Journal of Business Research 97 (2019) 198–207

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Comparison of banking innovation in low-income countries: A meta-frontier approach

Jean-Raymond Fontin, Shi-Woei Lin*

Department of Industrial Management, National Taiwan University of Science and Technology, Taipei 10607, Taiwan

ARTICLE INFO

Keywords:
Financial innovation
Technology gap ratio
Cost efficiency
Stochastic meta-frontier analysis
Low-income countries

ABSTRACT

Financial innovation is a crucial factor behind many of the improvements in the financial sector that directly affect the economy in a positive way. Financial innovation may also alter financial intermediation and increase reliability and transparency. Research has demonstrated that levels of financial innovation are similar among high-income countries; however, research has shown that financial development differs substantially in low income countries regardless of the economic size, suggesting that financial innovation may also differ. This study evaluated the levels of financial innovation and the determinants of innovation within the low-income countries. In particular, a new two-step meta-frontier approach was constructed to estimate technology gap ratios, and a censored model was built to establish their determinants. The results show that low-income countries do in fact vary greatly in terms of financial innovation. Competition, financial inclusion and banking access constitute major determinants of financial innovation.

1. Introduction

The global banking system has experienced tremendous changes in terms of innovation, with advances in telecommunication, financial theory, information technology, the rise of globalization, and banking liberalization. Financial innovation has occurred in many forms, including new products and services, production processes, and organizations. An example of such a product and services is subprime mortgages. Production processes encompass asset securitization, while the organizational forms include online-only banking. These innovations have mainly occurred in advanced economies such as the United States and Europe (Frame & White, 2009). In low-income countries, financial innovation often constitutes a transfer, an adaptation, and an adoption of an existing technology. The characteristics of local markets determine the adoption level or the occurrence of new inventions. For example, low-income countries tend to have lower levels of financial inclusion or higher barriers to entry. Poghosyan (2013) revealed that banks in low-income countries incur higher intermediation costs than those in emerging markets, indicating a less competitive, weaker economic environment. These characteristics hinder cost-reducing innovations.

Financial innovation is defined as anything new that allows banks to lower costs, reduce risks, and improve products, services, or processes so as to better satisfy their customers (Frame & White, 2009). Banks employ numerous tools to cut operating costs. These tools vary from credit scoring systems to computing software. Credit scoring gives banks the potential to limit underwriting and monitoring costs. Bank managers are able to limit the number and size of loans to borrowers with low credit scores, saving the time and money required to further assess a borrower. Accounting software also helps to reduce labor costs. Each of these innovative tools helps banks to reduce their operating costs. Cost reducing innovations therefore, help banks to enhance their cost efficiency.

In other words, the cost efficiency level shades some lights on banks' innovative approaches, on tools and measures used to manage cost, and on the innovative characteristics of banks' environment. In fact, there is a strong link between overall innovation and cost efficiency. The components of cost efficiency (Cost Efficiency = Technical Efficiency × Allocative Efficiency), technical efficiency and allocative efficiency, reflect the state of technology in the technical-physical (including skills and tools) aspect of production and the price incurred for inputs used (Cooper, Seiford, & Tone, 2007). The gap between individual and global (or meta-) cost frontier reflects technology gap or relative “overall innovation”.

Recently, cost frontier functions have been used extensively to study financial innovation in an individual country as well as in some cross-country studies. For example, Bos, Kolari, and Van Lamoen (2013) used stochastic cost frontiers to analyze how innovation by banks in the US

* Corresponding author.
E-mail addresses: d10501812@mail.ntust.edu.tw (J.-R. Fontin), shiwoei@mail.ntust.edu.tw (S.-W. Lin).

https://doi.org/10.1016/j.jbusres.2018.12.017
Received 25 May 2018; Received in revised form 3 December 2018; Accepted 5 December 2018
0148-2963/

leads to improvements in technology set and the link between innovation and competition. More recently, Huang, Hu, and Chang (2018) estimated the cost frontier function of banks in Taiwan to study the performance between financial holding and non-financial holding banks, and the link between financial innovation and competition.

In practice, technology and management styles vary across banks and banking systems, so does cost efficiency. At the cross-country level, technical efficiency reflects the degree to which technical innovation of a country is more advanced relatively to its peers. Likewise, allocative efficiency reflects the average market price associated with the operating process. However, banks in different countries are exposed to country-specific factors such as the local economy and the regulatory environment. Researchers thus avoid comparing banks across countries unless those differing factors are controlled for. Nevertheless, an analysis of the average cost efficiency in each country or country-specific frontier may reveal the homogeneity or heterogeneity in the banking system of that particular country. The homogeneity of cost efficiency then characterizes the market power, regulatory environment, and banking structure of a banking system. In particular, banking systems with average cost efficiencies above 80% are considered homogenous, otherwise they are heterogeneous. For instance, a low average cost efficiency may reflect a concentrated market, as larger banks tend to enjoy considerably higher cost efficiencies. In this case, large banks are located near to or on the edge of the cost frontier, while small banks are relatively distant from the cost frontier. A concentrated market is unfavorable to financial innovation, as large banks have no incentive to innovate. In other words, this characteristic may cause a banking system to lag behind its counterparts in terms of financial innovation.

Hence, at banks' level, the gap between individual country cost frontier and cross-country cost frontier determines “overall innovation”. This technique has been used in the literature to measure “overall innovation”. For example, Nguyen, Nghiem, Roca, and Sharma (2016) estimated country and meta cost efficiency frontier to examine innovation of banks in Vietnam, China and India, and how competition affects it. Abid and Goaied (2017) used the same approach to assess the technological gaps between countries in the Middle East and North Africa.

Studies investigating the cost efficiency of banks in low-income countries have found that cost efficiency is heterogeneous in some countries and homogeneous in others. This may signal different levels of financial innovation. Regarding Nepal, Jha and Hui (2013) revealed that the average technical efficiency of banks was 80.4%. Thagunna and Poudel (2013) found a 95.3% average profit efficiency for Nepal. Similarly, a study of 15 Ugandan banks yielded an average efficiency as high as 99% during the 1999–2004 period (Hauner & Peiris, 2005). Unlike the aforementioned studies, Abdallah, Amin, Sanusi, and Kusairi (2014) used the Stochastic Frontier Approach (SFA) to evaluate the cost efficiency of 21 Tanzanian banks during the 2003–2012 period. Their results indicated that the average bank is 77% efficient during that period. Cadet (2015) compared the performance of domestic and foreign banks in terms of cost and profit efficiency for the case of Haiti using the SFA for the 2001–2007 period. He found that on average, banks operating in Haiti had respectively profit and cost efficiencies of 75.8% and 62.1% (though the cost function estimation was not robust). Finally, Abel and Le Roux (2016) evaluated the cost efficiency of 18 Zimbabwean banks using Data Envelopment Analysis (DEA) for the period between 2009 and 2014. On average, banks were found to be 64.7% cost efficient. They also found that increases in cost efficiency reduce the amount of competition and vice versa, supporting the efficient structure hypothesis. Overall, the level of homogeneity in the cost efficiency of banks varies across low-income countries. Thus, financial innovation and cost efficiency may also vary across low-income countries.

However, the ways in which financial innovation and cost efficiency vary across low-income level countries and the factors that determine this variation are still unclear. Cross-countries studies targeting African countries have presented divergent results with regard to cost efficiency determinants. For example, Haque and Brown (2017) and Triki, Kouki, Dhaou, and Calice (2017) identified a positive relationship between size and cost efficiency, while Banya and Biekpe (2018) found a negative relationship. Likewise, Banya and Biekpe (2018) and Triki et al. (2017) determined that the effects of market power and banking concentration on cost efficiency differ. Because Banya and Biekpe (2018) and Triki et al. (2017) sampled countries with different income levels, they could not address the case of low-income countries and how levels of cost efficiency and financial innovation vary among them. Nonetheless, the literature fails to specifically analyze the evolution of banking systems in low-income countries or evaluate their relative levels of financial innovation.

