Another Great Convergence? Are Islamic and Conventional Banks Converging in Efficiency across All Countries?

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Abstract

Are the efficiency dynamics of Islamic and conventional banks similar? To answer this question we employ both parametric and non-parametric methods to analyse a panel of Islamic and conventional banks from 23 countries during the period 1999 to 2014. Within a stochastic frontier analysis both the steady state efficiency and the speed of convergence of Islamic and conventional banks are found to be most similar, but within a classification trees framework these bank types differ markedly in some countries in terms of their efficiency dynamics.

Keywords: Efficiency convergence • Random parameter estimation • Conditional β-convergence • Islamic banks • Classification trees

JEL classification: G21 • F36 • D24

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1. Introduction

Banking efficiency studies have long been of interest to a variety of stakeholders.¹ At a macro level, there is some evidence that economic growth (as measured by growth in GDP) is significantly and positively related to banking sector efficiency (Berger et al. 2004; Hasan et al. 2009; Abedifar et al. 2016). At a micro level, efficiency studies can provide benchmarking information that can be of interest to bank managers and policy makers in order to improve banks’ performance.

Banking efficiency has also been widely studied in comparative banking analyses, notably when comparing Islamic and conventional banks.² Measuring efficiency in Islamic banking is particularly important in countries where this type of banking accounts for a substantial part of the financial sector. The cases of Saudi Arabia and Malaysia, where the share of Islamic banking assets are 51.2% and 21.3% (respectively) are important examples (Ernst & Young 2016). From a macro level perspective, the efficiency of operations of Islamic banks that co-exist with their conventional counterparts has a significant positive effect on the development of a country’s entire banking sector (Gheeraert 2014).

At the micro level, a number of studies comparing the efficiency of the Islamic and conventional banking sectors have identified a significant efficiency gap between the two bank types at given points in time and for a variety of countries (Mokhtar et al. 2007; Abdul-Majid et al. 2008; Al-Muharrami 2008; Mokhtar et al. 2008; Abdul-Majid et al. 2010; Srairi 2010; Abdul-Majid et al. 2011a; 2011b; Johnes et al. 2014). Given the differences between Islamic and conventional banking business models, the variations in efficiency are perhaps to be expected. However, the underlying dynamics of this efficiency gap have barely been examined.

The dynamics are of particular importance in the context of competitive advantage. Within the resource-based theory (Chen et al. 2015) it is argued that superior profitability performance of firms (banks in this case) can arise because of differences in efficiency (Demsetz 1973; McGahan and Porter 1999). Such efficiency differences might arise from inter-bank differences in technology, experience or (of particular relevance here) the business model. According to neoclassical theory, the most efficient production techniques will be imitated by other banks within a competitive operating framework. In other words, efficiency differences would not persist; hence efficiency of banks would converge. Differences might nevertheless persist in the presence of “uncertain imitability” (Lippman and Rumelt 1982) if other banks are unable to identify (or unwilling to copy) the operations of the efficient banks.³ Consequently, efficiency differences and speed of convergence are indicative of the extent of such competitive advantage; slow convergence will allow the competitive advantage to be maintained for longer, with direct implications for bank managers. Policy-

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¹ The number of citations to the seminal paper by Aigner et al. (1977) on stochastic frontier analysis equals almost 10,000, while the number of citations to Berger and Humphrey (1997) and Berger and Mester (1997), the two seminal studies on banking efficiency, are close to 4,000 and 2,750, respectively.
² Johnes et al. (2014) provide a comprehensive review of empirical studies on efficiency of Islamic and conventional banks.
³ See Johnes and Johnes (2013) for a more detailed exposition of the resource-based view and uncertain imitability.
makers are also interested because faster convergence to a common long-run efficiency level is a sign of a competitive banking sector.\(^4\)

In an ideal world, any bank would optimise its business model to attain long-run efficiency. This, however, might be impeded by factors (relating to economic conditions, operation and regulatory frameworks) that affect the operational process and therefore both the convergence rate and the level of long-run efficiency. It is these dynamic interactions which determine how swiftly a bank can attain (or re-attain) its long-run efficiency following, for example, an economic shock. Differences in convergence rates (as well as the steady state efficiency levels) might arise because business practices and underlying principles differ. Compared to conventional banks, Islamic banks, for example, may opt for some modified (by the Accounting and Auditing Organization for Islamic Financial Institutions – AAOIFI) versions of the Basel regulatory framework.

Variations in efficiency convergence rates might not be as great as expected \textit{a priori} for various reasons. First, there may be differences between the theoretically envisaged Islamic banking model and what is observed in reality. For instance, the cornerstone of Islamic banking is equity finance (El Hawary \textit{et al.}, 2004), with profits and losses shared between the contracted parties according to some pre-determined ratio (Zaher and Kabir Hassan 2001; Usmani 2002). Yet, equity financing may constitute a small percentage of a typical Islamic bank’s asset portfolio (Zaman and Movassaghi 2002; El-Gamal 2009; Khan 2010). Instead, fee-based financial products are the norm, where an “implicit” interest rate is charged that is often highly correlated with the “explicit” interest rate observed in the conventional banking sector (Hussan and Masih 2014).

Second, the extent of compliance with Islamic principles tends to vary by bank size, product offerings and demographics. Products, such as Islamic microfinance, are more common in the Far East, whereas real estate finance is more dominant in the Gulf Cooperation Council (GCC) region. Therefore, we might expect differences in steady state efficiency and efficiency convergence rates \textit{within} the Islamic banking sector, thereby blurring any distinctions \textit{between} Islamic and conventional banks.

Third, over time we would expect financial integration to increase worldwide through common regulatory frameworks (such as the Basel Committee, the World Bank, and the International Monetary Fund),\(^5\) trade and monetary unions (for example the European Union) and an ever-increasing global banking presence (HSBC, for example, has branches in 80 countries). Therefore, and as financial and economic integration increases worldwide, efficiency convergence is expected to take place.

Given the importance of efficiency and efficiency convergence rate, this paper addresses two questions: do Islamic and conventional banks have different steady state efficiency levels? And, do Islamic and conventional banks have different rates of efficiency convergence?

\(^4\) Related to this, González (2009) examines the link between banking efficiency and market structure.

\(^5\) Delis \textit{et al.} (2011) highlight the contribution of such international organisations to the financial development of transitional economies.
Evidence of differences in both efficiency steady states and convergence rates would support the hypothesis that Islamic banks operate a different banking business model which would explain continuing differences in these two measures. On the other hand, the absence of a significant difference can be taken as an indicator of mimicking behaviour and would favour the hypothesis that the two banking models differ only theoretically and not in practice.

We address these two questions in three steps. First, we use a stochastic frontier output distance function (ODF) to provide estimates of efficiency. Second, a conditional $\beta$-convergence model with Islamic bank shift and slope dummies is estimated using pooled OLS, random effects (RE) and system-GMM. A random parameter model (RPM) that allows for both the steady state efficiency and the $\beta$-coefficient to vary by bank is also used. These estimation techniques allow for an increasing degree of heterogeneity in the convergence process across years, countries and bank type, while mitigate potential endogeneity concerns.

Third, we utilise a classification trees approach that offers a way to identify whether there are groups of banking systems which are similar in terms of steady state efficiency and efficiency convergence rate. This approach, novel in this context, is necessary for the following reasons. The fact that the substantial literature on the comparative efficiency of Islamic and conventional banks has reached no consensus on which of the two banking systems is consistently more (or less) efficient provides prima facie evidence that the conclusion is largely country and/or year and/or bank specific. The models employed in the earlier step, which are consistent with this relevant literature, are hindered by the vanishing degrees of freedom when trying to control for all such factors at once. Moreover, the small number of Islamic banks in any given country further complicates any attempt to fully capture heterogeneity, while the standard practice in the literature of sampling across countries is not optimal.

