Measuring convergence in Islamic and conventional banks: Evidence from global data

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Abstract

This paper compares efficiency dynamics (steady state and convergence) between Islamic and conventional banks using parametric (stochastic frontier analysis) and non-parametric methods (classification trees). Analysis is based on an unbalanced panel of Islamic and conventional banks from 23 countries over the period 1999 to 2012. We specify a $\beta$-convergence model with Islamic intercept (steady state efficiency) and slope dummies (efficiency convergence). Speed of convergence between the two banks is found to be similar, but conventional banks converge to a higher steady state efficiency. Classification trees are adopted to identify banking sector clubs with respect to these efficiency steady states and convergence rates. The analysis reveals differences between countries in the relative performance of Islamic and conventional banks, in terms of their rates of convergence and steady states. Thus in some countries the two banking sectors are clearly distinct, while in others they are not.

**Keywords:** Efficiency convergence • Random parameter estimation • Conditional $\beta$-convergence • Islamic banks • Classification trees

**JEL classification:** G21, F36, D24
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1. Introduction

Islamic banks are growing in number and this has been accompanied by an increase in the number of studies that compare Islamic and Conventional banks with respect to their business model, efficiency (Johnes et al. 2014), stability (Beck et al. 2013) and survival (Pappas et al. 2015). Of importance among the results of all these studies is the casual observation that Islamic banks were more protected in the recent financial crisis, a consequence, no doubt, of the operations of these banks being guided by Shariah principles. Thus the financial products which adversely affected the conventional banks were largely prohibited in the highly regulated Islamic banking regime. The apparently lower risk of investing in Islamic banks has led to an increasing demand for Islamic banking products in regions which are not traditionally Muslim: the UK, for example, aspires to be a western centre of Islamic finance (Osborne 2013).

Among the areas that are widely studied in Islamic banking is the measurement of efficiency underlying this type of banking and how it compares to that of conventional banks. Efficiency has long been of interest in the general context of banking (for reviews of the literature see Berger and Humphrey 1997; Fethi and Pasiouras 2010); this is because efficiency in the financial sector and economic growth are closely related and are considered vital for economic development and stability (Al-Jarrah and Molyneux 2005; Brissimis 2009). Studying efficiency is particularly important in economies where Islamic banking is a substantial part of the financial sector, such as Saudi Arabia or Malaysia, these studies are clearly of particular interest and importance (Ernst & Young 2013).

Previous studies suggest that there are significant differences between Islamic and conventional banks in terms of their efficiency at a given point in time (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). A meta-frontier analysis (Johnes et al. 2014) has revealed overall efficiency is determined by the business operation under which the bank operates and the technical efficiency with which it converts inputs into outputs. The latter is in turn made up of managerial and scale efficiency. The importance of these components in driving overall efficiency varies by bank type (Johnes et al. 2014). Each sector (conventional and Islamic) could therefore learn from the other in terms of performance.

An implicit assumption of efficiency studies is that the two banking systems, indeed all the banks, are fully synchronised. This may be a restrictive assumption as banks face and react to idiosyncratic and systemic shocks; hence at each point in time they might be at a different point on their trajectory towards equilibrium efficiency. In an efficiency convergence framework we can generalise this assumption by examining both the steady state efficiency scores and the efficiency convergence rates for the Islamic and conventional banks. A priori we might expect Islamic banks to have a lower steady state efficiency if we take the view that Islamic banking faces more structural problems (i.e. legal issues, standardisation of products and practices, double stamp duty\(^3\)) relative to the conventional.

However, we would expect high cross-country variation given that Islamic banking practices are quite disparate, with countries such as Malaysia and the UAE having more experience than, say, Oman or Indonesia. Convergence speed is also important, and differences between the two bank types are also expected given the differences in the financial products and the knowhow.

Our objectives can be summarised by the following two questions:

a) Do Islamic and conventional banks have different steady state efficiency levels?

b) Do Islamic and conventional banks have different rates of efficiency convergence?

We address these questions in three stages. We use a stochastic frontier output distance function to provide estimates of efficiency in the first stage. A conditional $\beta$-convergence model is estimated in the second stage using two techniques: a conventional OLS estimation technique with Islamic bank shift and slope dummies, followed by a random parameter model (RPM). The conventional OLS approach is criticised for not allowing heterogeneity in the convergence process as the $\beta$-coefficient does not vary by both time and country. The use of a RPM is introduced to overcome these criticisms and is novel in this context. It allows each bank to react differently to its past efficiency level and hence have a different rate of convergence; it also allows each bank to converge to a different steady state efficiency. We are then able to examine steady state efficiency and the efficiency convergence rate by type of bank.

