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Credit risk pricing and the rationality of lending decision-making within dual banking systems: A parametric approach

Awatef Louhichi[a,*], Younes Boujelbene[b]

[a] Research Unit in Applied Economics, Faculty of Economics and Management of Sfax, Airport Road Km 4, 3018 Sfax, Tunisia
[b] Faculty of Economics and Management of Sfax, Airport Road Km 4, 3018 Sfax, Tunisia

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ABSTRACT

The reduction of non-performing loans, and making correct provisions for them, plays a primary role in the management and minimization of banking credit risk. However, these actions depend primarily upon the cost at which banks may dispose of these bad loans. Hence, this study aims to perceive the price of banks' credit risk via estimating the shadow price of non-performing loans. We assess and compare the perceived price of the credit risk of Islamic and conventional banks operating in 9 countries from the Middle East and Asia, using a quadratic directional distance function. Following this, we evaluate the impact of different settings of directional vectors on shadow prices by conducting a risk-sensitivity analysis. Applying bootstrap regression, the factors affecting NPLs' prices are further investigated. The paper concludes that the estimation of the shadow prices of bad loans can provide important elements in favor of credit risk management and, therefore, credit risk mitigation.

1. Introduction

It is undoubtedly true that poor risk management is the main path to banking troubles and even bankruptcy (Kabir et al., 2015). Risks in banks and financial institutions are diverse; however, credit risk is often identified as the leading cause of severe banking problems (BIS, 2010; Boumedienne, 2011). The global financial crisis of 2008 – the subprime crisis – and the credit crunch that followed are an appropriate example as they were a result of inefficient credit risk management. In particular, the Basel committee on banking supervision pointed out that most systematic banking crises arise because of enormous portfolios of bad loans (BCBS, 2000). Accordingly, loans are an obvious source of credit risk (Chaibi and Ftiti, 2015). Also, it is widely argued that major financial shocks and turbulences occurred due to these bad loans, constituting the risky assets of banks and commonly known as "*non-performing loans*" (hereafter NPLs). International regulatory and supervisory bodies have attempted to bring clarity to this subject by harmonizing the definition of NPLs and non-performing expenses as a way to better monitor them and offer more comprehensive supervision. This issue relates particularly to International Accounting Standard 39 (IAS-39) on financial instruments.

Moreover, several studies focusing on NPLs in the banking industry pointed out that impaired loans represent a destructive factor for banks' health and efficiency (Mester, 1996; Berger and DeYoung, 1997). These studies concluded that banks should be conscious about the necessity to identify, measure, monitor and control credit risk that takes the form of NPLs. The question here is*: How to mitigate danger that arises from credit risk in the portfolio of loans in the banking sector?*

In fact, in agreement with Chaffai et al. (2007), effective credit risk management starts primarily by reducing NPLs and making correct provisions for them. However, these actions depend largely upon the cost at which the bank may dispose of these bad loans.

* Corresponding author.
E-mail addresses: awatef.lh@gmail.com (A. Louhichi), younes.boujelbene@gmail.com (Y. Boujelbene).

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Effectively, within this study, we seek to estimate the cost of bad loans (i.e., the shadow price) as a way of monitoring, controlling and managing banking credit risk.

The term "*shadow price*" has been extensively applied in the environmental sectors. A handful of studies have been conducted within the context of the banking industry (e.g., Chaffai et al., 2007; Assaf et al., 2013). The NPLs' shadow price displays the price of credit risk that the bank perceived at the time of the lending decision (Chaffai et al., 2007). It represents the default risk premium the banker should integrate into the price of loans. In other words, the shadow price is the risk premium incorporated into the loan rate to cover expected credit losses/credit risk. This measure could provide helpful information for bankers and should affect the bank management's lending policy and decision-making process. In this respect, Assaf et al. (2014) argued that shadow prices have important marginal implications as they show how much investment in inputs is needed to diminish the level of NPLs.

Our focus of interest in this paper is centered on a steadily growing banking system, the *Islamic banking system*. Indeed, while playing a similar role as a financial intermediary, Islamic banks differ from their conventional counterparts in that Islamic laws govern their operations. More specifically, as elaborated by Hussain et al. (2015), Islamic finance is guided by the principles of equity, participation and ownership. The fundamental feature is that it is *interest-free*. Islam bans Muslims from taking or giving interest (*ribã)* regardless of the purpose for which such loans are made and regardless of the rate at which interest is charged. The agreement among contracting parties must also be free from excessive uncertainty or *gharar*.

It is noteworthy that the adherence to *Sharia* (Islamic law) rules changes the contractual role as well as the risk statute of Islamic banks. Islamic banks mainly adopt two alternative instruments, namely mark-up finance and profit-loss sharing (PLS). This latter concept constitutes the main difference between Islamic and conventional banks. While conventional banks' customers have to pay the principal amount with interest, regardless of profit or loss from a venture, Islamic banks' suppliers of funds become investors instead of creditors. Put differently, the provider of financial capital and the entrepreneur share business risk in return for shares of the profits. Besides, the implementation of profit-sharing principles in Islamic banks actually contributes to altering the nature of the risks faced by these institutions. For instance, their credit risk exposure is special, given that this risk arises under each Islamic financing instrument. In this context, Errico and Sundararaja (2002) and Kabir and Worthington (2014) argued that Islamic financial contracts entail additional credit risk. Notably, Islamic banks are more exposed to withdrawal risk if they share their losses with depositors (Khan and Ahmed, 2001; Siddiqui, 2008).

