Modeling Sustainability Efficiency in Banking

Abstract

We decompose sustainability into four components reflecting different perspectives: social, environmental, economic and stability. The first two components are grouped into "external sustainability", while the latter two are grouped into "internal sustainability". In addition, we examine the factors influencing sustainability by controlling for firm-specific determinants, business environment determinants and economic environment determinants. The findings support the idea that the sustainability level in the Chinese banking industry (2003 – 2017) ranges from 0.45-0.75 (maximum sustainability score is 1 and minimum sustainability score is 0). There is a larger difference in terms of external sustainability in the sample, while stability is still one of the most serious issues, as reflected by the low stability efficiency score compared to other efficiency concepts. The results also show that internal sustainability is significantly affected by the firm specific determinants, business environment determinants and economic environment determinants.

Keywords: Sustainability; Chinese banking; Sequential Monte Carlo; Particle-filtering
JEL classification: G21; C58; C67

1. Introduction

The Chinese banking industry is the most vital part of the Chinese financial system compared to the other three pillars, which are the insurance industry, the securities industry and the trust industry. Figures 1a, 1b 1c, and 1d show that the total assets of the Chinese banking industry kept increasing during 2003-2017, reaching a peak point of 252,404 billion RMB by the end of the period. A similar trend has also been noted for after-tax profit; however, a slightly different trend has been noted for non-performing loan ratios. After the global financial crisis, the non-performing loan ratio was 2.4% in 2010, while this ratio kept declining to its lowest point in 2013 with a value of 1.5%. In turn, the Chinese banking sector experienced a surge in the risk level with the non-performing loan ratio peaking at 1.9% in 2017. Finally, as we can see from Figure 1d, the amount of non-performing loans kept increasing during 2011-2017, reaching the peak point by the end of the period with a volume of nearly 25 billion RMB. This figure clearly shows that the Chinese banking industry has gradually increased its size and contribution to the economy, as well as its owned profit on a year-by-year basis; however, the accumulation of non-performing loans, together with highly volatile non-performing loans ratios impede the stability and sustainability of the Chinese banking industry. Sustainability is of the greatest concern to the government due to the fact that it is related to the way banks are operated well in a long run, comparing to bank stability, which focuses on the safety of the banking industry on a temporary basis. Sustainable development of the banking industry will be beneficial to different parties in the economy, including depositors and companies as well as to the wider society. The investigation of sustainability in the banking industry is very scarce, although it is a really important issue. Sustainability has been defined by the empirical literature in few ways. Brundtland (1987) defined sustainability development as one which meets the needs of the current generation while it does not have any negative influence on the needs of future generations. In comparison, Pearce et al. (1989) defined sustainability development as a process in which a social and economic system is devised for the purpose of a rise in national income, an increase in educational standard, an improvement in national health and an advance in the general quality of life.

In the banking sector specifically, we argue that sustainability development mainly concerns the issue of self-development as well as contributing to the development of social welfare. Self-development mainly involves the performance and stability. Therefore, less volatility of non-performing loans ratios will contribute to the self-development of banks and further improve sustainability development.

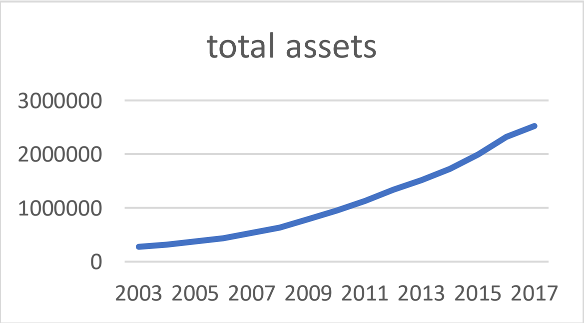
There is a growing field of research looking into performance and stability in the Chinese banking sector. One stream deals with the investigation of bank profitability (Lin and Zhang, 2009; Garcia-Herrero et al., 2009; Liang et al., 2013; Tan, 2016; among others), while the second stream of literature examines efficiency (see literature review for detail). There are also numerous studies investigating the stability or instability issues of Chinese commercial banks (Tan and Floros, 2013; Zhang et al., 2016; Zhu and Yang, 2016; among others). However, the more important question of how the Chinese banking industry can have sustainable development is an issue that has not been explored by the academic literature. In fact, this seems to be an open issue, both in efficiency and performance measurement studies as well as in the sustainability literature (Raut et al., 2017; Pampurini and Quaranta, 2018; among others).

Eccles et al. (2014) constructed a sustainability policy index considering two different perspectives: environmental and social. We argue that in the banking industry, but also more generally, sustainable development is composed of four different elements, viz. a social element, an environmental element, a stability element and an economic element. These four different elements can be further grouped into two parts: social and environmental elements are related to external operation; whereas the stability element and economic element are related to internal operation. To be more specific, we argue that pure increase in size and income of Chinese commercial banks (and in many other industries as well) does not directly lead to sustainable development (Fatemi and Fooladi, 2013). Sustainability not only relies on its internal operation, but also on its external aspect as well. In other words, in order to be sustainable, an industry needs to focus on giving back to society. The returns provided by the Chinese banks can be assessed using their social contributions as well as environmental impact. In terms of the social contribution, we suppose that banks make contributions to provide a fairer business environment and in particular, they provide more opportunities to medium and small sized companies to get loans. Tan (2017) argues that medium and small sized companies in China experience difficulties in getting loans compared to big and government-owned companies; however, their contribution to the economy is much larger. Chinese commercial banks contribute to a more or less fair business environment by providing loans to small and medium sized enterprises. Secondly, Chinese commercial banks promote equal development among different areas and also help to improve infrastructure construction and development in the economy. To be more specific, donations were made by the Chinese commercial banks in the poorer areas for their economic development. They also made donations to different economic sectors to support their research and development. According to the statistics, from 2013 onward, the Chinese banking industry donated 1 billion RMB annually to different sectors of the economy. Finally, commercial banks contribute to the society and economy by decreasing the unemployment rate through employing more people in the banking sector, which is, of course, a feature of many industries. The Chinese commercial banks can make contributions to the environment by helping the economy reduce the level of pollution by granting credits to environmentally-protected companies and projects. China Banking Regulatory Commission statistics show that Chinese banks granted green credits worth 8295.7 billion RMB by the end of 2017.

Our paper fills in the gap of the literature in both banking and operational research on efficiency and performance modeling in the following ways: 1) We investigate sustainability level by decomposing it into two groups: internal and external. 2) We further divide each of these two groups into different components. Internal sustainability includes stability sustainability and economic sustainability, while external sustainability is composed of environmental sustainability and social sustainability. 3) We consider three perspectives of social sustainability, including donations, loans to small and medium enterprises and number of employees. These three different aspects consider social contribution to different levels of the economy (i.e. donation is related to the whole society/economy level, loans to medium and small sized enterprises focuses on the company level, and the number of employees concentrates on the individual level). We also include the environmental perspective as one component of social sustainability. 4) In addition, we propose and evaluate the determinants of sustainability, which provides references to the banking regulatory authorities for policy making purposes.

Our findings show that sustainability score ranges between 0.45-0.75. Lower efficiency prevails regarding internal and external efficiencies with the former in the range 0.71-0.85 and the latter in a range of 0.72-0.9, which are, clearly, much higher. In terms of the sub-efficiencies within both internal and external efficiencies, the results show that environmental efficiency ranges between 0.6 and 0.94, followed by stability efficiency (0.575-0.855). The difference in spread between economic efficiency and social efficiency is quite small with the former estimated between 0.74-0.86, and the latter in the range 0.775-0.96. Regarding determinants of sustainability, the results show that social, environmental, economic and stability efficiencies are significantly affected by most of the determinants. The only exceptions are: 1) social efficiency is not significantly affected by liquidity, banking sector development and inflation; 2) bank size, stock market development and banking sector development are not significantly related to environmental efficiency.

The current paper has the following structure: section 2 reviews the literature regarding sustainability in the banking context. Section 3 reviews the empirical Chinese banking efficiency studies. In Sections 4 and 5 we present the theoretical model, data and the statistical model, respectively. In Section 6, we present and discuss the results, and some concluding remarks are provided in Section 7.



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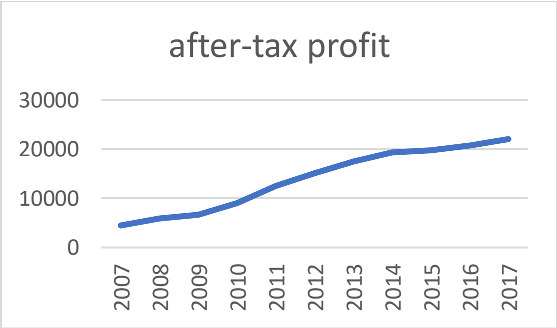

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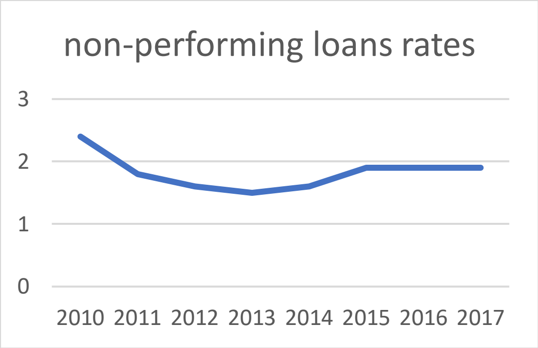

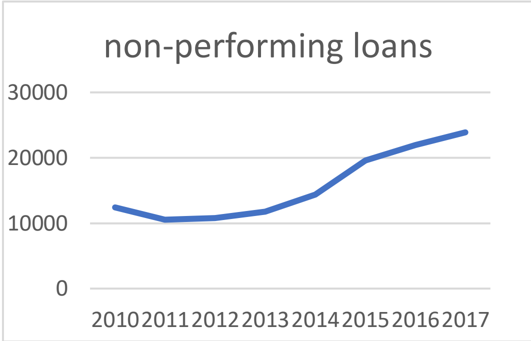

Unit: % unit: RMB 100 million

Datasource: China Banking Regulatory Commission

Figure 1: Overview of performance in the Chinese banking industry

2. Literature Review on Sustainability in the banking context

No study investigates sustainability considering both the internal operation as well as external operation in the banking context, although there are a handful of studies evaluating the issue of sustainability or eco or environmental efficiency in general. Using a sample of 2,752 financial institutions from EU-15 countries in 2014, San-Jose et al. (2018) assess the sustainability of European banking by examining the linkage between economic efficiency and social efficiency. They define bank sustainability as banks' ability to seek a balance between self-development and contributions to the society using the available resources. The economic efficiency reflects banks' ability to use available resources for profits generation. The inputs used to measure social efficiency for sustainability include equity and deposits, while four outputs are used, including customer loans, labor, social contributions/tax and risk. Total assets are used as an input to measure economic efficiency and output used is net profit. The authors used Data Envelopment Analysis to derive these two types of efficiency. In comparison, total assets are used as an input in evaluating the economic efficiency and net profit is used as output. The findings do not show any clear evidence regarding the linkage between economic efficiency and social efficiency. While we think bank sustainability cannot be only reflected from economic efficiency and social efficiency, focus should also be given to see banks' contributions to the society through estimation of environment efficiency. Furthermore, in order to be sustainable, banks should firstly achieve stability. Therefore, stability efficiency is one aspect that cannot be ignored when estimating sustainability in the banking sector. Our research significantly contributes to the empirical literature from this perspective.

Raut et al. (2017) propose an effective and integrated multi-stage fuzzy MCDM analysis to explore bank sustainability in the Indian context. Overall sustainability has been defined and evaluated from four different aspects, including bank stability, management of bank-customer relationship, internal resource allocation and environment-friendly elements of bank operation. It is suggested from the findings that the managers in the Indian banking industry did not consider environment-friendly management system as a priority. However, a specific bank is superior compared to other banks in terms of sustainability because of its consideration of environmental issues, while the advantage of taking environment issues into account, does not provide a strong competitive edge when compared to the banks which did not consider the issues. Although this piece of research significantly improves on San-Jose et al. (2018) by more comprehensively and accurately considering the aspect of sustainability in the banking sector, it seems that this research includes four aspects of sustainability: economic aspect, stability aspect, environment aspect and social aspect. The customer-relationship management is unable to capture all the components of "social" which should place emphasis on the social behaviour engaged in by the banks. Our research fills in this gap by incorporating banks' corporate social behaviour in the evaluation of sustainability.