Our main findings are as follows. The traditional $\beta$-convergence model finds no significant differences in steady state efficiency and efficiency convergence rates of the two bank types. Thus, Islamic banking practices (at an international level) are not sufficiently different from conventional ones to affect long run efficiency or convergence, although at any particular point in time there may be short run efficiency differences. Examination of differences in convergence rates by country suggests that convergence is significantly faster in certain countries than in others.

The classification trees analysis further reveals that steady state efficiencies and convergence rates vary both by bank type and by country in some cases, while in other cases that there are no significant bank type differences. For example, Islamic and conventional banking in Malaysia are indistinguishable in terms of steady state efficiency and convergence rates, whereas differences between the two banking systems are more evident in the GCC states. This finding can be plausibly attributed to variations in Islamic banking practices and product offerings between the GCC states and Malaysia, as well as to the degree of substitution between the two banking systems within each country.

Our paper contributes to the literature in three main ways. We provide the first formal approach that goes beyond simple efficiency analysis by comparing efficiency steady states and convergence rates between Islamic and conventional banks. Second, we use a random
parameter model, which is novel in this context and allows for increased heterogeneity in the efficiency steady states and convergence rates across banks. Third, we provide a country classification of the two bank types by steady state efficiency and efficiency convergence. This is important as it groups the countries where the two banking systems show differences and where they are similar; thereby offering a new approach to the fundamental question as to whether the Islamic and conventional banking models really do differ. Furthermore, it tallies with a recent trend in the literature suggesting that the practices of the two bank types are converging (Osln and Zoubi, 2016). The outcomes of our analysis will be of interest to researchers and policy-makers involved in measuring and developing banking sector efficiency, particularly where both bank types co-exist.

The remainder of the paper is organised as follows. In section 2 we review the received literature on efficiency convergence in the banking context. The methodological approaches employed to address our stated questions are presented in section 3. Data are presented in section 4. Results and discussion are presented in section 5. Finally, we draw conclusions and policy implications in section 6.

2. Literature Review

Studies of banking efficiency fall into two general categories. The first comprises studies which estimate banking sector efficiency at specific points in time, and possibly also examine, in a second stage, the determinants of efficiency. The second category contains studies which examine the presence and speed of efficiency convergence, and hence are more dynamic in nature. We consider each of these in turn.

Banking efficiency is typically measured using one of two approaches: a parametric frontier estimation, such as stochastic frontier analysis (SFA) or a non-parametric frontier estimation, such as data envelopment analysis (DEA). Both approaches have been widely used in the banking context (see, for example, Jackson and Fethi 2000; Ghroubi and Abaoub 2016). DEA is often used to estimate a production function because of its ease of accommodation of multiple inputs and multiple outputs. The downside is that it does not allow for stochastic shocks. Although SFA incorporates a stochastic error, and hence allows for random shocks, it is more difficult to accommodate multiple outputs and multiple inputs, which could explain the increased popularity of SFA in the context of cost or profit functions (see, for example, Fries and Taci 2005; Sririi 2010). The cost (profit) function approach, however, assumes banks minimize costs (maximize profits), which may not be fully reflective of the Islamic banking philosophy (Johnes et al. 2014).

There is a vast literature devoted to the measurement of banking efficiency (early reviews include Berger and Humphrey (1997), Berger and Mester (1997), Casu et al. (2001) and Brown and Skully (2002), while a more recent synthesis can be found in Fethi and Pasiouras (2010)). A growing literature that compares the efficiency of Islamic and conventional banks provides only mixed evidence regarding the efficiency of the two bank types. Some of these studies find no significant difference between the two bank types (El-Gamal and Inanoglu 2005; Grigorian and Manole 2005; Mokhtar et al. 2006; Bader 2008; Mohamad et al. 2008;
Hassan et al. (2009), while other studies find that Islamic banks are significantly more efficient than conventional banks (Al-Jarrah and Molyneux 2006; Al-Muharrami 2008; Olson and Zoubi 2008). But there is also evidence (including the most recent studies) that Islamic banks are significantly less efficient than conventional ones (Mokhtar et al. 2007; Abdul-Majid et al. 2008; Mokhtar et al. 2008; Abdul-Majid et al. 2010; Srairi 2010; Abdul-Majid et al. 2011a; 2011b; Kamarudin et al. 2014; Mobarek and Kalonov 2014).

Studies of banking efficiency which undertake a second stage analysis indicate that, besides bank type, other bank characteristics (such as size, composition of assets, risk-taking behaviour or liquidity) and variables related to banking context (such as the macroeconomic or the competitive environment) may affect banking performance (Berger and Mester 1997; Miller and Noulas 1997; Barajas et al. 1999; Dietsch and Lozano-Vivas 2000; Yudistira 2004; Staikouras et al. 2008; Awdeh and El Moussawi 2009; Koutsomanoli-Filippaki et al. 2009; Hasan and Dridi 2010; Beck et al. 2013).

Measuring efficiency convergence typically employs two approaches: the β- and σ-convergence models borrowed from the growth literature (Sala-I-Martin 1996) and the convergence framework of Phillips and Sul (2007; 2009). Many of the efficiency convergence studies relate to the banking sectors of the European Union (EU) member countries. A key hypothesis is that increasing global financial integration has led to banking efficiency convergence in a world-wide setting and there is plenty of evidence in support of such convergence (Fung 2006; Mamatzakis et al. 2008; Weill 2009; Rughoo and Sarantis 2012; Zhang and Matthews 2012; Kasman and Kasman 2013; Rughoo and Sarantis 2013; Andrieş and Căpraru 2014; Gallizzo et al. 2016).

While bank efficiency convergence is a well-researched topic within the EU and US context, there are other areas of efficiency dynamics where research would be useful. First, little interest has been shown in the steady state values which can be derived from these models. One exception (Fung 2006) highlights that bank efficiency convergence of US bank holding companies is conditional upon their initial differences in X-efficiency. Second, the relatively few studies devoted to Islamic banking do not deal with banking efficiency convergence. Yet, as Islamic banks must compete for business with conventional banks there is every reason to expect comparable efficiency convergence dynamics between the two bank types. These are the gaps in the literature which we aim to fill.

3. **Estimation framework - efficiency and convergence**

An implicit assumption underlying most efficiency studies is that all the banks under examination are fully synchronised. Yet, banks may face diverse – and react differently to – idiosyncratic and systemic shocks. Hence they might be at different stages on their path towards equilibrium efficiency. To allow for this we generalise the assumption of

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6 Olson and Zoubi (2016) test for convergence between the two bank types in an array of financial indicators. Their findings suggest that the two banking systems are converging in terms of profitability but not in terms of risk.
homogenous response to shocks by first estimating the efficiency of our sample banks and then examining more closely the steady state and convergence properties.

3.1. Efficiency Estimation using an ODF

We estimate the ODF using SFA,\(^7\) and apply a translog functional form as it is flexible, easy to estimate and permits the imposition of homogeneity (Coelli and Perelman 2000) – see Appendix 1 for further details. Given that the similarities between the Islamic and conventional banking practices can be both country and time specific, we opt to measure efficiency using an ODF that makes no specific assumptions about optimizing behaviour. A single ODF across all types of banks may be justified on the grounds that there is increasing competition between Islamic and conventional banks as evidenced by, for example, conventional banks establishing Islamic subsidiaries and/or Islamic windows, the availability of Islamic financial products and banks in non-Islamic countries, and the targeting of some Islamic products at all types of customers (Warde 2010).