Although Sharia-compliant banks account for only 1.5 % of total assets of the global banking sector (Beck et al., 2013; Abedifar et al., 2013), they have experienced tremendous growth over the last 30 years. According to ISRA and Thomson Reuters (2016) statistics, the size of the Islamic finance market ranged between $1.66 trillion to $2.1 trillion in 2016 and is expected to reach $3.4 trillion by the end of 2018. The exponential growth of the Ribã-free industry has evidently exceeded that of the conventional industry. Between 2013 and 2014, the 2016 World Islamic Banking Competitiveness report realised by Ernst and Young (2016) shows that the Islamic banking sector grew at twice the rate compared to conventional banks. For instance, Islamic banking assets in Saudi Arabia grew at an average rate of 18 % against 7 % for conventional banking assets. Also, the assets of Islamic banks in Qatar grew by 20 % vs. 7 % for conventional ones. In Pakistan, an average growth rate of 19 % vs. 8 % was reached for Islamic and conventional banking assets, respectively.

The objective of the present empirical work consists of evaluating, analyzing and comparing the shadow prices of NPLs of Islamic banks relatively to conventional banks. To do this, we use the distance function (Färe et al., 2005). This method allows evaluating bank efficiency while controlling for bad loans by deriving their shadow prices and, hence, the opportunity cost of reducing them. This study is the first to estimate the shadow prices of NPLs of Islamic banks. The directional distance function in quadratic form is used to quantify this perceived price for a sample of Middle Eastern and Asian banks. Next, we perform a sensitivity analysis by evaluating the impact of different directional vectors' settings on the shadow prices. We end with a discussion of the factors that could affect NPL's shadow prices.

The paper contributes to the literature in several ways. We seek to identify and further reduce the peril that arises from credit risk in loan portfolios in the banking industry, thereby increasing efficiency and stability. This can be accomplished by gaining a better understanding of the covariates and the cost of credit risk as well as the factors that are likely to impact bank lending behavior/ decisions. In the interim, the paper makes a comparison between interest-free and interest-based banking industries. Fundamentally, we believe that a carefully conducted empirical study, which identifies the fundamental differences between interest-based and interest-free banks that might matter for their efficiency, risk management and lending decisions, could be a valuable contribution to the literature.

Via the directional distance function approach, the study illustrates the portion of inefficiency attributed to risk. To the best of our knowledge, this is the first survey to consider this pattern in the Islamic banking industry. In particular, the quadratic directional distance function is a novel approach that helps evaluate bank efficiency while controlling for bad loans by deriving their shadow prices and, hence, the opportunity cost of reducing them. Put differently, the shadow price of NPLs reveals the price of credit risk that the bank perceived at the time of the lending decision and could provide helpful information for bankers as a way to affect the bank management's lending policy and decision-making process.

The remainder of this paper is structured as follows. The second section presents our theoretical framework. Section 3 highlights our research methodology, followed by a description of the data and variables in Section 4. The empirical results are presented in Section 5 and, finally, the conclusion and policy implications are discussed in the last section.

2. Literature review

2.1. Literature on bank efficiency using non-performing loans

A high level of non-performing loans might cause a significant drag on banks' soundness. In fact, banks' NPLs serve as an important indicator of bank failures and financial imbalances. Particularly, they are undesirable outputs for any bank that extends loans and decrease the bank's performance (Chang, 1999). Thus, controlling NPLs is very important both for an individual bank's performance (McNulty et al., 2001) and for an economy's financial soundness (Shen and Hsieh, 2002). Usually, NPLs were considered a primary source of banking system instability. To date, numerous studies treat bad loans as a control variable while exploring risk-efficiency issues (Berger and DeYoung, 1997; Podpiera and Weill, 2008). Nevertheless, Fernandez et al. (2002) have pointed out the necessity of incorporating undesirable output into efficiency analyses. The authors suggested that "*A production process must be clearly defined based on both desirable and undesirable outputs; using only desirable outputs will fail to credit a bank for its effort to reduce undesirable outputs*." This means that NPLs should be incorporated into the production function. The modeling tool used is the directional distance function. In fact, the directional distance function (DDE) methodology has been extensively applied to the environmental sectors. Berg et al. (1992) and Chang (1999) are considered as the primary essays taking up this model in the banking industry. Later, an important strand of literature developed following in this vein. In particular, Chen et al. (2007) treated NPLs as an undesirable output under a directional distance function to investigate the efficiency and productivity of 263 farmers' credit unions (FCUs) in Taiwan for the period 1998–2000. They provided evidence that the productivity of FCUs deteriorated over the study period. Moreover, they reported that this deterioration is mainly due to a regression in technology and finally concluded that Taiwan's FCUs should endeavor to invest in new technology. Fukuyama and Weber (2008) estimated both directional DEA and parametric linear programming specifications examining the inefficiency of the Japanese banking industry. They concluded that both methods gave similar inefficiency results and suggested that NPLs in Japanese banks should be controlled as an undesirable by-product of the loan production process.