Compared to the investigation of sustainability issue in the banking industry, there are larger volumes of research articles examining the sustainability issue in other sectors of the economy, including retail, automobile and production design (Gong et al; 2019; Umpfenbach et al., 2018; Chen et al., 2012). In addition, empirical studies used different methods to estimate the sustainability issue in the economy, including Data Envelopment Analysis and Multi objective programming (Sueyoshi and Goto, 2019; Zhu et al., 2018; Radulescu et al., 2009; Chen et al., 2012). In particular, one study evaluated the sustainability of major cities in China (Zhao et al., 2019). All the empirical research normally incorporated social performance, environment awareness and economic performance in the analysis.

As a part of the sustainability issue, some empirical studies investigated the eco or environmental efficiency under different econometric and statistical methods (Picazo-Tadeo et al., 2012; Mahlberg and Luptacik, 2014; Lukas and Welling, 2014; Kohornen and Luptacik, 2004; Neto et al., 2009; Govindan et al., 2014; Sahoo et al., 2011; Chen and Delmas, 2012). These studies mainly focused on the pure mathematical issues or application of the methods to different economic sectors except the banking industry.

3. Literature Review on Efficiency/Productivity in the banking industry

Various advanced operational research methods have been proposed and applied to the estimation of bank efficiency. The new methods can be grouped into: 1) Bayesian methods (Delis et al., 2017; Tsionas and Izzeldin, 2018); 2) conditional non-parametric frontiers/conditional directional distance approach (Matousek and Tzeremes, 2016; Tzeremes, 2015); 3) Network Data Envelopment Analysis (Fukuyama and Weber, 2015; Fukuyama and Matousek, 2017). Although the above studies have advanced methods, they all focus on "internal production process" rather than looking at the banking operation from a macroscopic view by considering the question of how to make banks sustainable instead of how to make banks save costs/inputs or increase profits/outputs. There is growing research on efficiency evaluation in the Chinese banking context. Using stochastic frontier analysis, Berger et al. (2009) find that foreign banks perform better than domestic banks. Fu and Heffernan (2009) suggest that bank reforms are helpful to improve bank performance. Jiang et al., (2013) find that Chinese banks have a higher ability to generate interest income, while in comparison, the ability to generate non-interest income is relatively lower. Dong et al. (2016) report that Chinese banks are better in using resources to generate profit than minimizing cost in bank operation.[1] One distinct feature of Dong et al. (2016) is that they use a panel vector autoregression model to examine the potential linkage between efficiency and shadow return on equity.[2] The findings show that highly efficient banks have smaller shadow return on equity. All the above-mentioned studies use the stochastic frontier analysis to examine bank efficiency.

The second stream of methods used in the empirical literature is Data Envelopment Analysis. Tan and Floros (2013) suggest that efficiency and risk are significantly related with each other. Wang et al. (2014) show that the two-stage DEA is more effective in analyzing the source of inefficiency compared to traditional DEA, and the source of inefficiency for the most part arises in the deposit-producing stage. Comparing to Wang et al. (2014), An et al. (2015) use different inputs and outputs under a network two-stage DEA. More specifically, An et al. (2015) use number of employees, equity capital and fixed asset as the inputs in the first stage with bank deposit as the intermediate output. The final outputs are loans, securities plus an undesirable output which is bad loans. In comparison, fixed assets and labour are used by Wang et al. (2014) as inputs in the first stage to generate the intermediate output (bank deposits), while both non-interest income and interest income are regarded as desirable outputs, non-performing loans are regarded as undesirable outputs . The results of An et al. (2015) show that the improvement in bank efficiency in China is attributed mainly to the improvement in the deposit-utilization stage. Zha et al. (2016) also use network two-stage DEA. The method used in their study is slightly different from the previous two studies, in that they divide the production process into a productivity stage and a profitability stage. In addition, the non-performing loans are treated as an intermediate production to link the first stage production to the second stage. The findings show that city commercial banks have the highest level of performance. Zhou et al. (2018) develop a three-stage DEA framework. In the three-stage multi-period model, banks carry over the unused assets from one period to the next, share inputs used in all three stages include fixed assets and employee salaries, while credit risk is incorporated in the model by treating the non-performing loans as the undesirable output. The findings suggest that the scale of operation should be carefully considered by commercial banks to improve their efficiency. This three-stage framework has the obvious advantage of identifying the sources of lower efficiency. The authors also find that bank performance is overestimated by ignoring

[1] This methodology is also problematic as estimating profit and cost efficiency by estimating separately profit and cost functions is incoherent from the point of view of econometric theory. The correct procedure is to estimate revenue and cost functions and revenue and efficiency, and, in turn, determine profit efficiency.

[2] As this is also a two-stage analysis, the suggested estimator is also inconsistent. Another source of misspecification comes from the problem of generated regressors and errors in the variables, as shadow return on equity is taken from derivatives of the cost function.

carryovers from previous periods. Du et al., (2018) test the influence of earning assets diversification on efficiency using a modified Simar and Wilson (2007) approach. Monte Carlo experiments have been conducted to show the advantages of the modification of the Simar and Wilson approach they used compared to the original one (Simar and Wilson, 2007). The results show that bank efficiency can be improved by increasing the assets share of other earning assets, decreasing the share of non-earning assets in total assets and increasing total equity. Finally, the results show that bank reforms are closely related to bank efficiency. Multi-directional efficiency analysis is used by Asmild and Metthews (2012) to investigate the efficiency level in China during 1998-2007. This methodology has an advantage over DEA in that it is able to investigate the differences in the patterns of efficiencies for different kinds of banks. Different patterns of efficiency are observed for these different ownership types of Chinese banks (which are attributed to different bank objectives and constraints). In addition, the findings report that the difference in efficiency patterns of different bank ownership types is not constant over time.

4. The model and data

As discussed in the previous sections, investigate bank sustainability in China. Sustainability is decomposed into internal and external components. The internal component includes two sub-components focusing on economic and stability components, whereas two sub- components are considered for the external effect, including social and environmental dimensions.

Regarding the inputs and outputs of the process, total deposits (x_1), fixed assets (x_2) and number of employees (x_3) are used as inputs. Equity capital is used as the fixed input (x_3). We use different outputs for different sub-efficiencies. We use three outputs to measure social sustainability, viz. donations, loans to SMEs, and number of employees (y_1, y_2, y_3). Note that for the estimation of social sustainability, we include the number of employees as output rather than input because we regard employment as banks' contribution to the economy by helping society reduce the unemployment rate. The selection of our output variables to measure the social efficiency is in line with Scholtens (2009), who provided the criteria to evaluate corporate social responsibility in International Banking. The framework focused on four aspects: 1) codes of ethics, sustainability reporting, and environmental management system; 2) environmental management; 3) rresponsible financial products; 4) social conduct. Different indicators are used to measure each of these four aspects. We argue that potential increase in the number of employees and loans to SMEs are in line with one indicator, "Diversity and Opportunity," under the "social conduct category". More specifically, we argue that potential increase in the number of employees will provide more opportunities to people who are looking for a job, and this will also reduce the unemployment rate. As discussed above, it is very difficult for the SMEs to get loans from the Chinese banks. Providing loans to them will provide more opportunities for them to engage in investments and further contribute to the economic growth in China. Our selection of donations as one output variable is in line with the indicator "community involvement" under the category of "social conduct". Thus, there is prior evidence from the literature that employment is strongly correlated (conceptually) with the social dimensions of sustainability (Spangenberg et al., 2002; Vachon and Mao, 2008; Dempsey et al., 2011; Floridi et al., 2011)[3].

For the estimation of economic sustainability, interest and non-interest income (y_4, y_5) are used as outputs. In terms of the estimation of environmental sustainability, balance of green credit (y_6) is used as the output. Our selection of green credit as the output to measure the environmental efficiency is in accordance with the indicator "sustainable financing" under the category of "responsible financial products" (Scholtens,2009). Finally, with regard to the stability sustainability, we use Loan Loss Provisions (y_7) as the output. Not only will we investigate the sustainability efficiency and sub-efficiencies, we will also investigate the determinants of these sub-efficiencies. We group the potential determinants into three categories, namely, firm-specific determinants, business environment determinants and economic environment determinants. Firm specific determinants include bank size, liquidity, and capitalization $(z_1, z_2, z_3,)$; business environment determinants include banking sector development, stock market development and banking sector competition are considered as the business environment determinants (z_4, z_5, z_6); Finally, macroeconomic variables include GDP growth, inflation and corruption (z_7, z_8, z_9). All determinants are collected in vector z. Roughly, our model is:

$$\begin{gathered} y_1 = f(x) + v_1 - u_{social}, \\ y_2 = f(x) + v_2 - u_{social}, \\ y_3 = f(x) + v_3 - u_{social}, \\ y_4 = f(x) + v_4 - u_{econ}, \\ y_5 = f(x) + v_5 - u_{econ}, \\ y_6 = f(x) + v_6 - u_{env}, \\ y_7 = f(x) + v_7 - u_{stab}. \end{gathered} \tag{1}$$

Of course, (1) is not an acceptable representation of technology as it does not allow for simultaneous production of all outputs. We use this representation only in the interest of clarity. In (1), u_{social}, u_{econ} are common in the first three and next two equations to enforce the notion that a single inefficiency/ sustainability measure can be attributed to social and economic sustainability. This allows a direct comparison of social and economic sustainability.

The novel approach in this paper is that we represent sustainability is efficiency, defined as $\exp(-u)$ where u is any of u_{social}, u_{econ}, u_{env}, and u_{stab}. As argued in Bazhanov (2015), most of the empirical literature on sustainability evaluation of an economy use the genuine investment as the indicator, while Bazhanov (2015) further contributes to the empirical studies by evaluating the impact of ignored inefficiencies on the reliability of sustainability indicators. The distinct feature of our paper is that we consider efficiency in the sustainability analysis in sustainability estimation. Gaitan-Cremaschi et al. (2018) argue that the sustainable performance can be measured by social profit inefficiency which mainly involves the normal production process with consideration of negative

[3] All these studies had an empirical investigation on the sustainability issues in a non-banking industry and all of them argue that employment is one aspect of social or socio-economic component of sustainability and this factor should not be ignored in the estimation of sustainability.

environmental externalities. Our study is unique by being the first to accurately and comprehensively define and evaluate sustainability from an (in)efficiency perspective.

We will assume that $u_{social}, u_{econ}, u_{env}, u_{stab}$ depend on z.

Of course, in (1), we have to allow for multiple production so that each output depends on all other outputs via a distance function.

Suppose the production possibilities set is

$T(z) = \{(x \in \mathbb{R}\hat{}K, y \in \mathbb{R}\hat{}M): y \text{ can be produced from } x, \text{given z}\}.$ (2)

It can be described using an output distance function (ODF):

$$D(x, y, z) = \min\{\varpi > 0: (x, y/\varpi, z) \in T(z)\}. \quad (3)$$

For technically efficient units we have $D(x, y, z) = \varpi = 1$. By linear homogeneity with respect to outputs we have $D(x, \lambda y, z) = \lambda D(x, y, z)\ \forall \lambda > 0$. Choosing $\lambda = 1/y_M$ we obtain $D(x, y/y_M, z) = D(x, y, z)/y_M$, from which we have:

$$1/y_M = D(x, \tilde{y}, z) = e^{v_M + u_M}, \quad (4)$$

where $\tilde{y} = [y_1/y_M, \ldots, y_{M-1}/y_M]'$, v_M is a two-sided error term and $u_M \geq 0$ is an error component that represents technical inefficiency. To economize on notation, suppose x and y are in logs so that:

$$y_M := -\log\ y_M = F(x, \tilde{y}, z) + v_M + u_M. \quad (5)$$

This can be used to determine inefficiency in the Mth output (non-sustainability level given by loan loss provision). However, the remaining outputs, $\tilde{y}$, are endogenous and, besides, we have to determine efficiency associated with them. We assume a reduced form:

$$\tilde{y} = \Pi[x', z']' + \tilde{v} - \tilde{u}, \quad (6)$$

where $\tilde{v}$ is an $(M-1)$-dimensional two-sided error term, $\tilde{u}$ is an $(M-1)$-dimensional non-negative error component. The purpose of the reduced form is to allow for the endogeneity of all outputs other than the first one. This is necessary as (5) provides a single equation but we have $M-1$ endogenous variables in (5).

Define $v = [\hat{v}', v_M]'$, $u = [\tilde{u}', u_M]'$.