Identifying the effects of bank type across countries, however, poses a challenge. The number of Islamic banks in any given country is small, and it is standard practice to sample across countries in order to increase sample size. Thus we need to be able to disentangle the effects on steady state efficiency and convergence rate of business model (Islamic or conventional banking) and country location (since financial regulation, banking industry conditions, economic context can vary by country). But this is hindered by the reduced degrees of freedom from increasingly dividing the sample. To overcome this issue, we apply in a third stage a classification trees methodology. Classification trees use a non-parametric approach to classify observations into similar groups revealed by the data rather than using researcher pre-conceptions. In our context, they offer a way for us to identify whether there are groups of banking systems which are similar in terms of a) steady state efficiency and b) efficiency convergence rate; we can examine whether the resulting groupings align with Islamic and conventional banking business models. We choose a classification tree approach which, owing to its non-parametric nature, can handle the vanishing degrees of freedom issues experienced once we drill down to country level. Because classification trees allow the combination of a statistical with an economic approach in grouping, the output is economically more meaningful than regression trees or latent class models.

Our main findings are as follows. The traditional $\beta$-convergence models suggest that there are significant differences in the steady state efficiency and the efficiency convergence rates of the two bank types: on average (across all countries), steady state efficiency (measured on a scale of 0 to 1) is around 0.015 points lower in Islamic than conventional banks. The $\beta$-convergence rate, however, is typically of greater magnitude (by around 0.062 points) for Islamic than conventional banks. Thus Islamic banks, when pushed by exogenous factors away from their steady state efficiency, converge back to it faster than the conventional banks. Examination of differences in convergence rates by country suggest that convergence is significantly faster in some countries (e.g. Egypt, Jordan,
Malaysia) than others; the converse is the case for Iraq. But this is as far as the parametric analysis can go.

The classification trees analysis reveals further that convergence rates and steady state efficiencies vary by sector and by country in some cases, and in other cases that there are no significant banking sector differences. For example, Islamic and conventional banking in Malaysia are indistinguishable in terms of convergence rate and steady state efficiency, while in the Arab Gulf states differences between the two banking systems are more evident. This can be plausibly linked to the variation of Islamic banking that is practised in the Far East compared to the Arab Gulf and 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 to allow 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 efficiency convergence and steady state efficiency. This is important as it answers a fundamental question as to whether Islamic and conventional banks do really differ. The findings clearly show that in some countries the Islamic and conventional banks’ operational models are not that distinct.

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 described in section 4 while section 5 presents the results. Finally we draw conclusions and policy implications in section 6.

2. Literature Review

To our knowledge, there is no empirical study to date of convergence in banking efficiency in the Islamic banking context. Considerable interest has been shown, however, in efficiency convergence of the banking sectors of the European Union (EU), and occasional interest in the US context. The underlying hypothesis of such literature is that economic union can cause the banking sectors of member states to converge. The model used can be generalised as follows:

\[ \ln(u_{c,t}) - \ln(u_{c,t-1}) = \alpha + \beta \ln(u_{c,t-1}) + \sum_{c=2}^{C} D_c + \varepsilon_{c,t} \]  

where \( u \) is a measure of efficiency, subscript \( c \) represents country or state \( (c = 1, \ldots, C) \), subscript \( t \) represents time \( (t = 1, \ldots, T) \), and \( D \) represents country (or state) dummies. The parameter \( \beta \) measures convergence. If \( \beta < 0 \) then countries are converging, and the larger the value of \(|\beta|\) the greater the speed of convergence between countries. Estimates of conditional \( \beta \)-convergence from various samples of EU countries are -0.26 (Weill 2009), -0.4466 (Casu and Giradone 2010) and -0.97 for a sample of countries which have newly entered the EU (Mamatzakis et al. 2008). Estimates from single-country studies are similar: for example -0.553 for the USA (Fung 2006) and from -0.8249 to -1.8300 for Indonesia depending on model specification and time period of estimation (Zhang and Matthews 2012). All these studies have in common that they focus on efficiency convergence, and

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4 Additional exogenous variables can be included in the model in which case \( \beta \) is a measure of conditional convergence.
little interest has been shown in the steady state efficiency estimates which can be derived from these models.