The importance of treating NPLs as undesirable output is further highlighted in the recent literature using advanced directional distance methodologies. For instance, Barros et al. (2012) have examined a sample of Japanese banks over the period 2000–2007 by applying a non-radial directional distance function (i.e., the weighted Russel directional distance model). They asserted that the implementation of NPLs in the model might provide bank managers and policymakers with guidance in their decision-making process to improve the efficiency of decision-making units. Fujii et al. (2014) applied the same technique investigating the Indian banking industry's technical inefficiency. They argued that NPLs are among the leading factors contributing to Indian banks' inefficiency. Furthermore, they provided evidence that a high percentage of NPLs is a serious source of technological downturn. Assaf et al. (2014) proposed a Bayesian distance function to estimate the efficiency and productivity of Turkish banks during 2002–2010. They showed that excluding NPLs from the estimating model could falsify the efficiency results.[1] Zhu et al. (2015) used a slack-based measurement of the directional distance function proposed by Fukuyama and Weber (2009) in addition to Cheng et al.'s (2013) model taking up the negative data problem. The authors measured the efficiency of 25 Chinese banks during the period 2004–2010. The estimation results indicated that NPLs remain a critical component of the inefficiency of Chinese banks. Zhu et al. (2016) also examined the efficiency of Chinese banks over the period 2004–2011, applying both parametric and non-parametric directional distance functions. Furthermore, by adjusting direction vectors, they measured efficiency under four different risk preferences. In particular, the authors attempted to identify the optimal risk preference for Chinese banks' technical efficiency. They found that a risk balance preference, expanding good output and contracting bad output simultaneously, is the appropriate strategy for Chinese banks, since technical efficiency improved over time under this preference. In the same context, Zhu et al. (2019) applied a MEA-based DDF method (i.e., multi-direction efficiency analysis) to explore the risk preferences and efficiency of 49 Chinese commercial banks during 2004-2012. Three risk preferences (i.e., conservative, moderate and aggressive) were considered to assess the impact of risk preference on banking efficiency. Their analysis lends support to the fact that a moderate risk preference is the optimal choice for the Chinese banking sector.

Recent papers by Simper et al. (2017) and Nasseri et al. (2018) provided further evidence of the importance of incorporating risk control variables into efficiency models. In their analysis of the Korean banking industry, Simper et al. (2017) used the non-parametric DEA method to scrutinize the most appropriate measure of risk while computing bank efficiency. As for Nasseri et al. (2018), they focused on commercial banks in Iran and adopted a fuzzy stochastic DEA model with a focus on non-performing loans as an undesirable output. In a more recent study, Partovi and Matousek (2019) explored the Turkish banking industry's efficiency by applying a modified DEA approach (initially adopted by Aparicio et al., 2015). This approach allows the assessment of firms' efficiency while accounting for the impact of a risk measure (i.e., non-performing loans) incorporated as an undesirable output. Effectively, they reported that non-performing loans might hamper banking efficiency.

2.2. On estimating the shadow price of undesirable outputs with efficiency models

Regarding the "shadow price", this concept is quite new in the context of the banking industry. Accordingly, the literature dealing with NPLs' pricing in the banking industry is somewhat limited. Fukuyama and Weber (2008) pointed out that the shadow price is a

[1] In the same vein, Delis et al. (2017) documented evidence suggesting that excluding risk from the efficiency model considerably biases the efficiency estimates.

measure of the *opportunity cost of reducing the bad output by one unit*. Furthermore, they explained that this price is the decline in value of desirable output needed to reduce the undesirable output by one unit. The directional distance function is constantly used to derive the shadow price of undesirable output following Färe et al. (2001), who argued that "*The directional distance function provides a complete characterization of the production technology and, when differentiable, can be used to derive shadow prices for nonmarket outputs*." In this context, Chaffai et al. (2007) estimated the shadow price of NPLs of 850 banks from 29 emerging countries in Eastern Europe, Asia and Latin America over the period 1996-2000. Employing a quadratic directional output distance function, they investigated the perceived price of bad loans under different banks' risk-taking behavior. Their funding indicated that the shadow price of NPLs is negatively correlated with banks' risk-taking behavior. Moreover, they reported that the shadow price is a good predictor of banks' default risk. Using a translog distance function, Li et al. (2009) assessed the shadow price of 40 Taiwanese banks between 1999 and 2001. They performed a comparison of private versus public and old versus new banks. They showed that reducing NPLs is cheaper for private banks than for public ones. Regarding old and new banks, the authors demonstrated that new banks need twice as many resources to reduce NPLs. Chaffai and Lassoued (2013) perceived the price of bad loans in the context of the Tunisian banking industry via two methods: the stochastic frontier approach and the parametric quadratic directional distance function. A comparison between public and private banks was also performed. The results suggested that the shadow price is higher for private than for public banks. Accordingly, the authors argued that private banks are more risk-averse than public ones. Using a Bayesian directional distance function, Assaf et al. (2014) evaluated Turkish banks' shadow prices between 2002 and 2010. Shadow prices were in decline until 2008 but then increased from 2009 due to the consequences of the subprime crisis. Moreover, their results showed that dealing with NPLs is more costly for domestic banks compared to foreign ones.