This study aimed to measure the technology gap between low-income countries and find the determinants of this gap using the stochastic meta-frontier approach. In particular, to evaluate and compare banking innovation in low-income countries, this study uses data collected from 168 banks in nine countries from different continents. Those nine countries are Ethiopia, Malawi, Mali, Mozambique, Nepal, Senegal, Uganda, Tanzania and Zimbabwe. Each of these countries has a more representative sample banks (the lowest representation is 64% of the total banks operating in the country) data compared to those not included in the study. Furthermore, this study used the novel stochastic meta-frontier approach developed recently by Huang, Huang, and Liu (2014) to estimate the technology gap ratio. This innovative approach allowed us to compare groups with different levels of production technology and different banking environments. Furthermore, by incorporating an SFA in the second step of the analysis to take the estimation errors of the predicted function in the first step into consideration, this approach also overcomes the drawback of using a nonparametric approach to calculate the meta-frontier function.

This paper contributes to the literature in many ways. First, we applied the most recent meta-frontier technique to a sample of banks from low-income countries. This method is highly suitable for low-income countries as data on research and development are not available. Second, we compare banking innovation across low-income countries. To the best of our knowledge, this is the first study to compare financial innovation between low-income countries using this novel meta-frontier approach. Finally, we identified the determinants of innovation using the Tobit model. This contribution is very crucial for low-income countries as it will allow them to draw lessons from their peers to improve their banking system.

The rest of the paper is divided as follows. The second section deals with the material and methods utilized to evaluate the cost efficiency of banks. The third section presents the results, discusses the most important findings, and provides managerial and policy recommendations. The fourth section draws conclusions and summarizes the most relevant findings of the paper.

2. Material and methods

2.1. Methodology

There are two main approaches to model cost functions in the literature: the data envelopment analysis (DEA) developed by Charnes, Cooper, and Rhodes (1978) and the stochastic frontier analysis (SFA) introduced by Aigner, Lovell, and Schmidt (1977). DEA is a non-parametric method using linear programming. It assumes the data to be deterministic, and does not account for measurement errors. On the other hand, SFA is a parametric approach and therefore has the benefit of accounting for inferences and random measurement errors. It assigns a functional distribution form to the data. Considering that banking data are subject to collection, random measurement and accounting errors, we use the SFA to model our cost functions. The SFA assumes that any deviation of the actual observations from the cost function stem from noise and inefficiency; this is contrary to the non-parametric

DEA approach that assumes any deviation is accounted for as inefficiency. Consider a bank *i* using a *N*-vector of input $W = (W_1, \ldots, W_N)'$ to produce *R*-vector of outputs $X = (X_1, \ldots, X_R)'$ at time *t* for a given group or country. The stochastic cost function is expressed as follows:

$$Y_{it} = f(X_{Rit}; W_{Nit}; Z_{Kit}; \beta)e^{V_{it}+U_{it}},\quad i = 1, 2, \ldots, I;\quad t = 1, 2, \ldots, T \tag{1}$$

where Z_{Kit} and β are respectively K-vector of the control variables of bank *i* at time t and an unknown parameter vector associated with a given country. Y_{it} is the cost function and represents the total costs of bank *i* at time *t*. V_{it} and U_{it} are vectors of disturbances and an inefficiency vector of bank *i* at time t, respectively. V_{it} is assumed to be independently and identically distributed as the $N(0, \sigma_v^{j2})$-random variable which is independent of U_{it}. As banks tend to have much higher cost in case of inefficiency, U_{it} is bounded below at 0 and, consequently, we expect the distribution of the total error ($\epsilon_{it} = V_{it} - U_{it}$) to be right-skewed. Therefore, U_{it} is assumed to follow the truncated-normal distribution as $N^+(q_{it}\delta, \sigma_u^{j2})$ where q_{it} denotes some exogenous variables (Battese & Coelli, 1995). There are two steps involved in the determination of the meta-frontier: constructing the group or country-specific frontier and the meta-frontier. The pooled estimates of the country-frontiers constitute the explained variable of the meta-frontier. The cost efficiency of bank (CE_{it}) *i* at time *t* for a given country is:

$$CE_{it} = \frac{f(X_{Rit}; W_{Nit}; Z_{Kit}; \beta)e^{V_{it}}}{Y_{it}} = e^{-U_{it}} \tag{2}$$

The cost efficiency based on the country frontier is the ratio of predicted value ($f(X_{Rit}; W_{Nit}; Z_{Kit}; \beta) = \widehat{Y}_{it}$) adjusted for stochastic disturbances over the explained variable (Y_{it}). The unknown parameter β, the errors vector (V_{it}) and the inefficiency vector (U_{it}) can be estimated using the Maximum likelihood estimation method. Eq. (2) then becomes:

$$\widehat{CE}_{it} = \frac{\widehat{Y}_{it}e^{\widehat{V}_{it}}}{Y_{it}} = e^{-\widehat{U}_{it}} \tag{3}$$

An inefficient bank incurs higher costs to produce one unit of output. Therefore, the estimated cost is lower than or equal to the actual cost value. In other words:

$$Y_{it} \geq \widehat{Y}_{it} \tag{4}$$

The estimated cost determines the optimal cost that would be incurred if a bank was as efficient as the best practice bank within its group or country. Given the country-specific optimal cost, the meta-cost function can be expressed as follows:

$$\widehat{Y}_{ijt} = f^M(X_{Rijt}; W_{Nijt}; Z_{Kijt}; \beta^M)e^{V_{ijt}^M+U_{ijt}^M},\quad j = 1, 2, \ldots, J;\ i = 1, 2, \ldots, I;\ t = 1, 2, \ldots, T \tag{5}$$

where X_{Rijt}, W_{Nijt} and Z_{Kijt} are respectively the R-vector of outputs, N-vector of inputs and Z-vector of control variables for bank *i* of country *j* at time *t*. $\widehat{Y}_{ijt}$ and β^M are respectively the estimated cost of bank *i* for country *j* at time t and an unknown parameter associated with all countries in the study. U_{ijt}^M is the technology gap reflecting the extent to which bank *i* adopts the technology accessible to all countries or group considered in the sample. It is positive and follows a truncated-normal distribution as defined in the work of Battese and Coelli (1995). V_{ijt}^M is the random noise obtained from estimating the meta-cost frontier. As Huang et al. (2014) pointed out, the estimation error is asymptotically and normally distributed, but may not be independently and identically distributed. The stochastic meta-frontier estimator is therefore a quasi-maximum likelihood estimator whose standard errors can be modified by following the method of White (1982).

Similar to the group specific frontier, the meta-cost efficiency is given as follows:

$$MCE_{ijt} = \frac{f^M(X_{Rijt}; W_{Nijt}; Z_{Kijt}; \beta^M)e^{V_{ijt}}}{Y_{ijt}} = TGR_{ijt} \times CE_{ijt} \tag{6}$$

Note that the predicted value of the meta-cost frontier is adjusted by the group frontier noise instead of the meta-frontier noise.[1] The estimated technology gap ratio ($\widehat{TGR}_{ijt}$) is by definition expressed as follows:

$$\widehat{TGR}_{ijt} = \frac{f^M(X_{Rijt}; W_{Nijt}; Z_{Kijt}; \beta^M)}{\widehat{Y}_{ijt}} = e^{-\widehat{U}_{ijt}^M} \tag{7}$$

In the literature, the cost function has been commonly assumed to have either a Translog or a Fourier Flexible form. For simplicity and data limitations we assume that the cost function has a Translog functional form and is specified as follows:

$$\ln\left(\frac{TC}{W_3}\right) = \beta_0 + \sum_m \beta_m \ln\left(\frac{W_m}{W_3}\right) + \sum_p \alpha_p \ln(X_p) + \frac{1}{2}\left[\sum_m\sum_n \beta_{mn}\ln\left(\frac{W_m}{W_3}\right)\times\ln\left(\frac{W_n}{W_3}\right) + \sum_p\sum_q \alpha_{pq}\ln(X_p)\times\ln(X_q)\right] + \sum_m\sum_p \theta_{mp}\ln\left(\frac{W_m}{W_3}\right)\times\ln(X_p) + T + V + U \tag{8}$$

where TC, W_3, W_m, X_p and T respectively denotes total costs, labor price, mth input price (m = 1, 2), pth output (p = 1, 2, 3) and time trend. V and U respectively reflects random noise and cost inefficiency. The total cost and the mth input price are divided by the labor price to allow for homogeneity.

