of adjustment costs in the banking sector, which force banks to remain inefficient in the short run. From the policy point of view, these results should draw the attention of the Chinese government and the banking regulatory authority, which should not only account for rigidities and adjustment costs when formulating green regulation and policies, but also to propose measures that may reduce these costs.

Regarding green credit, we identify in model 1 a significant and negative effect on cost efficiency (i.e., a significant and positive coefficient in the inefficiency specification). This negative impact might be related to the higher costs of granting this type of loans, which may include a higher difficulty of assessing green projects with respect to the traditional ones. Thus, this effect can be related to scale economies and thereby to bank size. Certainly, previous literature on bank efficiency have found that bank size explains the differences in costs of processes linked to loans assessment and monitoring given important scale economies in these activities (Hughes & Mester, 2013; Sarmiento & Galan, 2017). Thus, in model 2, we include size as a control variable in the inefficiency component. We identify bank size to affect positively cost efficiency, which suggests that large banks benefit from their larger scale to operate at lower costs. This finding is consistent with results identified before in several applications to banking sectors, both from advanced and emerging economies (Castro & Galan, 2019; Tecles & Tabak, 2010). Nonetheless, the impact of green credit on cost efficiency, although lower, is still negative and significant after controlling by size.

TABLE 3 Posterior mean estimates of the inefficiency parameters

	Model 1, Baseline	Model 2, Size	Model 3, Risk	Model 4, Capital
Green	0.0968***	0.0743***	0.0376***	0.0314***
Size		−0.0041***	−0.0040***	−0.0039***
Credit_risk			0.0139***	0.0142***
Capital				−0.0157***
ω	4.5106***	4.4103***	4.6751***	4.1872***
ρ	0.9514	0.9463	0.9362	0.9492
σ_v	0.0154	0.0154	0.0151	0.0149
σ_ε	0.2245	0.3077	0.3164	0.2885
σ_α	0.4826	0.4829	0.4666	0.4534
Mean efficiency	0.7045	0.7651	0.7688	0.7573
S.D. efficiency	0.2202	0.2025	0.2009	0.1989
# of observations	792	792	792	792
# of groups	72	72	72	72
log-ML	−918.32	−801.15	−762.06	−749.51

Note: Green credit has a significant positive association with inefficiency. That is, more exposures to green credit lead to lower efficiency. The marginal effect is larger than the one of credit risk. On the other hand, bank size and capital is negatively associated with inefficiency, suggesting that larger and more capitalized banks are more efficient. Positive coefficients of the inefficiency covariates imply higher inefficiency (lower efficiency). For the inefficiency covariates, *, **, *** represent that the 90%, 95%, 99% highest posterior density intervals do not contain the zero, respectively. All the inefficiency covariates are included lagged one period.

Another important factor that can be behind the negative impact of green credit on cost efficiency can be related to the higher risk associated to these loans. This characteristic is also observed in the bonds market, where green bonds are charged with a risk premium over conventional bonds (Nanayakkara & Colombage, 2019; Partridge & Medda, 2020). Certainly, the specific characteristics of borrowers of green loans and their funded projects in terms of less availability of collateral and lower expected returns are reflected into a higher risk (Bachelet et al., 2019; Chiesa & Barua, 2019; Wang, Yang, et al., 2019). Previous literature on green bonds has identified that counterparts of these issuances are riskier than those of conventional bonds (Demary & Neligan, 2018; Zerbib, 2019). Therefore, in model 3 we include credit risk as an additional control in the inefficiency component. We observe several interesting results. We identify that credit risk has a negative impact on cost efficiency. This finding is consistent with the bad luck hypothesis proposed by Berger and De Young (1997), according to which external shocks that increase risk will lead to greater expenditures on resources for monitoring and administering problem loans, negotiating workout arrangements or disposing collateral for possible defaults, which have a negative impact on cost efficiency. Kirkpatrick et al. (2008) also find evidence of this channel in emerging economies.

Nonetheless, it is important to remark, that the observable measure of credit risk is one that captures the materialization of risk via their observed non-performance ratio, which is not capturing latent risk or its expectations. In this regard, Agliardi and Agliardi (2019) argue that green bonds investors perceive green projects as riskier than conventional projects. Although, the uncertainty on the successfulness of green projects may imply higher default risk of borrowers of this type of credit (see Demary & Neligan, 2018; for a similar argument with green bond issuers), the long-term characteristics of these projects makes default rates less observable in the short-run. Thus, an important factor of the negative impact of green credit on cost efficiency would be related to the costs associated with the difficulty to assess these projects and monitoring their performance, rather than those derived from administering problematic loans or provisioning losses.

The effect of green credit on cost efficiency may also be influenced by the banks' balance structure in terms of leverage. Moreover, banks capitalisation has been previously found to play an important role on banks performance (Berger & De Young, 1997; Pessarossi & Weill, 2015). Thus, in model 4 we include the capital ratio as an additional control in the inefficiency component. We identify a positive and significant impact of capitalisation on cost efficiency, which is consistent with previous studies (Fiordelisi et al., 2011; Sarmiento & Galan, 2017). These studies argue that shareholders of highly capitalized banks have more incentives to control better costs and capital allocation than those of low capitalized banks. In this regard, Berger and De Young (1997) suggest that highly capitalized banks have less moral hazard incentives to take on higher risk, thereby incurring in lower costs. On the other hand, the impact of green credit on cost efficiency does not seem to change too much after adding this control, which suggest that the negative effect identified previously is not very dependent on banks leverage.