3. Research methodology

The estimation of shadow prices as undesirable output has been implemented in conformity with Färe et al.'s (2006) methodological approach by relying on the directional distance function. Accordingly, we find it appropriate to start by introducing the directional distance function before then deriving the shadow prices.

3.1. Theoretical support: the directional output distance function

The directional distance function stands as a generalizing mode of Shephard's output distance function (Shephard, 1970). Indeed, while the traditional output distance function tends to expand both desirable and undesirable outputs to the production frontier, the directional distance function helps undertake the simultaneous expansion of desirable outputs along with a regular contraction of the undesirable ones (Chaffai et al., 2007).

In this respect, the directional distance function seems worth considering as a production model representation. This way, and assuming that a producer employs a vector of inputs $x = (x_1, \ldots, x_N) \in \Re_+^N$ to produce a vector of good outputs $y = (y_1, \ldots, y_M) \in \Re_+^M$ along with a vector of bad outputs $b = (b_1, \ldots, b_l) \in \Re_+^l$, the technology turns out to be represented by the output set:

$$P(x) = \{(y, b): x can produce (y, b)\} \tag{1}$$

Thus, one might also assume that the technology helps to satisfy the axioms documented by Färe et al. (2005, 2006), mainly, convexity, null jointness, as well as strong disposability of desirable outputs and inputs along with the undesirable output's weak disposability (see Chung et al., 1997).

Once the above-cited assumptions are considered, the directional output distance function would stand for the production technology as defined by the following equation:

$$\overrightarrow{D}_0^t(x_k^t, y_k^t, b_k^t, g_y, g_b) = \max\{\beta: (y + \beta g_y, b - \beta g_b) \in P(x)\} \tag{2}$$

where $g = (g_y, -g_b)$ represents the directional vector defining the output vector's direction. In fact, the directional distance function serves to simultaneously determine the maximum expansion of good outputs along with the contraction of bad outputs as applicable for any given production technology, i.e., the directional output distance function would keep contracting b and expanding y along the g direction until hitting the frontier of $P(x)$ at $(b - \beta^* g_b, y + \beta^* g_y)$, in which $\beta^* = \overrightarrow{D}(x, y, b, g)$, with the distance β being non-negative ($\beta \geq 0$).

It is also noteworthy that the directional distance function derives its properties from the output possibility set $P(x)$. In this respect, Färe et al. (2006) distinguishes six major properties as listed below

i $\overrightarrow{D_0}(x, y, b; g_y, g_b) \geq 0$ if and only if (y, b) is an element of P(x)
ii $\overrightarrow{D_0}(x, y', b; g_y, g_b) \geq \overrightarrow{D_0}(x, y, b; g_y, g_b)$ for $(y', b) \leq (y, b) \in P(x)$
iii $\overrightarrow{D_0}(x, y, b'; g_y, g_b) \leq \overrightarrow{D_0}(x, y, b; g_y, g_b)$ for $(y, b') \leq (y, b) \in P(x)$
iv $\overrightarrow{D_0}(x, \theta y, \theta b; g_y, g_b) \geq 0$ for $(y, b) \in P(x)$ and $0 \leq \theta \leq 1$
v $\overrightarrow{D_0}(x, y, b; g_y, g_b)$ is concave in $(y, b) \in P(x)$
vi $\overrightarrow{D_0}(x, y + \alpha g_y, b - \alpha g_b; g_y, g_b) = \overrightarrow{D_0}(x, y, b; g_y, g_b) \geq 0$ for $(y, b) \in P(x)$ and $0 \leq \theta \leq 1$

The first property (*i*) deals with the directional distance function as being presumed to be non-negative for feasible output vectors. Property *(ii)* consists of a *monotonicity* property that corresponds to the highly available disposability of desirable outputs. Similarly, property *(iii)* is a *monotonicity* property denoting that once undesirable outputs prove to increase, with inputs and desirable outputs remaining constant, inefficiency will not turn out to increase. Property *(iv)* concerns the weak disposability of desirable and undesirable outputs, while concavity property *(v)* helps determine the sign of the outputs' substitution elasticity. The ultimate property *(vi)* refers to translation, whereby in case an undesirable output appears to be contracted by αg_b and a desirable output turns out to be expanded by αg_y, the value corresponding to the resultant directional distance function should demonstrate great efficiency attributable via the amount of α, or else the inefficiency related to the decision-making unit (DMU) would turn out to be reduced through the amount of α (α being a positive scalar) (Färe et al., 2005).

3.2. Empirical specification

It is worth highlighting that the directional distance function could be estimated either using a parametric or a non-parametric approach. With respect to our particular case study, the major advantage of the non-parametric method lies in the unnecessity of determining the functional form, although the parametric specification seems imposed in our study context owing to the fact that the directional distance function needs to be twice differentiable. Thus it follows that, given the fact that the quadratic function should help satisfy the translation property and be twice differentiable, it has been applied to determine the directional distance function's parameters (Färe et al., 2006).

