Correcting for productivity growth misspecification: a Local Likelihood estimation in global banking

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Abstract

Decomposing firm productivity has been challenging for some time. We propose a flexible functional form for total factor productivity that treats misspecification and endogeneity. The model also treats heteroscedasticity. Our productivity measure nests both the input distance function and output distance function. We provide details of a novel Local Likelihood estimation, a non-parametric technique, to estimate productivity which also has excellent finite-sample properties. In an empirical application, we measure bank productivity at the global level. Results show that productivity is correctly identified, and the flexibility of our methodology allows to estimate the impact of equity and non-performing loans on bank productivity. Technology has positively contributed to productivity. However, nonperforming loans, bank risk-taking and raising capital have had the opposite effect.

Keywords: Bank Productivity, misspecification, Local Likelihood estimation, global banking.

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1. Introduction

The accurate measurement and decomposition of firm performance are important for providing an understanding of the growth potential of micro foundation-based economies. However, to this day, the literature dealing with firm performance has provided no silver bullets. In this paper, we propose that it is worth bringing at the forefront the total factor productivity as a measure of firm performance. We argue that there could be a missing link in the operations management, which a well-specified measure of total factor productivity could provide.

The total productivity growth is by no means a new concept (Badunenko and Kumbhakar, 2017; Jaffry et al. 2013; Alfredo et al. 2013; Koutsomanoli and Mamatzakis, 2009;). Yet to date, no solution has been proposed on how to avoid misspecification errors when accurately measuring productivity growth. This is due to the complexity in measuring productivity, which involves multiple steps and is subject to endogeneity and misspecification issues. In addition, several critical points have been raised, mostly regarding parametric versus non-parametric estimations (Badunenko and Kumbhakar, 2017). These critical points relate to measuring firm productivity without misspecification. In this paper, we deal with the misspecification criticism. Moreover, we propose a novel model which deals with parametric versus non-parametric measurements and addresses endogeneity and heteroskedasticity issues. In an empirical application, we use our methodology in bank-specific data at the global level.

The number of papers that conduct a cross-country comparison on bank productivity is relatively small (for a review see Badunenko and Kumbhakar, 2017; and Ahmed and Bhatti

2020) though in recent years there has been a renewed interest on banking productivity measurement (e.g., Robin et al., 2019, Shair, et al., 2021; Bansal et al. 2022). Most of the studies examine productivity in banking in European countries (Koutsomanoli and Mamatzakis, 2009). However, recent studies also examine bank productivity in Pakistan (Shair et al. 2021), India (Bansal et al 2022) and Bangladesh (Robin et al. 2019). Regarding the methodology employed in banking productivity studies most of the empirical work (Berg et al., 1992; Alam, 2001; Orea, 2002; Cahnoto and Dermine, 2003; Tortosa-Ausina et al., 2008; Shair, et al., 2021) opt for non-parametric Data Envelopment Analysis (DEA) to estimate the Malmquist productivity index. However, starting from Kim and Weiss, (1989), Badunenko and Kumbhakar (2017), and Orea (2002) parametric approaches have gained some momentum (see also Boucinha et al., 2013). The productivity growth in these studies is examined through the implementation of a profit or cost function (Boucinha et al., 2013). Other studies focus on distance functions (Koutsomanoli and Mamatzakis, 2009), and there are some that employ Leontief technology (Alfredo et al. 2013). There are advantages and disadvantages of both non-parametric and parametric measures of productivity (for a review see Badunenko and Kumbhakar, 2017). To this date, the literature has not been settled as to which method is superior (see Badunenko and Kumbhakar, 2017; and Ahmed and Bhatti 2020).

This study contributes to bank productivity measurement using non-parametric estimation modelling while we leave for future statistical research to provide robustness analysis of non-parametric measurement vs parametric measurement. However, we deal with some of the criticism on parametric productivity measurement. In some detail, there is considerable criticism regarding the endogeneity bias inflicted in previous estimations of productivity growth (see Badunenko and Kumbhakar, 2017), whereas issues regarding misspecification and heteroscedasticity are not tackled. In addition, most of the previous studies provide little evidence on the decomposition of bank productivity (Koutsomanoli and Mamatzakis, 2009; Boucinha et al., 2013; Badunenko and Kumbhakar, 2017). This paper bridges a gap in the literature by dealing with misspecification, endogeneity issues and heteroscedasticity by providing a novel way of measuring and decomposing performance as measured by total factor productivity growth. Moreover, we propose a Local Likelihood function and a non-parametric estimation technique which has excellent finite-sample properties. This is useful for panel data analysis at bank level. Our methodology avoids any misspecification of the production functional and deals with endogeneity problems while it accounts for non-parametric heteroskedasticity in the underlying covariance matrix.

We apply our methodology at the global banking industry, there are several bank hypotheses, i.e., '*bad management', 'bad luck', 'moral hazard',* and *'agency theory'*, have been tested regarding bank performance and not productivity growth. According to the *'bad luck hypothesis'* (Berger and Mester, 2003), an exogenous event such as the financial crisis, can raise the level of problem loans of banks. Consequently, this increase of nonperforming loans can escalate risk and, which results in banks attempting to increase the monitoring and screening operations to manage the risk. However, such behaviour would also upsurge the resources used to monitor borrowers to secure the soundness of banks, particularly during periods of high financial distress. Therefore, under the "*bad luck hypothesis"*, an increase of nonperforming loans would raise bank costs and consequently reduce bank productivity.[1] Thus, our first hypothesis is as follows: an increase in non-performing loans could cause a reduction in bank productivity growth. Consistent with the '*bad management'* hypothesis,

[1] In fact, empirical work signals that there is consensus in the literature regarding the negative impact of problem loans on bank performance (see Koutsomanoli-Filippaki and Mamatzakis, 2009).

Wheelock and Wilson (2000) reported that banks with a higher probability of failure underperform compared to banks with a lower likelihood of default. We expect that those banks closer to failure (lower values of z-score) would divert more resources from daily operations towards screening operations to manage the soaring risk than banks with low default risk (higher values of z-score). Therefore, banks of high default risk would raise bank expenses and this in turn would reduce their productivity more than banks of low default risk. An increase in z-score could cause an increase in bank productivity growth. As above, there is no evidence between liquidity and productivity. The impact of liquidity ratio on bank performance has been reported.[2] However, there is no consensus in the literature whether the impact of liquidity on performance is positive or negative. Thus, our third hypothesis takes the following form: an increase in bank liquidity could cause an increase (a reduction) in bank productivity growth. In addition, in accordance with the *'moral hazard hypothesis'*, banks with a relatively low levels of capital (high capital risk) might be subject to managers' moral hazard incentives who would increase the risk-taking of banks by raising the riskiness of loan portfolios, which in turn would decrease bank performance.[3] Therefore, managers, who might act in conflict with shareholders, might raise the bank risk, which in turn would have a negative impact on productivity. Lastly, consistent with the '*agency cost hypothesis*' introduced by Jensen and Meckling (1979), an increase in leverage (decrease of capital) could act as a moderator of conflicts between shareholders and managers by means of the underlying

[2] On the one hand, there are several studies finding that a rise of banks' liquidity ratio (decrease of liquidity risk) increases bank performance. On the other hand, there are numerous studies reporting that increases of liquidity can reduce bank performance, as it is associated with high storage costs and low returns. This suggests that while liquid assets could reduce liquidity risk, they could also have a negative impact on bank performance due to high costs.