2.2. Data description

The World Bank defines low-income countries as those with a gross national income per capita (GNIPC) of equal to or less than US$995 in 2017. Our panel dataset covers the period between 2012 and 2017, and is unbalanced as the number of banks in a country varies over time. The countries were chosen on the basis of their cumulative number of observations during the 6-year period. The restriction was set to be greater than or equal to 30. Tanzania had the highest number of observations (129), while Malawi and Mali had the lowest (47). The data were scrutinized for suspicious entries and outliers. Data points with such characteristics were excluded from the sample. We used the intermediation approach to determine input prices and outputs. Banks in low-income countries are assumed to be intermediaries between depositors and borrowers. In our model, total cost (TC) is defined as the cost function, which is the sum of interest, staff and other operating expenses. It represents the minimum cost of operating the bank's intermediation process. Gross loans, customer deposits and short-term funding, and total earning assets are considered as outputs. Total earning assets are assets that generate interest or dividends, including stocks, bonds, income from rental property, certificates of deposit (CDs) and other interest or dividend earning accounts or instruments. The input prices are labor, fund and capital. The labor price is the ratio between staff expenses and total assets; interest expenses to total customer deposits and short-term funding ratio represent the fund price; and, capital price is the ratio of other operating expenses to fixed assets. Other operating expenses include depreciation, amortization, costs related to the occupancy of buildings, software costs, operating lease rentals, auditing fees, and legal fees. Staff expenses are wages, social security costs, pension costs and other personnel expenses. Table 1 contains a summary statistics of input prices and outputs. Nepal has the lowest labor price, while Mali has the lowest fund and capital price. Financial statement data was retrieved from the Orbis Bank Focus database.

[1] See Huang et al. (2014) for a decomposition of the meta-cost efficiency.

Table 1
Summary statistics of input prices (%) and outputs (US$000).
Data source: Orbis Bank Focus database.

	Ethiopia	Malawi	Mali	Mozambique	Nepal	Senegal	Tanzania	Uganda	Zimbabwe	Average
Total costs (TC):										
Mean	49,549.42	26,466.99	19,944.15	40,030.18	31,941.89	21,887.6	36,457.6	28,870.93	44,363.77	33,279.17
Std. deviation	94,007.82	15,445.06	11,263.38	49,286.74	15,954.19	18,781.16	46,661.79	30,528.24	35,411.15	35,259.95
Input variables										
Labor price:										
Mean	1.82	4.85	1.60	5.44	1.14	1.64	3.46	3.76	5.00	3.19
Std. deviation	0.61	2.54	0.54	4.30	0.66	0.79	2.12	2.26	2.40	1.80
Fund price										
Mean	5.70	7.93	1.72	5.88	121.55	2.28	4.76	4.69	4.25	17.64
Std. deviation	14.89	5.19	0.66	4.46	791.40	1.02	2.56	2.46	3.38	91.78
Capital price:										
Mean	52.84	107.13	24.18	88.61	91.86	88.53	195.18	236.60	50.17	103.90
Std. deviation	34.73	83.97	26.45	107.76	71.60	396.97	205.64	245.16	31.52	133.76
Output variables										
Gross loans:										
Mean	557,365.9	81,321.58	291,358.4	267,337	416,899.1	330,232.8	254,114.3	150,834.6	226,021.8	286,165.06
Std. deviation	1,138,710	62,490.88	154,669.7	415,871.7	208,072.8	307,819.3	354,738.1	167,759.6	244,702.1	339,426.05
Total earning assets:										
Mean	1,071,877	161,173.5	457,269.9	426,767.7	529,803.9	429,793.6	367,477.2	245,652.8	340,813.9	447,847.76
Std. deviation	2,660,316	130,943.9	263,418.2	627,931.9	279,898	355,392.3	481,703.8	263,715.1	374,787.9	604,234.10
Total deposits and short-term funding:										
Mean	910,578.7	159,991	474,355.5	403,761.3	517,323.6	437,281.2	372,570.2	221,805.4	380,534.5	430,911.25
Std. deviation	2,316,453	126,969	274,984.3	585,942.7	290,888.9	370,987.3	513,169.3	243,954.4	412,438.5	570,643.06

Total cost = staff expenses + other operating expenses + interest expenses.
Labor price = staff expenses / total assets.
Fund price = interest expenses / total customer deposits and short-term funding.
Capital price = other operating expenses / fixed assets.

3. Empirical results and discussion

3.1. Financial innovation

The time-varying frontier suggested in Battese and Coelli (1992) is considered in the specification to counter the small sample size issue and to limit the number of estimated parameters. Accounting for biased technological change by interacting output or input prices variables with time would greatly increase the number of parameters. To avoid convergence problems, the estimation was made using mean normalized input prices and outputs. The natural logarithm of the total assets, which is used to represent the size of the bank, is incorporated into the estimation of the country frontier to account for the size effect. Likewise, gross national income per capita (GNIPC) is included into the estimation of the meta-frontier to account for the country effect. Tables 2 and 3 presents the estimation results for both countries and meta-frontier, with the parameter gamma ($\gamma = (\sigma_u^2/\sigma_v^2)/(1 + \sigma_u^2/\sigma_v^2)$) expressing the level of variance due to inefficiency relative to the variance due to random errors. Gamma (γ) is between 0 and 1. The closer it is to 1, the greater is the variance due to inefficiency relative to random errors. Tables 2 and 3 reveal that inefficiency significantly represents more than 70% of the variability for seven of the nine countries. This confirms the existence of cost inefficiency. However, no cost inefficiency was identified within the banks of the other two countries (Malawi and Mali). The total error distribution is left-skewed, leading the parameter gamma to be insignificant for the other two countries. We perform a likelihood ratio test between the Ordinary Least Square (OLS) method and the Error Components Frontier method, the null hypothesis of no inefficiency is rejected for both countries. In other words, although gamma is left-skewed, variation is significantly accounted for inefficiency.

The input prices and output variables have the expected effect on total cost, except in a few cases where gross loans (Y2) affects total cost negatively. Results obtained in the meta-frontier model are consistent with economic theory. In particular, the effects of the cost elasticity of total customer deposits and short-term funding are 0.97. GNIPC is positively associated with operating cost. The time trend variable, however, suggests that on average, operating costs decrease by 0.5% per year in the low-income level countries considered in the sample.

A considerable disparity can be observed between the countries in the study in terms of financial innovation, especially between Nepal and Ethiopia, and the other seven countries (see Table 4), supporting findings in the literature that similar income levels do not necessarily imply similar levels of financial innovation (Hui & Jha, 2013; Rioja & Valev, 2004). Nepal has the highest level of financial innovation (TGR = 0.83) among the nine studied low-income countries, followed by Ethiopia (TGR = 0.72), Senegal (TGR = 0.42) and Tanzania (TGR = 0.35). The least innovative spot goes to Malawi, which has an average technology gap ratio of 0.12. Banks in Malawi would significantly increase their efficiency if they adopt the technology available to banks in other low-income countries. Technologies used in Malawi-based banks are equivalent to 12% of those available. In other words, the average bank in Malawi is up to 88% less efficient than the most innovative banks in other studied low income countries. Overall innovation increased (by 7.8%, from 0.425 to 0.503) during the 2012–2017 period within the low-income countries. Individually, Mozambique experienced the largest increase in the technology gap ratio (by 1.23%, from 0.169 to 0.182). Zimbabwe, by contrast, saw the technology gap ratio decline by 4% from 0.264 to 0.228 during the same period (See Fig. 1).