In our case

$$\begin{gathered} u = [u_{social,} u_{social}, u_{social}, u_{econ}, u_{econ}, u_{env}, u_{stab}]' = \\ [u_{social}\mathbf{1}'_3, u_{econ}\mathbf{1}'_2, u_{env}, u_{stab}]', \end{gathered} \quad (7)$$

where $\mathbf{1}_d$ is a vector consisting of ones in $\mathbb{R}^d$. So, there are four different inefficiency types but seven outputs. Define $u_o = [u_{social}, u_{econ}, u_{env}, u_{stab}]'$. Efficiency is $r_j = e^{-u_j}$ where j represents the social, environmental, economic of stability type.

A sample of 72 banks in the Chinese banking sector during 2007-2017 is selected for our analysis. Regarding the inputs and outputs variables, they are collected from FitchConnect database, which is the successor of BankScope, which stopped providing banking data by the end of 2016. FitchConnect provides financial information including bank balance sheet and income statement across

30,000 over the world. Also, the data is complemented by the annual financial statement published by the specific bank. Regarding the second stage bank sustainability determinants, the firm-specific determinants are also from the above two data sources. The business environment determinants are collected from 1) China Banking Regulatory Commission, which is the regulatory authority in the Chinese banking industry; 2) World Bank database. There are two data sources for the macroeconomic determinants: 1) world bank, which provide macroeconomic level related data for different countries across the globe; 2) Transparency International, which provides the data related to corruption of the countries on an annual basis. The table below statistically describe the variables in the sample for our analysis.

Table 1 Descriptive statistics of the variables for our analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
TotalDepos~s	792	1.78e+08	4.32e+08	49098	2.95e+09
FixedAssets	792	2329888	5736235	1008	3.80e+07
Numberofem~s	792	36784.79	90833.89	101	503082
EquityCapi~l	792	1.79e+07	4.11e+07	42371	3.29e+08
Donations	792	1327559	1911555	10091.28	9932249
LoantoSMen~s	792	1.51e+07	2.40e+07	118416.8	1.52e+08
Interestin~e	792	8576100	2.03e+07	790	1.39e+08
noninteres~e	792	1170670	2222337	305.3013	1.44e+07
BalanceofG~t	792	3221967	4732667	12693.71	4.19e+07
LoanLosspr~n	792	1009221	2405990	1007.888	1.91e+07
banksize	792	7.646906	.8898537	4.96383	9.602737
liquidity	792	.8572941	2.014396	.0191793	21.84444
capitaliza~n	792	.1462011	.1738733	.0188714	1.172799
bankingsec~t	792	2.492545	.31313	1.998	3.04
stockmarke~t	792	81.37455	39.34617	41.11	184.1
bankingsec~n	792	61.06455	8.43596	45.78	73.57
GDPgrowth	792	8.806182	2.140793	6.7	14.23
inflation	792	3.756727	3.174696	-.134	8.152
corruption	792	2.880091	.0290809	2.824	2.923

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5. Statistical model

We assume:

$$v \sim \mathcal{N}_M(\mathbf{0}, \Sigma_v). \tag{8}$$

To model sustainability, we proceed as follows. Define

$$u^* \equiv u^*_{int} + u^*_{ext}, \tag{9}$$

where u^*_{int} represents latent *internal inefficiency* and u^*_{ext} represents latent *external inefficiency*. Internal inefficiency refers to inefficiency generated by economic and stability considerations, whereas external inefficiency refers to inefficiency generated by social and environmental considerations. Overall our sustainability level is defined by (9). *Sustainability level is the product of internal and external efficiency*.

In the absence of reliable outside indicators of external and internal inefficiency, the model is incomplete as external and internal inefficiencies are unobserved. If we have panel data, we can test the hypothesis of stability using

$$\log\ u^*_{it,int} = \delta_1 + \delta_2 \log\ u^*_{int,i,t-1} + \varepsilon_{int,it}, i = 1,\dots,n, t = 1,\dots,T, \tag{10}$$

$$\log\ u^*_{it,ext} = \delta_3 + \delta_4 \log\ u^*_{ext,i,t-1} + \varepsilon_{ext,it}, i = 1,\dots,n, t = 1,\dots,T. \tag{11}$$

Sustainability is implied by the following parametric constraints:

$$\delta_1 = \delta_3 = 0, \sigma_{\varepsilon_{int}} = \sigma_{\varepsilon_{ext}} \simeq 0, \tag{12}$$

regardless of the values of δ_2 and δ_4. When $|\delta_2| < 1$, then the steady state inefficiency in (10) is $\frac{\delta_1}{1-\delta_2}$ and, therefore, we should have $\delta_1 = 0$ so that long run inefficiency is zero. When $\delta_2 = 1$ we still need $\delta_1 = 0$ so that first differences of $\log\ u^*_{int,it}$ behave as a stationary process centered at zero with "small enough" variance ($\sigma^2_{\varepsilon_{int}}$). The analysis for the parameters of (11) is the same. A generalization of (10) and (11) is the following:

$$\begin{bmatrix} \log\ u^*_{it,int} \\ \log\ u^*_{it,ext} \end{bmatrix} = \begin{bmatrix} \delta_{01} \\ \delta_{02} \end{bmatrix} + \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \end{bmatrix} \begin{bmatrix} \log\ u^*_{i,t-1,int} \\ \log\ u^*_{i,t-1,ext} \end{bmatrix} + \begin{bmatrix} \varepsilon_{int,it} \\ \varepsilon_{ext,it} \end{bmatrix}, \tag{13}$$

or

$$\log\ u^*_{it} = \delta_0 + \Delta \log\ u^*_{i,t-1} + \varepsilon_{it}. \tag{14}$$

This is a panel vector autoregressive model.

We assume:

$$\begin{bmatrix} \log\ u_{econ} \\ \log\ u_{stab} \end{bmatrix} = \log\ u^*_{int} \begin{bmatrix} \gamma_1 \\ \gamma_2 \end{bmatrix} + \Gamma_1 z + \epsilon_{int}, \tag{15}$$

$$\begin{bmatrix} \log\ u_{social} \\ \log\ u_{env} \end{bmatrix} = \log\ u^*_{ext} \begin{bmatrix} \gamma_3 \\ \gamma_4 \end{bmatrix} + \Gamma_2 z + \epsilon_{ext}, \tag{16}$$

where Γ_1 and Γ_2 are $2 \times d_w$ matrices of unknown parameters. So, *the various kinds of inefficiency act as indicators for the latent internal and external inefficiencies*. For purposes of interpretation we assume:

$$\gamma_j \geq 0, j = 1,\dots,4, \gamma_1 + \gamma_2 = 1, \gamma_3 + \gamma_4 = 1. \tag{17}$$

In turn, we can complete the system using (10) and (11).

The model allows us to examine whether overall sustainability level is sustainable at high levels and, at the same time, if this is not the case, it allows to attribute non-sustainability to internal inefficiency, external inefficiency or both. Quantification of each source is, of course, possible. Of course, there is the possibility that efficiency is "sustainable" at low levels which is, clearly, undesirable.

We can write (15) and (16) jointly as:

$$\begin{aligned}\log\, u_o \equiv \begin{bmatrix}\log\, u_{econ}\\ \log\, u_{stab}\\ \log\, u_{social}\\ \log\, u_{env}\end{bmatrix} &= \begin{bmatrix}\gamma_1 & 0\\ 1-\gamma_1 & 0\\ 0 & \gamma_3\\ 0 & 1-\gamma_3\end{bmatrix}\begin{bmatrix}\log\, u_{int}^*\\ \log\, u_{ext}^*\end{bmatrix} + \Gamma z + \epsilon\\ &\equiv \Phi(\gamma)\log\, u^* + \Gamma z + \epsilon,\end{aligned} \tag{18}$$

where $\gamma = [\gamma_1, \gamma_3]'$, $\Gamma = [\Gamma_1' \quad \Gamma'_2]'$, $\gamma_1, \gamma_3 \in [0,1]$, and $\epsilon = [\epsilon_{int}, \epsilon_{ext}]'$. We assume

$$\varepsilon_{it} \sim \mathcal{N}_2(0, \Sigma_\varepsilon), \epsilon_{it} \sim \mathcal{N}_4(0, \Sigma_\epsilon), i = 1, \ldots, n, t = 1, \ldots, T. \tag{19}$$

We write the model in compact form as follows:

$$\begin{aligned}y_{it} = [\tilde{y}_{it}', y_{it,M}]' &= \begin{bmatrix}\Pi[x_{it}', z_{it}']'\\ F(x_{it}, \tilde{y}_{it}, z_{it}; \beta)\end{bmatrix} + \begin{bmatrix}\tilde{v}_{it} - \tilde{u}_{it}\\ v_{it,M} + u_{it,M}\end{bmatrix}\\ &\equiv \begin{bmatrix}\Pi[x_{it}', z_{it}']'\\ F(x_{it}, \tilde{y}_{it}, z_{it}; \beta)\end{bmatrix} + v_{it} - u_{it},\end{aligned} \tag{20}$$

which we rewrite as:

$$\begin{aligned}\mathcal{F}(x_{it}, y_{it}, z_{it}; \beta) + v_{it} - \begin{bmatrix}\mathbf{1}'_{M-1} & \\ & -1\end{bmatrix} u_{it} = \mathbf{0}_M \Rightarrow\\ \mathcal{F}(x_{it}, y_{it}, z_{it}; \beta) - \boldsymbol{J}_o u_{it} = v_{it},\end{aligned} \tag{21}$$

$$\begin{aligned}u_{it} = \begin{bmatrix}u_{it,social}\mathbf{1}_3\\ u_{it,econ}\mathbf{1}_2\\ u_{it,env}\\ u_{it,stab}\end{bmatrix} &\equiv \begin{bmatrix}\mathbf{1}'_3 & & & \\ & \mathbf{1}'_2 & & \\ & & 1 & \\ & & & 1\end{bmatrix} u_{it,0} = \boldsymbol{J}_{(7\times 4)} u_{it,0}, u_{it,0}\\ &\equiv \begin{bmatrix}u_{it,social}\\ u_{it,econ}\\ u_{it,env}\\ u_{it,stab}\end{bmatrix},\end{aligned} \tag{22}$$

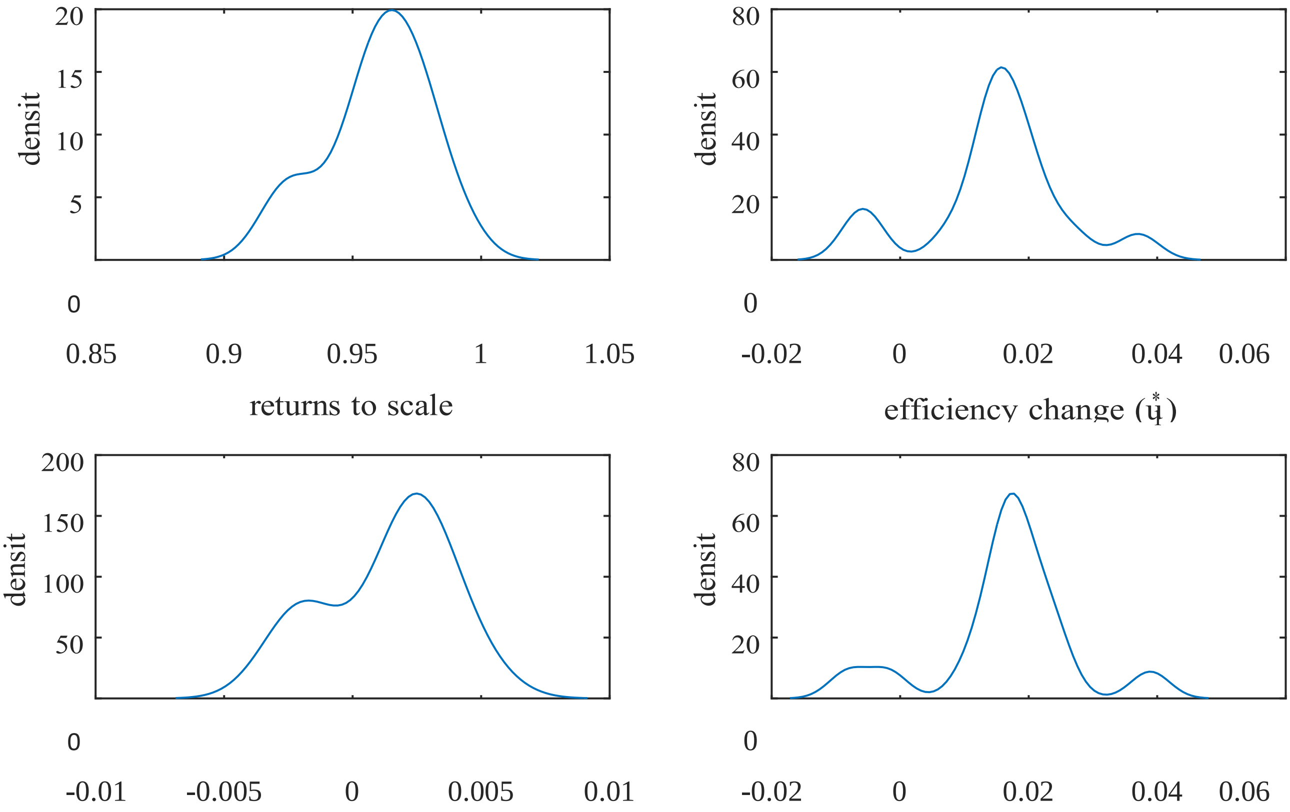
$$\log\, u_{0,it\ (4\times 1)} = \Phi(\gamma)\log\, u_{it\ (2\times 1)}^* + \Gamma_{(4\times d_w)} z_{it\ (4\times 1)} + \epsilon_{it}, \tag{23}$$

$$\log\, u_{it}^* = \delta_0 + \Delta \log\, u_{i,t-1}^* + \varepsilon_{it}. \tag{24}$$

Here, $\beta \in \mathbb{R}^{d_\beta}$ is a parameter vector in the ODF. Our free parameters are $\beta, \gamma, \delta_0, \Delta, \Sigma_v, \Sigma_\epsilon, \Sigma_\varepsilon$ which we denote collectively by $\theta \in \Theta \subset \mathbb{R}^d$. Notice that $\log\, u_{0,it}$ is 4×1 and $\log\, u_{it}^*$ is 2×1. The Jacobian of (21) with respect to y_{it} is unity, as the system is recursive.