The choice of variables qualifying for the distance function is guided by the previous literature (Casu and Giradone 2004; Casu et al. 2004; Abdul-Majid et al. 2008; 2010) and data availability. We follow the popular intermediation approach (see, for example, Pasiouras 2008). For the choice of inputs and outputs we follow Johnes et al. (2014), using: i) deposits and short term funding \((x_1)\), ii) fixed assets \((x_2)\), iii) general and administration expenses \((x_3)\) and iv) equity \((x_4)\) as inputs to produce: i) total loans \((y_1)\) and ii) other earning assets \((y_2)\). The justification for including these variables in the distance function model is explained in greater detail in Johnes et al. (2014).

Our efficiency model provides a measure of gross efficiency where no distinction is made between conventional or Islamic banks. Underlying structural differences between the two sectors which might affect steady state efficiency are addressed in the convergence model.

3.2. Modelling steady state efficiency and efficiency convergence

We utilise the concepts of \(\beta\)- and \(\sigma\)-convergence models (Young et al. 2008) to explore differences in steady state efficiency and efficiency convergence across the two bank types over the sample period. The convergence models used here and in other studies of banking efficiency convergence (see for example Weill (2009) and Casu and Girardone (2010)) are adapted from the growth literature (Sala-I-Martin 1996). The basic \(\beta\)-convergence model is:

\[
\ln(u_{i,t}) - \ln(u_{i,t-1}) = \alpha + \beta\ln(u_{i,t-1}) + \varepsilon_{i,t}
\]

where \(u_{i,t}\) is the measure of efficiency of bank \(i\) in time period \(t\). The value of the parameter \(\beta\) represents convergence (if \(\beta < 0\)) or divergence (if \(\beta > 0\)) in banking efficiency. The larger is \(|\beta|\) the greater is the speed of convergence or divergence. However the \(\beta\)-coefficient can be negative because of data measurement errors and random shocks rather than because

\(^7\) An ODF can be estimated using DEA or SFA. The former method is non-parametric and has the advantage that it can deal easily with multiple outputs and multiple inputs. DEA efficiency evaluations can be distorted by outliers, however, and stochastic errors are not allowed for as it is a deterministic estimation method. We therefore choose to use the parametric SFA which both addresses these issues and has the advantage (unlike DEA) that it can take into account the panel nature of the data we will be using.

\(^8\) All variables are in real values (based to 2005).
of genuine convergence (Fung 2006). In order to be sure that the $\beta$-coefficient signifies real convergence (rather than reversion towards the mean) it must coincide with significant $\sigma$-convergence (Fung 2006) which is a measure of convergence based on the dispersion of a bank’s efficiency around the sector average in a given time period. We therefore estimate $\sigma$-convergence in order to check that our $\beta$-convergence measures are valid. The basic $\sigma$-convergence model is given by:

$$\Delta w_{i,t} = \gamma + \sigma w_{i,t-1} + \epsilon_{i,t}$$  \hspace{1cm} (2)

Where $w_{i,t} = \ln(u_{i,t}) - \ln(\bar{u}_t)$ and $\Delta w_{i,t} = w_{i,t} - w_{i,t-1}$. Note that the value of the parameter $\sigma$ can be interpreted in a similar manner to the value of $\beta$.

We estimate a conditional $\beta$-convergence model whereby specific banks (Islamic or conventional) are permitted to have both different steady state efficiency levels and rates of convergence. For robustness, we use a variety of estimation methods including OLS, random effects and system-GMM.\(^9\) As an additional robustness check we allow the value of both $\alpha$ and $\beta$ to vary for each bank in the sample by using a random parameter method of estimation (Swamy 1970) for equation (1). These estimation methods address the issues of unobserved heterogeneity and endogeneity to differing extents. In particular, the RPM generalises the efficiency convergence framework by allowing each bank to have its own unique convergence dynamics. It is, therefore, better suited to cater for heterogeneous bank samples that is particularly relevant for the Islamic banks as there are important differences within their sector with regards to bank size, age, financial product focus and Shariah board compliance. More details on models and methods are provided in Appendix 2.

3.3. Classification trees

A difficulty in cross-country analysis is to identify precisely the impacts of bank type, country specific characteristics and regulation upon the quantity of interest (e.g., efficiency steady state or convergence rate). Traditional estimation methods often pose restrictions, due to the degrees of freedom limitations, when examining differences in the values of $\alpha$ and $\beta$ (see equation 1) by country and type. We therefore use a non-parametric classification tree methodology (see Appendix 3) to identify groups of banking sectors (by country) with similar steady state ($\alpha$) or convergence ($\beta$) characteristics. The classification tree method has previously been used in a banking efficiency setting (Emrouznejad and Anouze 2010), but has not been applied in the context of steady state efficiency or efficiency convergence.

Other grouping methods exist apart from the classification trees (e.g., regression trees). An advantage of classification trees is that the output generated is easy to interpret, mainly because there are predetermined characteristics on the groups that can be formed. In more technical terms, the number of potential groups is determined and their populating process is governed by the classification tree algorithm. For example, candidate banking systems may be split into high/low convergence rates according to a median split. Subsequently, the

\(^9\) We implement a two-step system GMM approach, in line with Mollah and Zaman (2015) and Casu and Giradone (2010). More information on GMM can be found in Arellano and Bover (1995), Blundell and Bond (1998) and Roodman (2009).
classification tree algorithm assigns specific banking systems either of the two groups. Conversely in regression trees, both the number of potential groups and their populating process are governed by the respective algorithm. As such, it represents a pure statistical approach to identify potential groups in the data. By contrast, classification trees allow the mix of a statistical approach with an economic intuition, where the algorithm verifies (or rejects) the researcher’s hypothesized groups.

We apply the classification tree algorithm to the convergence ($\beta$) and steady state efficiency ($\alpha$) estimates based on the RPM to examine whether there are groups of banks which behave similarly to each other. Classification trees can handle various types of control variables (i.e. continuous, categorical and binary), although the dependent variable must be binary. A $\beta$-convergence binary variable is constructed for the full sample and classifies banks into high/low $\beta$-convergence estimates according to a median split. In a similar manner, a steady state binary variable based on $\alpha$ estimated using the RPM is constructed. Our control variables are the bank type (Islamic or conventional) and the country indicator.

4. Data

The data are drawn predominantly from the balance sheets and income statements of the Bureau van Dijk Bankscope database for the period 1999 to 2014 and across 23 countries. A small number of observations for missing periods were obtained from the annual reports of individual banks. We finally derive an unbalanced panel of 4,864 bank-year observations for Islamic and conventional banks, with the number of banks ranging from 158 in 1999 to 502 in 2014. Of this total of bank-year observations, 1,089 relate to Islamic banks and 3,775 relate to conventional banks. There is clearly a large difference between the number of Islamic and conventional banks. While nearly 25% of our observations relate to Islamic banks this is similar or higher than in previous studies (Al-Jarrah and Molyneux 2005; see also, for example, Abdul-Majid et al. 2010; Čihák and Hesse 2010; Srairi 2010; Beck et al. 2013). We eschew a matched sample analysis (in terms of e.g., bank assets) because given the typically smaller asset size of Islamic banks, large conventional banks would be omitted. Table 1 presents the distribution of bank observations by operational mode and country. Every country has at least one bank of each type over the time period covered.