However, an inspection of the cost efficiency estimates of different types of banks by their characteristics of green credit involvement, risk, size and capital allows us to identify large heterogeneity in the posterior efficiency distributions between banks (see Figure 1). In particular, banks with more exposures to green credit and facing higher levels of credit risk tend to present lower cost efficiency than their counterparts. On the other hand, large institutions and those highly capitalized tend to be more efficient. In order to get more insights on these relationships and how these characteristics may affect the association between green credit and efficiency, we perform additional estimations by sub-samples below.

5.1 | Green credit and heterogeneity across banks

The analysis above identifies not only that the bank characteristics included in the one-sided error component are significant drivers of cost efficiency, but also that the level of these characteristics reflect differences in the efficiency distribution, which could also affect the association between green credit and efficiency. To study this in more detail, we carry out regressions by sub-samples. In particular, we divide the sample into two groups of observations with low and high values of: (i) the share of green credit, (ii) total assets, (iii) credit risk, and (iv) the capitalisation level. We use the median of each of these characteristics as the threshold for the classification.[10] We take advantage of the good properties of the Bayesian approach for the estimations of panel SFA models with small samples (see Koop et al., 1997). Table 4 presents the results for the posterior mean estimation of the inefficiency parameters after splitting the sample by degree of involvement in green credit, banks size, credit risk and capitalisation levels. In general, we observe that the impact of green credit on efficiency is highly dependent on these characteristics.

We identify that banks low involved in green credit present a larger negative impact of granting this type of credit on cost efficiency than that observed above for the

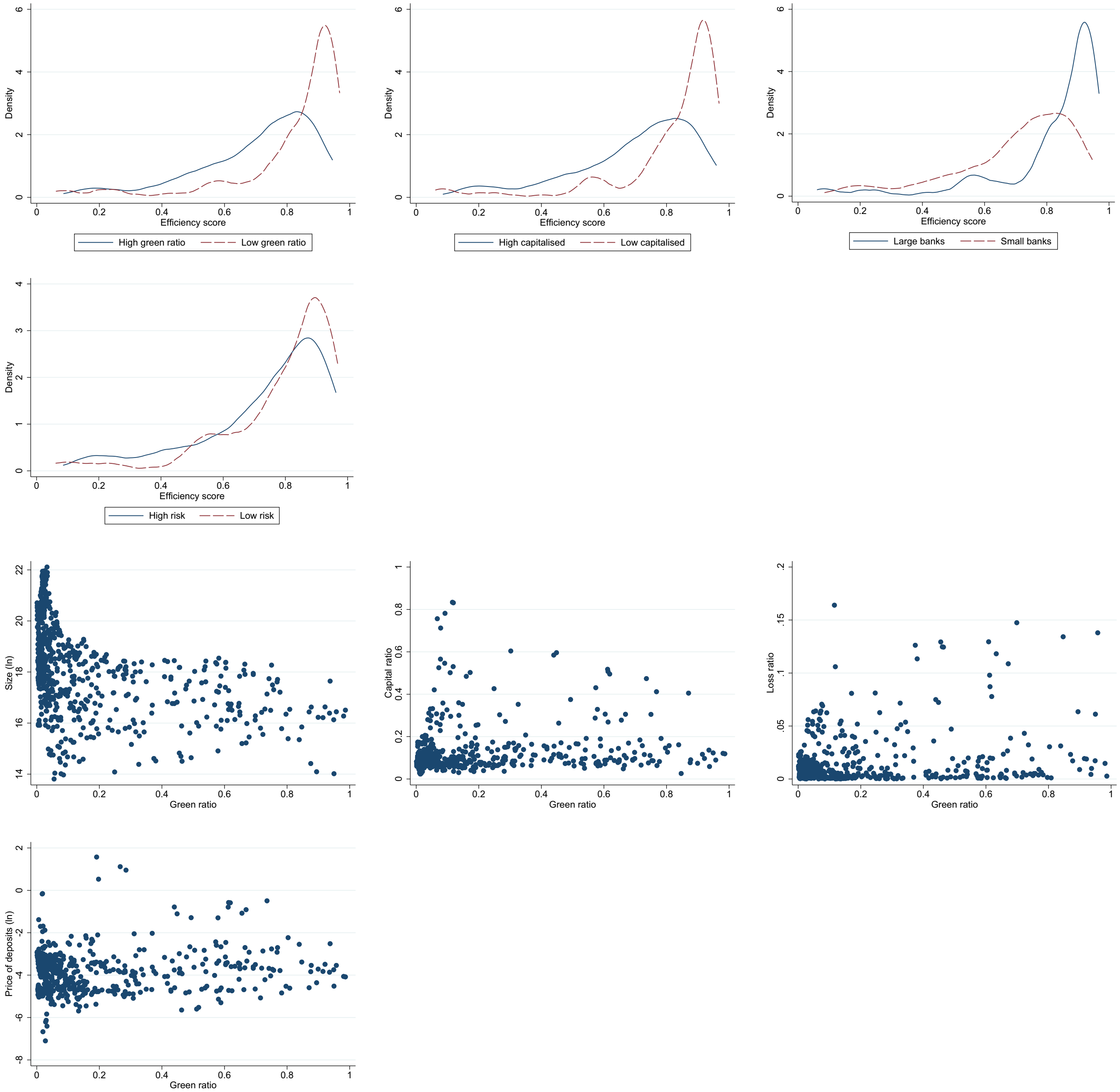

FIGURE 1 Average posterior cost efficiency distributions by banks characteristics. Banks highly involved in green credit and engaged on higher credit risk tend to be less cost efficient than their counterparts, whilemost of large and highly capitalized banks are more efficient. The efficiency score in the horizontal axis can take values from 0 to 1, where higher values imply higher cost efficiency. The lines represent the average posterior cost efficiency distributions estimated from model 4. Banks are classified as having high/low values of green credit, size, credit risk and capitalisation if they are above/below the median value of each variable. In the case of size, the relevant variable is total assets and in the case of credit risk, it is the loss ratio. [Colour figure can be viewed at wileyonlinelibrary.com]