6. Empirical results

This section will focus on the presentation and discussion of the results regarding the estimation of sustainability level as well as the determinants of sustainability. Figure 2 shows the returns to scale, efficiency change, change in technical efficiency and change in productivity level. These are sample distributions of posterior mean estimates of the respective quantities. The results show that most banks face diseconomies of scale. We attribute this finding to the specific management culture in China, where there is a strong hierarchy structure and many bureaucratic procedures in banking operation. Therefore, larger commercial banks will experience a larger amount of resource waste. Regarding efficiency change, most banks experienced a slight efficiency improvement (2%), while the number of banks facing efficiency decline and larger efficiency improvement is smaller. We also notice that most banks in the sample face slight technical and productivity improvements.



Technical change **Productivity change**

Figure 2: Returns to scale, changes in efficiency, technical efficiency and productivity level

Figure 3 shows the distribution of economic inefficiency, stability inefficiency, environmental inefficiency and social inefficiency. It is noticed that the environmental inefficiency has the largest spread, followed by stability inefficiency, while economic inefficiency has a lower spread compared to the previous two. However, it still has a wider spread compared to social inefficiency. This finding can be interpreted by taking into account that Chinese banks are quite heterogenous in terms of using inputs to generate loans granted to environmentally-protected companies and projects. It also shows that the ability in terms of using inputs to generate outputs in a "stable" way among banks in the sample is different, whereas, they have smaller differences among them in terms of generating economic and social outputs. This result is very interesting and provides important policy implications. Relevant regulation should be established to encourage the banks to provide loans to companies engaged in environmentally protected projects and also a more consistent, specific and targeted policy should be implemented in terms of loan loss provisions to reduce the heterogeneity in stability among Chinese commercial banks.

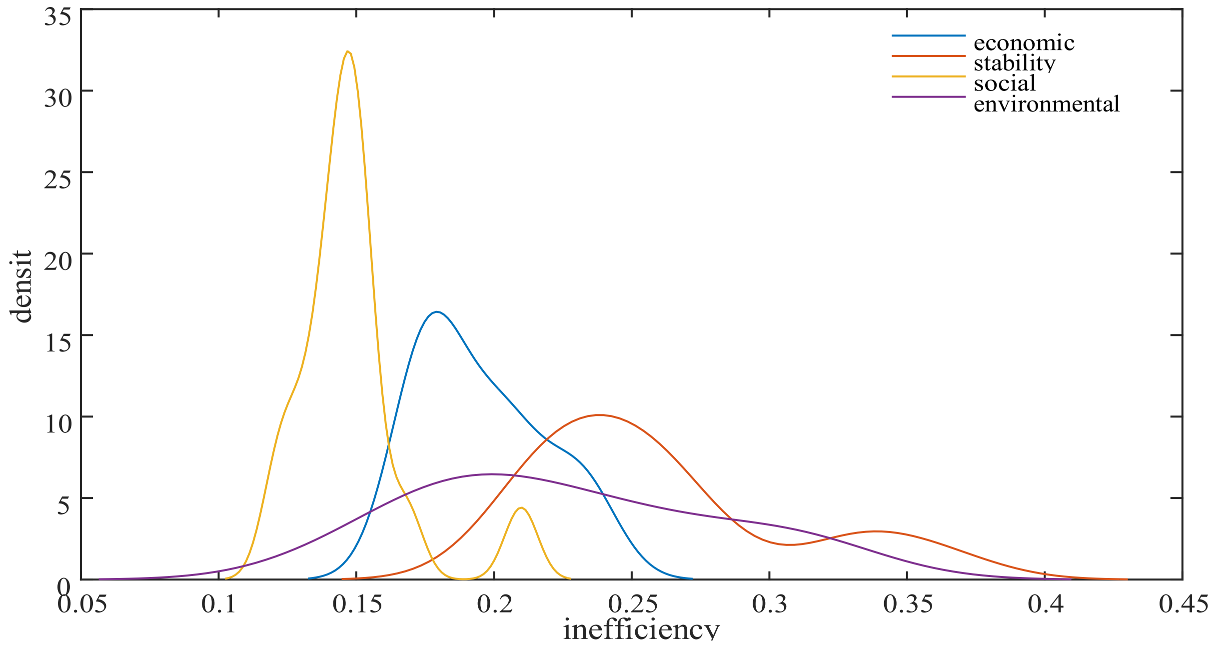


Figure 3: Inefficiency distribution of different sub-efficiencies

Figure 4 shows the distribution of internal, external inefficiencies and unsustainability level of Chinese commercial banks. We can see that commercial banks have considerable spread in terms of sustainability. The difference in spread between internal and external efficiency is relatively smaller although the smallest difference is observed for internal efficiency among Chinese commercial banks. This indicates that more effort should be allocated to improving resource allocation in generating returns to the society. This, in turn, will further reduce the difference in external efficiency among Chinese commercial banks, and will further reduce the differences in sustainability.

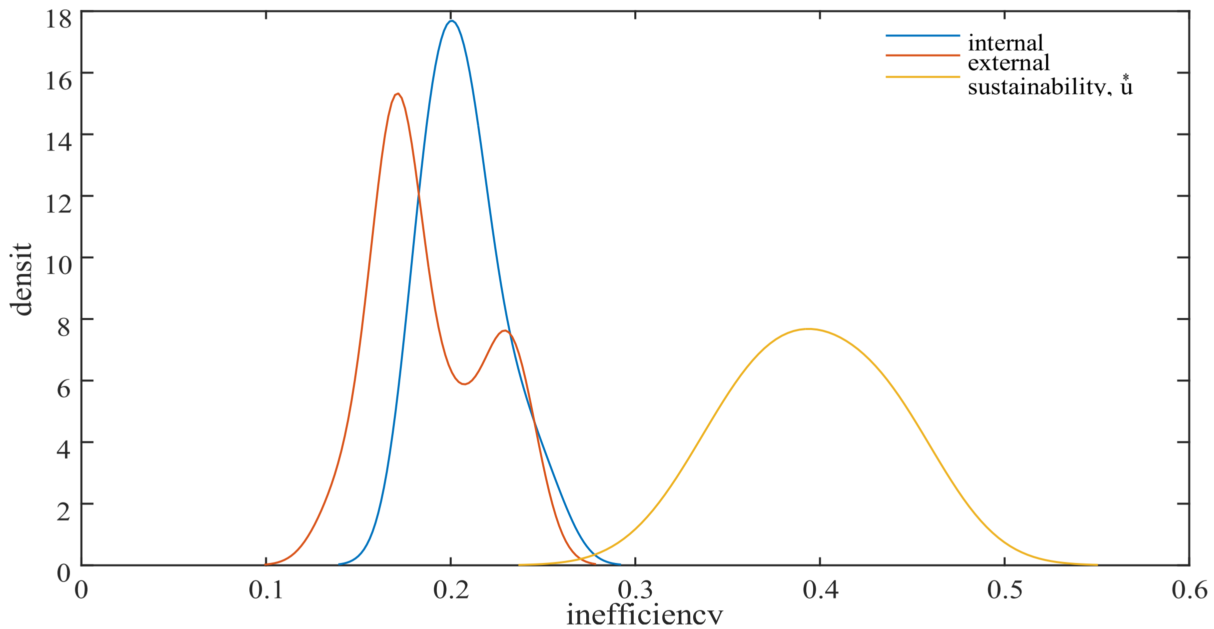


Figure 4: Distribution of internal, external inefficiencies and unsustainability level of Chinese commercial banks.

In Figure 5 we report the posterior density of maximum mod eigenvalue of Δ. The results show that the dynamical system in (24) is stable although highly persistent. Moreover, we cannot exclude the possibility of a unit root, as there is considerable posterior probability around unity (the Bayes factor in favor of a unit root is close to 0.93 so this would have been an acceptable hypothesis in the light of the data). In this case, it does not really matter whether or not we estimate a steady state, because under unit roots, one does not exist. However, we proceed with this computation, anyway, as there is considerably posterior probability between 0.2 and 0.95 in the maximum mod eigenvalue of matrix Δ in (24).

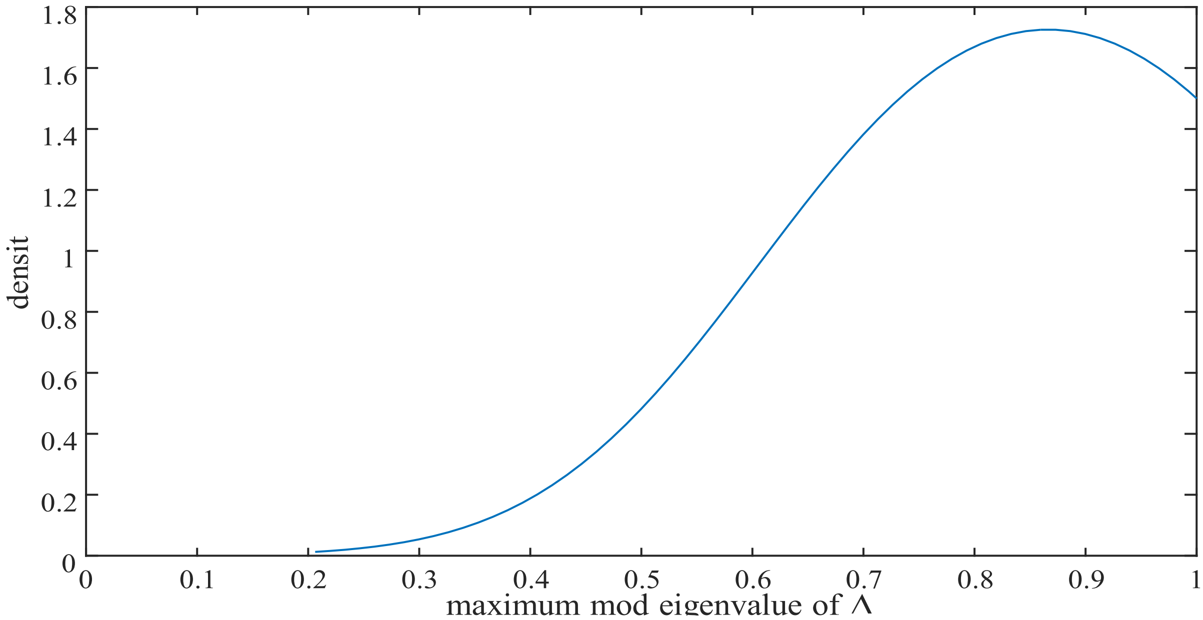


Figure 5: Posterior density of Maximum mod Eigenvalue

In Figure 6 (below) we present posterior densities of steady state for internal, external inefficiencies and unsustainability level. The Figure shows that external inefficiencies are lower compared to unsustainability level. Internal and external inefficiencies average approximately, 18% and 16%, while sustainability score averages 33%. The spread of these posterior densities indicates slight heterogeneity across banks, but this heterogeneity is much smaller for external inefficiency. Under the assumption that the system in (24) is stable, the evidence from Figure 6 shows that internal inefficiency, and external inefficiency are sizeable (close to 17% on the average. Sustainability has a lot of room to improve and the banking system is more or less trapped in an inefficiently sustainable trap.