[3] Koutsomanoli and Mamatzakis (2009) also find that banks with more capital are more cost efficient than banks that hold less capital. On the other hand, as capital increases, the level of leverage that a bank holds decreases.

risk of an investment choice.[4] The fourth hypothesis is, thus, as follows: an increase in bank capital could cause an increase (reduction) in bank productivity growth.

This paper bridges a gap in the literature by dealing with misspecification, endogeneity issues and heteroscedasticity by providing a novel way of measuring and decomposing performance as measured by total factor productivity growth. Firstly, we propose a novel and advantageous methodology that avoids any misspecification of the underlying functional form of productivity growth by opting for bank specific data, which reveals the underlying components of bank productivity, namely nonperforming loans, equity, and technology. Primarily, we focus on the role of nonperforming loans that capture credit risk of individual banks, which can raise bank costs and could impair productivity. Secondly, our proposed model of productivity growth deals adequately with endogeneity by applying a flexible local likelihood function, a non-parametric methodology that also allows for hypotheses testing. Thirdly, we also account for non-parametric heteroskedasticity in the covariance matrix of the error term. Lastly, having derived productivity growth and its underlying decomposition to its main components, which are nonperforming loans, equity, and technology, we proceed with second stage regression analysis, which tests traditional bank hypotheses. We opt for fixed and dynamic panel analysis to reveal mainly the impact of risk but also liquidity and capital adequacy on productivity growth. This allows testing well-established hypotheses such as '*bad luck', 'bad management'*, *'moral hazard', and 'agency cost'*, which have been widely tested regarding the firm performance as measured by firm efficiency, but not by firm

[4] This is since managers do not have the incentive to take excessively risky investments, as their main priority is to secure the funding needed to service the outstanding debt. Also, increases in leverage would reduce the agency costs through the thread of liquidation that would put the salary and reputation of managers in danger (Williams, 1987).

productivity. We argue that productivity based on the micro-foundations measures more accurately the firm's performance.

Results show that productivity is correctly identified, and the flexibility of our methodology allows to estimate the impact of equity and non-performing loans on bank productivity. Technology has positively contributed to productivity. However, nonperforming loans, bank risk-taking and raising capital have had the opposite effect.

The rest of the paper is structured as follows. Section 2 presents the proposed methodology. Section 3 describes the global data set. Section 4 discusses our results and the panel regression analysis. Section 5 presents further second stage empirical analysis, whilst section 6 offers some final points and policy implications.

2. Methodology

2.1. Performance based on micro-foundations: a productivity framework.

The starting point of our analysis is a transformation function as $A \cdot F(X, Y, t) = 1$ where A is the efficiency parameter; X and Y are bank inputs and outputs, respectively, and t is time. This follows from standard duality theory. This function is flexible enough to allow nesting both the input distance function (IDF thereafter) and output distance function (ODF thereafter).

From such function, we derive performance as productivity growth (where *dot* above the variables would indicate growth) as:

$$Perf\dot{o}rmance = \sum_{m=1}^{M} R_m \dot{Y_m} - \sum_{k=1}^{K} S_k \dot{X_k} \quad (1)$$

where $R_m = \frac{P_m Y_m}{\sum_{m'=1}^{M} P_{m'} Y_{m'}}$, and $S_k = \frac{W_k X_k}{\sum_{k'=1}^{M} W_{k'} X_{k'}}$ are the shares of bank outputs and inputs, respectively and *m*, *k* are subscripts.

Totally differentiating with respect to time the transformation function we have:

$$\frac{dlnA}{dt} + \sum_{m=1}^{M} \frac{dlnF}{dlnY_m} \dot{Y_M} + \sum_{k=1}^{K} \frac{dlnF}{dlnX_k} \dot{X_k} + \frac{dlnF}{dt} = 0 \quad (2)$$

Suppose $\alpha = \dot{A}$, $\beta_k(X,Y,t) = \frac{\partial \ln F}{\partial \ln X_k}, k = 1,...,K$, $\gamma_m(X,Y,t) = \frac{\partial \ln F}{\partial \ln Y_m}, m = 1,...,M$, and $\delta(\cdot) = \frac{\partial \ln F}{\partial t}$ so that

$$\alpha + \sum_{m=1}^{M} \gamma_M \dot{Y_M} + \sum_{k=1}^{K} \beta_k \dot{X_k} + \delta = 0 \quad (3)$$

Adding and subtracting productivity we have:

$$\alpha + \sum_{m=1}^{M} \{\gamma_M + R_m\} \dot{Y_M} + \sum_{k=1}^{K} \{\beta_k - S_k\} \dot{X_K} + \delta = T\dot{F}P \ (4)$$

We consider an ODF and thereby we can express productivity growth as follows:

$$\dot{Y}_1 = \beta_0\left(\ln \tilde{Y}, \ln X, t\right) + \sum_{k=1}^{K} \beta_k\left(\ln \tilde{Y}, \ln X, t\right) \dot{X}_k + \sum_{m=2}^{M} \gamma_m\left(\ln \tilde{Y}, \ln X, t\right) \dot{\tilde{Y}}_m - u, \quad (5)$$

where $\tilde{Y}_m = Y_m / Y_1, m = 2,...,M$, and $u = \mathring{A}$, which can be treated residually.

If we estimated the above equation non-parametrically using kernel-based functions, we would ignore endogeneity problems with $\Psi = \left[\ln \tilde{Y}', \ln X'\right]'$ and issues related to finite-sample properties. To account for such problems, we pair the equation with a reduced form, in the spirit of limited information maximum likelihood (LIML) estimation:

$$\Psi = \Pi(z,t) + U_*, \quad (6)$$

Where $\Pi(\cdot)$ is a non-parametric functional form, z is a vector of instruments[5], and U_* is a vector error term.

So, herein we employ the Local Likelihood estimation, a non-parametric technique, to estimate (5) and (6), which also have excellent finite-sample properties. For details of the Local Likelihood estimation and the non-parametric technique see the Appendix.

The proposed herein methodology has certain advantages, primarily because we avoid any misspecification of the functional forms in (5) and (6). In addition, endogeneity problems are considered when estimating (5) and thereby productivity growth is not biased. We also account for non-parametric heteroskedasticity in the covariance matrix of the error term $U=\left[u,U_*'\right]'$. By doing so we can model the residual component, for example how variances and covariances depend on certain pre-determined variables, which are present in the Local Likelihood estimation. To the best of our knowledge, all other techniques, simply assume that this is an IID component.

Thus, productivity is defined as:

$$TFP=\frac{\sum_{m=1}^{M}P_mY_m}{\sum_{k=1}^{K}W_kX_k}. \quad (7)$$

[5] Natural instruments are all available at relative prices.

2.2. The productivity *growth decomposition*

Given estimates from the Local Likelihood procedure, productivity growth can be computed using the estimated local coefficients. The computed productivity growth is robust to functional form misspecification, endogeneity problems with the inputs and outputs, and heteroskedasticity of the error terms and reduced form.

To relate productivity growth to certain determinants, say *D*, we opt for the following form:[6]

$$T\dot{F}P = D'\lambda + \xi \quad (8)$$

where λ is a vector of parameters and ξ is a classical error term.