These studies vary in their derivation of the efficiency variable in model (1). Some use data envelopment analysis (DEA) to derive the efficiencies from an output-oriented or production model (Fung 2006; Casu and Giradone 2010), while others use stochastic frontier analysis (SFA) to derive the efficiency variable from an estimated cost or profit function (Mamatzakis et al. 2008; Weill 2009; Zhang and Matthews 2012). In the context of a production approach, DEA is often the method of choice because of its ease of accommodation of multiple inputs and multiple outputs. The downside is, of course, that the method does not allow for stochastic shocks which is likely to be problematic in the banking sector context. SFA has the advantage that it incorporates a stochastic error and hence allows for random shocks. The disadvantage is that it is more difficult to accommodate multiple outputs and multiple inputs, which is why SFA is often used in the context of cost or profit functions; however the cost (profit) function approach assumes firms in the data set minimize costs (maximize profits), which may not always be a valid assumption.

It is therefore clear that there is a gap in the literature when it comes to comparing steady state efficiency and efficiency convergence across different banking sectors (such as Islamic and conventional). There is evidence that efficiency levels vary significantly between the Islamic and conventional banking sectors at given points in time when the banks’ performance might not be synchronised (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); but there is no evidence on what is the underlying steady state efficiency, or how quickly different bank types revert to it.

3. Methodological approach

3.1. Parametric estimation of efficiency using an output distance function

There is a choice of methods for measuring banking efficiency. Traditional financial ratio analysis (FRA), which measures performance rather than efficiency, is eschewed because of its various drawbacks (Ho and Zhu 2004; Hasan 2005) the most notable of which is the underlying behavioural assumption (i.e. banks are assumed to maximize revenue or profits or to minimize costs, depending on the financial ratio used). To evaluate using FRA the performance of Islamic banks, for whom compliance with Shariah law and ethical investment considerations are of particular importance, is unlikely to provide meaningful findings. The cost function approach which has commonly been used to evaluate banking efficiency is similarly inappropriate in an Islamic banking context because of its underlying assumption of cost minimization. The output distance function approach, however, makes no assumptions about optimizing behaviour and is therefore preferred.

The output distance function can be estimated using data envelopment analysis (DEA) or stochastic frontier analysis (SFA). The former method is non-parametric and has the advantage that it can deal easily with multiple outputs and multiple inputs. Efficiency evaluation 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. The increasing and direct 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) permits a direct comparison between the two types of banks. In addition, the parametric approach assumes a functional form for the distance function which means that estimates of the parameters are provided, and the significance of these can be tested.

We will use a translog functional form as it is flexible, easy to estimate and permits the imposition of homogeneity (Coelli and Perelman 2000). The translog distance function is defined below for \( N \) banks using inputs \( x_k \) \((k = 1, \ldots, K)\) to produce outputs \( y_m \) \((m = 1, \ldots, M)\):

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

(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

\[
\sum_{m=1}^{M} \alpha_m = 1 \quad \text{and} \quad \sum_{n=1}^{M} \alpha_{mn} = 0 \quad m = 1, 2, \ldots, M \quad \text{and} \quad \sum_{m=1}^{M} \delta_{km} = 0 \quad k = 1, 2, \ldots, K
\]

(2a) and (2b) and (2c)

b) Symmetry:

\[
\alpha_{mn} = \alpha_{nm} \quad m, n = 1, 2, \ldots, M \quad \text{and} \quad \beta_{kl} = \beta_{lk} \quad k, l = 1, 2, \ldots, K
\]

(3a) and (3b)

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

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

(4)

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

The quantity which is of interest here is the distance (or efficiency) \( D_{it}(x, y) \) which is measured by the error term in equation (4). We assume this error term can be split into two components i.e. \( \epsilon_{it} = v_{it} - u_{it} \) where \( v_{it} \) to represent 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).

The choice of variables qualifying for the distance function is guided by previous literature (Casu and Giradone 2004; Casu et al. 2004; Abdul-Majid et al. 2008; 2010) and data availability. We follow the widely used intermediation approach which posits that banks perform an intermediary role between borrowers and depositors (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 full in Johnes et al. (2014).

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5 All variables are in real values (based to 2005)
The precise specification of the parametric distance function to be estimated is therefore:

\[
-\ln y_{2it} = a_0 + a_1 \ln \left( \frac{y_{1it}}{y_{2it}} \right) + \frac{1}{2} a_1 \ln \left( \frac{y_{2it}}{y_{1it}} \right) \ln \left( \frac{y_{1it}}{y_{2it}} \right) + \sum_{k=1}^{4} \beta_k \ln x_{kit} + \\
\frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{4} \delta_{k1} \ln(x_{kit}) \ln \left( \frac{y_{1it}}{y_{2it}} \right) + v_{it} - u_{it}
\]

where the numeraire is \( y_2 = \text{other earning assets} \). This model provides a measure of gross efficiency where the regime under which the bank operates—conventional or Islamic—is not taken into account. All banks are therefore judged against the same frontier. Underlying structural differences between the two sectors which might affect steady state efficiency are introduced into the convergence model.