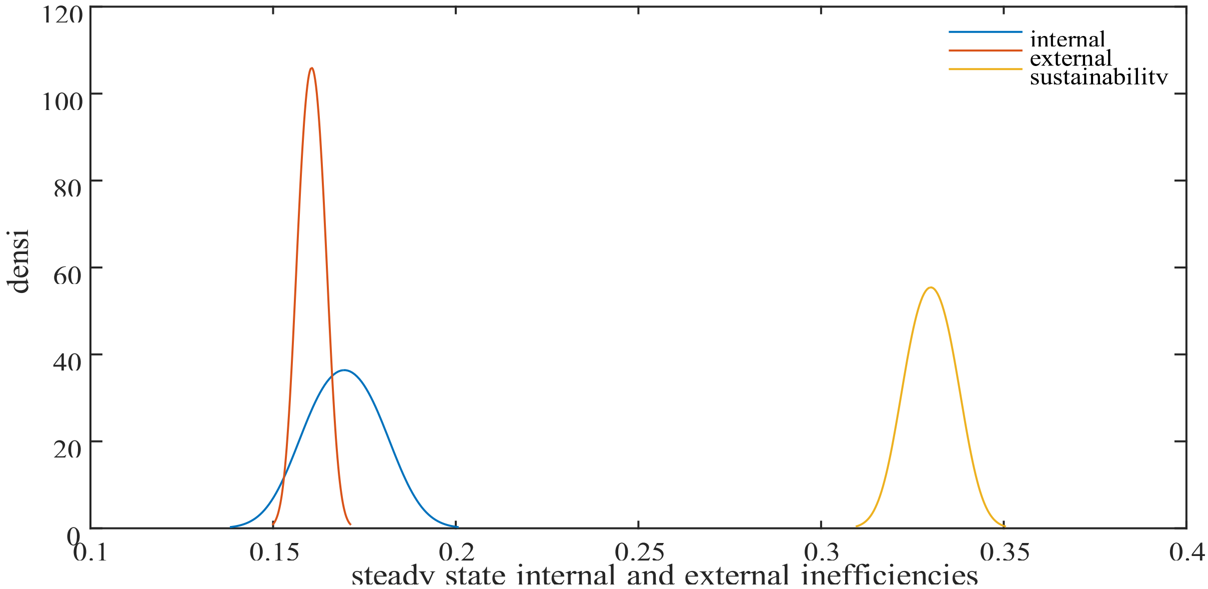


Figure 6: Posterior density of steady state internal and external inefficiencies

In Figure 7, we present the posterior densities of factor loadings for internal and external efficiencies related to the sustainability level. The evidence shows that internal efficiency (blue line) is more closely related to economic sustainability and ranges between 0.74 and 0.92. In comparison, the estimates for external efficiency (red line) range between 0.42 to 0.55, indicating an equal loading on social and environmental sustainability. Clearly, all these posterior densities are away from zero, so these parameters cannot be zero in the light of the data. Moreover, the posterior density of γ_1 is bimodal with two modes around 0.8 and 0.9, showing some evidence that asymptotic inferences may be misleading in this instance. The bimodality of the posterior density of γ_3 is less pronounced.

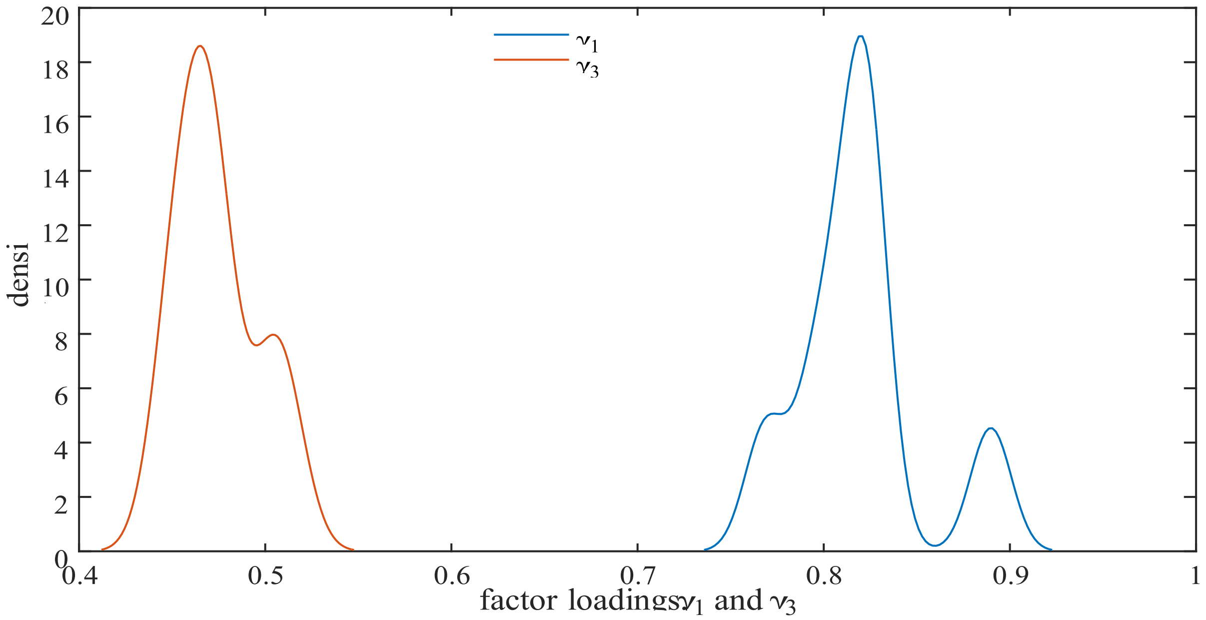


Figure 7: Posterior densities of factor loadings for internal and external efficiencies related to the sustainability level

In Figure 8 we present the scale parameters of internal (blue line) and external (red line) efficiencies. The figure shows that the external efficiency, as represented by the red line, looks like a symmetric distribution. Internal efficiency has a larger spread and it is clearly skewed to the right and bimodal. Therefore, sampling-theory approaches would deliver estimates where the usual asymptotics provide a more or less misleading picture in finite samples.

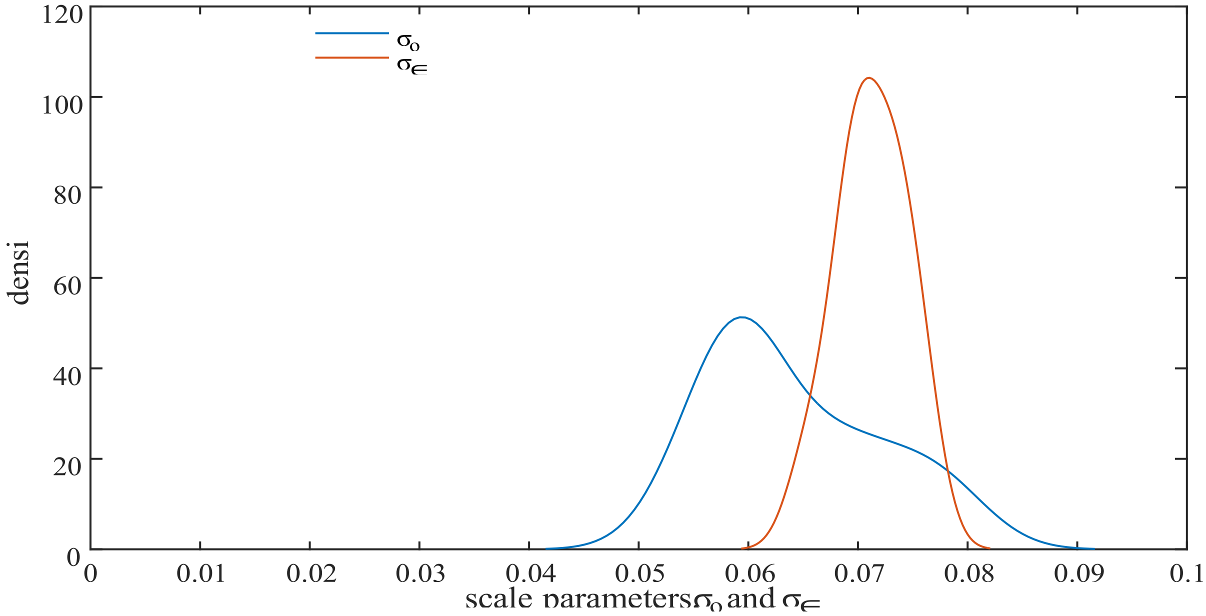


Figure 8: Scale parameters of internal (blue line) and external (red line) efficiencies

To examine sustainability, we have to test (12). Although $\delta_1 = \delta_3 = 0$ is easy to impose, this is not so for the scale parameters so we set $\sigma_{\varepsilon_{ext}} = \tau_\varepsilon \overline{\sigma}_{\varepsilon_{ext}}$ and $\sigma_{\varepsilon_{int}} = \tau_\varepsilon \overline{\sigma}_{\varepsilon_{int}}$, where $\overline{\sigma}_{\varepsilon_{ext}}$ and $\overline{\sigma}_{\varepsilon_{int}}$ are posterior means in the baseline model, and we set τ_ε to different values, as shown in Figure 4. Evidently, log Bayes factors do *not* favour sustainability (Figure 9 below).

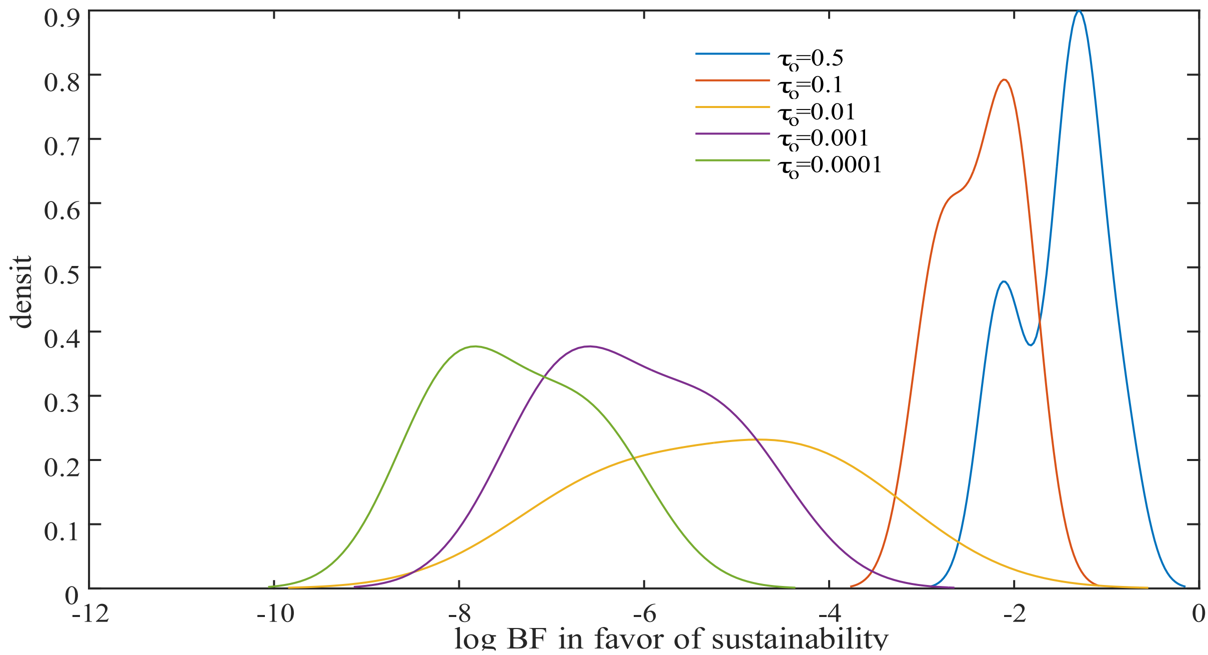


Figure 9: Densities of log BF in favorr of sustainability

Here we examine convergence of MCMC (shown in upper left panel of Figure 10 below), and sensitivity of posterior means of θ, λ_{it}, returns to scale and u_{it}^{*} (upper right panel). Sensitivity is examined relative to the baseline prior, by adopting 10,000 different prior specifications. To perform MCMC with the new priors we use sampling-importance-resampling with the 25% of the original MCMC sample.