On applying the methodology devised by Färe et al. (2005), the directional vector $(g_y, g_b) = (1, -1)$ is introduced as a means whereby additional desirable output can be reached and undesirable output reduced. Maintaining that $k = 1, \ldots, K$ banks, $n = 1, \ldots, N$ inputs, $m = 1, \ldots, M$ desirable outputs and $l = 1, \ldots, L$ undesirable outputs, the quadratic directional distance function corresponding to the k-th company turns out to be rendered through the following equation:

$$\begin{aligned} \overrightarrow{D_0^t} &= (x_k^t, y_k^t, b_k^t, 1, -1) = \alpha + \sum_{n=1}^{N} \alpha_n x_{nk}^t + \sum_{m=1}^{M} \beta_m y_{mk}^t + \sum_{l=1}^{L} \gamma_l b_k^t + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \alpha_{nn'} x_{nk}^t x_{n'k}^t \\ &+ \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} \beta_{mm'} y_{mk}^t y_{m'k}^t + \frac{1}{2}\sum_{l=1}^{L}\sum_{l'=1}^{L} \gamma_{ll'} b_{lk}^t b_{l'k}^t + \sum_{n=1}^{N}\sum_{m=1}^{M} \delta_{nm} y_{mk}^t \\ &+ \sum_{n=1}^{N}\sum_{l=1}^{L} \eta_{nl} x_{nk}^t b_{lk}^t + \sum_{m=1}^{M}\sum_{l=1}^{L} \mu_{ml} y_{mk}^t b_{lk}^t + \upsilon T + \frac{1}{2}\upsilon_{tt} T^2 + \frac{1}{2}\upsilon_{tt} T^2 \\ &+ \sum_{n=1}^{N} \psi_n x_{nk}^t T + \sum_{m=1}^{M} \phi_m y_{mk}^t T + \sum_{l=1}^{L} \lambda_l b_{lk}^t + \sum_{i=1}^{I-1} \tau_i D_i \end{aligned} \tag{3}$$

Following Aigner and Chu (1968), the unknown parameters of Eq. (1) will be estimated using a linear programming method. In this regard, the aim consists in minimizing the sum of the deviations relevant to the distance function's value as derived from the production technology frontier:

$$\text{Minimize} \sum_{k=1}^{K} [\overrightarrow{D_0}(x_0, y_k, b_k; 1, -1) - 0] \tag{4}$$

s.t.

(i) $\overrightarrow{D_0}(x_k, y_k, b_k; 1, -1) \geq 0,\ k = 1, \ldots., K$

(ii) $\frac{\partial \overrightarrow{D_0}(x_k, y_k, b_k; 1, -1)}{\partial b_l} \geq 0,\ l = 1, \ldots, L;\ k = 1, \ldots, K$

(iii) $\frac{\partial \overrightarrow{D_0}(x_k, y_k, b_k; 1, -1)}{\partial y_m} \leq 0,\ m = 1, \ldots, M;\ k = 1, \ldots, K$

(iv) $\frac{\partial \overrightarrow{D_0}(x_k, y_k, b_k; 1, -1)}{\partial x_n} \geq 0,\ n = 1, \ldots, N$

(v) $\sum_{m=1}^{M} \beta_m - \sum_{l=1}^{L} \gamma_l = -1;\quad \sum_{m'=1}^{M} \beta_{mm'} - \sum_{l=1}^{L} \mu_{ml} = 0,\ m = 1, \ldots, M \quad \sum_{l'=1}^{L} \gamma_{ll'} - \sum_{m=1}^{M} \mu_{ml} = 0,\ l = 1, \ldots, L \quad \sum_{m=1}^{M} \delta_{nm} - \sum_{l=1}^{L} \eta_{nl} = 0,\ n = 1, \ldots, N$

(vi) $\alpha_{nn'} n \neq n';\ \beta_{mm'} m \neq m';\ \gamma_{ll'} l \neq l'$

In this respect, the first restriction *(i)* relates to the feasibility aspect, i.e., it entails that the output-input vector should be applicable with respect to the k units. As for restrictions *(ii)* and *(iii),* they concern the imposition of a number of relevant monotonicity conditions, while restriction *(iv)* deals with the inputs' positive monotonicity for the mean input usage level to be maintained. Finally, restriction *(v)* relates to the translation property, while restriction *(vi)* imposes symmetry conditions.