whole sample. Moreover, for banks highly involved in green credit the effect of green credit turns positive, although weakly significant. This would unmask the potential benefits of green credit on bank efficiency and explain why banks more specialized in this type of loans continue performing this activity. This suggests that banks that have reached a certain level of involvement in green credit allocation might have adjusted their business models and corporate governance strategies to the characteristics of this type of credit. The adaptation of these banks to these characteristics is reflected in the lower estimate for the inefficiency persistence within this subsample. While for these banks 78% of the inefficiency, on average, is transmitted to the next period, for other types

TABLE 4 Posterior mean estimates of inefficiency parameters

	Model 5A, Low green	Model 5B, High green	Model 6A, Small banks	Model 6B, Large banks	Model 7A, Low risk	Model 7B, High risk	Model 8A, Low capital	Model 8B, High capital
Green	0.0814***	−0.0349***	0.0557***	−0.0071**	0.0753***	0.0319***	0.0914***	0.0046
Size	−0.0049***	−0.0045***	−0.0088***	−0.0039***	−0.0047***	−0.0045***	−0.0052***	−0.0041***
Credit_risk	0.0114***	0.0927***	0.0107***	0.0892***	0.0108***	0.0765***	0.0134***	0.0658***
Capital	−0.0106***	−0.0192***	−0.0174***	−0.0086***	−0.0104***	−0.195***	−0.0172***	−0.0091***
ω	4.5714***	4.9618***	4.2421***	4.9139***	4.5147***	4.0863***	4.1752***	4.3638***
ρ	0.9341	0.7822	0.8575	0.9180	0.8578	0.9153	0.9236	0.8425
σ_v	0.0181	0.0351	0.0230	0.0159	0.0177	0.0241	0.0365	0.0294
σ_ε	0.7114	0.6539	0.3983	0.4278	0.6469	0.3285	0.5961	0.4429
σ_α	0.3510	0.4836	0.5779	0.3427	0.2696	0.5282	0.3072	0.4804
Mean eff.	0.8116	0.7681	0.7558	0.8242	0.8035	0.7823	0.7753	0.8311
S.D. eff.	0.1430	0.1831	0.1936	0.1496	0.1672	0.1825	0.1860	0.1377
Obs.	390	378	394	391	371	369	380	383
Groups	50	52	44	46	41	46	47	45
log-ML	−466.95	−308.42	−369.707	−159.56	−332.37	−250.69	−311.05	−241.36

Note: Analysis by subsamples. Large banks and those highly involved in green credit benefit in terms of cost efficiency from this type of credit. On the other hand, small institutions, banks with low exposures to green credit, and low-capitalized banks are negatively affected. Positive coefficients of the inefficiency covariates imply higher inefficiency (lower efficiency). For the inefficiency covariates, *, **, *** represent that the 90%, 95%, 99% highest posterior density intervals do not contain the zero, respectively. Banks below and above the median values of green loans ratio, total assets, credit risk and capital ratio, are classified as being in the low and high subgroups in each time period, respectively.

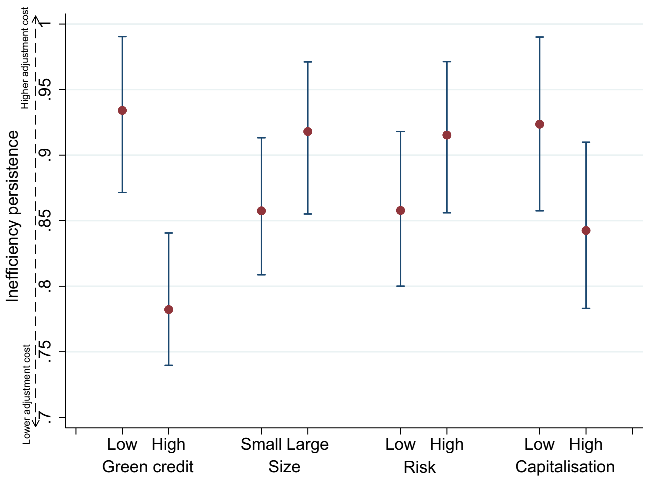

FIGURE 2 Inefficiency persistence of different types of banks. Banks highly involved in green credit have significantly lower inefficiency persistence, suggesting that these banks are able to adjust their processes more rapidly towards higher cost efficiency. Similarly, small, highly capitalized, and banks engaged on low credit risk tend to present lower inefficiency persistence. The vertical axis represents the inefficiency persistence or proportion of the inefficiency transmitted to the next period. Higher values imply slower adjustment towards efficiency improvements; thereby, in the limit, a value equal to 1 would imply that no efficiency improvements are made between one period and the next. The red dots represent the posterior mean of the inefficiency persistence parameter estimated using the sub-samples models, and the blue lines represent the 95% credible intervals. Banks are classified as having high/low values of green credit, size, credit risk and capitalisation if they are above/below the median value of each variable. In the case of size, the relevant variable is total assets and in the case of credit risk, it is the loss ratio. [Colour figure can be viewed at wileyonlinelibrary.com]

of banks this percentage is over 90%. Both posterior mean estimates are statistically different with a probability greater than 95%, as it can be observed in Figure 2, where the posterior mean estimates of the inefficiency parameter (ρ) and their 95% credible intervals are plotted for each of the sub-samples. This suggests that banks highly specialized in green credit have been able to lower their adjustment costs. In terms of efficiency, it is also interesting that banks highly specialized in green credit are less heterogeneous, which could be related to more similar corporate governance (see Figure 1).