Financial innovation, measured by the technology gap ratio, is directly linked to input prices. Banks on the meta-frontier enjoy superior managerial skills and favorable banking environments, which are conducive to reducing input prices. Cost-reducing technologies available for all banks in the industry are therefore within their reach. The Pearson correlation matrix in Table 5 captures the relationship between the technology gap ratio, input prices and total costs. As expected, total costs are negatively related to the technology gap ratio. In other words, financial innovation helps banks lower their total costs. Overall, labor price is affected most by financial innovation, as shown in the

Table 2
Estimation results of the stochastic frontiers.

	Ethiopia	Malawi	Mali	Mozambique	Nepal
(Intercept)	−8.778***	−14.955***	−14.518***	−6.394***	−1.798
Ln(W1/W3)	0.023	0.2***	0.12***	0.207***	0.034
Ln(W2/W3)	0.566***	0.366***	0.464***	0.369***	1.224***
Ln(Y1)	0.422***	0.192	0.373	0.65***	1.272***
Ln(Y2)	0.052	0.176***	−0.072	0.211*	0.012
Ln(Y3)	−0.117	−0.538***	−0.348	−0.353	−0.567*
Ln(W1/W3)2	0.049*	0.076***	0.012	0.072	−0.048***
Ln(W2/W3)2	0.047	0.238***	0.138***	0.018	0.163***
Ln(W1/W3) * Ln(W2/W3)	−0.021	−0.071***	−0.063**	0.077	0.003
Ln(Y1)2	−0.006	1.214	3.178	0.556	0.221
Ln(Y2)2	0.045	0.386**	0.552	0.03	−2.26***
Ln(Y3)2	0.699	2.497***	2.837	1.857***	−2.02***
Ln(Y1) * Ln(Y2)	0.638*	0.893*	−0.248	0.714***	−0.095
Ln(Y1) * Ln(Y3)	−0.457	−1.83***	−2.998	−1.232***	−0.044
Ln(Y2) * Ln(Y3)	−0.529	−1.067**	−0.07	−0.692**	2.181***
Ln(Y2) * Ln(W1/W3)	0.121*	0.048	0.037	0.109	−0.174**
Ln(Y2) * Ln(W2/W3)	0.101	0.012	0.338*	−0.165	0.014
Ln(Y1) * Ln(W1/W3)	−0.016	0.121	0.446**	−0.108	0.033
Ln(Y1) * Ln(W2/W3)	0.019	0.137	−0.032	0.059	0.2**
Ln(Y3) * Ln(W1/W3)	−0.101	−0.15	−0.376	0.025	0.106
Ln(Y3) * Ln(W2/W3)	−0.062	−0.163	−0.188	0.106	−0.178**
Size	0.661***	1.238***	1.102***	0.528***	0.377***
σ^2	0.009	0.001***	0.001***	0.021**	0.002**
γ	0.93***	0	0.013	0.768***	0.836***
Time	−0.042	1.532***	0.596**	−10.301***	0.084
Likelihood ratio	159.6255	87.95309	94.7607	77.4727	285.0596
# of observations	81	47	47	66	125

W1, W2 and W3 are respectively capital, fund and labor prices. Y1, Y2 and Y3 are respectively total deposits and short-term funding, gross loans and total earning assets. Size is log (Total assets).

*** Denotes significance at 1% level.

** Denotes significance at 5% level.

* Denotes significance at 10% level.

Table 3
Estimation results of the stochastic frontiers (cont.).

	Senegal	Uganda	Tanzania	Zimbabwe	Meta-frontier
(Intercept)	−10.549***	−14.018***	−7.895***	−13.154***	0.07
Ln(W1/W3)	0.098***	0.093***	0.152***	0.158***	0.076***
Ln(W2/W3)	0.441***	0.329***	0.435***	0.295***	0.808***
Ln(Y1)	0.317*	0.244***	0.609***	0.132	0.97***
Ln(Y2)	0.014	−0.124**	0.222***	0.181***	0.053
Ln(Y3)	−0.107	−0.212**	−0.405***	−0.303***	−0.045
Ln(W1/W3)2	−0.019*	−0.019	0.006	0.063***	0.028***
Ln(W2/W3)2	0.247***	0.257***	0.181***	0.079***	0.188***
Ln(W1/W3) * Ln(W2/W3)	−0.075***	0.019*	−0.023	−0.035***	−0.018***
Ln(Y1)2	−1.019**	0.087	−0.113	−0.67***	0.164***
Ln(Y2)2	0.374***	−0.136	0.134	0.243***	0.011
Ln(Y3)2	−2.439***	0.471	−0.414*	−0.495	−0.059
Ln(Y1) * Ln(Y2)	−0.586***	0.134	−0.101	0.254**	−0.051*
Ln(Y1) * Ln(Y3)	1.945***	−0.246	0.285	0.664***	−0.088**
Ln(Y2) * Ln(Y3)	0.183	−0.064	0.041	−0.451***	0.106***
Ln(Y2) * Ln(W1/W3)	−0.103**	0.007	0.087**	0.12**	0.011
Ln(Y2) * Ln(W2/W3)	−0.005	−0.072*	−0.026	0.044*	−0.018
Ln(Y1) * Ln(W1/W3)	−0.013	0.123***	0.009	0.044	0.015
Ln(Y1) * Ln(W2/W3)	0.546***	0.181***	0.173***	−0.026	0.143***
Ln(Y3) * Ln(W1/W3)	0.156*	−0.161***	−0.072	−0.132*	−0.043**
Ln(Y3) * Ln(W2/W3)	−0.539***	−0.125	−0.143**	0.094*	−0.092***
size	0.799***	1.116***	0.615***	1.001***	
GNIPC					0.00014**
σ^2	0.041**	0.01**	0.044**	0.077**	1.471***
γ	0.971***	0.86***	0.973***	0.987***	0.998***
Time	0.014	0.073**	−0.003	−0.012	−0.005***
Likelihood ratio	120.862	146.6571	195.7675	95.99013	566.0318
# of observations	80	92	129	62	729

W1, W2 and W3 are respectively capital, fund and labor prices. Y1, Y2 and Y3 are respectively total deposits and short-term funding, gross loans and total earning assets. GNIPC stands for gross national income per capita, while size is log (Total assets).

*** Denotes significance at 1% level.

** Denotes significance at 5% level.

* Denotes significance at 10% level.

Table 4
Summary statistics for the TGRs and cost efficiency obtained from the country stochastic frontiers and the meta frontier for banks in low-income countries.