One consideration that deserves attention is the assumption that x_{it}s is weakly exogenous, that is the coefficients of x in (6) are jointly zero. To investigate this issue, we consider i) the Bayes factor (BF) in favour of the hypothesis that these coefficients are *not* zero and, ii) the predictive BF for the same hypothesis. The BF of case (i) is computed as the ratio of marginal likelihoods $\frac{M_1(D)}{M_o(D)}$ where $M_1(D)$ is the marginal likelihood in the full model (i.e. the coefficients are not zero) and $M_o(D)$ is the marginal likelihood when the xs do not appear in (6). The marginal likelihood in both cases is standard output of the particle filtering algorithm. We report the distribution of BF across all 10,000 priors in the bottom panel of Figure 3. Clearly, the evidence in favor of endogeneity of xs is rather weak. The predictive BF is computed using the ratio of marginal likelihoods $\frac{\widetilde{M}_1(D)}{\widetilde{M}_o(D)}$ where $\widetilde{M}_1(D)$ and $\widetilde{M}_o(D)$ are the predictive likelihoods. These are computed by setting aside data for 2015-2017 for all banks, re-estimating the models using sampling-importance-resampling and evaluating the predictive distributions at the set-aside data (Geweke and Amisano,2010). Again, the evidence in favor of endogeneity of xs is rather weak.

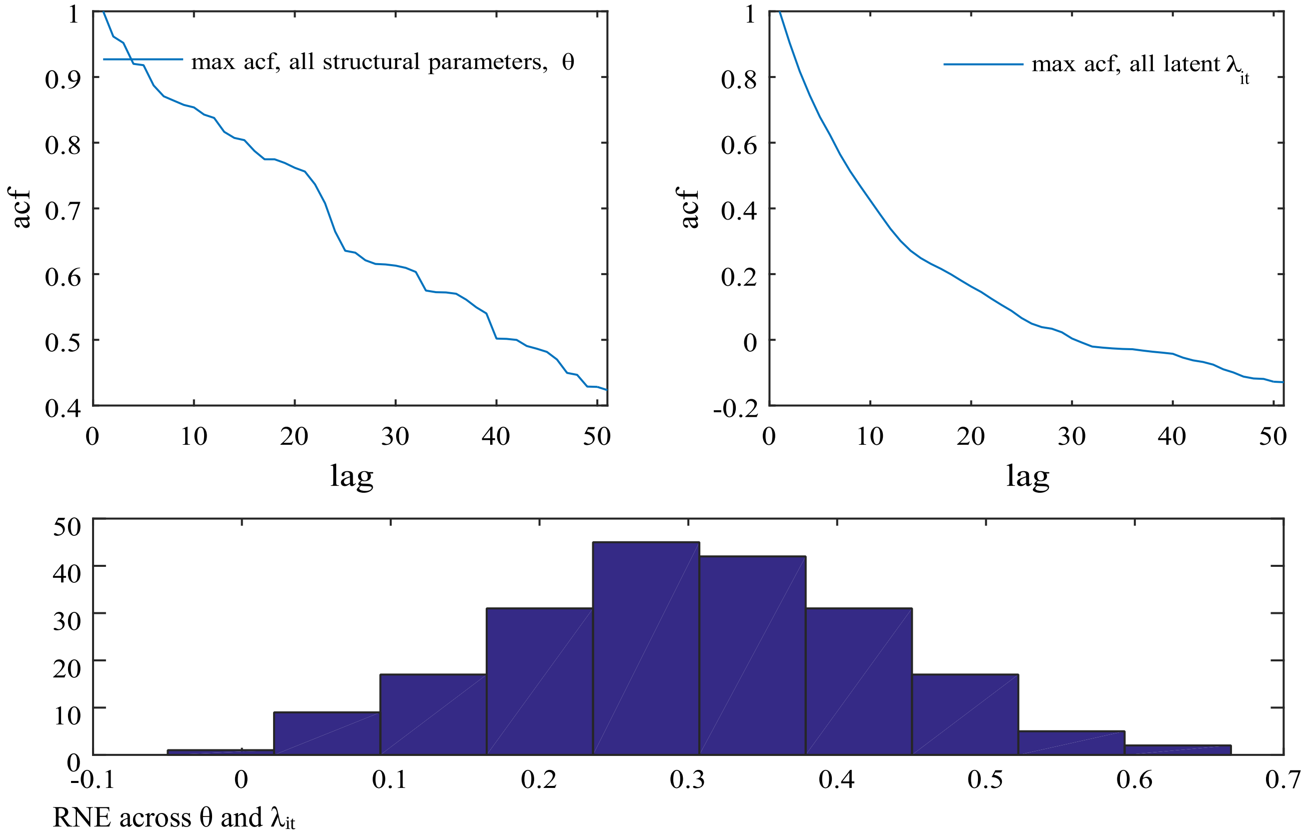
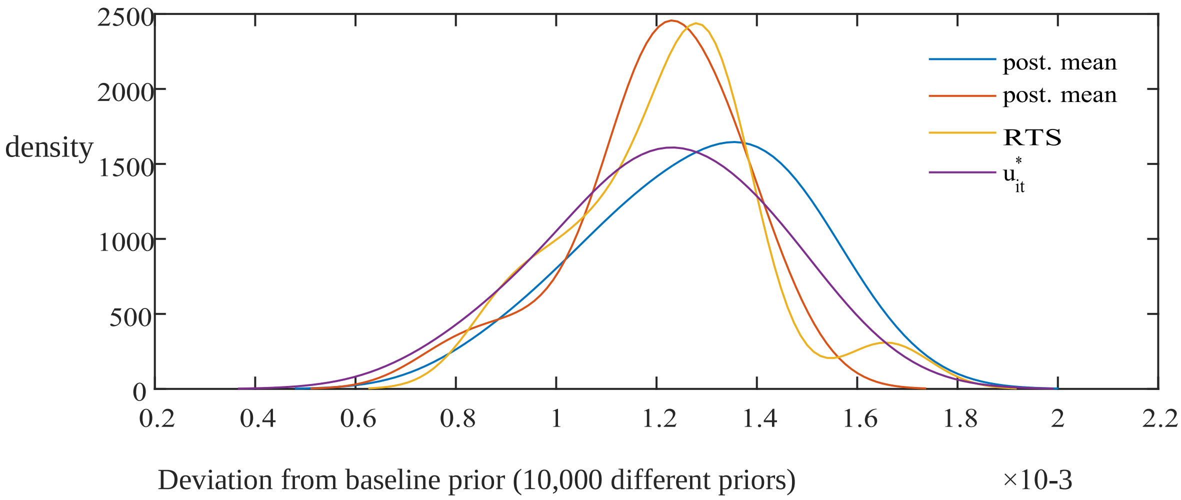


Figure 10: Convergence of MCMC, sensitivity of posterior means and relative numerical efficiency

The figure (Figure 11) below reports the results regarding the sensitivity analysis with respect to the prior. 10000 different priors with parameters randomly drawn using the baseline specification are used. For sensitivity analysis, the figure shows the posterior mean of economic efficiency, stability efficiency, return to scale on social efficiency and inefficiency in environmental efficiency. The results indicate that the posterior means are robust to the prior means. We also report the results regarding the sensitive analysis with regard to the post means of θ and λ_{it}. We use different numbers of particles and the results show that the results are robust.



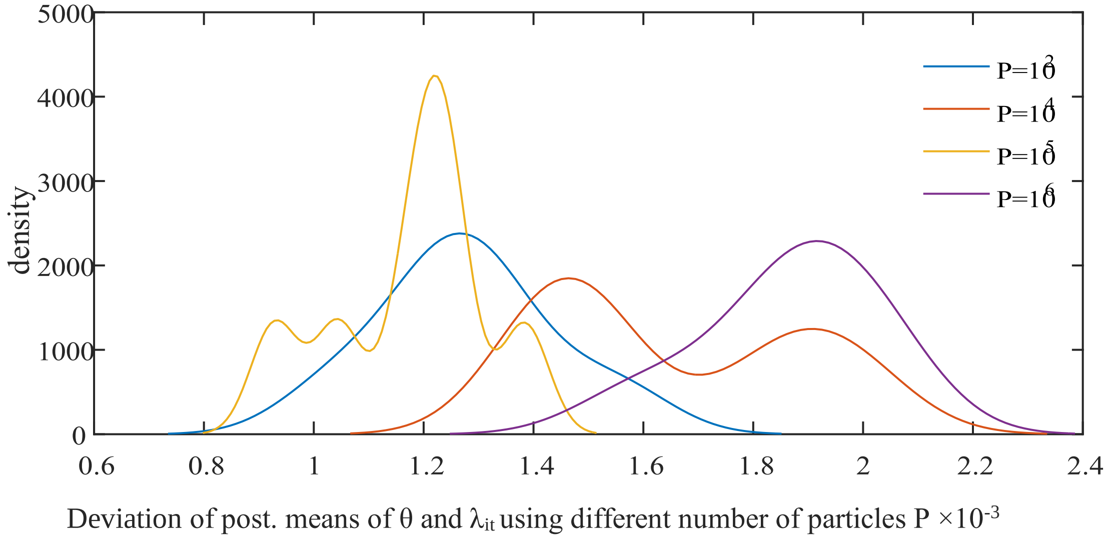


Figure 11: Sensitivity analysis of deviation from baseline prior and deviation of posterior means

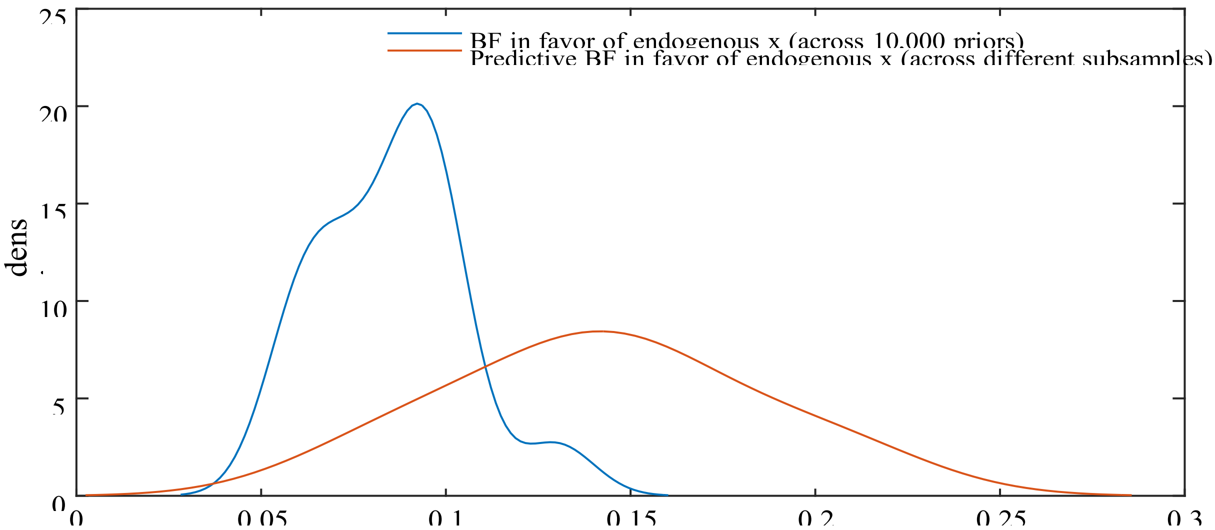


Figure 12: Bayes factors for endogeneity

The table below reports the results in regard to the determinants of economic inefficiency, stability inefficiency, social inefficiency and environmental inefficiency. We control for three different types of determinants, including firm-specific determinants, business environment determinants and economic environment determinants. We argue that bank size will influence the economic efficiency in a positive way due to the effects of economies of scale and economies of scope. A higher level of stability is expected to be achieved by larger banks because of the strong support provided by the government. Banks will set aside lower volumes of loan loss provisions, and stability efficiency would be lower under this case. The purpose for the banks to engage in positive social behaviour and also actively participate in the environmental protection is to uplift bank image and build a competitive edge for the bank. Large banks are very well established with long time operating experience and have strong customer trust and a higher level of competitive power. They have less incentive to engage in positive behavior to create value for the society and the environment. A higher level of liquidity will enhance banks' ability to deal with sudden withdrawals and further reduce the insolvency risk, so it is expected that higher level of liquidity will make banks set aside small volumes of loan loss provisions. This will lead to a decrease in stability efficiency. A higher level of liquidity reflects the fact that banks focus on short-term loan businesses. As compared to the long-term loans, banks will generate lower volumes of interest income, and this will further result in a lower level of economic efficiency. The more profitable the bank is, the greater the probability that it will engage in corporate social behavior. More liquid banks would be less profitable compared to the ones engaged in allocating credits in longer terms, therefore, we suppose that liquidity will affect social efficiency and environmental efficiency in a negative way. A higher level of capitalization will strengthen banks' ability to absorb the negative unexpected losses, and this will reduce the volumes of loan loss provisions held and further decrease stability efficiency. More capitalized banks will have higher abilities to allocate credits to high risk projects and companies, which will increase the level of economic efficiency assuming the risk-return hypothesis holds. More capitalized banks are more capable of providing returns back to the society through engaging in businesses contributing to environment protection and promoting the development of the society, therefore, we argue that capitalization has a positive impact on social efficiency and environmental efficiency.