Table 1 here

Table 2 displays the mean values of the inputs and outputs of the ODF by bank type (panel a) and the number of bank observations by type and country (panel b). While Islamic banks are typically smaller than conventional banks in terms of deposits, loans and other earning assets, they are remarkably similar in terms of administrative expenses and are larger in terms of

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10 An example of a regression tree application can be found in Postiglione et al. (2010).
11 Thus, we do not assume that the differences will be precisely between Islamic and conventional banks.
12 Note that regression trees, in contrast, can handle continuous dependent variables at the expense of more complicated tree structures.
13 The countries are: United Arab Emirates, Bangladesh, Bahrain, Brunei, Egypt, Indonesia, Iran, Jordan, Kuwait, Lebanon, Mauritania, Malaysia, Oman, Philippines, Pakistan, Qatar, Saudi Arabia, Sudan, Singapore, Syria, Tunisia, Turkey, and Yemen.
fixed assets. The relatively large mean administrative expenses for Islamic banks is reflective of the extra costs related to the Shariah board; while the high value of mean fixed assets is expected due to some of the Islamic banking products requiring collateral; hence banks would typically have tangible assets (e.g., buildings, commodities) at their disposal for such use.

Table 2 here

5. Results and Discussion

5.1. Parametric estimation of efficiency using an ODF

Figure 1 presents the efficiency scores derived from the first stage stochastic ODF, from which it appears that conventional banks have a higher efficiency than Islamic banks (Mokhtar et al. 2007; Abdul-Majid et al. 2008; Mokhtar et al. 2008; Abdul-Majid et al. 2010; Srairi 2010; Abdul-Majid et al. 2011a; 2011b; Johnes et al. 2014). This difference is significant at the 10% significance level for the sample as a whole and for all individual years apart from 2011. Whether these efficiency differences between Islamic and conventional banks at given points in time represent a difference in long term or steady state efficiency will be investigated in the second stage convergence analysis. For robustness purposes, we have winsorized at the 1st and 99th percentiles, in line with Beck et al., (2013), without any material change in the results.

Figure 1 here

5.2. Steady state efficiency and efficiency convergence

a) OLS, random effects and system-GMM estimation

Table 3 reports parameter estimates of absolute and conditional β-convergence models using, respectively, OLS, random effects (RE) and system-GMM estimation methods. The parameter estimates are similar across all estimation methods. The significance of the σ coefficient in the associated σ-convergence model (see Appendix 4 for full σ-convergence results) confirms that the estimates of β-convergence in these models can be considered to be genuine, rather than reversion to the mean (see also Casu and Girardone, 2010).

Table 3 here

A first inspection of the estimated parameters of models in columns I, IV and VII provide interesting reading. The (exponentiated) estimated intercepts suggest that the banks are converging on a steady state efficiency value of around 0.92 to 0.95, depending on estimation method. While there is no obvious link between steady state efficiency and financial development (as proxied by stock market capitalisation), the three countries with the markedly lowest steady state efficiency in the sample (see Figure 2), namely Syria, Brunei

14 The estimated parameters of this distance function are available on request.

15 Note that the system-GMM estimations satisfy the conditions that there is significant AR(1) serial correlation, no AR(2) serial correlation and high Sargan/Hansen test (Casu and Giradone 2010).
and Mauritania with a 3.85% average percentage point difference to Egypt, do not feature a stock market. The estimated $\beta$ coefficient ranges between -0.283 and -0.442 and is comparable with estimates reported in previous studies using EU and US banking data, suggesting comparable efficiency convergence dynamics in the banking systems of our sampled countries.

Figure 2 here

The slope and intercept dummies for bank type show no statistical significance across all models (columns II, V and VIII). The same conclusion is reached when country intercept and slope effects and time intercept effects are taken into account (columns III, VI and IX). The result suggests that Islamic and conventional banks are not different in terms of long-term (steady state) efficiency and convergence (to the steady state) rates. This finding offers an affirmation to the literature contradicting any differences between the two bank types (see also section 2). Therefore, any differences in efficiency observed in the first stage (figure 1) of the analysis, and which are also echoed in a substantial part of the literature, are merely short-term, transitory ones.

Figure 3 presents the steady state efficiencies over time. The countries in the sample have been through several instances of financial crises and instability, most notably the late 1990s Far East Crisis, the 2003 Iraq War, the 2005 Crash of the Saudi Arabian stock market, and the 2008 global financial crisis. The patterns suggest that these events are negatively associated with steady state efficiency.

Figure 3 here

b) RPM estimation

Table 4 presents the average estimated coefficients of the RPM model (see equation A2.2) and figure 4 presents their kernel densities per bank type. The average steady state efficiency is 0.90 with no significant difference between Islamic and conventional banks. Likewise, the average convergence rate is -0.554, again with no significant difference between Islamic and conventional banks. These (average) results are in line with those of the alternative estimation methods reported in table 3. Thus, once the individual circumstances of each bank are accounted for (i.e., each bank is permitted to have its own steady state efficiency and convergence rate) there appears to be no significant difference between Islamic and conventional banks either in terms of their steady state efficiency or the speed with which they converge to it. Our a priori clubs (Islamic and conventional) are thus far not confirmed empirically.

However, the kernel densities suggest that the efficiency convergence dynamics of the two bank types may still be different, albeit country factors may be concealing such variations. Here, we want to elaborate on this rather crucial point. Suppose that the average efficiency steady state of conventional banks in our sample is 0.93. All the regression based techniques we have deployed up to this point are valid for the average efficiency steady state of Islamic banks, while potentially allowing for country and time effects. However, such (parametric)
techniques cannot allow for interactions between country, time effects and bank type due to the vanishing degrees of freedom. Therefore, these models cannot allow for the fact that in some countries Islamic banks may have a higher efficiency steady state than conventional banks while in others the opposite may be true. The RPM estimation offers a way to take this into account, but when the results are averaged, for reporting purposes as in table 4 for example, this information is lost. Instead, kernel density plots of the estimated parameters allow for the extraction of such information. Kernel densities by country are even better in this respect and show precisely that the Islamic banks are not always (i.e., in every country) inferior to conventional banks.\footnote{These kernel densities by country are available upon request.}

Therefore, before concluding that the two banking models are truly similar, we need to explore the possibility that country differences are concealing variations between the two bank types. For this purpose, the following section presents the results of the classification trees approach.

5.3 Classification trees

Table 5 presents goodness of fit statistics for the classification trees, in line with those reported in West (2000); Delen et al. (2013), and Irimia-Dieguez et al. (2015): namely, accuracy, area under curve (AUC), expected misclassification cost (EMC),\footnote{The calculation of these statistics is explained in greater detail in Appendix 3.} and pseudo R-squared. The statistics show that when using both country and banking type information the classification works the best.

Table 6 presents the clubs generated by the classification tree approach based on steady state (Panel A) and $\beta$-convergence according to bank type and country. The upper (lower) part of the table represents the high (low) steady state and $\beta$-convergence groups, respectively. Each panel lists the Islamic and conventional banking system of each country and the intersection region. It is the intersection region that provides the most interesting conclusion as it identifies those countries for which the two banking systems are similar according to the classification tree algorithm.\footnote{Figure 5 presents an optical illustration of Table 6 contents using Venn diagrams.}

The classification tree results of Table 6 show clear evidence as to why the parametric approaches of the previous steps failed to identify any differences. In particular, in some countries, the Islamic banks are the ones exhibiting the highest speed of convergence; in other countries, it is the conventional ones (Panel B). In addition, disparities in the initial
conditions of banks in terms of economic and financial development of the country in which they are located, and the implementation of policies and reforms across countries, mean that banks operating therein may have different steady state efficiency levels as observed in panel A. In some countries, the two banking systems are indistinguishable from one another in terms of steady state efficiency and/or convergence speed; these lie in the intersection of areas in panels A and B of table 6 respectively. A few notable examples are discussed below.