We argue that the second-stage regression (which requires a full bootstrap) is not needed provided the variables in *D* are a subset of those in *Z* from equation (2) in the Appendix. If this is so, one can consider the derivatives:

$$\psi(\mathrm{Z}) \triangleq \frac{\partial T\dot{F}P}{\partial \mathrm{D}}, \quad (9)$$

which are available if we have the derivatives $\frac{\partial \beta(Z)}{\partial D'}$ from the Local Likelihood estimation (see Appendix), we remind that $\beta(Z)$ is a subset of the entire parameter vector, $\theta(Z)$.[7]

It is worth noting that there are several prior studies of alternative productivity measurements such as non-parametric productivity indices like Malmquist or Luenberger indexes compared to our parametric measurement of TFP in Equation (8) (see e.g., Beveren, 2012; Ahmed and Bhatti, 2020; and Shair, et al., 2021).

[6] In the empirical section, *D* includes non-performing loans, equity, and technology.
[7] The three key underlying components of productivity growth are non-performing loans, equity, and technology. Non-performing loans' role is key to productivity growth, as failure would have detrimental effects for bank survival. Along these lines, equity is also of important. Last, technology is key to productivity growth and yet no study has examined its significance for the banking industry despite substantial steps towards innovation in banking.

3. An Application to global banking sector

We start the construction of our sample by including all the banks in the Bankscope database.[8] Our final sample is an unbalanced dataset that includes 17399 observations for 31 advanced countries, 7130 observations for 35 emerging countries, and 2471 observations for 40 developing countries. The classification of countries- in various groups is based on the IMF World Economic Outlook of April 2014. All the bank-specific financial variables are obtained in thousands of Euros from the Bankscope database. Data for country-level variables are collected from the World Bank Indicators database.

We follow the *'intermediation approach'* (Sealey and Lindley**,** 1977) to define input prices and outputs for our ODF function used to estimate productivity growth, in line with Koutsomanoli-Filippaki and Mamatzakis (2009). The two outputs are net loans (y_1) and other earning assets (y_2). There are three input prices: price of fund (w_1), which is the ratio of total interest expenses to total customer deposits; price of physical capital (w_2) defined as other operating expenses over fixed assets; and price of labour (w_3), which is calculated as personnel expenses divided by total assets. Equity (E) is included as a netput (Berger and Mester, 2003), and nonperforming loans (NPL) are considered as negative quasi-fixed inputs. The statistical summary of these variables is provided in Table 1 for each country-group. Interestingly, we notice that the average amount of nonperforming loans in advanced economies' banking industries is almost twice than that in emerging economies and eight times than that in developing economies.

[8] We exclude banks for which: (i) we had less than three observations over time; (ii) we had no information on the country-level control variables; (iii) we had no information of non-performing loans. Please note that our sample period if dictated by measurement issues and the discontinuity of the data provider.

Table 1. Descriptive statistics of variables.

	Advanced economies	Emerging economies	Developing economies
Variables	**Mean**	**Mean**	**Mean**
Bank outputs and input prices			
Total assets	17951329	9659393	1255046
Total costs	644465	441730	82203
Net loans	9036183	5152601	626854
Other earning assets	7354650	3796769	449156
Price of fund	2.4624	8.9291	5.7072
Price of physical capital	201.4653	415.9367	140.6929
Price of labour	1.1191	2.5210	2.1607
Non-performing loans	336033	179375	48030
Equity	1032482	754589	133758
Banks specific and control variables			
Z-score	0.6965	0.8081	0.8443
Capital ratio	8.3162	14.7165	13.0949
Fees	0.4040	1.1228	1.2440
Liquidity ratio	15.1238	26.3849	23.4960
Securities	30.0283	40.3673	32.3383
GDP per capita	10.5394	8.3914	7.6975
Inflation	1.2208	10.4568	7.6531
Population density	242.0769	93.6112	226.5159
Market size	28.5054	25.5037	19.4081

Notes: The Table reports the average values of variables used for estimation in each group of economies for the period 2001 to 2013. Total assets; total costs = total interest expenses + overheads; net loans = gross loans – nonperforming loans; other earning assets; non-performing loans; equity are reported in thousand USD. Price of fund = total interest expenses/total customer deposits; price of physical capital = other operating expenses/fixed assets; price of labour = personnel expenses/total assets. Z-score= (1+ROE)/ (Standard Deviation of ROE); Size= natural logarithm of total assets; Capital ratio = equity over total assets; Liquidity ratio= liquid assets over total assets; Investment Banking Fees= net fees, commission, and trading income over total assets; Securities/TA= total securities over total asset. As country variables we employ GDP per capita; Inflation; Population density is the number of people per square kilometre; Market size= value of total shares traded on the stock market exchange.

We characterise bank risk using three measures widely employed in the existing literature. Firstly, we employ the z-score, which measures bank's individual insolvency risk. This is defined as *z-score* = $(1+ ROE)/\sigma_{ROE}$, where ROE is the return on equity and σ_{ROE} is the estimate of standard deviation of ROE. In our regressions, we employ the natural logarithm of z-score because it is largely skewed. The z-score has been employed in several recent banking studies (Lepetit et al., 2008) to measure the distance of a bank from default. Secondly, we use the ratio of liquid assets over total assets. Liquid assets are the sum of trading assets, loans, and advances with maturity less than three months. Therefore, liquidity ratio denotes the amount of liquid assets that a bank holds, and thus low values of liquidity ratio signify high liquidity risk for a bank. Thirdly, we also use the ratio of equity over total assets as a proxy for capital risk as used in previous studies (Lepetit et al., 2008). The higher the capital ratio of an individual bank, the lower the capital risk, as equity could work as a buffer for banks against financial turmoil. Table 1 includes some descriptive statistics of the three measures of bank risk employed in our analysis. Interestingly, our data reveal that banks in advanced countries are closer to default than banks in emerging and developing countries, as z-score (0.6965) of the former is lower than the z-score values of the latter (0.8081 and 0.8443). Similarly, Table 1 shows that banks in emerging and developing countries are more capitalized and have more liquidity than banks in developed economies.

To capture other potential determinants of productivity growth, we use several bank-specific and country-level control variables. Table 1 reports country-group averages of the control variables used in the panel data regressions. Regarding bank-specific variables, we use the natural logarithm of total assets to proxy for the size of banks (Berger and Mester, 2003). We further employ a non-interest income ratio, estimated by the sum of the net fees and commissions over total assets, and securities over total assets ratio to proxy for the non-lending activities of banks. Moreover, we control the impact of financial conditions and include a crisis dummy, which takes the value of 1 for the years between 2007 and 2009, and 0 otherwise. Following several cross-country studies that examine bank performance (Berger and Mester, 2003), we also account for cross-country differences in macroeconomic and structural conditions. To control the general level of economic development, we use real GDP per capita. We also use inflation to capture the monetary stance and the value of total shares traded on the stock market exchange to control the market size of an economy. Lastly, we use population density to proxy the demand density in each country.