3.2. Steady state efficiency and efficiency convergence

3.2.1. OLS estimation

Efficiency convergence has been investigated in the context of economic unions, such as the European Union (Casu and Giradone 2010; Andrieş and Căpraru 2014) and the USA (Fung 2006). In line with these studies, this paper follows Fung (2006) who adapts the models of real income growth (Barro and Sala-i-Martin 1991). Thus we refer to \( \beta \)-convergence and \( \sigma \)-convergence. In its basic form, \( \beta \)-convergence assumes that banks with lower efficiency have faster growth rates than firms with higher efficiency, while \( \sigma \)-convergence assesses whether dispersion in efficiency levels decreases over time. Since we are interested in whether there are differences in convergence behaviour between Islamic and conventional banks, we use conditional convergence models whereby banks can have both different steady state efficiency levels and different rates of convergence. Steady state efficiencies might vary if banks experience different behavioural and/or technological conditions, and we test whether this is the case for Islamic and conventional banks.

We estimate the following conditional \( \beta \)-convergence model:

\[
\ln(u_{it}) - \ln(u_{i,t-1}) = \alpha + \beta \ln(u_{i,t-1}) + \gamma \text{TYPE} + \delta \text{TYPE} \ln(u_{i,t-1}) + \sum \theta_c \text{COUNTRY}_c + \omega \text{YEAR} + \epsilon_{it}
\]

Country dummies (COUNTRY) and year dummies (YEAR) are included to account for differences in financial regimes and technology across countries and time. The value of the parameter \( \beta \) represents convergence (if \( \beta < 0 \)) or divergence (if \( \beta > 0 \)) in banking efficiency. The larger is \( |\beta| \) then the greater is the speed of convergence or divergence.

In addition 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.

Note that the \( \beta \)-test of convergence has its limitations. The condition for convergence (that \( \beta < 0 \)) means that those with low starting values grow (in efficiency) faster than those with high starting values. But this could lead to low-initial-efficiency banks actually overtaking high-initial-efficiency banks and hence violates the idea of convergence. In addition it provides no information about the evolution of dispersion in efficiency over time.

The limitations of \( \beta \)-convergence are addressed by the \( \sigma \)-convergence test which is based on the dispersion of a bank’s efficiency around the sector average in a given time period. The usual \( \sigma \)-
convergence model can be adapted to investigate how quickly each bank’s efficiency level (in a given year) is converging to the average efficiency level across all banks for the given year. The value of the parameter \( \sigma \) represents convergence (if \( \sigma < 0 \)) or divergence (if \( \sigma > 0 \)) in banking efficiency. The larger is \(|\sigma|\) then the greater is the speed of convergence or divergence. It should be noted that \( \beta \)-convergence is a necessary but not a sufficient condition for \( \sigma \)-convergence to take place (Mamatzakis et al. 2008); but for \( \beta \)-convergence to measure real convergence (rather than regression towards the mean) it must coincide with significant \( \sigma \)-convergence (Fung 2006).

3.2.2. RPM estimation

The convergence models presented above presuppose 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) we allow the value of both \( \alpha \) and \( \beta \) to vary for each bank in the sample using a random parameter method of estimation for equation (1) as specified below (Swamy 1970):

\[
\ln(u_{i,t}) - \ln(u_{i,t-1}) = \alpha_i + \beta_i \ln(u_{i,t-1}) + \varepsilon_{i,t} \tag{7}
\]

These parameters 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 \( \alpha \) and \( \beta \) values to investigate 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.

3.3. Classification trees

With a cross-country sample it is difficult to know precisely what effects are a consequence of bank type and what are caused by country specific characteristics and financial legislation. What is more, it is difficult using traditional estimation methods, because of degrees of freedom limitations, to examine, by country, differences between banks in their values of \( \alpha \) and \( \beta \). We therefore use a classification tree methodology to identify groups of banking sectors (by country) with similar convergence characteristics. The advantage of this approach is that the groupings (and their number) are determined by the data rather than researcher pre-conceptions; the methodology allows the data to speak.