In Malaysia, the two bank types under investigation are indistinguishable in terms of the speed of the steady state efficiency and convergence. In contrast, these banks in Bahrain share a similar, low steady state grouping, while the Islamic (conventional) banks belong to the high (low) convergence rate club. This finding confirms that these countries represent two variants of the Islamic banking model; the more progressive one mainly practised in the Far East (Malaysia) and the more restrictive one mainly practised in the GCC state of Bahrain. The high interconnectedness of Malaysia to global financial markets is likely to be associated with an increased convergence speed for the banking sector in general but also for the Islamic banking sector in particular for two main reasons. First, in Malaysia, it is common practice for Islamic and conventional banks to be part of a bank holding company, thereby sharing knowhow, experience and clientele. The case of the CIMB Group, headquartered in Malaysia, is an example of a universal bank offering both conventional and Islamic financial products through its subsidiaries. In contrast, Islamic banks in the GCC cannot be part of a bank holding company as there are strict rules requiring such banks not to share any ties with conventional financial institutions. Furthermore, Islamic banks in Malaysia use certain financial instruments, whose Shariah conformity has been challenged in the GCC region and as a consequence are not used there, mainly allowing Malaysia to enhance the marketability and outreach of its Islamic Finance. In contrast, the GCC comprises a dominant, concentrated, mainly domestic banking sector and traditional loan-taking/deposit-making activities constitute the bulk of operations there. The banking portfolio of these countries features large exposures in real estate, infrastructure and household financing, while securities investments are limited. Consequently, there is wider scope for Islamic finance contracts to be applied, allowing these banks to play to their advantage. Therefore, it may be expected that the steady state efficiency and/or the efficiency convergence rate of the Islamic banks in the GCC region is higher (on average) than that of conventional banks.

Pakistan is another interesting case as Islamic banks belong to a low steady state/low convergence club, while the high steady state/high convergence club is populated by the conventional banks. This apparent underperformance of Islamic banking may be linked to the history of this institution, with Pakistan being one of the (very) few countries that had opted in the past for a pure Islamic banking model, and which was subsequently abandoned due to implementation problems. Pakistan now implements a dual-banking system, like the majority of the countries where Islamic banks operate.

---

19 During the 80s and 90s Pakistan was operating on a non-interest, Islamic banking model, which faced several implementation issues and was subsequently used in parallel to the conventional banking since 1999. The other two countries being Sudan and Iran; Iran still operates a pure Islamic banking model, albeit it has recently allowed for conventional foreign bank branches to open in special economic free zones.
The fact that there is no common equilibrium average efficiency level for Islamic and conventional banks across some countries may give evidence of a dual-banking model (Zhang and Matthews 2012). Conversely the existence of a common equilibrium average efficiency level for the two bank types may give evidence of a single banking model. In the latter case, the country would appear in the intersection of the graph. Drivers of this distinction, albeit latent, may be linked to country-specific characteristics, implementation of Islamic banking and the degree of substitution between the two banking systems on behalf of its users. The classification trees help to bring out differences in such a context where there is a mix of Islamic banking systems with high steady state efficiency coupled with conventional banking systems with low steady state efficiency and vice versa. 20 The fact that there is: a) a significant distinction between the bank types in terms of steady state efficiency, and b) that the distinction varies by country (in that some Islamic banks have a higher equilibrium efficiency than conventional banks and in others the converse is the case) could explain why parametric analysis of an earlier section failed to reveal differences between the bank types.

6. Conclusion

Measuring and comparing banking efficiency has received much attention, but there have been few empirical studies focusing on the dynamics of efficiency (steady state and convergence), and none comparing conventional and Islamic banks. In this paper, we compare and contrast estimates of steady state efficiencies and efficiency convergence rates of Islamic and conventional banks. We use an extended dataset spanning more than a decade and a half, i.e., from 1999 to 2014, and covering 23 countries, to obtain estimates of the banks’ efficiency scores using stochastic frontier analysis.

For the efficiency steady states and the efficiency convergence rates we borrow the concept of $\beta$-convergence from the growth literature, a concept which has already been applied in the context of banking in economic unions. The convergence model is estimated using OLS, RE, GMM and RPM estimation, the last being one of the novelties of the paper. Furthermore, we use classification trees, a multi-dimensional separation procedure, which circumvent the vanishing degrees of freedom faced by parametric techniques, to identify clubs of countries and banking sectors with similar characteristics.

Our results from the $\beta$-convergence model estimated using OLS, random effects and system-GMM find no significant differences between the two bank types in terms of the steady state efficiency and efficiency convergence rates. These results are further confirmed by the RPM estimation method. Classification trees reveal that the degree of distinctiveness of Islamic and conventional banking (in terms of efficiency steady states and convergence rates) varies across countries. The two extreme examples are Malaysia, in which we observe similarity in practice between the two bank types, and Bahrain where the distinction is marked. This may be attributed to the variant of Islamic banking that is practised in the Far East whereby the

---

20 Traditional techniques such as regression analysis would require a large number of degrees of freedom. Statistical significance tests are also not useful here given that they are either bivariate or require an a priori assumption on the banking system groupings.
nature of the products and banking activities of both bank types are closely aligned. This is in contrast to the GCC countries where differences in product, regulation and operational models that set the two banking models apart.

Our research cleanly identifies countries where the two banking sectors are distinct (in terms of long run efficiency as well as the speed with which banks converge to the steady state) and those where they are similar. Our findings thereby inform the debate concerning the existence of a mimicking behaviour by Islamic banks, i.e., the claim that Islamic banks mimic conventional banks across all countries. The observation of similar banking models only in some countries suggests that such behaviour may not necessarily be caused by mimicking but rather by the nature of the products and regulations specific to those countries. It is then the task of the regulators and jurisdiction authorities to devise mechanisms and platforms that respect the identity of the two banking models. Future work should examine the forces which underpin these results and which might relate, for example, to demographic, educational, cultural or business and financial screening.
Figure 1: Efficiencies over time and by bank types
Figure 2: Steady state efficiencies and convergence rates by country

Notes: United Arab Emirates is the base country. The figure is based on the results of column 3 in table 3.
Figure 3: Steady state efficiencies over time

Notes: The base year is 1999. The figure is based on the results of column 3 in table 3.
Figure 4: Kernel density plots for convergence rate ($\beta$) and steady state ($\alpha$)

Notes: The figure shows the kernel density plots for the convergence rate ($\beta$) and exponentiated steady state ($\alpha$) estimates from the RPM model for conventional and Islamic banks.
Figure 5: Steady State and Convergence Rate Classifications

Panel A: Steady State
Conventional Islamic

High

Conventional Islamic

Low

Notes: Classification based on the steady states as estimated from the random coefficients model. A transformation is applied to convert the continuous beta steady states into a binary variable denoting as 1 the High steady state banking systems (average value=-0.0597; average efficiency=0.942) and as 0 the Low steady state ones (average value=0.1506; average efficiency=0.860). The threshold for this separation is the median value here (-0.090; average efficiency=0.914). Classification is based on 2 variables, Bank Type and Country Identifier.