Differentiating by size also provides interesting results. While cost efficiency of small banks is negatively affected by green credit, a positive and significant impact is observed for large banks. These banks may benefit from their scale of operation and larger diversification that allows them to offset the higher costs that granting green credit might imply. Precisely, scale economies derived from granting green credit can be an important factor for large banks, which are relatively low involved in green loans, as described in the data section. Thus, these banks would have large room to increase green exposures. Large banks might also be able to take advantage of the positive effect on corporate reputation and image by translating it into an increase in the output volume. On the other hand, although the probability of differences in the inefficiency persistence between small and large banks is not very high, large banks face, on average, higher adjustment costs than small institutions (see Figure 2). This could be due to the higher costs and difficulties that imply implementing changes in more complex structures (see Galan et al., 2015).

Regarding the impact of green credit in banks with different levels of credit risk, we identify that banks engaging on higher credit risk are less affected by granting green loans. This may suggest that, although these banks are still negatively affected by involving in green credit, they may have implemented specific procedures to deal with administering problematic loans, workout arrangements or provisioning for defaults that lowers the marginal cost of risk-related characteristics of green credit. On the other hand, we find that banks with higher credit risk face more difficulties to adjust their processes, which is probably due to the challenges of improving efficiency in a context of high losses and provisions.

As to the capitalisation level, we also identify important heterogeneous effects of green credit. On one hand, for low capitalized banks the negative impact of green credit on cost efficiency is around three times that identified with the whole sample. On the other hand, the impact of green credit on the efficiency of highly capitalized banks is not significant. Therefore, the more capitalized banks are able to neutralize the negative effect of green loans on cost efficiency. This can be due to the fact that these banks are more resilient and thereby less affected by the implicit risk of these loans. Also, this can be related to a more efficient corporate governance and operational structure of highly capitalized banks derived from the incentives of shareholders (Berger & De Young, 1997). These banks also seem to face lower adjustment costs than low capitalized banks. Besides better corporate governance practices of these banks, their more resilient position might facilitate to adjust their processes.

5.2 | Green credit and profit efficiency

As most of studies on bank efficiency, we have focused our analysis on costs. However, highly cost inefficient banks may compensate their costs with higher revenues, which would lead to different conclusions in terms of profit efficiency. Certainly, noninterest income activities

TABLE 5 Posterior mean estimates of inefficiency parameters.

	Model 9, Profit eff. baseline	Model 10, Profit eff. size	Model 11, Profit eff. risk	Model 12, Profit eff. capital
Green	0.0261***	0.0194***	0.0187***	0.0181***
Size		−0.0207***	−0.0235***	−0.0294***
Credit_risk			0.0158***	0.0166***
Capital				−0.0159***
ω	2.8263***	2.6101***	2.8263***	2.8993***
ρ	0.8092	0.7912	0.8020	0.7985
σ_v	0.0369	0.0374	0.0369	0.0405
σ_ε	0.2882	0.2889	0.2882	0.3226
σ_α	0.6072	0.6306	0.6072	0.5980
Mean efficiency	0.5317	0.5729	0.5817	0.5855
S.D. efficiency	0.1904	0.1907	0.1904	0.1914
# of observations	792	792	792	792
# of groups	72	72	72	72
log-ML	−549.493	−572.127	−549.493	−505.427

Note: Green credit and profit efficiency. Similarly, to cost efficiency, green credit affects negatively profit efficiency (positive effects on inefficiency). The same is valid for credit risk, while size and capital have a negative association with profit inefficiency. For the inefficiency covariates, *, **, *** represent that the 90%, 95%, 99% highest posterior density intervals do not contain the zero, respectively.

that have associated low costs and high revenue opportunities derived from the risk–return trade-off have been previously found to explain differences in bank performance and to be behind the low correlation between cost and profit efficiency. In the case of green credit, it is possible that the higher risk of this type of credit is associated to higher revenues, which compensate the negative effect found, on average, in terms of costs efficiency. To uncover the effects on profits, we estimate an alternative variable profit frontier efficiency model that considers output quantities and input prices as exogenous (Humphrey & Pulley, 1997). This allows us to hold the same specification in Equation (5) but replacing the dependent variable by net profits and inverting the sign preceding the inefficiency component, in order to estimate a maximum profit frontier. From this specification, we estimate four additional models departing from a baseline specification where only size is included as a covariate in the inefficiency component (model 9). Then, we add green credit (model 10), risk (model 11) and capital (model 12) in order to replicate the main models estimated for the cost efficiency analysis.

Table 5 presents the posterior mean results. In general, we observe that the effect of green credit is consistent with the results obtained for the cost efficiency specifications. That is, green credit also affects negatively profit efficiency, suggesting that the revenue obtained from these operations does not compensate their associated higher costs. Results hold when adding controls by size, credit risk and capitalisation level. Similar results have been documented in recent green bond literature, where green bonds have been identified to be less profitable than conventional bonds (Gianfrate & Peri, 2019).[11] The main reasons are associated to characteristics of the issuer and the funded projects, which imply that net returns on these projects are negative at least in the short and mid-run (Bachelet et al., 2019; Chiesa & Barua, 2019).

Regarding other bank characteristics, we observe that the effect of banks' size on profit efficiency is significant and positive across models, as we identified in the case of cost efficiency. Certainly, large banks have been previously identified to benefit from exploiting market power in order to charge higher interest rates for loans of similar quality, thereby increasing profit efficiency (see Boyd & De Nicolo, 2005; Wagner, 2010).