Other grouping methods exist apart from the classification trees (e.g. regression trees or latent class models). The main advantage of classification trees in this context 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 numbers of potential groups are predetermined and their populating process is governed by the classification tree algorithm. For example candidate banking systems can be split into high/low convergence rates according to a median split. Conversely in regression trees and latent class models, both the number of potential groups and their population is

\[\text{Denote by } \bar{u}_t \text{ is the mean efficiency of all banks at time } t. \text{ Thus an absolute } \sigma \text{-convergence model takes the form } \Delta w_{i,t} = \gamma + \sigma w_{i,t-1} + \epsilon_{i,t} \text{ where } w_{i,t} = \ln(u_{i,t}) - \ln(\bar{u}_t) \text{ and } \Delta w_{i,t} = w_{i,t} - w_{i,t-1}. \text{ A conditional } \sigma \text{-convergence model would include additional explanatory variables.}\]
governed by the algorithm. As such, these techniques represent two pure statistical approaches to identify potential groups in the data. Conversely, classification trees allow the combination of both a statistical with an economic approach where the algorithm would verify (or reject) the researcher’s potential groups. An example of a regression tree application can be found in Postiglione et al. (2010) where the task is to arrange 191 European Union regions into groups based on their GDP per capita with no a priori assumptions on the 20 explanatory variables. However, there is little reasoning neither why “Hours worked in Agriculture, Forestry and Fishing” nor the identified realisations should have actual economic implications.

Classification trees provide a non-parametric way of identifying multiple data groups or ‘clubs’ from a set of control variables. We use the methodology to form groups comprising banking sectors based on their bank type (Islamic or conventional), their location (country) and a) steady state efficiency (α as estimated using the RPM) and b) convergences rate (β as estimated using the RPM). The classification tree method has previously been used in a banking efficiency context (Emrouznejad and Anouze 2010), but has not been applied in the context of steady state efficiency or efficiency convergence. The method is described below.

While no asymptotic theory exists, the virtue of the algorithm underpinning the 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 endogenous 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)\(^8\). 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:

\(^8\) For a full exposition of impurity metrics used in this context we direct you to (Berzal, Cubero, Cuenca, & Martín-Bautista, 2003)
\[
\Delta(h) = \min_{js} \left\{ \min_{c_1} \left( 1 - \sum_i \left( \frac{c_1}{c_1 + c_2} | x_i \in R_{1,js} \right) \right) + \min_{c_2} \left( 1 - \sum_i \left( \frac{c_2}{c_1 + c_2} | x_i \in R_{2,js} \right) \right) \right\}
\]

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 \((c_1, c_2)\)\(^9\) 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.

3 Data

The data are drawn predominantly from the balance sheets and income statements in the Bureau van Dijk Bankscope database for the period 1999 to 2012 and across 23 countries\(^10\). A small number of observations for missing periods were obtained from the annual reports of individual banks. We finally derive an unbalanced panel of 4153 observations relating to commercial banks, ranging from 173 banks in 1999 to 439 banks in 2011. Of this total of observations, 805 are Islamic banks and 3348 are conventional banks. Table 1 displays the mean values of the inputs and outputs of the output distance function by bank type. It is clear that for the largest part of the sample the two banking systems are comparable in terms of average size and dynamics. The Islamic banks show a rise an increase in operations (as evident by the rise in deposits and loans) following the 2008 global financial crisis.

Table 1 here

4 Results

5.1. Parametric estimation of efficiency using an output distance function

Figure 1 presents the efficiency scores derived from the first stage stochastic distance function\(^11\), 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). Moreover this difference is significant at the 10% significance level for the sample as a whole (i.e. across all years) and for individual years 2001, 2002, 2006 and 2008 to 2011 (inclusive). Whether these differences between Islamic and conventional

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\(^9\) For ease of exposition we assume that the predictor variables are dummy variables.

\(^10\) 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.

\(^11\) Results for the SFA distance function are computed with and without winsorizing (see, for example, Beck et al. 2013) at 1st and 99th percentiles; conclusions do not differ between approaches and so results reported here are without winsorizing.

\(^12\) The estimated parameters of this distance function are available on request.
banks in efficiency at given time points represent a difference in long term or steady state efficiency will be investigated in the second stage convergence analysis.