Panel B: Convergence Rate
Conventional Islamic

Conventional Islamic

Low

Notes: Classification based on the beta convergence rate as estimated from the random coefficients model. A transformation is applied to convert the continuous beta convergence rates into a binary variable denoting as 1 the Low convergence banking systems (average beta=-0.338) and as 0 the High convergence ones (average beta=-0.770). The threshold for this separation is the median value here (-0.530). Classification is based on 2 variables, Bank Type and Country Identifier.
<table>
<thead>
<tr>
<th>Country</th>
<th>All banks</th>
<th>Conventional banks</th>
<th>Islamic banks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bahrain</td>
<td>213</td>
<td>118</td>
<td>95</td>
</tr>
<tr>
<td>Bangladesh</td>
<td>161</td>
<td>136</td>
<td>25</td>
</tr>
<tr>
<td>Brunei</td>
<td>18</td>
<td>16</td>
<td>2</td>
</tr>
<tr>
<td>Egypt</td>
<td>361</td>
<td>325</td>
<td>36</td>
</tr>
<tr>
<td>Indonesia</td>
<td>854</td>
<td>785</td>
<td>69</td>
</tr>
<tr>
<td>Iran</td>
<td>156</td>
<td>3</td>
<td>153</td>
</tr>
<tr>
<td>Jordan</td>
<td>187</td>
<td>151</td>
<td>36</td>
</tr>
<tr>
<td>Kuwait</td>
<td>145</td>
<td>65</td>
<td>80</td>
</tr>
<tr>
<td>Lebanon</td>
<td>409</td>
<td>394</td>
<td>15</td>
</tr>
<tr>
<td>Malaysia</td>
<td>195</td>
<td>127</td>
<td>68</td>
</tr>
<tr>
<td>Mauritania</td>
<td>93</td>
<td>76</td>
<td>17</td>
</tr>
<tr>
<td>Oman</td>
<td>92</td>
<td>88</td>
<td>4</td>
</tr>
<tr>
<td>Pakistan</td>
<td>153</td>
<td>99</td>
<td>54</td>
</tr>
<tr>
<td>Philippines</td>
<td>230</td>
<td>224</td>
<td>6</td>
</tr>
<tr>
<td>Qatar</td>
<td>119</td>
<td>84</td>
<td>35</td>
</tr>
<tr>
<td>Saudi Arabia</td>
<td>173</td>
<td>128</td>
<td>45</td>
</tr>
<tr>
<td>Singapore</td>
<td>111</td>
<td>103</td>
<td>8</td>
</tr>
<tr>
<td>Sudan</td>
<td>227</td>
<td>66</td>
<td>161</td>
</tr>
<tr>
<td>Syria</td>
<td>87</td>
<td>74</td>
<td>13</td>
</tr>
<tr>
<td>Tunisia</td>
<td>180</td>
<td>178</td>
<td>2</td>
</tr>
<tr>
<td>Turkey</td>
<td>311</td>
<td>282</td>
<td>29</td>
</tr>
<tr>
<td>United Arab Emirates</td>
<td>314</td>
<td>220</td>
<td>94</td>
</tr>
<tr>
<td>Yemen</td>
<td>75</td>
<td>33</td>
<td>42</td>
</tr>
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</table>
Table 2: Descriptive Statistics of ODF model variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>All banks</th>
<th></th>
<th></th>
<th>Conventional banks</th>
<th></th>
<th></th>
<th>Islamic banks</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
<td>Median</td>
<td>Mean</td>
<td>S.D.</td>
<td>Median</td>
<td>Mean</td>
<td>S.D.</td>
<td>Median</td>
</tr>
<tr>
<td>Deposits and Short-Term Funding (x1)</td>
<td>5,276</td>
<td>11,949</td>
<td>1,209</td>
<td>5,715</td>
<td>13,077</td>
<td>1,280</td>
<td>3,755</td>
<td>6,483</td>
<td>1,025</td>
</tr>
<tr>
<td>General and Administration Expenses (x3)</td>
<td>128</td>
<td>265</td>
<td>33</td>
<td>129</td>
<td>268</td>
<td>34</td>
<td>127</td>
<td>257</td>
<td>30</td>
</tr>
<tr>
<td>Fixed Assets (x2)</td>
<td>92</td>
<td>239</td>
<td>18</td>
<td>75</td>
<td>171</td>
<td>19</td>
<td>151</td>
<td>386</td>
<td>16</td>
</tr>
<tr>
<td>Equity (x4)</td>
<td>732</td>
<td>1,641</td>
<td>170</td>
<td>784</td>
<td>1,787</td>
<td>166</td>
<td>552</td>
<td>954</td>
<td>177</td>
</tr>
<tr>
<td>Total Loans (y1)</td>
<td>4,864</td>
<td>8,975</td>
<td>785</td>
<td>3,923</td>
<td>9,789</td>
<td>795</td>
<td>2,978</td>
<td>5,188</td>
<td>680</td>
</tr>
<tr>
<td>Other Earning Assets (y2)</td>
<td>2,331</td>
<td>5,666</td>
<td>471</td>
<td>2,667</td>
<td>6,295</td>
<td>524</td>
<td>1,168</td>
<td>2,071</td>
<td>344</td>
</tr>
</tbody>
</table>

Note: Source Bankscope. All data have been adjusted to 2005 prices using the appropriate GDP deflator for each country.
Table 3: $\beta$-convergence model estimated using various estimation methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Pooled OLS robust</th>
<th>Random Effects robust</th>
<th>System-GMM two-step robust</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(I)</td>
<td>(II)</td>
<td>(III)</td>
</tr>
<tr>
<td>Absolute $\beta$-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>convergence</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TYPE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.283***</td>
<td>-0.282***</td>
<td>-0.332***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.004)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>TYPE</td>
<td>-0.017</td>
<td>0.018</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.059)</td>
<td></td>
</tr>
<tr>
<td>$\times \ln(\mu_{t-1})$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.053***</td>
<td>-0.051***</td>
<td>-0.059***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Country shift</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>dummies</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year shift</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>dummies</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Country slope</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>dummies</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year slope</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>dummies</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>m1 p-value</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>m2 p-value</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sargan/Hansen</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.0254</td>
<td>0.209</td>
<td>0.259</td>
</tr>
<tr>
<td>R²</td>
<td>0.205</td>
<td>0.209</td>
<td>0.259</td>
</tr>
</tbody>
</table>

Notes: The table reports estimated coefficients and standard errors in parentheses. OLS=ordinary least squares. TYPE takes the value 1 for Islamic banks and zero otherwise. $N = 4179$ bank year observations for all models, and $T = 15$ years. Tests for first- and second order autocorrelation in the system-GMM model are denoted by m1 and m2, respectively. Sargan/Hansen is a test of the over-identifying restrictions relevant to the system-GMM model. *** denotes statistical significance at the 1, 5, 10% level respectively.
<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Islamic</th>
<th>Conventional</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>-0.554</td>
<td>-0.525</td>
<td>-0.564</td>
<td>0.209</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>-0.105</td>
<td>-0.112</td>
<td>-0.102</td>
<td>0.175</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>3955</td>
<td>84</td>
<td>304</td>
<td></td>
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<tr>
<td>No of groups</td>
<td>436</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chi-sq</td>
<td>315.47</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table reports the average estimated coefficients for All banks, Islamic banks and Conventional banks, while the p-values are given in parentheses. The p-value column reports the results of the Wald tests for the equality of the convergence rates ($\beta$) and steady states ($\alpha$) between Islamic and conventional banks.
### Table 5: Classification Trees Goodness of Fit Statistics