	Mean			StdDev			Max			Min		
	TGR	MCE	CE	TGR	MCE	CE	TGR	MCE	CE	TGR	MCE	CE
Ethiopia	0.72	0.67	0.93	0.06	0.05	0.04	0.84	0.77	0.99	0.63	0.59	0.85
Malawi	0.12	0.12	0.99	0.03	0.03	0.03	0.18	0.18	1.00	0.08	0.08	0.84
Mali	0.33	0.33	0.98	0.04	0.05	0.02	0.43	0.42	1.00	0.28	0.27	0.89
Mozambique	0.19	0.19	0.99	0.04	0.04	0.04	0.26	0.26	1.00	0.15	0.13	0.75
Nepal	0.83	0.80	0.96	0.05	0.06	0.02	0.99	0.96	1.00	0.74	0.69	0.87
Senegal	0.42	0.35	0.84	0.08	0.08	0.09	0.67	0.54	0.99	0.24	0.22	0.70
Tanzania	0.35	0.30	0.85	0.06	0.05	0.09	0.53	0.41	0.99	0.26	0.21	0.59
Uganda	0.20	0.19	0.92	0.04	0.04	0.06	0.28	0.27	0.99	0.13	0.12	0.77
Zimbabwe	0.24	0.20	0.81	0.03	0.03	0.12	0.30	0.25	0.98	0.18	0.13	0.63

TGR: Technology Gap Ratio.
MCE: Meta-Cost Efficiency.
CE: Cost Efficiency.

correlation table. This is the case for Tanzania, Uganda, Nepal, Mali, and Zimbabwe. Processes to reduce labor use can help close the gap between a bank's frontier and the meta-frontier. Labor factors appear to be greater drivers of banking performance for the average bank. As the correlation matrix shows, labor price has a stronger relationship with technology gap ratio than any other prices. However, the technology gap ratio has a significant negative relationship with fund price for Mali and a significant positive relationship for Malawi, Nepal, and Zimbabwe. A negative relationship with the technology gap ratio corresponds to the adverse effect of limited access to customer funds. It could be that limited access to funding is caused by low financial inclusion. A positive relationship reflects the extent to which banks are constrained to improve their intermediation processes and services to compensate for their interest expenses. Likewise, capital prices in Ethiopia, Malawi, Mali, Mozambique, and Nepal are positively related to the technology gap ratio at 1% and 5% levels of significance. Improving services and processes through technology can reduce labor costs and in turn decrease total costs.

Innovative banking markets tend to be more competitive and possess higher financial inclusion and greater market depth. Nepal stands out in this study group, enjoying a more favorable banking environment. As presented in Table 6, Nepal has far greater market depth than

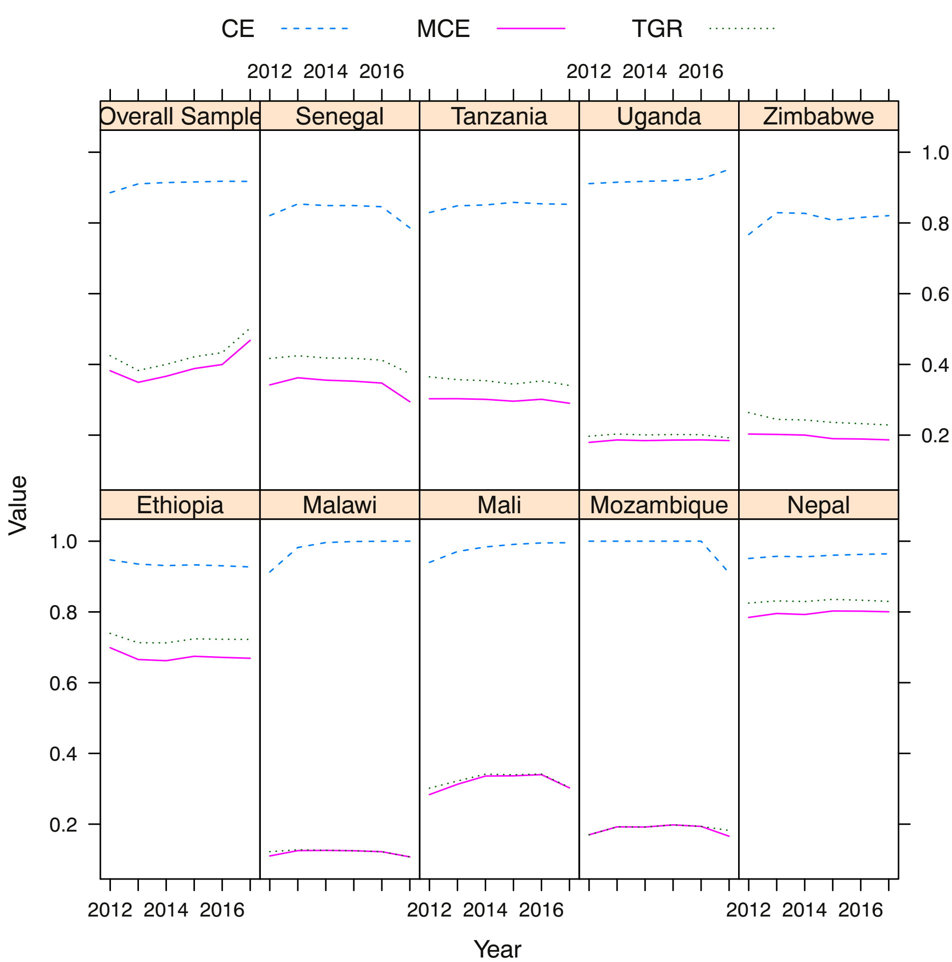

Fig. 1. Evolution of Cost Efficiency (CE), Meta-Cost efficiency (MCE) and Technology Gap Ratio (TGR) by country over the 2012–2017 period.

Table 5
Pearson correlation matrix between TGRs, total costs and input prices.

	Total cost	Labor price	Fund price	Capital price
Overall sample	−0.009	−0.468**	0.128**	−0.088*
Ethiopia	−0.360**	0.038	−0.131	0.651**
Malawi	−0.825**	0.102	0.623**	0.339*
Mali	−0.438**	−0.044	−0.422**	0.588**
Mozambique	−0.534**	0.765**	0.204	0.380**
Nepal	−0.441**	−0.264**	0.335**	0.759**
Senegal	−0.068	0.459**	0.066	0.074
Tanzania	−0.161	−0.011	0.072	0.122
Uganda	−0.755	−0.202	0.058	0.136
Zimbabwe	0.525**	−0.315*	0.566**	−0.506**

* 5% level of significance.
** 1% level of significance.

any other country in the sample, with gross loans to deposits and short-term funding reaching 22.4 on average. Nepal seems to also have a higher level of financial inclusion. The average ratio of deposits and short-term funding to GDP is higher for Nepal than for other countries in the sample. Furthermore, Nepal has the highest H-statistic and the lowest Herfindahl-Hirschman Index (HHI) (see Table 7). Likewise, Malawi exhibits the lowest financial intermediation level with the gross loans to deposits and short-term funding ratio of 0.52 (see Table 6). Furthermore, its financial stability proxies reflect the least favorable conditions among all countries in the sample. These characteristics may explain their rank within the sample as the least efficient and least innovative banking system.

3.2. The determinants of financial innovation

Next, we establish the factors that determine financial innovation and cost efficiency in low-income countries. The explained variable is the technology gap ratio representing financial innovation. The estimation equation accounts for bank and country specific determinants.

3.2.1. Country specific determinants

The country specific determinants include competition, banking access, financial inclusion and financial intermediation. The proxy of competition is the H-statistic developed by Panzar and Rosse (1987). It is the sum of input prices coefficients in the revenue equation. For $H < 0$ there is a monopoly. For $H = 1$ the market is perfectly competitive. $0 < H < 1$ indicates monopolistic competition. For direct comparison we switched the H-statistic with the Herfindahl-Hierschman Index (HHI) (a concentration proxy) in the regression. There are mixed results with regard to the relationship between competition and concentration in the literature. Some yield a negative relationship supporting the Structure-Conduct-Performance paradigm; while some support a positive relationship (Claessens & Laeven, 2005). Market structure, through competition, plays a pivotal role in building innovative industries and institutions. Aghion, Harris, Howitt, and Vickers (2001) argued that competition foster innovation as a firm seeks to escape competition. This implies that the more competitive a market is, the more innovative it tends to be. Therefore, innovation is expected to increase with competition. Banking access is measured using the number of bank branches (CBB100k) and the population density (PD). PD is the number of inhabitants divided by land area measured in square kilometers. Banks have the potential to benefit from economies of scale as they serve more customers. Financial inclusion is measured by the ratio of customer deposits and short-term funding to gross domestic product. This is the extent to which people participate in the financial market. The level of participation drives the level and quality of financial services provided, and therefore incentivizes banks to innovate. The ratio of gross loans to customer deposits and short-term funding is the proxy of financial intermediation. It is a measure of financial resources in the form of loans, purchases of non-equity securities or trade credits provided by banks. Innovative banking systems tend to have higher levels of financial intermediation (as observed with Nepal). We also control for economic growth via the gross national income growth (GNIG). More growth encourages more financial innovation.