Figure 1 here

5.2. Steady state efficiency and efficiency convergence

5.2.1. OLS estimation

OLS is applied in the first instance to derive estimates of both absolute and conditional \( \beta \)-convergence, and these results are displayed in table 2. The estimated intercept in the absolute convergence model (column 1) suggests that banks are converging on a steady state efficiency value of 0.947. The value of \( \beta \) is -0.302 and is therefore comparable with estimates for the EU and the USA. When the dummy variable representing type of bank is included (column 2), we find that conventional banks are converging to a higher rate of efficiency than Islamic banks in the steady state (0.950 compared to 0.939 holding all else constant), and that this is a significant difference. The value of \( \beta \) remains largely unchanged (at -0.295) and there is no significant difference between Islamic and conventional banks in terms of convergence. However, once country and time are taken into account\(^{13}\) (column 3), both steady state efficiency and efficiency convergence rates differ significantly between the bank types, but the differences are quite small. For example, holding all else constant, the typical conventional bank has steady state efficiency of 0.962 and converges on it at a rate of -0.268, whereas the typical Islamic bank has a steady state efficiency of 0.960 and converges on it at a rate of -0.330.

Table 2 here

There are additional differences in both steady state efficiency and efficiency convergence rates by country as revealed by figure 2. We can infer from the results that the steady state bank efficiency is negatively associated with financial development. For example, the upper end of the steady state efficiency graph is populated by countries such as Iran and Yemen which tend to have lower market capitalisation compared to those at the lower end such as Mauritania and Malaysia. It is to be expected that the steady state efficiency will be determined by the structural development in a country.

Figure 2 here

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 owing to 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 exhibited in the figure suggest that the impact of such events is negatively associated with the steady state efficiency.

Figure 3 here

5.2.2. RPM estimation

In order to capture better the unique circumstances in which each bank operates we now use a random parameter model to estimate the steady state efficiency and convergence rate for each bank. Results are presented in table 3. The average steady state efficiency is 0.911 and this does not vary

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\(^{13}\) Note that country and time intercept dummies are included as well as slope country dummies.
significantly between Islamic and conventional banks. The average convergence rate is -0.544 and, again, this does not vary significantly between Islamic and conventional banks. Thus, once the individual circumstances of each bank are allowed 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. Our a priori clubs (Islamic and conventional) are not confirmed empirically by the data and model. This might be because the differences between bank types vary by country, and with only 388 banks we have insufficient degrees of freedom to explore this further with parametric methods.

Table 3 here

5.3 Classification trees

To account for issues of degrees of freedom we turn to classification trees to drill down into the convergence rate and steady state efficiency (respectively) estimated for each bank to examine whether there are groups of banks which behave similarly to each other. Thus we do not assume that the differences will be precisely between Islamic and conventional banks; it might be the case that in some countries, conditions are such that Islamic and conventional banks behave similarly whereas in others that is not the case.

We apply the classification tree algorithm to the $\beta$-convergence and steady state efficiency estimates based on the RPM (equation 7). Although classification trees can handle various types of control variables (i.e. continuous, categorical and binary), the dependent variable must be in a binary format. A $\beta$-convergence binary variable is constructed for the full sample and classifies banks into high/low $\beta$-convergence groups according to a median split. In a similar manner a steady state binary variable based on $\alpha$ as estimated using the RPM is constructed. Our control variables are the bank type (Islamic or conventional) and the country indicator.

Panel A of figure 4 displays the clubs based on $\beta$-convergence according to bank type and country. The two circles represent the two banking systems (Islamic and conventional), while the upper (lower) part of each circle represents the high (low) beta convergence groups respectively. The intersection encloses the countries where the two banking systems are indistinguishable (i.e. not significantly different) from one another according to the classification tree algorithm. Panel B of figure 4 shows the clubs when the classification tree methodology is applied to the steady state efficiency according to bank type and country.

Figure 4A and 4B here

The results indicate that there is not a consistent relationship between speed of convergence and bank type; in some countries Islamic banks exhibit greater speed of convergence than conventional banks; in other countries the converse is observed. 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 (Sala-I-Martin 1996). In the short run, banks may deviate

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14 Note that regression trees, in contrast, can handle continuous dependent variables at the expense of more complicated tree structures.

15 We opt not to use $\beta$-convergence and steady state efficiency in the same classification tree so as to avoid potential endogeneity issues.
from the long run equilibrium because of financial and economic shocks. Thus a bank’s observed efficiency at a given point in time may reflect a short-run position away from the long-run steady state. In some countries the two banking systems are indistinguishable from one another in terms of convergence speed and/or steady state efficiency (because they lie in the intersection of areas in panels A and B of figure 4), while in others these are markedly different.