An increase in the demand for banking services derived from a well-developed banking sector is helpful for banks to achieve scale economies and scope economies. The resultant cost reduction increases economic efficiency, while a large demand for banking services also reflects the fact that banks engaged in a large variety of different businesses. This resultant diversification will reduce bank risk and further decrease the volumes of loan loss provision held. Therefore, we argue that stability efficiency will be affected by banking sector development in a negative way. A more developed banking sector indicates a substantial increase in the volumes of assets held by banks. The assets include loans in general, while more specifically, the loan businesses can be divided according to the size of the companies being allocated the credits, such as big enterprises as well as medium and small sized companies. Also, the loan businesses will disperse across different industries and various types of projects, including the heavy industries as well as environmentally friendly projects. Therefore, we argue that a higher developed banking sector will improve social efficiency and environmental efficiency. Stock market development takes away business from the banking industry; also, when investors invest their money to the stock market, this will reduce the volumes of interest and non-interest income and lead to a decrease in the level of economic efficiency. In order to increase the volume of business, banks will reduce the credit requirement, and this will deteriorate bank risk and banks will keep a relatively larger amount of loan loss provisions to deal with this issue. Thus, we expect that stability efficiency will be positively affected by stock market development. A deterioration of bank income will reduce banks' incentive and ability to provide returns back to the society, therefore, we expect that stock market development will affect social efficiency and environmental efficiency in a negative way. Finally, stronger competition among banks will lead to a decrease in the level of income (profit) according to the structure-conduct-performance theory; in other words, economic efficiency will decrease. Higher level of competition will also induce banks to undertake higher levels of risk; banks will put aside larger volumes of loan loss provisions to absorb potential losses, and therefore, we expect that stability efficiency will benefit from a stronger competitive banking environment. In order to get a competitive advantage, banks will have more incentive to improve their image through engaging in corporate social behavior, thus, we expect that social efficiency and environmental efficiency can be enhanced by stronger bank competition.

We argue that a higher GDP growth reflects that there is a boom in economic activity and the economy produces more goods and services. This is mainly attributable to the increase in the credit allocation in the banking industry, therefore, it is supposed that GDP positively affects the economic efficiency. A higher level of economic growth will encourage banks to expand their credit allocation; banks will be less "picky" in terms of the types or the conditions of the businesses they allocate the credit to, therefore, there is a higher potential risk derived from the non-performing loans, and the resultant increase in the loan loss provisions held will increase the stability efficiency. The credit expansion derived from a higher level of economic growth will benefit the medium and small sized companies as well as environmentally friendly projects, therefore, we argue that social efficiency and environmental efficiency will be improved by a higher GDP. Corruption will benefit bank managers at the expense of higher bank risk (Park, 2012). The resultant accumulation of non-performing loans will make banks keep larger volumes of loan loss provisions, from which the stability efficiency is improved. The reduction in bank income derived from the accumulation of non-performing loans is supposed to negatively affect economic efficiency. A more corrupted country or a more corrupted period within a country will have managers take care of their own benefit as the main priority in the bank's operation. Obviously, these banks are not supposed to generate any positive returns to the society. Therefore, we think that social efficiency and environmental efficiency are lower in a period of high corruption. Finally, the erosion of purchasing power derived from higher levels of inflation will reduce the volumes of deposits attracted by the banks, without which banks are unable to make loans to businesses to get income, therefore, we think that higher levels of inflation will affect economic efficiency in a negative manner. In order to increase the volumes of business, banks will undertake higher levels of risk, and stability efficiency will be improved because banks prepare more loan loss provisions to deal with the potential risk. During this difficult time, banks do not have enough incentive to provide positive returns back to the society, therefore, the social efficiency and environment efficiency will be lower.

The measurement of the variables as well as the results are presented in Table 1 below.

Table 1. Posterior moments

	Measurement	log u_{econ}	log u_{stab}	log u_{social}	log u_{env}
FIRM SPECIFIC VARIABLES					
bank size	Natural logarithm of	0.035 (0.0045)	0.043 (0.010)	0.014 (0.0023)	-0.024 (0.019)

	total assets				
liquidity	Ratio of liquid assets to total assets	-0.061 (0.012)	-0.012 (0.0031)	0.034 (0.032)	0.023 (0.0071)
capitalization	Ratio of equity capital to total assets	-0.055 (0.013)	-0.077 (0.014)	0.068 (0.013)	-0.014 (0.0030)
business environment VARIABLES					
banking sector development	Ratio of banking sector assets to GDP	-0.025 (0.0071)	-0.055 (0.016)	-0.023 (0.0071)	-0.054 (0.019)
stock market development	Ratio of market capitalization of domestic listed firms to GDP	-0.053 (0.012)	-0.030 (0.013)	-0.019 (0.0014)	0.022 (0.017)
banking sector competition	5-bank concentration ratio	0.044 (0.0092)	0.0034 (0.0011)	0.0017 (0.0024)	0.034 (0.029)
economic environment VARIABLES					
GDP growth	Annual GDP growth rate	-0.035 (0.014)	-0.017 (0.0041)	-0.035 (0.0018)	0.057 (0.0071)
inflation	Annual inflation rate	0.0014 (0.0002)	0.0022 (0.0004)	-0.0017 (0.0021)	0.045 (0.014)
corruption	Corruption perception index	0.027 (0.0034)	0.014 (0.0021)	0.054 (0.014)	0.071 (0.013)
γ_1		0.770 (0.015)			
γ_3		0.332 (0.017)			

Our results from the above table show that large banks are less efficient from the economic, stability and social perspective. The impact on economic efficiency is not in line with our expectations. Large banks are able to generate higher levels of income derived from cost reduction, however, due to the special Chinese culture, there is a hierarchy structure in the large Chinese companies, this system makes banking operation full of wasting time and resources, this possibly explains our results. Higher levels of liquidity lead to higher economic efficiency, higher stability efficiency and lower environmental efficiency. The positive impact on economic efficiency and stability efficiency is different from our expectations. More liquid banks are conservative banks; they are concerned with the risk more than other factors. In order to reduce bank risk these banks normally will keep larger volumes of loan loss provisions. The positive influence of liquidity on economic efficiency found is the same as the findings of Sufian (2009). Higher capitalized banks have higher economic efficiency, higher stability efficiency, higher environmental efficiency, but lower social efficiency. This result is different from our expectation. Higher capitalized banks are more likely to and capable of engaging in risky businesses, and relatively more loan loss provisions will be put aside to absorb the unexpected losses derived from the potential non-performing loans. The negative effect of capitalization on social efficiency is also different from our expectation; we attribute this finding to the fact that higher capitalized banks have higher levels of market power through occupying a larger amount of market shares. They have less incentive to further improve their corporate image and competitive power through providing returns to the society and they mainly target their credit allocations to big and state-owned enterprises.

The positive relationship between banking sector development on economic efficiency is in accordance with our expectation, while the positive influence on stability efficiency can be explained from the perspective that the economy will have a higher degree of reliance on the banking sector to allocate credits when there is a more developed banking sector. Then different types and sizes of enterprises across various economic sectors will seek loans from banks, although diversification seems to reduce banks' risk, the results from our study indicates that higher levels of risk derived from credit expansion override the risk reduction from diversification. A positive relationship between stock market development and economic efficiency is in contrast with our expectation. A more highly developed stock market takes away bank business; this will incentivize bank managers to optimize the resources in banking operation, and the effect of cost reduction is stronger than the shrinkage of bank income. The positive influence on social efficiency can be explained from the perspective that reduction in the volumes of bank business will force banks to allocate credits to medium and small sized companies and increase in returns to society through donations aims to improve customer confidence and win back some businesses from the stock market. Positive influence of bank competition on economic efficiency is different from our expectation and we argue that this is similar to stock market development; higher levels of bank competition comes with a substantial improvement in resource allocation, and the significant cost reduction overcomes the potential decrease in bank income.

Finally, we find that the environmental efficiency is affected by GDP growth in a negative manner,. These results reflect the fact that the heavy industries or non-environmentally friendly projects still play a dominant role in the Chinese economy. Higher economic growth relies heavily on these relatively highly polluting productions, and the consequent reduction in allocating credits to green companies and projects will lead to a reduction in the level of environmental efficiency. Tan and Floros (2013) find that inflation positively affects bank Z-scores; less loan loss provisions will be kept by banks resulting from this, and this explains the negative impact of inflation on stability efficiency. The positive relationship between corruption and economic efficiency can be explained from the perspective that in a culture with a higher degree of tolerance of corruption bank managers have more incentive to work hard in optimizing bank operation, while the positive impact on social efficiency is attributed to the fact that medium and small sized companies are the main entities that bribe bank managers to induce them to increase the allocation of credit to this type of companies. Wang and Zhang (2014) argue that green credit allocation comes with a higher level of risk, therefore, we think these environmentally friendly projects and companies possibly will bribe the banks in order to get loans. A higher level of corruption in a country reflects, to a certain extent, the degree of corruption in the banking sector; a higher level of corruption will make bank managers allocate more credits to risky green projects and companies, which further results in an improvement in environmental efficiency.

7. Concluding Remarks

The Chinese economy has undergone a series of reforms over recent decades, the focus of which had been on innovation and sustainable development. In the banking sector specifically, the banking regulatory authorities have recently introduced private banking into the financial system. Together with financial innovation, such as third-party payment, the level of competition kept increasing. Although overall, the Chinese banking industry has increased its size and profit over the last few years, while the overall level of risk, as represented by the non-performing loans ratios, did not have a consistent decline. Instead, it is noticed that there is a relatively more volatile trend. This is not a good sign for the stability and sustainability in the Chinese banking sector.

In order to be sustainable, not only did the banks need to improve performance, but, more importantly, the banks needed to attach greater importance to providing returns to society. In other words, the corporate social behaviour engaged in by the banks will not only improve their corporate image, but it will also enhance the customer trust and confidence, which will further promote sustainable development. Although the empirical literature has comprehensively investigated the issue of performance (efficiency and profitability) and stability in the banking sector, no study has examined the issue of sustainability development in a careful way.

Our study fills in the gap in the empirical literature in banking as well as operational research of efficiency by being the first study investigating the issue of sustainability in a careful and comprehensive manner. We are the first piece of research explaining sustainability from the perspectives of internal and external efficiencies. We are also able to decompose the internal efficiency into two components reflecting the economic operation and stability conditions of banks. In addition, we further classify external efficiency into two other components reflecting different perspectives of bank contribution, including social efficiency and environmental efficiency. Regarding the estimation of social efficiency, we use indicators reflecting bank contributions to different parties. More specifically, we use donations to reflect bank contribution to society and economy, we use loans to medium and small sized companies to reflect bank contribution to different types of companies, and, finally, we use number of employees to reflect the benefits received from the individual person in the society from the banks' corporate social behaviour. Not only did we focus on the evaluation of sustainability, but we also engaged in examining the determinants of sustainability, which is of paramount importance in providing policy implications.

The results show that sustainability level has ranged between 0.45-0.75. In terms of internal and external efficiencies, our findings show that the latter has a slightly wider spread, while regarding the sub-efficiencies, we find that Chinese commercial banks are highly efficient in providing returns to society, with a highest score of 0.96, whereas stability is still the most serious issue, with the lowest score of 0.575. Regarding the determinants of sustainability, our results suggest that all the firm-specific, business environment and economic environment determinants are significantly related to economic efficiency and stability efficiency, while most of the determinants are significant for social efficiency and environmental efficiency. The only exceptions are liquidity, banking sector development and inflation, which do not appear to be quantitatively important for social efficiency. Moreover, environmental efficiency is not significantly affected by bank size, stock market development and banking sector development.

Our findings have interesting policy implications: 1) Banks should reduce their size at the current stage. As reflected from the results, it is indicated diseconomies of scale exist; large banks are full of bureaucratic procedures in their operations, which leads to a waste of resource; 2) relevant policies should be implemented to increase the importance of banks in the financial system by expanding the banking sector assets. More specifically, the Chinese banking industry should allocate more funds for research and development activities, and the resulting increase in the volumes of innovation will expand banking services and products and further lead to an expansion of banking sector assets; 3) Chinese financial regulatory authorities should further improve stock market development and intensify the level of bank competition. To be more specific, more favorable policy should be given to smaller banks to help them flourish; the gradual increase in their size will give them a stronger competitive power with large banks and stronger competitive condition will emerge.