3.3. Shadow price of undesirable outputs

To determine the shadow price, we look at the duality relationship between the output-oriented distance function and the revenue function (Färe et al., 1993, 2006). The latter helps account for the undesirable outputs' negative revenue. Suppose that

$p(p_1,...,p_m) \in \Re_+^M$, $q = (q_1,...,q_l) \in \Re_+^L$ stand for the desirable and undesirable output prices, respectively. In relation to the directional distance function, the revenue function can be determined as follows (Färe et al., 2006):

$$R(x, p, q) = \max_{y,b}\{py - qb: (y, b) \in P(x)\} \tag{5}$$

Note that the revenue function helps determine the highest feasible revenue likely to be drawn once the unit appears to meet the desirable output prices p as well as the undesirable ones q. Thus, in the case of a feasible directional vector$g = (g_y, g_b)$, the revenue function Eq. (5) may well be formulated as follows:

$$R(x, p, q) \geq (py - qb) + p\cdot \overrightarrow{D_0}(x, y, b; g)\cdot g_y + q\cdot \overrightarrow{D_0}(x, y, b; g)\cdot g_b \tag{6}$$

So, while the first part (left) of Eq. (6) stands for the maximum feasible revenue, the second part (right) represents the observed revenue along with the improved technical efficiency. The gains related to technical efficiency simultaneously involve both the gains from the desirable outputs' increase along g_y and those from the undesirable outputs' decrease along g_b.

By relying on the dual relationship between the distance and revenue functions (Shephard, 1970), the directional distance function and the maximal revenue function are intermingled in the following way:

$$\overrightarrow{D_0}(x, y, b; g) = \frac{R(x, p, q) - (py - qb)}{pg_y - qg_b} = \min_{p,q}\left\{\frac{R(x, p, q) - (py - qb)}{pg_y - qg_b}\right\} \tag{7}$$

Thus, Eq. (7) represents an unconstrained minimization problem. On presuming that Eq. (2) (the directional distance function) and Eq. (5) (the revenue function) are differentiable, the first-order condition associated with the desirable output turns out to be as depicted by Eq. (8), and that connected with undesirable outputs will be illustrated by Eq. (9):

$$\nabla_y \overrightarrow{D_0}(x, y, b; g) = \frac{-p}{pg_y - qg_b} \tag{8}$$

$$\nabla_b \overrightarrow{D_0}(x, y, b; g) = \frac{q}{pg_y - qg_b} \tag{9}$$

The shadow price estimation relating to undesirable outputs appears to denote that the shadow prices of desirable output coincide well with the market price. By presuming that the observed market price of the m-th desirable output is equal to its absolute shadow price p_m, it turns out to be applicable as our normalizing price and is likely to help draw the shadow price concerning the l-th undesirable outputs as depicted by:

$$q_j = -p_m\cdot\left(\frac{\partial \overrightarrow{D_0}(x, y, b; g)}{\partial b_j} \Big/ \frac{\partial \overrightarrow{D_0}(x, y, b; g)}{\partial y_m}\right) \tag{9}$$

For the unknown parameters to be estimated, the entirety of the input and output variables should be normalized. Thus, for the shadow price to be calculated in Equation (10), the mean value ratio of y has to be multiplied by the average value of b (Färe et al., 2005, 1993).

4. Data and variables

The data used in this study comes from a cross-country sample derived from the Organization of Islamic Conference (OIC) country members. We only consider countries that provide both Islamic and conventional banking services. We notably exclude Iran and Sudan, which have a full-fledged Islamic banking system. Moreover, we focus exclusively on banks operating in the Middle East and Asian regions given the Islamic banking industry is growing quickly in these countries[2] (IMF, 2015). Our sample consists of an unbalanced panel dataset of 103 banks, including 27 Islamic banks, observed over the period 2005–2014. Table 1 presents the distribution of these banks by type and country.

To construct the sample, we used information drawn from the financial statements of individual banks provided by the Fitch IBCA Bankscope database, Thomson One Datastream and individual bank websites[3] (when not available in the Bankscope database or on DataStream).

4.1. Output and input sets

Concerning the inputs and outputs used in Eq. (1), we follow the widely used intermediation approach from Sealey and Lindley (1977). Thereby, banks in our study utilize three inputs, namely (x_1) *fixed assets*, (x_2) *interest expenses* and (x_3) *non-interest expenses* to produce two good outputs, (y_1) *interest income* and (y_2) *non-interest income* (y_3), jointly with *non-performing loans* (b), which represent

[2] Despite the significance of Islamic banks' assets in Malaysia, this country has been excluded from the analysis as data on non-performing loans are often missing (particularly in the case of Islamic banks).

[3] In the case of unavailability of financial statement from Bankscope or DataStream, the financial statements, which were taken from the bank websites and reported in the local currency, were converted to US dollars using exchange rates available on DataStream for the corresponding year.

Table 1
Sample countries, banks and observations.

	No. Of banks			No. Of observations		
	Islamic	Conventional	All	Islamic	Conventional	All
UAE	5	9	14	43	87	130
Kuwait	3	7	10	27	62	89
Saudi-Arabia	2	9	11	17	86	103
Bahrain	4	7	11	22	61	83
Qatar	3	6	9	28	55	83
Jordan	2	9	11	19	80	99
Turkey	3	14	17	26	123	149
Bangladesh	2	9	11	15	64	79
Indonesia	3	6	9	16	54	70
All-Banks	27	76	103	213	672	885

Table 2
Descriptive statistics of the variables by bank type (US$ millions).