We also identify negative effects of credit risk on profit efficiency. This is consistent with findings in previous studies, where measures based on NPL are used as risk proxies. Certainly, this is an ex-post measure for credit risk, which is observed once this type of risk materializes. Thus, this measure captures the impact of loss provisions on bank profits, rather than the expected risk–return relationship, which would be more associated to an ex-ante risk measure (see Castro & Galan, 2019, for a discussion).

In terms of capital, results are also consistent with our findings in terms of cost efficiency. That is, higher capitalisation is positively associated to higher efficiency in terms of profits. On this regard, highly capitalized banks have more incentives to incorporate better corporate governance mechanisms and have less moral hazard incentives to take on high risk, thereby reducing their associated costs (Berger & De Young, 1997; Fiordelisi et al., 2011; Pessarossi & Weill, 2015). Finally, we also find high persistence of profit inefficiency, though lower than that identified in terms of costs. That is, adjusting processes towards more profitable business models are difficult and costly, which implies that a large proportion of banks' inefficiency is transmitted to the next period.

6 | CONCLUSION

In the upcoming years, the consolidation process towards a green economy will deepen. These new projects will demand large amounts of funding, and bank credit is one of the main sources. At the same time credit to contaminating companies will continue to be penalized, changing the structure of the loans portfolio of banks. This change will have implications for the business strategies of banks given the uncertainty on the success of green projects. The impact that this change has on bank performance will determine banks strategies, public policies and banking regulation. In this context, we study the impact of green credit on bank efficiency by the first time in the empirical literature in banking and green finance in a thorough and comprehensive manner.

In particular, we use a Bayesian dynamic stochastic frontier model to identify the impact of green credit on bank cost and profit efficiency. This model allows us to account for adjustment costs in the banking sector and identifying how green credit is related to inefficiency persistence. For these purposes, we use a broad sample of Chinese banks, which is of interest for studying these effects due to several reasons: (i) China is the country with the highest levels of pollution in the world; (ii) Chinese authorities and regulators have introduced different measures in the last decade to incentivize banks to grant credit for green projects; (iii) green credit has rapidly increased its importance within loan portfolios of Chinese commercial banks during the last decade; and (iv) Chinese banks classify loans granted to green projects under a specific and well-defined category.

Our results suggest that engaging in green credit may be harmful for banks' cost efficiency. However, a deeper inspection of the effects by type of banks allows us to identify that these effects are heterogeneous. In particular, banks that are already highly involved in green credit benefit from granting this type of loans in terms of cost efficiency. These banks also present lower inefficiency persistence, which may suggest that these banks have been able to lower their adjustment costs by modifying their business strategies accordingly with the specificities of green credit. We also identify that green credit is beneficial for large banks, which might take advantage of their larger scales of operation and diversification to offset the negative effects of green credit on cost efficiency. These banks may also benefit from corporate reputation and image by translating a larger share of green credit within its portfolio into an increase in the total output volume.

Regarding credit risk, consistently with previous literature, we identify that it has a negative effect on cost efficiency, which would be related to higher costs of monitoring and administering problematic loans (Kirkpatrick et al., 2008; Sarmiento & Galan, 2017). Moreover, we identify a strong relationship between green credit and credit risk, which would indicate that an important fraction of the negative effect that green credit has on banks cost efficiency is due to higher credit risk of this type of credit. This is in line with recent literature on the characteristics of green bonds (Baker et al., 2018; Nanayakkara & Colombage, 2019).

We also identify that the capitalisation level of banks is an important inefficiency driver, and that highly capitalized banks are able to neutralize the negative effect of green loans on cost efficiency. These banks could be less affected by the implicit risk of these loans given their higher resilience. Also, these banks may have more incentives from shareholders to have a more efficient operational structure and corporate governance, as well as less moral hazard incentives to take on higher risk (Berger & De Young, 1997; Fiordelisi et al., 2011; Pessarossi & Weill, 2015).

In terms of profit efficiency, we also identify a negative effect of green credit, suggesting that the revenue obtained from these operations does not compensate their associated higher costs. In this regard, characteristics of the borrowers of these loans and the long-term features of green projects would imply that net returns on these projects are negative at least in the short and mid-run (Bachelet et al., 2019; Chiesa & Barua, 2019; Wang, Yang, et al., 2019).

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CONFLICT OF INTEREST

The authors have no relevant financial or non-financial interests to disclose.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] In the United Kingdom, the government launched the Green Investment Bank to provide public funding and support for green projects in 2012. Nonetheless, in 2017, it was acquired by a private financial group, which may indicate that these projects are becoming profitable for the private sector.

[2] According to the World Economic Forum, China has occupied the first position as the country with the highest carbon dioxide (CO_2) and greenhouse gas (GHG) in the world during the last 30 years. In absolute terms, Jun et al. (2018) find that CO_2 and GHG emissions have continuedly increasing in China from 1982, reaching the highest point in 2016.

[3] It is important to clarify that while green credit is related to the concept of sustainable finance, these two terms are different from technical perspectives. The former mainly refers to the fact that banks provide credit to sustainable and environmental projects that lead to sustainable development, whereas the latter mainly focuses on transforming environmental risk through special financial instruments designed by commercial banks (Wang, Yang, et al., 2019).

[4] The pollution free credit category, referred as green credit, includes credit to fund projects for pollution control facilities, environmental protection and infrastructure, renewable energy, circular economy, and environment friendly agriculture. Control pollution projects are those with the aim of reducing pollution emissions in the industries of thermal power, steel, cement, electrolytic aluminium, coal, metallurgy, chemical, petrochemical, building material, paper making, brewing, pharmaceutical, fermentation, textile, tanning, and mining, as identified by the Ministry of Ecology and Environment of the People's Republic of China (MEE) (see MEE, 2010 and PBC, 2015, for details).