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Steady State</th>
<th>Convergence Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (%)</td>
<td>65.10</td>
<td>64.90</td>
</tr>
<tr>
<td>AUROC</td>
<td>0.703</td>
<td>0.711</td>
</tr>
<tr>
<td>EMC</td>
<td>0.840</td>
<td>1.050</td>
</tr>
<tr>
<td>Pseudo-R²</td>
<td>0.406</td>
<td>0.422</td>
</tr>
</tbody>
</table>

**Explanatory Variables**

<table>
<thead>
<tr>
<th>Country</th>
<th>Yes</th>
<th>Yes</th>
<th>No</th>
<th>Yes</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Islamic Bank</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: AUROC and EMC denote the Area Under the Receiver Operating Characteristic curve and Expected Misclassification Cost respectively.
<table>
<thead>
<tr>
<th>Country</th>
<th>Conventional</th>
<th>Islamic</th>
<th>Conventional</th>
<th>Islamic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indonesia</td>
<td>Egypt</td>
<td>UAE</td>
<td>Lebanon</td>
<td>UAE</td>
</tr>
<tr>
<td>Oman</td>
<td>Lebanon</td>
<td>Bangladesh</td>
<td>Sudan</td>
<td>Bahrain</td>
</tr>
<tr>
<td>Pakistan</td>
<td>Qatar</td>
<td>Iran</td>
<td>Egypt</td>
<td>Yemen</td>
</tr>
<tr>
<td>Philippines</td>
<td>Sudan</td>
<td>Jordan</td>
<td>Oman</td>
<td>Brunei</td>
</tr>
<tr>
<td>Tunisia</td>
<td>Kuwait</td>
<td>Pakistan</td>
<td>Egypt</td>
<td>Iran</td>
</tr>
<tr>
<td>Turkey</td>
<td></td>
<td>Philippines</td>
<td>Singapore</td>
<td>Jordan</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Kuwait</td>
</tr>
<tr>
<td>Bahrain</td>
<td>Malaysia</td>
<td>Bahrain</td>
<td>Malaysia</td>
<td>Indonesia</td>
</tr>
<tr>
<td>Bangladesh</td>
<td>Mauritania</td>
<td>Brunei</td>
<td>Bangladesh</td>
<td>Oman</td>
</tr>
<tr>
<td>Brunei</td>
<td>Saudi Arabia</td>
<td>Indonesia</td>
<td>Indonesia</td>
<td>Saudi Arabia</td>
</tr>
<tr>
<td>Iran*</td>
<td>Singapore</td>
<td>Oman</td>
<td>Iran*</td>
<td>Philippines</td>
</tr>
<tr>
<td>Jordan</td>
<td>Syria</td>
<td>Pakistan</td>
<td>Jordan</td>
<td>Singapore</td>
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<td>Kuwait</td>
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<td>Tunisia</td>
<td>Turkey</td>
<td>Syria</td>
<td>Tunisia</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Notes: Classification based on the steady state as estimated from the random coefficients model. A transformation is applied to convert the continuous beta steady states into a binary variable denoting as 1 the High steady state banking systems (average value=-0.0597; average efficiency=0.942) and as 0 the Low steady state ones (average value=-0.1506; average efficiency=0.860). The threshold for this separation is the median value here (-0.090; average efficiency=0.914). Classification is based on 2 variables, Bank Type and Country Identifier. Classification based on the beta convergence rate as estimated from the random coefficients model. A transformation is applied to convert the continuous beta convergence rates into a binary variable denoting as 1 the Low convergence banking systems (average beta=-0.338) and as 0 the High convergence ones (average beta=-0.770). The threshold for this separation is the median value here (-0.530). Classification is based on 2 variables, Bank Type and Country Identifier. * Iran is typically considered an Islamic-banking country; however conventional banks are allowed to operate within specific free economic zones (Rooz Online, 2010; Presstv.com, 2010).
References


Jackson, P. M. and M. D. Fethi (2000). 'Evaluating the technical efficiency of Turkish commercial banks: an application of DEA and Tobit analysis.' Efficiency and Productivity Research Unit. https://lra.le.ac.uk/bitstream/2381/369/1/dpno5.pdf University of Leicester.


Appendix 1: The translog output distance function

The translog output distance function is defined below for \( N \) banks using inputs \( x_k \) (\( k = 1, \ldots, K \)) to produce outputs \( y_m \) (\( m = 1, \ldots, M \)):

\[
\ln D_{it}(x, y) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K} \sum_{m=1}^{M} \delta_{km} \ln x_{kit} \ln y_{mit} \quad i = 1, 2, \ldots, N \quad (A1.1)
\]

where subscript \( it \) refers to bank \( i \) in time period \( t \). Distance function restrictions require the following conditions to hold:

a) Homogeneity of degree +1 in outputs

\[
\sum_{m=1}^{M} \alpha_m = 1 \quad \text{and} \quad (A1.2a)
\]

\[
\sum_{m=1}^{M} \alpha_{mn} = 0 \quad m = 1, 2, \ldots, M \quad \text{and} \quad (A1.2b)
\]

\[
\sum_{m=1}^{M} \delta_{km} = 0 \quad k = 1, 2, \ldots, K \quad (A1.2c)
\]

b) Symmetry:

\[
\alpha_{mn} = \alpha_{nm} \quad m, n = 1, 2, \ldots, M \quad \text{and} \quad (A1.3a)
\]

\[
\beta_{kl} = \beta_{lk} \quad k, l = 1, 2, \ldots, K \quad (A1.3b)
\]

By the homogeneity restriction \( D(x, \omega y) = \omega D(x, y) \) and so one output can be chosen arbitrarily, for example the \( M \)th output, such that \( \omega = 1/y_M \). Thus equation (A1.1) can be written as:

\[
-\ln y_{Mit} = \\
\alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \left( \frac{y_{mit}}{y_{Mit}} \right) + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \alpha_{mn} \ln \left( \frac{y_{mit}}{y_{Mit}} \right) \ln \left( \frac{y_{nit}}{y_{Mit}} \right) + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \\
\frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K} \sum_{m=1}^{M-1} \delta_{km} \ln x_{kit} \ln \left( \frac{y_{mit}}{y_{Mit}} \right) + \varepsilon_{it} \quad i = 1, 2, \ldots, N \quad (A1.4)
\]

where \( \varepsilon_{it} = -\ln D_{it}(x, y) \)

The quantity which is of interest here is the distance (or efficiency) \( \ln D_{it}(x, y) \) which is measured by the error term in equation (A1.4). We assume this error term can be split into two components i.e. \( \varepsilon_{it} = v_{it} - u_{it} \) where \( v_{it} \) represents statistical noise, i.e., \( v_{it} \sim N(0, \sigma_v^2) \), and \( u_{it} \) represents the efficiency of bank \( i \) in time period \( t \) and is distributed as half-normal i.e. \( u_{it} \sim N^+(\mu, \sigma^2) \), following (Aigner et al. 1977).
Appendix 2: Convergence model estimation

The following conditional $\beta$-convergence model is estimated

$$\ln(u_{i,t}) - \ln(u_{i,t-1}) = \alpha + \beta \ln(u_{i,t-1}) + \gamma \text{TYPE}_{i,t} + \delta \text{TYPE} \times \ln(u_{i,t-1}) + \sum \theta_c \text{COUNTRY}_{c,i,t} + \sum \omega_t \text{YEAR}_{i,t} + \varepsilon_{i,t}$$ (A2.1)

TYPE is a binary variable with 1 denoting an Islamic bank, zero otherwise. Country dummies (COUNTRY) and year dummies (YEAR) are included to account for differences in financial regimes and technology across countries and time.