3.2.2. Bank-specific determinants

Bank-specific determinants include financial stability, capital adequacy (with ETA, or equity-to-asset ratio, as a proxy), profitability (with ROAA, or return on average assets, as a proxy) and size. Z-score captures the level of financial stability. It is the sum of return on average assets and equity ratio (equity/total assets) divided by the standard deviation of return on average assets. A stable financial system is the result of a stable economy which is conducive to innovation. Low-income countries are substantially affected by instability due to political turmoil and bad governance. Therefore, financial instability has a tendency to deter innovation. Size here refers to the natural logarithm of assets and reflects the effects of economies of scale on cost-reducing innovations. The equity-to-assets ratio is used to capture the regulatory environment facing banks in their individual country. It typically has a positive relationship with cost efficiency, as observed in the literature (Carvallo & Kasman, 2005; Staikouras, Mamatzakis, & Koutsomanoli-Filippaki, 2007) supporting the “moral hazard” hypothesis. Banks with higher equity capital tend to be more risk averse. Profitability, with ROAA as a proxy, is closely linked to the competitive conditions of the market and institutional settings.

3.2.3. Determinants of financial innovation with competition proxy

The results of the Tobit (Tobin, 1958) regression are provided in Table 8. We included the time variable into the regression to account for time effects. We also estimated the parameters using fixed effects panel least squares and generalized method of moments for comparison

Table 6
Characteristics of banking system in low income countries.
Data Source: World Bank Database and Orbis bank focus database.

	PD	Z-score	GNIG	ROAA	ETA	GL/DSF	DSF/GDP	CBB100K
Ethiopia	100.05	51.80	9.61	2.59	14.65	1.30	0.02	2.93
Malawi	184.03	9.84	3.75	2.39	13.50	0.52	0.02	3.17
Mali	14.05	27.65	4.90	1.42	10.55	0.66	0.03	5.63
Mozambique	35.46	12.49	5.22	−1.43	20.17	0.88	0.03	4.04
Nepal	199.75	34.41	4.37	1.75	10.20	22.40	0.06	8.77
Senegal	76.44	33.53	4.88	0.37	12.23	0.72	0.05	4.76
Tanzania	60.18	50.15	7.00	0.15	16.58	0.70	0.02	2.42
Uganda	196.49	168.12	4.50	1.59	18.57	0.74	0.01	2.84
Zimbabwe	40.35	15.80	5.19	0.92	18.35	0.67	0.02	9.22

PD: Population density (population/km^2); Z-score = (ROAA + Equity asset ratio)/Standard Deviation of ROAA; GNIG (%): Gross National Income Growth; ROAA (%): Return on Average Assets; ETA (%): Equity to asset ratio; GL/DSF: Gross loans to deposits and short-term funding ratio; CBB100K: Commercial bank branches per 100,000 adults.

Table 7
Evolution of HHI, H-statistic and Z-score over the studied period.

	Hirfindahl-Hirshman Index (HHI)						*H-statistics*						*Z-score*					
	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017
Ethiopia	0.55	0.43	0.39	0.38	0.39	0.10	0.71	0.69	0.64	0.51	0.11	0.08	45.37	50.78	56.95	51.49	51.10	49.66
Malawi	0.36	0.18	0.17	0.17	0.18	0.21	0.04	0.03	0.05	0.03	0.01	−0.01	10.55	10.48	9.93	9.25	9.02	10.14
Mali	0.27	0.13	0.13	0.12	0.13	–	0.23	0.33	0.23	0.09	0.08	–	19.99	31.45	27.77	26.69	28.17	23.98
Mozambique	0.51	0.27	0.24	0.26	0.24	0.24	0.11	0.19	0.50	0.35	0.20	0.26	20.54	9.92	11.13	12.53	12.21	15.00
Nepal	0.10	0.08	0.07	0.06	0.05	0.04	0.82	0.80	0.73	0.75	0.25	0.33	31.77	29.53	31.08	30.82	35.35	43.44
Senegal	0.16	0.11	0.10	0.10	0.10	0.42	0.66	0.61	0.50	0.48	0.13	–	34.62	30.86	46.01	24.38	35.88	14.82
Tanzania	0.32	0.10	0.10	0.11	0.12	0.17	0.42	0.41	0.41	0.49	0.21	0.68	29.15	77.15	75.63	29.26	30.97	34.99
Uganda	0.24	0.10	0.10	0.11	0.13	0.39	0.37	0.46	0.33	0.53	0.68	–	31.65	343.79	311.75	27.17	28.62	28.16
Zimbabwe	0.22	0.16	0.16	0.16	0.16	0.19	–	0.19	0.04	0.36	0.46	0.11	9.91	16.02	15.71	17.67	17.11	16.13

HHI and Z-score values are calculated by the authors using banks financial statement data. H-statistics for 2012–2015 period are retrieved from Čihák, Demirgüç-Kunt, Feyen, & Levine (2012), while values for 2016 and 2017 are estimated by the authors.

Table 8
Estimation results of the determinants of the TGRs, with competition proxy (H-statistic).

	ML-Censored Normal	Fixed effect	Generalized method of moments
C	0.653563***	0.594053***	0.382893***
CBB100K	−0.021816***	−0.021816***	−0.006008
GL/DSF	0.000129***	0.000129***	0.000252***
DSF/GDP	2.117691***	2.117691***	3.025421***
Equity/assets	−0.002798***	−0.002798***	−0.003238***
Z-score	0.00000298	0.00000298	0.00000627
H-statistic	0.186657***	0.186657***	0.290262***
H-statistic^2	0.060539	0.060539	0.01413
Population density (PD)	−0.002376***	−0.002376***	−0.001831***
PD*CBB100K	0.00056***	0.00056***	0.000451***
Log (total assets)	−0.025933***	−0.025933***	−0.023357***
ROAA	0.001809*	0.001809	0.000479
GNIG	0.009177***	0.009177***	0.018615***
YEAR = 2013	−0.059588***		
YEAR = 2014	−0.057085***		
YEAR = 2015	−0.074164***		
YEAR = 2016	−0.061791***		
YEAR = 2017	−0.141951***		
Likelihood ratio	648.0223	648.0223	
# of observations	541	541	392

Estimates with respectively ML-Censored Normal (TOBIT) method, fixed effect panel least squares method and the panel generalized method of moments (GMM), where the dependent variable is the TGR. Lag regressors from 1 period are used as instrument variables in the GMM estimation, except for CBB100K, ETA, PD and log (TA), to control for endogeneity.
*** Denotes 1% level of significance.
** Denotes 5% level of significance.
* Denotes 10% level of significance.

purposes. Each method produced similar results. The dependent variable is left- and right-censored at 0 and 1, respectively, as the TGR is bounded by 0 and 1. The estimated coefficients take the expected signs. Particularly, competition was found to have a positive relationship with innovation, supporting the Escape Competition Hypothesis (Aghion et al., 2001).