For example, both bank types in Malaysia are indistinguishable from one another in terms of the speed of convergence and the steady state efficiency. In contrast, Islamic and conventional banks in Bahrain appear in different clubs with the former belonging to a low convergence/high steady state club and the latter being part of a high convergence/low steady state club.

This finding is of special interest given that these two 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 Arab Gulf region (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. Furthermore, the Islamic banks in Malaysia are allowed to use certain controversial financial instruments not permitted in the Arab Gulf region; mainly allowing Malaysia to enhance the marketability and outreach of Islamic Finance.

In contrast, the Arab Gulf region comprises a dominant, concentrated, mainly domestic banking sector and traditional loan-taking/deposit-making activities constitute the bulk of operations. 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 of the Islamic banks in the Arab Gulf region is higher than that of conventional banks.

There are cases, for example in Pakistan, where the Islamic banks belong to a high convergence/low steady state club, while the low convergence/high steady state club is populated by the conventional banks. Pakistan is one of the few countries that have opted in the past for a pure Islamic banking model, which was subsequently abandoned due to implementation problems, and the country now implements a dual-banking system.

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. 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

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16 The other two countries being Sudan and Iran, which still operates a pure Islamic banking model.
systems with low steady state efficiency and vice versa. 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 the RPM analysis of section 4 failed to reveal differences between the bank types: drilling down to country level is clearly vital but something which is precluded in the statistical work by too few degrees of freedom.

5 Conclusion

Banking efficiency has received much attention, partly because of its link with economic growth. Several studies have addressed the efficiency of Islamic versus conventional banks. In contrast, very little work has been undertaken into the dynamics of efficiency. In this paper we compare and contrast estimates of steady state efficiencies and efficiency convergence rates for Islamic and conventional banks. For this purpose we use an extended dataset spanning 1999 – 2012 covering 23 countries. To obtain estimates of the banks’ efficiency scores we use 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 and RPM estimation (respectively), the latter being one of the novelties of the paper. Classification trees are adopted to identify country clubs of banking sectors with similar characteristics in terms of the steady state efficiency and the efficiency convergence rate.

Our results from the \( \beta \)-convergence model estimated using the traditional OLS approach shows that there are significant differences between the two bank types in terms of the steady state efficiency and efficiency convergence rates. These results are not confirmed when we use the RPM estimation method. It appears that there are distinctions between countries which cannot be entirely disentangled from differences between banking business models using parametric methods. Classification trees circumvent the vanishing degrees of freedom faced by parametric techniques and reveal that the degree of distinctiveness of Islamic and conventional banking varies across countries with regards to convergence rate and efficiency steady state. In Malaysia the two banking systems behave as one, while in Bahrain the separation is more marked. This may be possibly driven by the variant of Islamic banking that is practised in the Far East, where the Islamic banks may operate with the conventional banks under one roof. However this is not allowed in the countries of the Arab Gulf. Eventually the degree of substitution between the two banking systems would be a key determinant to how close these systems perform in each country.

While this research identifies countries where the two banking sectors are distinct and those where it is more similar, we can only speculate on reasons for this. Future work could examine the underlying forces which might relate, for example, to demographic, educational, cultural or religious characteristics.

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17 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 \textit{a priori} assumption on the banking system groupings.
Figure 1: Efficiencies over time and by bank types
Figure 2: Steady state efficiencies by country

Notes: United Arab Emirates is the base country. Brunei, Jordan, Lebanon, Mauritania, Malaysia and Syria have steady state efficiencies significantly lower than United Arab Emirates; Iran and Sudan have steady state efficiencies significantly higher than United Arab Emirates. Egypt, Mauritania, Syria, Malaysia, Jordan and Lebanon have convergence rates significantly lower than the United Arab Emirates. Iran is the only country that shows significant evidence in favour of efficiency divergence.
Figure 3: Steady state efficiencies over time

Notes: The base year is 1999. The year 2000 has steady state efficiency significantly higher than the base year (1999); 2003, 2005 and 2008 have steady state efficiencies significantly lower than the base year (1999).
Figure 4: Beta Convergence Rate and Steady State Classifications