Appendix A

Appendix A.1 Likelihood and posterior

From (21), (22), (23), and (24) we can build the likelihood as follows. Since

$$\begin{gathered}L(\theta;\mathcal{D},\{u_{0,it},u_{it}^{*}\}_{i=1,\dots,n,t=1,\dots,T})\propto\\|\Sigma_v|^{-nT/2}\exp\left\{-\frac{1}{2}(\mathcal{F}(x_{it},y_{it},z_{it};\beta)-\boldsymbol{J}_o u_{it})'\Sigma_v^{-1}(\mathcal{F}(x_{it},y_{it},z_{it};\beta)-\boldsymbol{J}_o u_{it})\right\}\cdot\\|\Sigma_\epsilon|^{-nT/2}\exp\left\{-\frac{1}{2}\left(\log\,u_{0,it}-\Phi(\gamma)\log\,u_{it}^{*}-\Gamma z_{it}\right)'\Sigma_\epsilon^{-1}\left(\log\,u_{0,it}-\Phi(\gamma)\log\,u_{it}^{*}-\Gamma z_{it}\right)\right\}\\|\Sigma_\varepsilon|^{-nT/2}\exp\left\{-\frac{1}{2}\left(\log\,u_{it}^{*}-\delta_0-\Delta\log\,u_{i,t-1}^{*}\right)'\Sigma_\varepsilon^{-1}\left(\log\,u_{it}^{*}-\delta_0-\Delta\log\,u_{i,t-1}^{*}\right)\right\},\end{gathered}\tag{A.1.1}$$

we have:

$$L(\theta;\mathcal{D})\propto\int_{\mathbb{R}_+^{6nT}}L\,(\theta;\mathcal{D},\{u_{0,it}u_{it}^{*}\}_{i=1,\dots,n,t=1,\dots,T})d\{u_{0,it},u_{it}^{*}\}_{i=1,\dots,n,t=1,\dots,T},\tag{A.1.2}$$

where $\mathcal{D}$ denotes the data. Since the multivariate integral is not available in closed form, we use Bayes' theorem to derive the augmented posterior:

$$p(\theta|\mathcal{D},\{u_{0,it},u_{it}^{*}\}_{i=1,\dots,n,t=1,\dots,T}) \\ \propto L(\theta;\mathcal{D},\{u_{0,it},u_{it}^{*}\}_{i=1,\dots,n,t=1,\dots,T})\cdot p(\theta), \tag{A.1.3}$$

which, in obvious notation, becomes:(0.017)

$$p(\theta|\mathcal{D},\{\lambda_{it}\}_{i=1,\dots,n,t=1,\dots,T}) \propto L(\theta;\mathcal{D},\{\lambda_{it}\}_{i=1,\dots,n,t=1,\dots,T})\cdot p(\theta). \tag{A.1.4}$$

We introduce the following prior:

$$p(\beta) \propto \mathbb{I}_{\mathcal{B}}(\beta), \tag{A.1.5}$$

where $\mathbb{I}_{\mathcal{B}}(\beta)=1$ if $\beta\in\mathcal{B}$ and zero otherwise. Here, $\mathcal{B}$ is the set where monotonicity and curvature conditions hold for the ODF. Additionally, we have:

$$\delta_0 \sim \mathcal{N}(\underline{\delta_0},\underline{h}^2\boldsymbol{I}_2), \tag{A.1.6}$$

$$\mathrm{vec}(\Delta) \sim \mathcal{N}(\underline{\delta},\underline{h}^2\boldsymbol{I}_4), \tag{A.1.7}$$

$$\gamma_1,\gamma_3 \sim \mathcal{N}(\underline{\gamma},\underline{h}^2),\gamma_1,\gamma_3\geq 0, \tag{A.1.8}$$

$$p(\Sigma) \propto |\Sigma|^{-(\underline{\nu}+1)/2}\exp\left\{-\frac{1}{2}\underline{A}\Sigma^{-1}\right\}, \tag{A.1.9}$$

where Σ denotes any of $\Sigma_v,\Sigma_\epsilon,\Sigma_\varepsilon$ and an underbar indicates prior parameters. In out baseline model we set:

$$\underline{\delta_0}=\mathbf{0},\underline{h}=1,\underline{\delta}=\mathbf{0},\underline{\gamma}=0,\underline{\nu}=0.1,\underline{A}=0.1\boldsymbol{I}. \tag{A.1.10}$$

We use the same scale parameter $\underline{h}$ mostly for convenience to economize on prior settings and make sensitivity analysis easier.

Appendix A.2 MCMC and Particle filtering

We use an advance in sequential Monte Carlo methods, known as the particle Gibbs (PG) sampler, see Andrieu et al. (2010). The algorithm allows us to draw paths of the state variables in large blocks. Particle filtering is a simulation-based algorithm that sequentially approximates continuous, marginal distributions using discrete distributions. This is performed by using a set of support points called ‘‘particles’’ and probability masses; see Creal (2012) for a review.

The PG sampler draws a single path of the latent or state variables from this discrete approximation. As the number of particles M goes to infinity, the PG sampler draws from the exact full conditional distribution. As mentioned in Creal and Tsay (2015, p. 339): “The PG sampler is a standard Gibbs sampler but defined on an extended probability space that includes all the random variables that are generated by a particle filter. Implementation of the PG sampler is different to a standard particle filter due to the ‘‘conditional’’ resampling algorithm used in the last step. Specifically, in order for draws from the particle filter to be a valid Markov transition kernel on the extended probability space, Andrieu et al. (2010) note that there must be positive probability of sampling the existing path of the state variables that were drawn at the previous iteration. The pre-existing path must survive the resampling steps of the particle filter. The conditional resampling step within the algorithm forces this path to be resampled at least once. We use the conditional multinomial resampling algorithm from Andrieu et al. (2010), although other resampling algorithms exist, see Chopin and Singh (2013).”

In this paper, we follow Creal and Tsay (2015). Suppose the posterior is $p(\theta, \lambda_{1:T}|\boldsymbol{y}_{1:T})$ where $\lambda_{1:T}$ denotes the latent variables whose prior can be described by $p(\lambda_t|\lambda_{t-1}, \theta)$. By definition, $\lambda_{1:T} = [\lambda_{i,1:T}, i = 1, \ldots, n]$.

In the PG sampler we can draw the structural parameters $\theta|\lambda_{1:T}, \boldsymbol{y}_{1:T}$ as usual, from their posterior conditional distributions. This is important because, in this way, we can avoid mixture approximations or other Monte Carlo procedures that need considerable tuning and may not have good convergence properties. As such posterior conditional distributions are standard, we omit the details and focus on drawing the latent variables.

Suppose we have $\lambda_{1:T}^{(1)}$ from the previous iteration. The particle filtering procedure consists of two phases.

Phase I: Forward filtering (Andrieu et al., 2010).

- Draw a proposal $\lambda_{it}^{(m)}$ from an importance density $q(\lambda_{it}|\lambda_{i,t-1}^{(m)}, \theta), m = 2, \ldots, M$.
- Compute the importance weights:

$$w_{it}^{(m)} = \frac{p(y_{it}; \lambda_{it}^{(m)}, \theta) p(\lambda_{it}^{(m)}|\lambda_{i,t-1}^{(m)}, \theta)}{q(\lambda_{it}|\lambda_{i,t-1}^{(m)}, \theta)}, m = 1, \ldots, M. \tag{A.2.1}$$

- Normalize the weights: $\widetilde{w}_{it}^{(m)} = \frac{w_{it}^{(m)}}{\sum_{m'=1}^{M} w_{it}^{(m')}}, m = 1, \ldots, M.$
- Resample the particles $\{\lambda_{it}^{(m)}, m = 1, \ldots, M\}$ with probabilities $\{\widetilde{w}_{it}^{(m)}, m = 1, \ldots, M\}$.

In the original PG sampler, the particles are stored for t = 1, . . . , T and a single trajectory is sampled using the probabilities from the last iteration. An improvement upon the original PG sampler was proposed by Whiteley (2010), who suggested drawing the path of the latent variables from the particle approximation using the backwards sampling algorithm of Godsill et al. (2004). In the forwards pass, we store the normalized weights and particles and we draw a path of the latent variables as we detail below (the draws are from a discrete distribution).

Phase II: Backward filtering (Chopin and Singh, 2013, Godsill et al., 2004).

- At time $t = T$ draw a particle $\lambda_{iT}^{*} = \lambda_{iT}^{(m)}$.
- Compute the backward weights: $w_{t|T}^{(m)} \propto \tilde{w}_{t}^{(m)} p(\lambda_{i,t+1}^{*} | \lambda_{it}^{(m)}, \theta)$.
- Normalize the weights: $\tilde{w}_{t|T}^{(m)} = \frac{w_{t|T}^{(m)}}{\sum_{m'=1}^{M} w_{t|T}^{(m')}}, m = 1, \ldots, M$.
- Draw a particle $\lambda_{it}^{*} = \lambda_{it}^{(m)}$ with probability $\tilde{w}_{t|T}^{(m)}$.

Therefore, $\lambda_{i,1:T}^{*} = \{\lambda_{i1}^{*}, \ldots, \lambda_{iT}^{*}\}$ is a draw from the full conditional distribution. The backwards step often results in dramatic improvements in computational efficiency. For example, Creal and Tsay (2015) find that $M = 100$ particles are enough. There remains the problem of selecting an importance density $q(\lambda_{it} | \lambda_{i,t-1}, \theta)$. We use an importance density implicitly defined by $\lambda_{it} = a_{it} + \sum_{p=1}^{P} b_{it} \lambda_{i,t-1}^{p} + h_{it} \xi_{it}$ where ξ_{it} follows a standard (zero location and unit scale) Student-*t* distribution with $\nu = 5$ degrees of freedom. That is, we use polynomials in $\lambda_{i,t-1}$ of order P. We select the parameters a_{it}, b_{it} and h_{it} during the burn-in phase (using $P = 1,2,3$) so that the weights $\{\tilde{w}_{it}^{(m)}, m = 1, \ldots, M\}$ and $\{\tilde{w}_{t|T}^{(m)}, m = 1, \ldots, M\}$ are approximately not too far from a uniform distribution. After some initial experimentation, we set $P = 2$.

Chopin and Singh (2013) have analyzed the theoretical properties of the PG sampler and proved that the sampler is uniformly ergodic. They also prove that the PG sampler with backwards sampling strictly dominates the original PG sampler in terms of asymptotic efficiency.

Alternatively, when the dimension of the state vector is large, we can draw $\lambda_{i,1:T}$, conditional on all other paths $\lambda_{-i,1:T}$ that are not path i. Therefore, we can draw from the full conditional distribution $p(\lambda_{i,1:T} | \lambda_{-i,1:T}, \boldsymbol{y}_{1:T}, \theta)$. To draw the parameters θ we use a random-walk Metropolis-Hastings algorithm which is tuned to provide acceptance rates close to 30% during the burn-in phase. We use 10^6 particles and $150{,}000$ MCMC iterations, the first $50{,}000$ of which are discarded to mitigate possible start-up effects. To impose (A.1.5) we define set $\mathcal{B}$ so that monotonicity and curvature hold at $0.25nT$ randomly selected data points in $\mathcal{B}$, one of which is given by the means of the data.[4] The restrictions are enforced using rejection sampling in the random-walk Metropolis-Hastings algorithm. The ODF is given by a translog specification, which is used widely in empirical research. Specifically, we have:

[4]It is known that if we enforce monotonicity and curvature at all data points then the ODF is no longer flexible. So a compromising solution has to be found in the sense that the restrictions hold at the means and a few other points.

$$y_M = \beta_0 + \beta'_1\tilde{y} + \frac{1}{2}\tilde{y}'\boldsymbol{\beta}_{11}\tilde{y} + \beta'_2 x + \frac{1}{2}x'\boldsymbol{\beta}_{22}x + \beta_3{}'z + \frac{1}{2}z'\boldsymbol{\beta}_{33}z \quad (A.2.2)$$
$$x'\boldsymbol{\beta}_{12}\tilde{y} + z'\boldsymbol{\beta}_{13}\tilde{y} + x'\boldsymbol{\beta}_{23}z,$$

where boldface letters denote matrices and a time trend is included in z along with the quasi-fixed input.

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