	All banks			Islamic banks			Conventional banks		
	Obs.	Mean	Std.Dev	Obs.	Mean	Std.Dev	Obs.	Mean	Std.Dev
Inputs									
Interest expenses (model A)	885	4.790	7.869	213	1.858	2.222	672	5.720	8.743
Non-Interest expenses (model A)	885	3.482	1.582	213	2.032	2.399	672	3.941	5.165
Fixed Assets (models A + B)	885	2.501	5.075	213	2.321	4.914	672	2.020	2.347
Personal expenses (model B)	885	1.812	2.180	213	1.131	1.300	672	2.557	5.126
Total deposits (model B)	885	142.3	158.6	213	84.57	108.8	672	160.1	167.1
Good Outputs									
Interest income (model A)	885	10.87	15.28	213	5.371	6.181	672	12.612	16.82
Non-Interest income (model A)	885	2.738	3.584	213	1.682	2.488	672	3.072	3.808
Total loans (model B)	885	112.1	125.4	213	72.46	90.58	672	124.1	132.1
Other earning assets (model B)	885	55.41	75.91	213	22.42	37.09	672	65.51	81.68
Bad Output									
Non-performing loans (models A + B)	885	3.896	5.046	213	3.227	5.445	672	4.101	4.904

the bad output (hereafter referred to as Model A).

Alternatively, to test the sensitivity of the efficiency scores, we estimate a second DEA model by using a different input-output combination (hereafter referred to as Model B). This latter model was run using *fixed assets* (x_1), *personal expenses* (x_2)and *total deposits* (x_3)as inputs and *total assets* (y_1), *other earning assets* (y_2) and *non-performing loans* (b) as outputs. Table 2 describes the summary statistics of the output and input variables used to construct our models.

4.2. Dynamics in NPLs

Our survey basically focuses on two banking business models and seeks to explore differences in their risk-taking behavior. Non-performing loans as a primary source of banking credit risk remain our primary interest. Whether Islamic banks have higher NPLs than conventional banks remains a crucial question, since these two entities operate in tandem in the majority of countries and have different financial characteristics. In particular, while the basis of the conventional banking system is '*interest*', Islamic banks mainly rely on profit and loss sharing (PLS) and use two types of financial products, namely PLS contracts and mark-up instruments. In this respect, Sundararajan and Ericco (2002) and Kabir et al. (2015) argue that the adoption of different modes of financing exposes Islamic banks to additional credit risk. In order to scrutinize whether Islamic banks exhibit higher risk compared to their conventional counterparts, we report the trends in the non-performing loans ratios[4] (NPL ratio) across the observed countries and by bank type in Table 3.

Table 3 shows that, on average, conventional banks exhibit higher risk levels compared to Islamic banks. In fact, it is clear that the conventional banks' NPL ratio considerably surpasses that of the Islamic banks (4.3 % vs. 3.7 %, respectively). The same result was found by Beck et al. (2013).

Over time, it is apparent in Fig. 1 that Islamic and conventional banks exhibit about the same credit risk level until 2008. However, since 2009, conventional banks' average ratio markedly surpassed that of Islamic banks. Alternatively, the tendency of the NPL ratio over the sample period as plotted in Fig. 1 plainly demonstrates the effect of the 2008 global financial crisis. A notable rise

[4] We measure the NPL ratio by dividing the total amount of impaired loans held by a bank by the gross amount of loans. The NPL ratio is widely used in the banking literature as a proxy of credit risk (Berger and DeYoung, 1997; Das and Gosh, 2007; Nurul-Kabir et al., 2015, among others).

Table 3
Dynamics in NPLs across countries by bank tye.

	Nonperforming loans (US$ millions)			NPL ratio (%)		
	All	Islamic	Conventional	All	Islamic	Conventional
UAE	5.405	5.113	5.547	4.7	3.1	5.4
Kuwait	6.614	7.450	6.250	6.0	6.7	5.7
Saudi Arabia	4.076	4.396	4.002	2.3	2.5	2.2
Bahrain	1.944	2.776	1.617	2.7	3.9	2.3
Qatar	0.723	0.667	2.203	1.8	1.6	2.0
Jordan	2.654	0.735	3.072	7.5	4.1	8.0
Turkey	5.989	1.906	6.825	4.2	3.9	4.2
Bangladesh	0.403	0.670	0.362	4.1	2.1	4.4
Indonesia	3.063	0.639	3.721	4.1	5.4	3.8
Global Mean	**3.896**	**3.227**	**4.101**	**4.2**	**3.7**	**4.3**

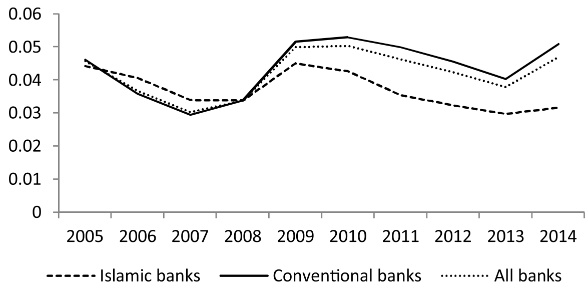

Fig. 1. NPL ratio by year and bank type.

in the mean value of the Islamic and conventional banks' ratios can be observed in 2009, at the onset of the global financial crisis. Such an outcome indicates that both banking systems suffered the consequences of the financial crisis equally and thereby disproves the claim that Islamic banks are better immunized in times of economic crisis.