[5] An extension to include unobserved heterogeneity in the frontier of dynamic SFA models has been previously proposed by Galán and Pollitt (2014).

[6] Sensitivity analysis is performed on prior parameters in the distributions of ω, k, and σ_{ε}^{2} and posterior results are found to converge to the same values.

[7] We hand-collected the data on green credits from the annual corporate social responsibility report, which is a complementary material in addition to the bank's annual financial statement. In the corporate social responsibility report, relevant indicators are reported including the volumes of green credits and social donations. This report is available to access through the bank's website. We hand-collected this data by contacting the head office of the bank for those years and/or banks that do not provide relevant information from the bank's website. All the data related to green credits follow the same reporting standard.

[8] According to these definitions, green credit is categorized into regional- and industry-based green credit. The former mainly refers to allocating loans to regional environmental projects across different economic sectors, whereas the latter focuses on credit to environmental industries including new energy and soil remediation industry (see PBC, 2015). For the identification of projects intended to control pollution, the MEE identified heavily polluted industries including thermal power, steel, cement, electrolytic aluminium, coal, metallurgy, chemical, petrochemical, building material, paper making, brewing, pharmaceutical, fermentation, textile, tanning, and mining sectors (see MEE, 2010).

[9] Using transition probabilities of efficiency for Spanish banks, Tortosa-Ausina (2002) also find that most of banks remain in the same state of relative inefficiency in consecutive periods.

[10] It is important to notice that the separation is made by observations and not by bank. That is, it is possible that a bank is included in both groups but in different periods. This would be the case of a bank that from a given period of time starts to present shares of green credit above the median. The only requirement for the consistency of the estimation under the proposed dynamic framework is the existence of a minimum of three consecutive observations (see Tsionas, 2006; Galán et al., 2015). If this is not accomplished, the observations are dropped from the subsample.

[11] The authors find that green bonds offer returns about 0.2% lower than conventional bonds in the European green bond market.

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APPENDIX A

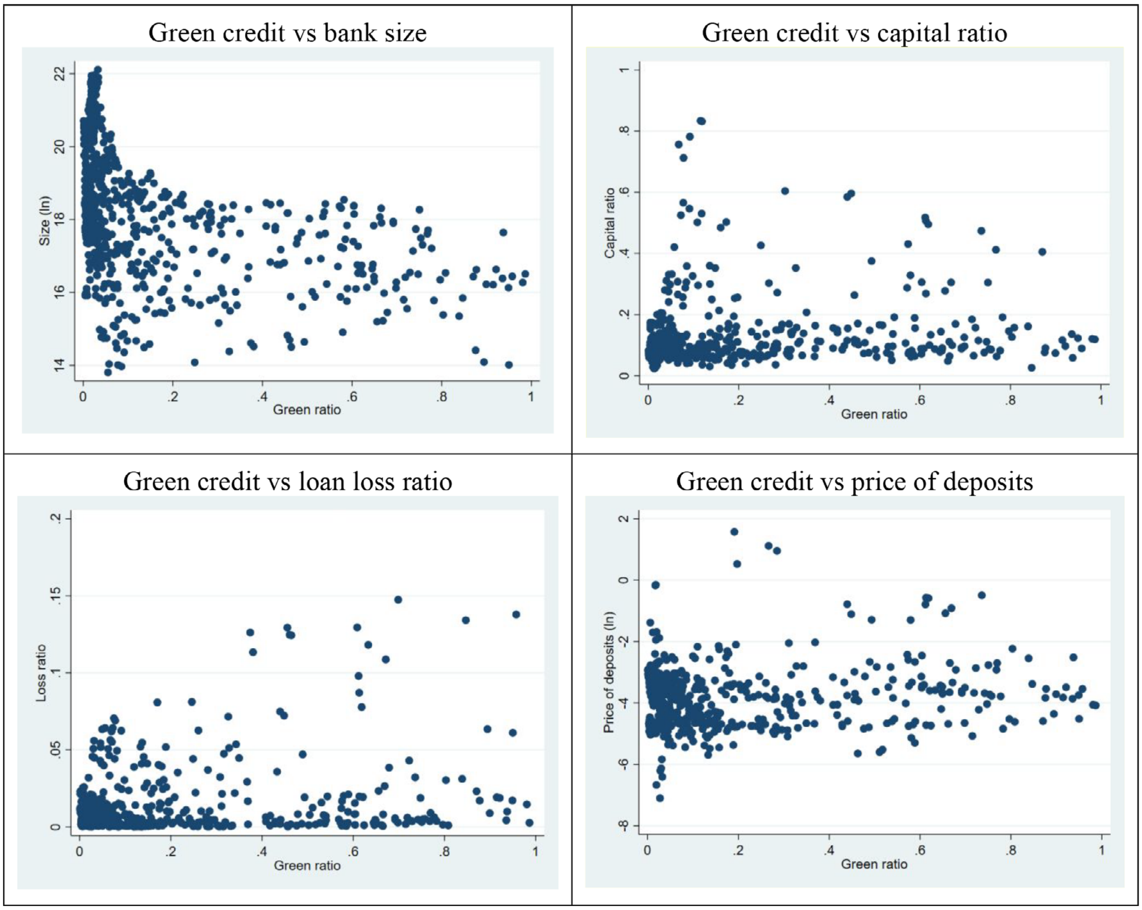

FIGURE A1 Green credit versus bank characteristics. The largest banks are relatively low involved in green credit, while some few institutions with high levels of loan losses present a mid-high share of green loans. In terms of capital and price of deposits, the correlation is not very clear. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE A1 Posterior mean estimates of frontier coefficients: Main models