4. Empirical Results

4.1. Productivity elasticities with respect to nonperforming loans and equity

The flexibility of our methodology allows to estimate the impact of quasi-fixed inputs on bank productivity. To this end, we report the elasticities of productivity with respect to nonperforming loans and equity in the Table 2. In general, the average productivity elasticity of nonperforming loans is negative across all economies and note that is higher than that of equity. The productivity elasticity with respect to nonperforming loans is the highest value at -0.324 for emerging economies compared to -0.211 (-0.217) for advanced (developing) economies. Developing economies report an elasticity of productivity with respect to equity at -0.219, the highest among the three groups of economies, insinuating that raising equity capital reduces productivity. It is worth noticing that there is some variability in elasticities over time with the productivity elasticity of equity reporting positive values across all economies during the financial crisis from 2007 to 2010. Thus, during crisis, raising equity appears to boost productivity. On the other hand, nonperforming loans, a quasi-fixed input, asserts a negative effect on productivity over the whole sample. After the global financial crisis, the productivity elasticity with respect to nonperforming loans subdues, yet remains clearly negative.

Table 2. The elasticity of productivity with respect to nonperforming loans and equity.

	Advanced economies		Emerging economies		Developing economies	
Year	**Equity**	**NPLs**	**Equity**	**NPLs**	**Equity**	**NPLs**
2001	-0.21	-0.142	-0.233	-0.155	-0.314	-0.125
2002	-0.32	-0.151	-0.127	-0.161	-0.322	-0.129
2003	-0.373	-0.192	-0.017	-0.213	-0.441	-0.117
2004	-0.515	-0.181	-0.034	-0.335	-0.517	-0.135
2005	-0.532	-0.177	-0.054	-0.371	-0.522	-0.137
2006	-0.303	-0.125	-0.061	-0.421	0.107	-0.182
2007	0.221	-0.216	0.077	-0.551	0.001	-0.338
2008	0.227	-0.227	0.093	-0.525	0.225	-0.441
2009	0.245	-0.313	0.091	-0.533	0.313	-0.415
2010	0.325	-0.315	0.045	-0.471	0.329	-0.481
2011	-0.042	-0.237	-0.081	-0.223	-0.466	-0.102
2012	-0.441	-0.212	-0.313	-0.125	-0.613	-0.111
2013	-0.482	-0.252	-0.417	-0.127	-0.627	-0.113
2000-2013	-0.169	-0.211	-0.079	-0.324	-0.219	-0.217

Notes: The Table reports the elasticity of productivity growth with respect to equity and nonperforming loans (NPLs) for each group of economies. The figures are averaged per year. Figures may not sum due to averaging and rounding.

4.2. Productivity growth over time.

The average bank productivity growth over time for each country-group is reported in Table 3. The strongest growth over 13 years is found for advanced economies at 0.07. Emerging and developing economies experience negative productivity growth at -0.01 and -0.086 respectively.[9] In 2002, all three groups of economies experience negative bank productivity growth, with the largest value found for advanced economies at an average of -0.41. This finding could reflect the impact of the stock market downturn across the US, Canada, Asia, and Europe. Since advanced economies were at the centre of the crisis, the destructive effect was more pronounced for those economies.

Table 3. Average productivity growth across the world.

[9] Detailed discussion is provided in section 5.3.

Year	Advanced economies	Emerging economies	Developing economies
2001	0.520	0.110	0.150
2002	-0.410	-0.150	-0.210
2003	-0.320	-0.150	0.260
2004	0.140	0.020	0.320
2005	0.530	0.310	0.150
2006	0.410	0.220	0.350
2007	-0.170	-0.250	-0.320
2008	-0.220	-0.350	-1.200
2009	-0.370	-0.440	-1.300
2010	0.140	0.030	0.170
2011	0.210	0.140	0.200
2012	0.200	0.170	0.150
2013	0.190	0.210	0.160
2000-2013	0.070	-0.010	-0.086

Notes: The Table reports average productivity growth every year for each group of economies. Values may not sum due to averaging and rounding.

After 2002, bank productivity growth increased across all groups, reaching its peak in 2005. The strongest growth is found for banks in advanced economies at 0.53 followed by emerging economies at 0.31.[10] The productivity growth in emerging economies could be related to the performance of economies such as Brazil, China, and India, which contribute significantly to the global economy (Jaffry, et al. 2013). China and India, which account for one-third of the world population, have grown rapidly. From the 1990s to 2005, their GDP per capita had increased to nearly 6% for India and more than 9% for China (Jaffry et al. 2013).

Alas, productivity growth dropped dramatically in 2007. During the 2007-2009 global financial crisis, we find high volatility in bank productivity growth in advanced economies, while a fall in productivity growth is also identified for the other two country-groups. Bank

[10] Behind this strong performance could be the rapid credit expansion to the private sector in the Central and Eastern European economies between 2004 and 2006. The rise of bank lending in advanced and emerging countries from 1965-2005, which preceded the crisis.

productivity growth dramatically declined to -0.37 (-0.44) in 2009 in advanced (emerging) economies. Some variability, resembling a roller coaster movement, in productivity growth is evident for banks in developing economies from 2009 onwards. Advanced economies also witnessed a similar pattern in bank productivity growth in 2011-2013. Advanced and developing economies show a double dip in their productivity growth in recent years, though not as severe as during the financial crisis, whereas emerging economies demonstrate a somewhat relatively stable performance. Our results suggest that bank productivity growth in emerging economies perform more consistently in recent years than bank productivity in advanced economies.

Tables 4, 5, and 6 report the productivity growth for the banking industry in advanced, emerging, and developing economies respectively. Among 31 advanced economies, banks in Greece, Italy, and Ireland are the least productive with negative average growth at -0.76, -0.7, and -0.65, respectively. Japan and the US, the two most developed economies in Asia and America, have bank productivity growth of 0.47 and 0.55 respectively. Productivity growth in Japan appears to have benefited from an extensive and successive restructuring of the sector following the banking crisis in late 2000. Regarding the USA, previous finding for bank productivity (see Feng and Serletis, 2010) report an average productivity growth at around 0.5% for large US banks from 1997 to 2010. The most productive group is constituted from economies whose banking systems perform productivity growth greater than 0.1, with Germany reporting the highest value at 0.72.

Table 4. Average productivity growth per country: advanced economies.

Country	Productivity growth	Country	Productivity growth
Australia	0.43	Japan	0.47
Austria	0.15	Latvia	0.02
Belgium	-0.13	Malta	0.03
Canada	0.51	Netherlands	0.51
Cyprus	-0.52	New Zealand	0.37
Czech Republic	0.13	Norway	0.11
Denmark	0.34	Portugal	-0.57
Finland	0.15	Singapore	0.19
France	0.33	Slovakia	0.1
Germany	0.72	Slovenia	0.08
Greece	-0.76	Spain	-0.61
Hong Kong	0.32	Sweden	0.17
Ireland	-0.65	Switzerland	0.21
Israel	0.37	Taiwan	0.1
Italy	-0.75	United Kingdom	0.31
USA	0.55		

Notes: The Table reports annual average productivity growth for each group of economies for the period 2001 to 2013. Values may not sum due to averaging and rounding.

The disparity between productivity growths of banks in emerging countries is larger than that in advanced economies. Overall, the fastest growing banking systems within emerging countries have considerably more productivity growth scores than those in advanced economies. The annual average growth of these banking industries is close to -0.01. This group consists of a mixture of geographic regions. In descending order of positive bank productivity growth, it includes Philippines, India, Poland, United Arab Emirates, Saudi Arabia, South Africa, Qatar, Colombia, and China. Indian banks perform strongly insinuating that they are quite progressive (Jaffry et al. 2013).[11] Chinese banks also perform well, with an average growth at 0.253. A low score of bank productivity growth is reported for Argentina at -0.171. This may not come as a surprise as Argentina has been at financial turmoil since the currency crisis in 2002.