Panel A: Convergence Rate

Panel B: Steady State

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 rate into a binary variable denoting as 1 the Low convergence banking systems (average beta= -0.252) and as 0 the High convergence ones (average beta= -0.835). The threshold for this separation is the median value (median= -0.499). Classification is based on 2 variables, Bank Type and Country Identifier. Classification based on the steady states as estimated from the random coefficients model. A transformation is applied to convert the continuous steady state into a binary variable denoting as 1 the High steady state banking systems (average value= -0.0442) and as 0 the Low steady state ones (average value= -0.1421). The threshold for this separation is the median value (median= -0.0833). Classification is based on 2 variables, Bank Type and Country Identifier.
<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>4579.64</td>
<td>10524.50</td>
<td>1022.32</td>
<td>4860.28</td>
<td>11243.53</td>
<td>1078.84</td>
<td>3491.01</td>
<td>6973.49</td>
<td>849.48</td>
</tr>
<tr>
<td>Fixed Assets (x2)</td>
<td>85.00</td>
<td>231.24</td>
<td>16.76</td>
<td>70.03</td>
<td>165.42</td>
<td>17.65</td>
<td>141.69</td>
<td>385.27</td>
<td>14.22</td>
</tr>
<tr>
<td>General and Administration Expenses (x3)</td>
<td>114.30</td>
<td>253.43</td>
<td>26.63</td>
<td>113.75</td>
<td>245.02</td>
<td>27.74</td>
<td>116.33</td>
<td>282.62</td>
<td>23.98</td>
</tr>
<tr>
<td>Equity (x4)</td>
<td>632.38</td>
<td>1446.99</td>
<td>135.09</td>
<td>641.87</td>
<td>1508.88</td>
<td>128.42</td>
<td>597.31</td>
<td>1190.68</td>
<td>168.82</td>
</tr>
<tr>
<td>Total Loans (y1)</td>
<td>3152.52</td>
<td>7570.36</td>
<td>634.27</td>
<td>3240.15</td>
<td>8016.23</td>
<td>658.20</td>
<td>2819.31</td>
<td>5548.54</td>
<td>551.63</td>
</tr>
<tr>
<td>Other Earning Assets (y2)</td>
<td>2009.16</td>
<td>5152.24</td>
<td>363.11</td>
<td>2265.21</td>
<td>5667.69</td>
<td>400.68</td>
<td>1035.57</td>
<td>2037.78</td>
<td>291.75</td>
</tr>
</tbody>
</table>

Notes: Source Bankscope. All data have been adjusted to 2005 prices using the appropriate GDP deflator for each country.
Table 2: $\beta$-convergence model estimated using OLS

<table>
<thead>
<tr>
<th>Model</th>
<th>(1) Absolute $\beta$-convergence</th>
<th>(2) Conditional $\beta$-convergence</th>
<th>(3) Conditional $\beta$-convergence</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$ coefficient</td>
<td>-0.302 (0.000)</td>
<td>-0.295 (0.000)</td>
<td>-0.268 (0.001)</td>
</tr>
<tr>
<td>TYPE</td>
<td>-0.012 (0.023)</td>
<td>-0.018 (0.003)</td>
<td></td>
</tr>
<tr>
<td>TYPE $\times \ln(u_{i,t-1})$</td>
<td>-0.027 (0.189)</td>
<td>-0.062 (0.015)</td>
<td></td>
</tr>
<tr>
<td>COUNTRY $\times \ln(u_{i,t-1})$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.054 (0.000)</td>
<td>-0.051 (0.000)</td>
<td>-0.045 (0.003)</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>Adjusted $R^2$</td>
<td>0.223</td>
<td>0.224</td>
<td>0.335</td>
</tr>
<tr>
<td>$N$</td>
<td>3522</td>
<td>3522</td>
<td>3522</td>
</tr>
<tr>
<td>$T$</td>
<td>13</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>P-value ($\sigma$-convergence)</td>
<td>0.000</td>
<td>0.000</td>
<td>0.044</td>
</tr>
</tbody>
</table>

Notes: The table reports estimated coefficients and standard errors in parentheses. Type takes the value 1 for Islamic banks and zero otherwise. $N$ refers to the bank-year observations. $T$ refers to the time period in years. P-value ($\sigma$-convergence) refers to the statistical significance of the explanatory variable in the $\sigma$-convergence model, which is a necessary condition for the existence of $\beta$-convergence (check also footnote 9).
Table 3: RPM conditional $\beta$-convergence

<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>-0.544</td>
<td>-0.504</td>
<td>-0.555</td>
<td>0.250</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>-0.093</td>
<td>-0.094</td>
<td>-0.093</td>
<td>0.917</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>3342</td>
<td>84</td>
<td>304</td>
<td></td>
</tr>
<tr>
<td>No of groups</td>
<td>388</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chi-sq</td>
<td>19.02</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 standard errors 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.
References