Variable	Model 1	Model 2	Model 3	Model 4	Model 5A	Model 5B
y1 (loans)	0.0097***	0.1585***	0.0689***	0.0774***	0.0084***	0.0429***
y2 (dep.)	1.1444***	0.9165***	1.1576***	1.2247***	1.1267***	1.1757***
y3 (NII)	0.2232**	0.3844**	0.1929**	0.1942**	0.1879**	0.1909**
w1 (dep.)	0.7205***	0.5985***	0.7117***	0.7424***	0.6926***	0.7175***
w2 (labour)	0.0783***	0.2078***	0.0454***	0.0635***	0.0866***	0.0750***
k (equity)	0.0424**	0.2633****	0.066**	0.0018***	0.0225***	0.0121***
cr (credit risk)	0.0241**	0.0372**	0.0172**	0.0253**	0.0092**	0.0172**
lr (liq. risk)	0.0350	0.1628	0.0292*	0.0269*	0.0393*	0.0331*
y11	0.0219	0.0256	0.0171	0.0115	0.0163	0.0136
y12	−0.0077	−0.0171	0.0003	0.0047	0.0051	0.0048
y13	−0.0004	−0.0012	−0.0074	−0.0068	−0.0083	−0.0075
y22	0.0966***	0.1173**	0.0921***	0.0952***	0.0812***	0.0882***
y23	−0.0001	−0.0082	0.0041	0.0038	0.0039	0.0034
y33	0.0046	−0.0005	0.0041	0.0048	0.0043	0.0044
w11	0.1146***	0.1211***	0.1202***	0.1188***	0.1196***	0.1189***
w12	−0.071***	−0.0719***	−0.0715***	−0.0694***	−0.0695***	−0.0695***
w22	0.0547***	0.0507***	0.0542***	0.0594***	0.0526***	0.0533***
y1w1	−0.0201*	−0.0143	−0.0171	−0.0214	−0.0174	−0.0194
y1w2	0.0295*	0.0267**	0.0305**	0.0238**	0.0219**	0.0228***
y2w1	0.0973***	0.0971***	0.0978***	0.0998***	0.0934***	0.0966***
y2w2	−0.0742***	−0.0769***	−0.0732***	−0.0717***	−0.0681***	−0.0699***
y3w1	−0.0197***	−0.021*	−0.0183**	−0.0161**	−0.0174**	−0.0167**
y3w2	0.0135***	0.0187	0.0127**	0.0146**	0.0126***	0.0133***
t (time)	0.0065	−0.0165	0.0163	0.0111	0.0145	0.0128
ty1	0.0111***	0.0093*	0.0115***	0.0119***	0.0132***	0.0124***
ty2	0.0035	0.0033	0.0035	0.0036	0.0031	0.0033
ty3	−0.0015	−0.0012	−0.0018	−0.0021	−0.0016	−0.0018
ky1	−0.0245	−0.0239	−0.0186	−0.0177	−0.0263	−0.0225
ky2	−0.0917***	−0.0879***	−0.0987***	−0.1094***	−0.0927***	−0.1011***
ky3	0.0031	0.0259	0.0054	0.0059	0.0064	0.00615
cry1	0.0043	0.0127	0.0031	0.0004	0.0048	0.0024
cry2	−0.0129	−0.0243	−0.0084	−0.0059	−0.0113	−0.0086
lry1	−0.0055	0.0033	−0.0059	−0.0025	−0.0067	−0.0046
lry2	0.0152*	0.0008	0.0115	0.0119	0.0107	0.0113
lry3	0.0004	−0.0042	0.0016	0.0013	0.0004	0.0007
tw1	0.0077***	0.0053	0.0084***	0.0084***	0.0087***	0.0085***
tw2	−0.0037***	−0.002	−0.0041***	−0.0043***	−0.0033**	−0.0038***
kw1	−0.0395***	−0.0348**	−0.0425***	−0.0449***	−0.0384***	−0.0415***
kw2	0.0231*	0.0172	0.0238**	0.0283**	0.0248**	0.0265***
crw1	−0.0092	−0.0046	−0.0063	−0.0095	−0.0089	−0.0085
crw2	0.0065	0.0121	0.0069*	0.007	0.0059	0.0064
lrw1	0.0029	0.0006	0.0005	0.0049	−0.0016	0.0016
lrw2	0.0215***	0.0178**	0.0291***	0.0220***	0.0207***	0.0215***