If $\gamma \neq 0$ then Islamic and conventional banks are converging on different steady state efficiency levels; if $\delta \neq 0$ then Islamic and conventional banks have different convergence rates.

The convergence model presented above presupposes that differences between banks will depend solely on the business model (i.e. Islamic or conventional). Yet there may be some Islamic banks whose behaviour is more typical of conventional banks than of Islamic banks, and vice versa. In order to allow for differences between individual banks as revealed by the data (rather than as imposed by the analyst) the following $\beta$-convergence model is estimated using the random parameter model (RPM).

$$\ln(u_{i,t}) - \ln(u_{i,t-1}) = \alpha_t + \beta_t \ln(u_{i,t-1}) + \varepsilon_{i,t}$$ (A2.2)

The estimated parameters ($\alpha_t, \beta_t$) therefore allow each bank a) to have a different steady state efficiency and b) to react differently to its past efficiency level. In order to see whether there are differences between Islamic and conventional banks we subsequently examine the $\alpha_t$ and $\beta_t$ estimates for possible differences between the bank types. While a random parameter stochastic frontier approach has been applied to estimating bank efficiencies in the context of Mexico (Barros and Williams 2013), the random parameter approach has not been applied in the context of banking efficiency convergence.
Appendix 3: Classification trees

While no asymptotic theory exists, the virtue of the algorithm underpinning the classification trees methodology lies in its ability to reveal multidimensional data splits (Durlauf and Johnson 1995). Classification trees can be seen as a type of variable selection procedure. The main difference is that in a stepwise regression the sample remains unchanged and the control variables are selected; in a classification tree the control variables are selected and the sample is allowed to vary. The classification trees procedure may be viewed as a union of piecewise linear functions, where observations are grouped according to the control variables. The splits are chosen with respect to minimising misclassification costs (Breiman et al. 1984). The essence of the algorithm is described here; for a full exposition of the classification tree algorithm see among others Breiman et al. (1984) and Durlauf and Johnson (1995).

Assume $Y$ to be the variable of interest and $X_1, \ldots, X_j$ the control variables. The aim is to find a model for predicting $Y$ from $X_1, \ldots, X_j$ through binary recursive splits. Starting from a club equivalent to the entire population of banking systems, say $\{i_1, i_2, \ldots, i_n\}$ (this can be referred to as step 0) the algorithm searches for the best binary splits in the dataset.

Step 1. For the data under investigation select a binary split, which is of the form $x_j < s$ versus $x_j \geq s$. The choice of the binary split consists of two components, the selected control variable ($j$) and the realisation of the control variable ($s$). The binary split creates two nodes that are subsequently tested for impurity. Impurity of a node is measured by the Gini’s Diversity Index (GDI). The GDI of a node is given as $1 - \sum_i p^2(i)$ where the sum is over the clubs $i$ at the node and $p(i)$ is the observed fraction of clubs with club $i$ that populate the node. A pure node has only one club and a GDI equal to zero; otherwise positive values of GDI measure the degree of impurity in the node where more than one clubs are present.

Therefore, at each splitting level the following expression is minimised:

$$\Delta(h) = \min_{js} \left\{ \min_{c_2} \left( 1 - \sum_i \left( \frac{c_1}{c_1 + c_2} |x_i \in R_{1,js}\right) \right) + \min_{c_1} \left( 1 - \sum_i \left( \frac{c_2}{c_1 + c_2} |x_i \in R_{2,js}\right) \right) \right\}$$

where the parameter $h$ denotes the splitting level with $h = 1$ denoting the first level that two nodes exist. The variables of interest to the algorithm ($j, s$) split the realisations of the $Y$ variable ($c_1, c_2$) into two nodes $R_1, R_2$. The lower the value of the quantity $1 - \frac{c_1}{c_1 + c_2}$ the higher the purity level of the first node.

Step 2. If one of the resulting nodes has zero impurity score then this is classified as a pure node and the branch is terminated here. Conversely, if one of the resulting nodes has a positive impurity score, then a further split may be possible.

Step 3. For the impure nodes, continue from step 1.

The algorithm finishes when the resulting nodes are either pure or cannot be broken down any further due to observation requirements.

---

21 For a full exposition of impurity metrics used in this context we direct you to Berzal et al. (2003).
22 For ease of exposition we assume that the predictor variables are categorical variables.
Accuracy is defined as the percentage of banking systems that are correctly predicted by the model as being of high/low convergence rate; see also Delen et al. (2013).

The area under the receiver operating characteristic (AUROC) curve is used to gauge the performance of a binary classifier system, such as classification trees. An AUROC curve that is convex to the diagonal indicates that the proposed model is better in distinguishing positive and negative ranks (or in our case high vs low convergence banking systems) than randomness would imply. Irimia-Dieguez et al. (2015) offer an application of the AUROC curve in classification trees, with Swets (1996) offering a more detailed analysis.

Expected misclassification cost (EMC) is given as:

$$EMC = C_{12} \pi_2 FPR + C_{21} \pi_1 FNR$$

where $C_{12}$ and $C_{21}$ are the relative costs of misclassification with $C_{12}$ representing the case where a low convergence banking system is classified as a high one and $C_{21}$ represents the case where a high convergence banking system is not classified as a high one; $\pi_2, \pi_1$ are prior probabilities of high and low convergence banking systems; FPR and FNR denote the False-Positive-Rate and False-Negative-Rate respectively. In terms of values, $C_{12}$ and $C_{21}$ are assumed equal to 1 and 5 respectively, in line with Irimia-Dieguez et al. (2015) and West (2000); $\pi_2, \pi_1$ are equal to 0.5 by definition of the median-split we imposed, while FPR and FNR are estimated from the data.
### Appendix 4: Estimated σ-convergence models

**Table A4: σ-convergence model estimated using various estimation methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Pooled OLS robust</th>
<th>Random Effects robust</th>
<th>System-GMM two-step robust</th>
</tr>
</thead>
<tbody>
<tr>
<td>(I) Absolute σ-convergence</td>
<td>(II) Conditional σ-convergence</td>
<td>(III) Conditional σ-convergence</td>
<td>(IV) Absolute σ-convergence</td>
</tr>
<tr>
<td>σ coefficient</td>
<td>-0.281***</td>
<td>-0.279***</td>
<td>-0.325***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.038)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>TYPE</td>
<td>-0.011***</td>
<td>-0.012***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>TYPE</td>
<td>-0.019</td>
<td>-0.015</td>
<td></td>
</tr>
<tr>
<td>× ln(ut-1)</td>
<td>(0.055)</td>
<td>(0.060)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.001***</td>
<td>0.003***</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Country shift dummies</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Year shift dummies</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Country slope dummies</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Year slope dummies</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>m1 p-value</td>
<td>0.203</td>
<td>0.203</td>
<td>0.252</td>
</tr>
<tr>
<td>m2 p-value</td>
<td>0.553</td>
<td>0.528</td>
<td>0.421</td>
</tr>
<tr>
<td>Sargan/Hansen p-value</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.203</td>
<td>0.203</td>
<td>0.252</td>
</tr>
</tbody>
</table>

Notes: The table reports estimated coefficients and standard errors in parentheses. OLS=ordinary least squares. TYPE takes the value 1 for Islamic banks and zero otherwise. N = 4179 bank year observations for all models, and T =15 years. Tests for first- and second order autocorrelation in the system-GMM model are denoted by m1 and m2, respectively. Sargan/Hansen is a test of the over-identifying restrictions relevant to the system-GMM model.