Therefore, the results confirm our expectation that competition fosters innovation. As previously shown, Nepal has the highest H-statistic value and the highest TGR. These results imply that policymakers should develop policies that encourage market competition, such as reducing barriers to market entry or increasing market contestability. The number of commercial bank branches, as well as PD positively affect innovation. However, there must be at least five (=0.00238/0.00056) commercial banks per 100,000 adults (given the PD) for banks to reach as many customers as possible and benefit from cost-reducing innovations. Likewise, the ratio of customer deposits and short-term funding to GDP was found to have a positive relationship with cost-reducing innovations as shown in Table 8. Therefore, banks have the potential to reduce their costs through innovation, given that customers have access to their services and the customers' participation in the financial market for a given PD. For example, Nepal, which has the highest level of cost-reducing innovations, also has the second highest number of bank branches and the highest ratio of deposits and short-term funding to GDP. Government and central banks can promote financial inclusion with special policies and strategies. For example, Kabakova and Plaksenkov (2018) revealed that socially and politically advanced ecosystem foster financial inclusion where enhanced economic measures may not be required. Cost-reducing innovations increase with financial intermediation, as the GLDSF proxy shows. Financial depth plays a significant role in boosting financial innovation in low-income countries. As demonstrated in the literature (Mensah, Abor, Aboagye, & Adjasi, 2015), financial intermediation boosts growth and vice versa. Nepal has the highest GLDSF in the sample and Malawi has the lowest. Z-score has no significant effect on financial innovation. This result suggests that in a competitive market financial instability does not prevent banks from innovating.

We now examine the regulatory proxy, the equity-capital to assets ratio. The relationship is negative between equity ratio and the technology gap ratio. This runs counter to studies that support the "moral hazard" hypothesis, in which capital adequacy reduces capital and asset risks, thereby increasing asset quality and cost innovation (Nguyen et al., 2016). It does, however, support the theory that banks in low-income countries are constrained by policy makers to preserve a sound capital adequacy ratio to compensate for credit risk preventing the bank to explore more innovative ways to reduce costs. It also supports the literature that indicates that debt pressure may lead to more innovation (Aghion, Bloom, Blundell, Griffith, & Howitt, 2002). This is similar to the escape competition effect in that banks innovate more to escape debt pressure. The profitability proxy was found to have a slight positive effect on innovation. One explanation is that, banks may be constrained to employ adequate innovative practices to reduce operating cost leading to higher return as the market become more competitive. Growth triggers higher innovation as the results show. Banks may apply more preventive measures through innovative practices to palliate credit risk as intermediation businesses increase. Notably, size was found to have a negative effect on the technology gap ratio. This result suggests that small banks benefit more from competition, and this is in line with the escape competition hypothesis.

3.2.4. Determinants of financial innovation with concentration proxy

When we use the concentration proxy (HHI), the regressions yield very similar results to the previous ones, except in three cases (see Table 9). Concentration was found to have a non-linear relationship with innovation contrasting the competition-innovation relationship. Most particularly, the relationship is U-shaped, supporting the results expected under Structure-Conduct-Performance (SCP) paradigm. In

Table 9
Estimation results of the determinants of the TGRs, with concentration proxy (HHI).

	ML-Censored Normal	Fixed effect	Generalized method of moments
C	1.260064***	1.128763***	0.473787*
CBB100K	−0.028495***	−0.028495***	−0.036624***
GL/DSF	0.000109***	0.000109***	0.000129***
DSF/GDP	−0.0973	−0.0973	2.013651*
Equity/assets	−0.001876***	−0.001876***	−0.000227
Z-score	−0.00000752***	−0.00000752***	−0.00000329
HHI	−2.761674***	−2.761674***	2.405769
HHI^2	3.998599***	3.998599***	−11.36102
Population density (PD)	−0.002864***	−0.002864***	−0.00305***
PD*CBB100K	0.000594***	0.000594***	0.00071***
Log (total assets)	−0.026552***	−0.026552***	−0.017361***
ROAA	0.000344	0.000344	−0.003091*
GNIG	0.002293*	0.002293*	0.017517**
YEAR = 2013	−0.136784***		
YEAR = 2014	−0.143595***		
YEAR = 2015	−0.148647***		
YEAR = 2016	−0.155039***		
YEAR = 2017	−0.138707***		
Likelihood ratio	737.1225	737.1225	
# of observations	548	548	399

Estimates with respectively ML-Censored Normal (TOBIT) method, fixed effect panel least squares method and the panel generalized method of moments (GMM), where the dependent variable is the TGR. Lag regressors from 1 period are used as instrument variables in the GMM estimation, except for CBB100K, ETA, PD and log (TA), to control for endogeneity.

*** Denotes 1% level of significance.

** Denotes 5% level of significance.

* Denotes 10% level of significance.

other words, a higher concentration leads to less competition and higher innovation. Under the Structure-Conduct-Performance paradigm, HHI proxies competition. Because a higher HHI indicates a more concentrated market, the relationship with innovation is U-shaped when the first degree coefficient of HHI is negative and the second degree is positive. Under the SCP paradigm this result is consistent with both the Escape Competition (Aghion et al., 2001) and Schumpeterian (Schumpeter, 1934) hypotheses. Schumpeter (1934) stated that monopolistic markets encourage greater innovation. At small monopoly rents, the increase in market power impedes financial innovation until it reaches a certain turning point. Then, as monopoly rents increase, market power triggers financial innovation. For example, according to Table 9, the turning point is 0.35 $\left(\frac{2.762}{2 \times 3.999}\right)$. In other words, beyond 0.35, market power has a Schumpeterian effect on financial innovation. In sum our result contrast with Claessens and Laeven (2005) who argues that uncompetitive markets are not linked to concentration, rather to the market contestability. Z-score affects innovation negatively. Surprisingly, this result suggests that in a concentrated market financial stability dampens cost innovation. This is in line with the Quiet Life Hypothesis in that banks may focus on ways to increase their income neglecting practices to tackle operating cost. Contrarily to the previous results ROAA yield a slight negative effect on innovation. This is in contrast with those in the literature, supporting however, the result found between financial stability and innovation. Beck (2006) states that inefficiencies lead to wider interest spreads. This implies that banks' inability to adequately monitor their borrowers leads them to set higher lending rates to compensate for credit risk and extra monitoring costs. In other words, banks remain innovative while enjoying high returns.

Overall, the results are robust. The generalized method of moments resulted in a slight difference for HHI where the quadratic relationship is not significant.

4. Conclusion

This study evaluates cost-reducing innovation in nine low-income countries. We used a new parametric two-stage meta-frontier model developed by Huang et al. (2014) to calculate the technology gap ratio, and a Tobit regression approach to estimate their determinants. The results demonstrate that Nepal has the most favorable cost-reducing innovations, while Malawi has the worst. These two countries have markedly different banking environments. Nepal enjoys high financial depth, banking access, financial inclusion, and competition relatively to the eight other countries considered. Malawi, however, possesses the lowest financial depth and competition. There is a positive relationship between competition and innovation. Under the SCP paradigm, however, both the Schumpeterian and “Escape Competition” hypotheses are confirmed, suggesting that competition leads to financial innovation along the first part of the curve, and that a monopoly leads to financial innovation along the second part. Financial inclusion, financial depth, and banking access have a positive relationship with the technology gap ratio. However, capital adequacy is negatively related to financial innovation. Profitability on the other hand yields mixed results. Financial stability has a negative effect on financial innovation, supporting the Quiet Life Hypothesis. Size, by contrast, has a negative effect on financial innovation.

Policy makers are recommended to set policies that encourage both market competition and contestability. On the other hand, bank managers can implement standards that allow them to reduce labor expenses through information technology.

Acknowledgements

This study was partially supported by the Ministry of Science and Technology of Taiwan under grant number MOST 103-2410-H-011-012-MY3 and MOST 106-2410-H-011-004-MY3. Any opinions, findings, and conclusions or recommendations expressed herein are those of the authors and do not necessarily reflect the views of the sponsors.