Table 5. Average productivity growth per country: emerging economies.

[11] The Authors disaggregate the Luenberger Productivity Indicator of productivity growth into technical change and efficiency change. The components of productivity growth are obtained from the Weighted Russell directional distance model. Their results also emphasize the non-performing loan problem in shifting the production frontier down.

Country	Productivity growth	Country	Productivity growth
Albania	-0.151	Malaysia	-0.54
Angola	-0.32	Namibia	-0.32
Argentina	-0.171	Nigeria	-0.43
Azerbaijan	-0.142	Oman	-0.91
Bahrain	0.114	Pakistan	-0.14
Bolivia	-0.32	Peru	-0.22
Bosnia and Herzegovina	-0.17	Philippines	0.82
Brazil	-0.18	Poland	0.55
Bulgaria	0.18	Qatar	0.32
Chile	0.14	Romania	-0.22
China	0.253	Russian Federation	-0.1
Colombia	0.32	Saudi Arabia	0.43
Hungary	0.26	South Africa	0.35
India	0.71	Thailand	-0.44
Indonesia	-0.32	Trinidad and Tobago	-0.17
Kazakhstan	-0.101	Turkey	-0.2
Kuwait	0.122	United Arab Emirates	0.51
Venezuela	-0.10		

Notes: The Table reports annual average productivity growth for each group of economies for the period 2001 to 2013. Values may not sum due to averaging and rounding.

Similarly, large discrepancies of bank productivity growth exist in developing economies (see Table 6). Banking systems in Armenia, Bangladesh, Belarus, Benin, Botswana, Cambodia, Egypt, Botswana, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Georgia, Ghana, Honduras, Nepal, Mozambique, Senegal, Swaziland, Tanzania, Uganda, and Ukraine appear to be less productive with negative average productivity growth. The largest growth is reported for banks in Croatia, Bermuda, Jamaica, and FYROM with an average productivity growth of around 0.3.

Table 6. Average productivity per country: developing economies

Country	Productivity growth	Country	Productivity growth
Andorra	0.17	Jordan	0.15
Armenia	-0.19	Kenya	0.032
Bahamas	0.16	Lebanon	0.03
Bangladesh	-0.42	Lithuania	0.15
Belarus	-0.14	FYROM	0.33
Benin	-0.12	Mauritius	0.016
Bermuda	0.32	Moldova Republic	0.022
Botswana	-0.01	Mozambique	-0.33
Cambodia	-0.15	Nepal	-0.22
Costa Rica	0.18	Panama	0.23
Croatia	0.35	Senegal	-0.25
Dominican Republic	-0.12	Serbia	0.017
Ecuador	-0.14	Sri Lanka	0.25
Egypt	-0.32	Swaziland	-0.36
El Salvador	-0.3	Tanzania United	-0.32
Ethiopia	-0.15	Uganda	-0.41
Georgia	-0.35	Ukraine	-0.54
Ghana	-0.44	Uruguay	-0.03
Honduras	-0.33	Vietnam	0.14
Jamaica	0.32	Zambia	0.22

Notes: The Table reports annual average productivity growth for each group of economies for the period 2001 to 2013. Values may not sum due to averaging and rounding.

It is worth noting that across the six regions, a few banks in the Commonwealth of Independent States appear to be the most productive with an annual average growth at 0.3.

4.3 Productivity Growth Decomposition

Next, we turn to the contribution of each component in productivity growth, we perform a productivity growth decomposition as shown in Table 7. The components of productivity growth are the impact of technology and the effects of nonperforming loans and equity. Nonperforming loans considerably impair bank productivity growth in all three country-groups, especially in emerging countries (-0.089 on average). During the global financial crisis (2008-2009), the destructive effect of nonperforming loans on bank productivity growth was evident in all groups, about -0.13, -0.42, and -0.17 for advanced, emerging, and developing economies, respectively. However, we also observe some different patterns on the effect of nonperforming loans over time apart from the crisis period. In developing economies, nonperforming loans exhibited an even positive contribution to bank productivity growth in 2004, but thereafter is negative. In emerging economies, nonperforming loans improve productivity growth from 2002 to 2004, though anaemically. However, since 2005, nonperforming loans constantly harm bank productivity growth in emerging economies. After the financial crisis in 2009, the impact of nonperforming loans dropped from -0.514 in 2009 to -0.015 in 2011, followed by some fluctuation until 2013. On the other hand, bank productivity growth in advanced economies is consistently impaired by nonperforming loans across the whole period and in 2008 to 2009. Overall, the bank productivity across all three economies is impaired by the impact of nonperforming loans at about -0.14, -0.1 and -0.4, respectively.

Table 7. Productivity growth decomposition to equity, NPLs and technology (*t*).

	Advanced			**Emerging**			**Developing**		
	Equity	**NPLs**	***t***	**Equity**	**NPLs**	***t***	**Equity**	**NPLs**	***t***
2001	-0.120	-0.150	0.010	-0.030	-0.015	-0.042	-0.150	-0.120	0.110
2002	-0.130	-0.170	0.010	-0.030	0.018	-0.045	-0.170	-0.010	0.170
2003	-0.150	-0.180	0.020	-0.040	0.240	-0.017	-0.090	-0.100	0.190
2004	-0.140	-0.150	0.030	-0.090	0.320	-0.019	-0.110	0.003	0.210
2005	-0.170	-0.190	0.030	-0.012	-0.550	0.150	-0.065	-0.140	0.230
2006	-0.190	-0.210	0.410	-0.140	-0.810	0.150	-0.020	-0.210	0.125
2007	0.210	-0.250	0.470	0.150	-0.970	0.810	-0.030	-0.350	0.125
2008	0.500	-0.144	0.510	0.170	-0.331	0.151	0.220	-0.393	0.160
2009	0.320	-0.122	0.717	0.320	-0.514	0.174	0.150	-0.383	0.035
2010	-0.330	-0.045	0.571	-0.170	-0.810	0.440	-0.105	-0.105	0.045
2011	-0.240	-0.041	0.122	-0.030	-0.150	0.320	-0.105	-0.130	0.032
2012	-0.190	-0.010	0.330	-0.070	-0.180	0.210	-0.066	-0.150	0.150
2013	-0.050	-0.150	0.101	-0.020	-0.210	0.150	-0.060	-0.180	0.155
2000-13	-0.052	-0.139	0.256	0.001	-0.089	0.187	-0.046	-0.174	0.134

Notes: The Table reports the average effects of equity, nonperforming loans, and technological change on productivity growth for each group of economies. Values may not sum due to averaging and rounding. NPLs: Nonperforming loans and *t* is technology.

Interestingly, our findings also indicate that equity imposes a negative impact on bank productivity growth at -0.05 and -0.046 on average in advanced and developing economies respectively, whilst for emerging economies the contribution is positive but very small in magnitude. As discussed in section 5.1, the inclusion of equity raises total costs for all banks in our sample, for banks in developing economies. The reported results in Table 7 demonstrate that during crisis, an increase in equity would support bank productivity growth as it acts as a reassurance to the markets that banks would enhance their capitalisation. However, as our results demonstrate, a continuous raise in capital through equity would not contribute to bank productivity growth.