TABLE A1 (Continued)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5A	Model 5B
t2	−0.0012	−0.0022*	−0.0014**	−0.0016**	−0.0014**	−0.0015**
tk	−0.0118***	−0.0093*	−0.0124***	−0.0124***	−0.0135***	−0.0125***
tcr	0.0009	−0.0002	0.0009	0.0009	0.0012	0.0010
tlr	0.0045***	0.0045*	0.0047***	0.0043***	0.0047***	0.0045***
k2	0.1212***	0.0879**	0.1181***	0.1319***	0.1231***	0.1275***
kcr	0.0064	0.0084	0.0026	0.0034	0.0033	0.0033
klr	−0.0128	−0.0137	−0.0134	−0.0153	−0.0119	−0.0136
cr2	−0.0027	−0.0012	−0.0019	−0.0027	−0.0016	−0.0025
crlr	−0.0031	−0.0011	−0.0047	−0.0082	−0.0049	−0.0035
Variable	**Model 6A**	**Model 6B**	**Model 7A**	**Model 7B**	**Model 8A**	**Model 8B**
y1 (loans)	0.0648***	0.0207***	0.0560***	0.4239***	0.6379***	0.4640***
y2 (dep.)	1.1691***	1.0635***	1.1373***	0.8625***	0.5781***	0.7337***
y3 (NII)	0.1784**	0.1451*	0.0865**	0.1396**	0.1889**	0.1718*
w1 (dep.)	0.6794***	0.6432***	0.6063***	0.8588***	0.8521***	0.7398**
w2 (labour)	0.1178***	0.0996**	0.0298***	0.5132***	0.6949***	0.6578***
k (equity)	0.0489***	0.0766***	0.0153**	0.2335**	0.1184**	0.2059**
cr (credit risk)	0.0074**	0.0150**	0.0099**	0.1419**	0.3953*	0.2596**
lr (liq. risk)	0.0527*	0.0446*	0.1161*	0.0840*	0.1863*	0.2450*
y11	0.0091	0.0099	0.0241	−0.0156	0.0231	0.0081
y12	0.0022	−0.0016	−0.0108	0.0096	0.0041	0.0098
y13	−0.0075	−0.0066	−0.0002	0.0238	0.0169	0.0214
y22	0.0883***	0.0867***	0.1009***	0.0319	0.0259	0.0276
y23	0.0014	0.0082	−0.0041	−0.0553**	−0.0536**	−0.0522**
y33	0.0062	0.0074	0.0053	0.0439***	0.0403**	0.0451***
w11	0.1162***	0.1166***	0.1174***	0.0675**	0.0605**	0.0532**
w12	−0.0717***	−0.0714***	−0.0646***	−0.1053***	−0.1148***	−0.1095***
w22	0.0534***	0.0529***	0.0474***	0.0287*	0.0441***	0.0422***
y1w1	−0.0204	−0.0181	−0.0258**	−0.0537**	−0.0478*	−0.0417*
y1w2	0.0234**	0.0261*	0.0174	0.0317	0.0382	0.0365
y2w1	0.0944***	0.0946***	0.0973***	0.0771***	0.0749***	0.0717***
y2w2	−0.0737***	−0.0702***	−0.0649***	−0.0746***	−0.0834***	−0.0855***
y3w1	−0.0188***	−0.0186**	−0.0142*	−0.0621***	−0.0522***	−0.0605***
y3w2	0.0133**	0.0072	−0.0004	0.0243*	0.0205	0.0231
t (time)	0.0084	0.0106	−0.0016	0.0041	0.0501	0.0945
ty1	0.0117***	0.0118***	0.0065	−0.0013	−0.0027	−0.0013
ty2	0.0043	0.0016	0.0065*	−0.0186**	−0.0102	−0.0114
ty3	−0.0015	0.0002	−0.0005	−0.0007	−0.0028	−0.0025
ky1	−0.0123	−0.0136	−0.0163	−0.0512	−0.0823*	−0.0657
ky2	−0.0972***	−0.0883***	−0.0953***	0.0098	0.0329	0.0143
ky3	0.0052	−0.0063	0.0009	−0.0323	−0.0224	−0.0344
cry1	0.0014	−0.0013	0.0033	−0.0044	0.0129	0.0086
cry2	−0.0116	−0.0079	−0.0149	0.0014	−0.0071	−0.0061
lry1	−0.0035	−0.0029	0.0018	0.0907***	0.1056***	0.1095***

(Continues)

TABLE A1 (Continued)

Variable	Model 6A	Model 6B	Model 7A	Model 7B	Model 8A	Model 8B
lry2	0.0111	0.0054	−0.0144	−0.0523**	−0.0447	−0.0389
lry3	−0.0012	−0.0032	−0.0052	−0.0087	−0.0105	−0.0096
tw1	0.0082***	0.0071***	0.0062***	0.0075	0.0136*	0.0126
tw2	−0.003**	−0.0031**	−0.0031**	0.0001	−0.0079	−0.0087
kw1	−0.0339***	−0.0338**	−0.0291**	0.0108	−0.0057	0.0016
kw2	0.026**	0.0246*	0.0443***	0.0348	0.0551**	0.0521*
crw1	−0.0092	−0.0063	−0.0001	−0.0382**	−0.0335*	−0.0386**
crw2	0.0058*	0.0026	0.0016	−0.0054	−0.0107	−0.0072
lrw1	0.0019	−0.0047	−0.0123	−0.0446**	−0.0693**	−0.0592**
lrw2	0.0187***	0.0213***	0.0145*	−0.0257	−0.0469	−0.0376
t2	−0.0015*	−0.0013*	−0.0014*	0.0026	0.0038	0.0029
tk	−0.0129***	−0.0123***	−0.0118***	0.0227**	0.0166	0.0131
tcr	0.0012	−0.0007	−0.0006	−0.0082**	−0.0048	−0.0041
tlr	0.0052***	0.0069***	0.0066***	0.0098*	0.0098	0.0077
k2	0.1134***	0.1129***	0.1241***	0.0899*	0.0678	0.0923
kcr	0.0072	0.0072	0.0117	−0.0137	−0.0349	−0.0275
klr	−0.0139	−0.0024	0.0203	−0.0471	−0.0816*	−0.0928**
cr2	−0.0023	−0.0076*	−0.0083*	−0.0055	0.0079	0.0068
crlr	−0.0037	−0.0002	0.0024	0.0115	0.0011	0.0072

Note: For the inefficiency covariates, *, **, *** represent that the 90%, 95%, 99% highest posterior density intervals do not contain the zero, respectively.