References

Abdallah, Z. M., Amin, M. A. M., Sanusi, N. A., & Kusairi, S. (2014). Impact of size and ownership structure on efficiency of commercial banks in Tanzania: Stochastic frontier analysis. *International Journal of Economic Perspectives, 8*(4), 66–76.

Abel, S., & Le Roux, P. (2016). An evaluation of the nexus between banking competition and efficiency in Zimbabwe. *Journal for Studies in Economics and Econometrics, 40*(3), 1–19.

Abid, I., & Goaied, M. (2017). A meta-frontier assessment of bank efficiency in Middle East and North Africa countries. *International Journal of Productivity and Performance Management, 66*(2), 266–296. https://doi.org/10.1108/IJPPM-01-2016-0020.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2002). *Competition and innovation: An inverted U relationship (NBER Working Paper Series No. 9269). Working paper.* (Cambridge).

Aghion, P., Harris, C., Howitt, P., & Vickers, J. (2001). Competition, imitation and growth with step-by-step innovation. *Review of Economic Studies, 68*(3), 467–492. https://doi.org/10.1111/1467-937x.00177.

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6*(1), 21–37. https://doi.org/10.1016/0304-4076(77)90052-5.

Banya, R., & Biekpe, N. (2018). Banking efficiency and its determinants in selected frontier african markets. *Economic Change and Restructuring, 51*, 69–95. https://doi.org/10.1007/s10644-016-9200-3.

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: With application to Paddy farmers in India. *Journal of Productivity Analysis, 3*, 153–169.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*, 325–332.

Beck, T. (2006). *Efficiency in financial intermediation: Theory and empirical measurement.* World Bank.

Bos, J. W. B., Kolari, J. W., & Van Lamoen, R. C. R. (2013). Competition and innovation: Evidence from financial services. *Journal of Banking & Finance, 37*, 1590–1601. https://doi.org/10.1016/j.jbankfin.2012.12.015.

Cadet, R. L. (2015). Cost and profit efficiency of banks in Haiti: Do domestic banks perform better than foreign banks? *International Journal of Banking, Accounting and Finance, 6*(1), https://doi.org/10.1504/IJBAAF.2015.070507.

Carvallo, O., & Kasman, A. (2005). Cost efficiency in the Latin American and Caribbean banking systems. *Journal of International Financial Markets Institutions and Money,*

15(1), 55–72. https://doi.org/10.1016/j.intfin.2004.02.002.
Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8.
Čihák, M., Demirgüç-Kunt, A., Feyen, E., & Levine, R. (2012). *Benchmarking financial systems around the world (Policy Research No. 6175).* (Washington D.C.).
Claessens, S., & Laeven, L. (2005). *Financial dependence, banking sector competition, and economic growth (World Bank Policy Research No. 3481).* (Washington D.C., USA).
Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis a comprehensive text with models, applications, references and DEA-solver software (second).* Springer.
Frame, W. S., & White, L. J. (2009). *Technological change, financial innovation, and diffusion in banking (Working Paper No. 2009–10). Working paper. Vol. 2009–10* (Atlanta).
Haque, F., & Brown, K. (2017). Bank ownership, regulation and efficiency: Perspectives from the Middle East and North Africa (MENA) Region. *International Review of Economics and Finance, 47*, 273–293. https://doi.org/10.1016/j.iref.2016.10.015.
Hauner, D., & Peiris, S. J. (2005). *Bank efficiency and competition in low-income countries: The case of Uganda (IMF Working Paper No. WP/05/240). IMF working papers.* https://doi.org/10.5089/9781451862591.001.
Huang, C. J., Huang, T.-H., & Liu, N.-H. (2014). A new approach to estimating the metafrontier production function based on a stochastic frontier framework. *Journal of Productivity Analysis, 42*, 241–254. https://doi.org/10.1007/s11123-014-0402-2.
Huang, T.-H., Hu, C.-N., & Chang, B.-G. (2018). Competition, efficiency, and innovation in Taiwan's banking industry — An application of copula methods. *The Quarterly Review of Economics and Finance, 67*, 362–375. https://doi.org/10.1016/j.qref.2017.08.006.
Hui, X., & Jha, S. (2013). The impact of commercial banking performance on economic growth. *Proceedings of the Institute of Industrial Engineers Asian Conference* (pp. 1503–1511). Springer Science + Business Media Singapore. https://doi.org/10.1007/978-981-4451-98-7_176.
Jha, S., & Hui, X. (2013). Commercial banking efficiency in Nepal: Application of DEA and tobit model. *Information Technology Journal*. https://doi.org/10.3923/itj.2013.306.314.
Kabakova, O., & Plaksenkov, E. (2018). Analysis of factors affecting financial inclusion: Ecosystem view. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2018.01.066.
Mensah, E., Abor, J., Aboagye, A. Q. Q., & Adjasi, C. K. D. (2015). Enhancing the economic growth of Africa: Does banking sector efficiency matter? *Finance and Development in Africa, 12B*(10), 1–23. https://doi.org/10.1108/S1479-3563(2012)000012B005.
Nguyen, T. P. T., Nghiem, S. H., Roca, E., & Sharma, P. (2016). Efficiency, innovation and competition: Evidence from Vietnam, China and India. *Empirical Economics, 51*, 1235–1259. https://doi.org/10.1007/s00181-015-1045-5.
Panzar, J. C., & Rosse, J. N. (1987). Testing for monopoly equilibrium. *The Journal of Industrial Economics, 35*(4), 443–456. https://doi.org/10.2307/2098582.
Poghosyan, T. (2013). Financial intermediation costs in low income countries: The role of regulatory, institutional, and macroeconomic factors. *Economic Systems, 37*(1), 92–110. https://doi.org/10.1016/j.ecosys.2012.07.003.
Rioja, F., & Valev, N. (2004). Finance and the sources of growth at various stages of economic development. *Economic Inquiry, 42*(1), 127–140. https://doi.org/10.1093/ei/cbh049.
Schumpeter, J. A. (1934). *The theory of economic development; an inquiry into profits, capital, credit, interest, and the business cycle.* Harvard University Press.
Staikouras, C., Mamatzakis, E., & Koutsomanoli-Filippaki, A. (2007). Cost efficiency of the banking industry in the south eastern European region. *Journal of International Financial Markets Institutions and Money, 18*(5), 483–497. https://doi.org/10.1016/j.intfin.2007.07.003.
Thagunna, K. S., & Poudel, S. (2013). Measuring bank performance of Nepali banks: A data envelopment analysis (DEA) perspective. *International Journal of Economics and Financial Issues, 3*(1), 54–65.
Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica, 26*(1), 24–36. https://doi.org/10.2307/1907382.
Triki, T., Kouki, I., Dhaou, M. B., & Calice, P. (2017). Bank regulation and efficiency: What works for Africa? *Research in International Business and Finance, 39*, 183–205. https://doi.org/10.1016/j.ribaf.2016.07.027.
White, H. (1982). Maximum likelihood estimation of misspecified models. *Econometrica, 50*(1), 1–25.

Jean-Raymond Fontin is a Ph.D. student in the Department of Industrial Management at the National Taiwan University of Science and Technology. His current research interests focus on the application of benchmarking methods and techniques, such as data envelopment analysis (DEA) and stochastic frontier approach (SFA), to efficiency evaluation and assessment of decision making process, with applications to banking or technology innovation.

Shi-Woei Lin is an Associate Professor in the Department of Industrial Management at the National Taiwan University of Science and Technology. His current research interests include the application of game theory to risk-informed regulation and to pricing mechanism design of sharing public systems, and the use of mathematical model to aggregate experts' uncertainty judgment. Other interests include data mining for medical informatics, service performance evaluation using data envelopment analysis (DEA), and methods for effective risk communication, both to decision makers and to the general public.