Perhaps not surprisingly, bank productivity growth is driven by technology. The impact of technological change has been increasing over time across the world, with the strongest contribution of technology on productivity growth reported for banks in advanced economies at 0.25 on average. These findings are in line with Alfredo et al. (2013) for Spanish banks. It is worth noticing that this strong contribution increased from 2009 to 2013, and supports the fact that banks moved away from the negative spirals observed during the financial crisis. In general, technical progress also positively contributes to bank productivity growth in emerging and developing economies, though its magnitude is considerably less than that in advanced economies, suggesting that there is significant room for technological improvement in those economies.

Overall, bank productivity growth decomposition reveals the detrimental impact of nonperforming loans across the world. Policy intervention, at bank and economy wide level, towards scaling down such loans should assist raising productivity growth. Also, we show that when it comes to productivity, resorting to equity capital would not be ideal after the financial crisis.

5. Second Stage Analysis

5.1. Fixed effect panel regressions

In this section, we examine the impact of various control variables on productivity growth as derived from the previous section. Our first identification to test the main bank hypotheses, i.e., *'bad luck hypothesis', 'bad management hypothesis',* follows:

$$T\dot{F}P_{i,t} = a_0 + a_1 \sum_{j=1}^{n} (Risk)_{i,t} + a_2 (CRS)_t + b_j \sum_{j=1}^{n} (Control)_{i,t} + e_{i,t} \qquad (27)$$

where $T\dot{F}P_{i,t}$ is the productivity growth of a bank *i* at a time *t*; $Risk$ is a vector of bank risk variables; CRS is a crisis dummy that takes the value of 1 for the 2007-2009 years and 0 otherwise; $Control$ is a vector of bank-specific and country-level control variables; $e_{i,t}$ is the error term.

Our results reveal that higher default risk (lower z-score values) exerts a negative impact on bank productivity for all three country-groups considered in our sample. We observe a highly positive impact of z-score on bank productivity at the 1% significance level for advanced, emerging, and developing countries (Table 8, Models 1, 2 and 3). Overall, the above findings confirm the *'bad luck hypothesis'*, suggesting that banks with higher default risk (lower values of z-score) divert more resources from day-to-day activities to screening and monitoring operations, which in turn can increase bank operational costs and consequently reduce bank productivity, compared to banks of lower default risk (higher values of z-score).

Table 8. Fixed effects results for z-score, capital and liquidity as bank productivity growth determinants.

	Fixed effects		
Variables	Advanced Economies (1)	Emerging Economies (2)	Developing Economies (3)
Z-score	0.017***	0.042***	0.031***
	(0.003)	(0.004)	(0.003)
Size	0.151***	0.115***	0.051***
	(0.015)	(0.007)	(0.003)
Capital ratio	-0.021***	-0.006***	-0.004**
	(0.002)	(0.001)	(0.001)
Liquidity ratio	0.617***	0.521***	0.388***
	(0.021)	(0.012)	(0.013)
Fees	-0.008	0.021***	-0.021***
	(0.002)	(0.003)	(0.005)
Securities	0.032*	0.007***	0.022
	(0.002)	(0.001)	(0.011)
Crisis	-0.014	-0.032***	-0.027
	(0.001)	(0.002)	(0.005)
GDP per capita	-0.033***	-0.015***	-0.017***
	(0.012)	(0.001)	(0.003)
Inflation	-0.001	-0.003*	-0.008***
	(0.001)	(0.002)	(0.001)
Population density	0.001	0.001	0.002***
	(0.001)	(0.001)	(0.001)
Market size	0.025***	0.017**	0.023
	(0.002)	(0.002)	(0.004)
Country effects	Yes	Yes	Yes
Time effects	Yes	Yes	Yes
F-test	47.81***	49.20***	31.12***
Observations	17399	7130	2471
R-squared	0.295	0.122	0.214
Number of banks	2870	1455	450

Notes: The Table reports the regression results based on a fixed effect model over the period 2001 to 2012. The dependent variable is the productivity growth. As bank-specific independent variables we employ: z-score= (1+ROE)/ (Standard Deviation of ROE); Size= natural logarithm of total assets; Capital ratio = equity over total assets; Liquidity ratio= liquid assets over total assets; Investment Banking Fees= net fees, commission and trading income over total assets; Securities/TA= total securities over total asset. As country variables we employ: GDP per capita; Inflation; Population density; Market size= value of total shares traded on the stock market exchange; Crisis dummy that takes the value of 1 for the 2007-2009 period and zero otherwise. For bank-specific variables we use FITCH Bankscope database while for country variables we use World Development indicators from World Bank. To avoid collinearity problems with the selected variables, we first analyse correlations of all the selected variables. We check that there is not a high level of correlation between the variables used in the models. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. These are second-stage regressions with bootstrap standard errors in parentheses. We have used 5,000 bootstrap replications.

Regarding the impact of liquidity ratio on bank productivity growth, we observe that an increase of liquidity asserts a positive impact on bank productivity for all the three groups in our sample (advanced, emerging, and developing countries). The effect is positive and significant at the 1% level (Table 8, Model 1, 2 and 3). The results clearly reveal the positive impact of liquidity on bank productivity, again consistent with the *"bad management hypothesis"*. Banks with higher liquidity (lower liquidity risk) can perform better than banks of lower liquidity (higher liquidity risk). Here, we provide evidence that liquidity would also raise bank productivity growth. Our finding is important, particularly over periods of high liquidity constraints, such as in financial crisis, when banks are ardent to source funding to cope with the excessive risk.

Turning our attention to the impact of capital on bank productivity growth, we find that there is a negative effect of equity over total assets on bank productivity at the 1% significance level for advanced and emerging countries (Table 8, Models 1 and 2) and at the 5% for developing countries (Table 8, Model 3). We recall the results of productivity decomposition, which show that equity restraints productivity growth. This effect is reaffirmed by the fixed effect analysis, as the capital ratio has a statistically significant negative impact on productivity growth in line with the *agency cost hypothesis'* (Jensen and Meckling, 1979). A decrease of leverage that increases the equity over total assets, would raise agency costs between shareholders and managers. Under this hypothesis, managers would have incentives to increase the risk-taking of banks due to the absence of the liquidation threat (Williams, 1987) that exists when a bank increases its debt (decreases its capital) and this, in turn, would reduce their productivity growth.

Regarding the bank-specific control variables, we find that size has a positive and significant impact on bank productivity at the 1% level for all the three groups of economies (Table 8, Models 1, 2 and 3), suggesting that large banks, particularly in advanced and emerging markets, would benefit from economies of scale. In addition, we find that the fee ratio is positively associated to productivity growth in emerging economies, while is negatively related to productivity growth for banks in developing economies. The reason could be that banks in developing economies resort to high interest income and perform worse than banks with relatively low-interest income. Given that interest income is more volatile than non-interest income, putting the emphasis on interest income can raise bank risk, which in turn can reduce productivity growth. On the other hand, a rise of fee-income for banks in emerging countries has a positive effect on bank productivity. Note that most banks in these countries have a mixed business line, yet they focus primarily on interest income operations. Similarly, securities over total assets ratio have a statistically significant and positive impact on productivity growth for banks in advanced and emerging countries (Table 8, Models 1 and Model 2). In addition, as expected, weak financial conditions, e.g., the global financial crisis, dampens bank productivity particularly in emerging countries (Table 8, Model 2).

With respect to country-level control variables, we find that GDP per capita exerts a positive and significant impact on bank productivity growth in all economies (Table 8, Models 1, 2 and 3). An increase in GDP per capita could raise bank activity and productivity. There is a negative relationship between bank productivity growth and inflation for emerging and developing countries (Table 8, Models 2 and 3). This result indicates that banks in an inflationary environment would face higher uncertainty to manage, for example, their operating expenses including bank salaries. Inflation pressures would harm bank productivity growth. We observe a positive and significant relationship between population density and bank productivity growth (see Table 8, Model 3) in developing economies, in line with gravity-type models. Lastly, market size asserts a positive impact on productivity growth in advanced and emerging economies (Table 8, Models 1 and 2).

5.2. Dynamic results

We also opt for an identification that employs a dynamic panel analysis as follows:

$$T\dot{F}P_{i,t} = a_0 + \beta T\dot{F}P_{i,t-1} + a_1 \sum_{j=1}^{n}(Risk)_{i,t} + a_2(CRS)_t + b_j \sum_{j=1}^{n}(Control)_{i,t} + e_{i,t} \quad (28)$$

where $T\dot{F}P_{i,t}$ is the productivity growth of a bank *i* at a time *t*; $Risk$ is a vector of bank risk variables; CRS is a crisis dummy that takes the value of 1 for the 2007-2009 years and 0 otherwise; $Control$ is a vector of bank-specific and country-level control variables; $e_{i,t}$ is the error term.

For the dynamic panel estimation, we employ the two-step system GMM estimator (). Moreover, in the regressions we set all bank-specific variables as endogenous while all the country-level control variables are strictly exogenous. Our dynamic panel estimations confirm our fixed effect specifications and report a positive association between productivity growth and z-score (Table 9, Models 1 and 2). We also document a positive association between liquidity and productivity growth for all banks in the sample (Table 9, Models 1, 2 and 3). Several previous studies observe a positive relationship between liquidity and bank performance. Furthermore, the dynamic panel specifications show that capital is negatively associated to productivity growth, however, it is significant only for emerging countries (Table 9, Model 2).

Table 9. GMM dynamic panel results for z-score, liquidity, and capital as bank productivity growth determinants.

Variables	Advanced Economies	Emerging Economies	Developing Economies
Lag productivity	0.231***	0.055***	0.103***
	(0.015)	(0.011)	(0.012)
Z-score	0.083***	0.071***	0.023
	(0.010)	(0.011)	(0.014)
Size	0.015	0.031***	0.0437**
	(0.007)	(0.007)	(0.012)
Capital ratio	-0.005	-0.007*	-0.009
	(0.001)	(0.001)	(0.002)
Liquidity ratio	0.313**	0.725***	0.441**
	(0.015)	(0.028)	(0.032)
Fees	-0.004	-0.014***	-0.021***
	(0.015)	(0.001)	(0.002)
Securities	0.332**	0.425	0.323
	(0.008)	(0.0120)	(0.017)
Crisis	-0.012	-0.021**	-0.047
	(0.003)	(0.014)	(0.011)
GDP per capita	0.001	0.0022***	0.003
	(0.001)	(0.003)	(0.001)
Inflation	-0.007***	-0.005***	-0.004**
	(0.001)	(0.002)	(0.003)
Population density	0.001	-0.001	0.001
	(0.000)	(0.000)	(0.000)
Market size	0.0025***	0.013**	0.0034
	(0.001)	(0.001)	(0.001)
Country effects	Yes	Yes	Yes
Time effects	Yes	Yes	Yes
Wald chi2 test	713.22***	802.14***	322.15***
Hansen *j* (p-value)	0.221	0.332	0.370
AR(1)	-14.35***	-9.17***	-7.11**
AR(2)	0.81	0.77	0.23
Observations	14475	5449	1917
Number of banks	2815	1351	422

Notes: The Table reports the dynamic panel regression results for the period 2001 to 2012. The dependent variable is the productivity growth. As bank-specific independent variables we employ: z-score= (1+ROE)/(Standard Deviation of ROE); Size= natural logarithm of total assets; Capital ratio = equity over total assets; Liquidity ratio= liquid assets over total assets; Investment Banking Fees= net fees, commission and trading income over total assets; Securities/TA= total securities over total asset. As country variables we employ: GDP per capita; GDP growth; Inflation; Population density; Market size= value of total shares traded on the stock market exchange; Crisis dummy that takes the value of 1 for the 2007-2009 period and zero otherwise. For bank-specific variables we use FITCH Bankscope database while for country variables we use World Development indicators from World Bank. To avoid collinearity problems with the selected variables, we first analyze correlations of all the selected variables. We check that there is not a high level of correlation between the variables used in the models. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. Bootstrapped-Windmeijer (2005) corrected (robust) standard errors are in parentheses.

Regarding the rest of the bank-specific control variables, the dynamic panel analysis also confirms the positive relationship between bank size and productivity growth (Table 9, Models 1 and 2). Our finding reports a positive association between bank size and productivity growth for a sample of European emerging countries. We report a negative relationship between fee-income ratio and bank productivity growth in emerging and developing economies (Table 9, Models 2 and 3). Turning our attention to the country-level control determinants, we find a negative impact of inflation (Table 9, Models 1, 2 and 3) on productivity growth (Table 9, Models 1 and 2), whereas GDP per capita is positively related to productivity growth in emerging economies (Table 9, Model 2). There is some variability compared to the fixed effects estimations, which is explained as the dynamic analysis deals with endogeneity issues whilst is also refers to the short run.

6. Conclusion

In this study, we employ a local likelihood estimation of flexible transformation function to decompose productivity growth to account for the effect of negative quasi-fixed input of nonperforming loans. Our results reveal the destructive effect of nonperforming loans on bank productivity for all the country-groups considered in our sample. We also find that technological progress is the driving force of worldwide bank productivity, and in advanced economies. Our panel regression analyses show that there is a negative association between risk and productivity growth. Moreover, we document that liquidity raises bank productivity growth, in line with the "*bad luck hypothesis*". On the other hand, capital is negatively related to bank productivity growth, consistent with the "*agency cost hypothesis*" (Jensen and Meckling, 1979).

The results remain robust across the three different country-groups (advanced, emerging, and developing) and further emphasise the damaging effect of nonperforming loans on productivity growth. In terms of policy implications, our results reveal that all possible efforts should be assumed to assess information regarding the creditworthiness of borrowers. Enhancing access of creditworthiness information could also enhance the discipline of borrowers and reduce moral hazard problems. In addition, our findings highlight the importance of liquidity in improving bank productivity, whereas caution is raised for the negative impact of capital ratio on productivity growth. In terms of policy, as results are valid across global banking, bank regulation amendments should focus on an international level rather than on a single country when it comes to required capital ratios.

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Appendix

A.1. The Local Likelihood Estimation.

For simplicity, we can write equation (5) as:

$$y_1 = \mathrm{B}b\left(\Upsilon\right) + u, \quad (1)$$

where $y_1 = \overset{\circ}{Y}_1$, $\beta\left(\Psi\right) = \left[\left\{\beta_k\left(\ln\tilde{Y}, \ln X, t\right)\right\}_{k=0}^{K}, \left\{\gamma_m\left(\ln\tilde{Y}, \ln X, t\right)\right\}_{m=1}^{M}\right]'$ is the entire vector of functional coefficients. Note, we suppress the dependence on the time trend, t.

Suppose $\mathbb{Z} = \left[z', t\right]'$ so that we can write the reduced form in (6) as:

$$\tilde{Y} \triangleq \left[\tilde{Y}_1,\ldots,\tilde{Y}_{M'}\right] = \begin{bmatrix} Z & & & \\ & Z & & \\ \cdots & & \ddots & \\ & & & Z \end{bmatrix} \begin{bmatrix} \pi_1(Z) \\ \pi_2(Z) \\ \vdots \\ \pi_{M'}(Z) \end{bmatrix} + \begin{bmatrix} U_{*,1} \\ U_{*,2} \\ \vdots \\ U_{*,M'} \end{bmatrix}, \quad (2)$$

where $\pi_{m'}(\mathbb{Z})$ is the vector of functional coefficients corresponding to the $m\square^{\text{th}}$ equation ($m' = 1,\ldots,M'$).

Equation (9) can be written as:

$$\tilde{Y} = \left(I_{M'} \otimes Z\right)\pi\left(Z\right) + U_*. \quad (3)$$

Whilst we model the dependence of the covariance matrix on all endogenous and pre-determined variables so as to have flexibility as follows:

$$U \triangleq \left[u', U_*'\right]' \sim N_M\left(O,\ \Sigma(\Psi, Z)\right). \quad (4)$$

To model the dependence, we use the decomposition:

$$S(Y,Z) = C(Y,Z)\square C(Y,Z). \quad (5)$$

where

$$c(Y,Z) = vec\left[C(Y,Z)\right], \quad (6)$$

which is the vector consisting of the upper diagonal elements of $C(\Psi,\mathbb{Z})$.
Then for

$$W = \square Y\,\square Z\square, \quad (7)$$

we use a local linear model:

$$c_j(\Psi,\mathbb{Z}) = \mathbb{W}\delta_j\left(\mathbb{W}\right),\ j = 1,\ldots,\tfrac{M(M+1)}{2}. \quad (8)$$

Whilst, in vector notation we have:

$$c(W) = \left(I_{\frac{M(M+1)}{2}}\ \text{Ä}\ W\right)d\left(W\right). \quad (9)$$

Given equations (8) to (16) our model is formulated as follows:

$$y_1 = \mathrm{B}\beta\left(\Psi\right) + u,$$
$$\tilde{Y} = \left(I_{M'} \otimes \mathrm{Z}\right)\pi\left(\mathrm{Z}\right) + U_*,$$
$$U = \left[u', U_*'\right]' \sim N_M\left(O,\ \Sigma(\Psi, \mathrm{Z})\right),$$
$$\Sigma(\Psi, \mathrm{Z}) = C(\Psi, \mathrm{Z})'C(\Psi, \mathrm{Z}),\ c(W) = \left(I_{\frac{M(M+1)}{2}} \otimes W\right)\delta(W). \quad (10)$$

With the expressions for the local coefficients as follows:

$$\beta_{m'}\left(\Psi\right) = \beta_{m',0} + \beta_{m',1}'\left(\Psi_i - \Psi\right), m' = 1, \ldots, M', \quad (11)$$

or collectively $\beta\left(\Psi\right) = \beta_0 + B_1\left(\Psi_i - \Psi\right)$.

Similarly, the remaining functional coefficients are:

$$\pi\left(\mathrm{Z}\right) = \pi_0 + \Pi_1\left(\mathrm{Z}_i - \mathrm{Z}\right),$$

$$c(W) = \delta_0 + \Delta_1\left(W_i - W\right), \quad (12)$$

where small letters indicate vectors and capital letters indicate matrices of coefficients.

A.2. The Nonparametric Estimation.

In the context of a local likelihood estimator, a given parametric likelihood, say

$$L = L\left(\mathrm{y};\theta\right) = \prod_{i=1}^{N} f\left(\mathrm{y}_i;\theta\right) \quad (13)$$

can be made nonparametric through a local linearization.

The new conditional log-likelihood at y is:

$$l\left(\theta_0, \Theta_1\right) = \sum_{i=1}^{N} \log f\left(\mathrm{y}_i;\ \theta_0 + \Theta_1 \cdot (\mathrm{y}_i - y)\right) \cdot K_H\left(\mathrm{y}_i - y\right), \quad (14)$$

where $K_H(u) = |H|^{-1} K\left(H^{-1}u\right)$, for some bandwidth matrix and kernel $K(z) = \left[K_1\left(z_1\right), \ldots, K_d\left(z_d\right)\right]'$, where d is the dimensionality of the parameter vector. The kernels satisfy the standard property that they are symmetric, univariate density functions. In this case, we have $\int uu'K\left(u\right)du = \left(\int z_1^2 K_1(z_1)dz_1\right)I_d$.

Then the local linear estimator, say of $\pi(Z)$ is $\hat{\pi}(Z) = \pi_0(Z)$ where parameter estimates are obtained by maximizing the conditional local log-likelihood:

$$\hat{\theta}_0(\psi) = \underset{\theta_0(\psi),\Theta_1(\psi)}{\arg\max} : \sum_{i=1}^{N} \log f\left(\psi_i;\ \theta_0 + \Theta_1 \cdot (\psi_i - \psi)\right) \cdot K_H\left(\psi_i - \psi\right). \quad (15)$$

In our case the parameter vector

$$\hat{\theta}_0(\psi) = \left[\beta_0(\Psi)', \pi_0(Z)', \delta_0(W)'\right]' \text{ and } \psi \triangleq \left[\Psi', Z', W'\right]'. \quad (16)$$

To construct the local likelihood, we use Pagan's (1977) seemingly-unrelated-regression (SUR) interpretation of limited information maximum likelihood (LIML). Specifically, for a single observation, we can write:

$$f\left(y_1, \Psi \mid Z, \theta\right) = (2\pi)^{-M/2} \left|\Sigma(\Psi, Z)\right|^{-1/2} \exp\left\{-\tfrac{1}{2} S(\theta)\right\}, \quad (17)$$

where $S(\theta) \triangleq U(\theta)' \Sigma(\Psi, Z)^{-1} U(\theta)$, $U(\theta) \triangleq \begin{bmatrix} y_1 - B\beta(\Psi) \\ \tilde{Y} = (I_{M'} \otimes Z)\pi(Z) \end{bmatrix}$.

We use a normal kernel for $K_j(z_j), j = 1,\dots,d$ and a diagonal bandwidth matrix, H, with different bandwidth parameters for β, π, δ but common for the entire vector β, then π and then δ. So, we have three different bandwidth parameters $h = \left[h_\beta, h_\pi, h_\delta\right]$, which are selected through cross-validation. Since the sample size is rather large, the bandwidth parameters are selected using all observations for 500 randomly selected banks.

To maximize each localized likelihood, we use a standard Gauss-Newton algorithm with analytic first and second derivatives, which can be computed easily for this model. This guaranteed convergence in many cases where a standard conjugate-gradients algorithm has failed to converge starting from a variety of reasonable starting values.[12]

[12] The conjugate-gradients algorithm we use is a Fortran 77 implementation of D. C. Liu and J. Nocedal, “On the limited memory BFGS method for large scale optimization methods”, Mathematical Programming 45 (1989), pp. 503-528. It is available as lbfgs in netlib. Our Gauss-Newton version is SNOPT and is based on http://www.ccom.ucsd.edu/~peg/papers/snpaper.p