Regarding the dynamics in NPL ratios across countries, Table 3 reports the decomposition of NPL ratios by geographic location. As can be seen, the differences in the average values are significant. For instance, the average NPL ratio ranges from 1.8 % in Qatar to 7.5 % in Jordan.

Comparing the average values by banking type, Table 3 shows that most of the sample countries exhibit a significant difference in credit risk between Islamic and conventional banks. In most cases, Islamic banks exhibited a lower average NPL ratio, except in Saudi Arabia, Kuwait, Bahrain and Indonesia. Islamic and conventional banks in Saudi Arabia do not exhibit a significant difference in terms of credit risk, whereas Islamic banks in Kuwait, Bahrain and Indonesia have significantly higher credit risk than their conventional counterparts.

5. Empirical results and interpretation

We first present the results by comparing Islamic and conventional banks according to their technical efficiency scores. Then we explore and compare their shadow prices (i.e., perceived costs of NPLs), estimated via Equation 10. Next, we analyze the risk sensitivity of both banking types by adjusting the directional vector g (1, -1). Finally, we regress the estimated shadow prices to a number of bank-specific, industry-specific and macroeconomic factors.

5.1. Efficiency analysis

For the linear problem (Eq. (3)) to be solved and the parameters of the directional distance function to be estimated, we resort to applying the GAMS (General Algebraic Modelling Software) with the CEPLEX solver. The values of the quadratic function parameters are reported in Table A1 in Appendix A.[5] It is worth noting in this respect that by applying Färe et al.'s (2005) method, the entirety of the input and output variables have been normalized by dividing them by their mean value for any convergence problem to be solved.

Table 4 reports technical efficiency scores over the whole sample for Islamic and conventional banks. The results clearly indicate that efficiency scores change with the choice of input-output combination, in accordance with Avkiran (1999). For instance, the results from Model (A) postulate that the average technical efficiency of all banks over the entire period is about 78 %, suggesting that the banks in our sample can improve their performance by simultaneously expanding desirable outputs and contracting undesirable

[5] The parameter estimates of the directional distance function of model (A) are shown in the Table A1 in Appendix A. The parameters relative to model (B) are available upon request.

Table 4
Average technical efficiency estimates by year and bank type.

	All banks			Islamic			Conventional			
	Mean	Median	Std.Dev	Mean	Median	Std.Dev	Mean	Median	Std.Dev	WRS
Model A (y_1 = interest income, y_2 = non interest income, x_1 = fixed assets, x_2 = interest expenses, x_3 = non-interest expenses, b = nonperforming loans)										
2005	0.836	0.838	0.091	0.723	0.738	0.093	0.864	0.861	0.065	−4.731***
2006	0.813	0.836	0.110	0.687	0.699	0.121	0.843	0.853	0.084	−4.742***
2007	0.786	0.816	0.136	0.673	0.722	0.182	0.818	0.836	0.102	−4.179***
2008	0.792	0.809	0.119	0.699	0.721	0.140	0.823	0.831	0.102	−4.353***
2009	0.804	0.824	0.111	0.699	0.702	0.119	0.840	0.853	0.083	−5.293***
2010	0.782	0.799	0.104	0.691	0.675	0.097	0.810	0.828	0.089	−5.028***
2011	0.773	0.803	0.135	0.653	0.637	0.144	0.815	0.824	0.105	−5.033***
2012	0.762	0.789	0.135	0.660	0.665	0.157	0.798	0.808	0.106	−4.536***
2013	0.720	0.718	0.122	0.606	0.631	0.101	0.761	0.764	0.101	−4.536***
2014	0.689	0.675	0.153	0.618	0.626	0.109	0.710	0.701	0.159	−2.212**
Global mean	**0.778**	**0.803**	**0.128**	**0.672**	**0.686**	**0.131**	**0.812**	**0.827**	**0.107**	–
Model B ((y_1 = total loans, y_2 = other earning assets, x_1 = personal expenses, x_2 = fixed assets, x_3 = total deposits, b = nonperforming loans)										
2005	0.776	0.783	0.065	0.702	0.708	0.067	0.793	0.792	0.052	−4.320***
2006	0.815	0.820	0.080	0.732	0.743	0.084	0.836	0.838	0.064	−4.924***
2007	0.840	0.848	0.087	0.752	0.759	0.092	0.862	0.864	0.070	−4.658***
2008	0.822	0.840	0.103	0.707	0.725	0.087	0.856	0.852	0.081	−6.105***
2009	0.798	0.813	0.099	0.723	0.716	0.108	0.821	0.824	0.084	−4.221***
2010	0.761	0.780	0.090	0.698	0.709	0.094	0.783	0.796	0.078	−4.162***
2011	0.717	0.732	0.117	0.624	0.655	0.133	0.750	0.760	0.091	−4.494***
2012	0.683	0.695	0.135	0.630	0.601	0.151	0.701	0.720	0.125	−2.271**
2013	0.682	0.682	0.142	0.705	0.746	0.162	0.675	0.671	0.136	0.947
2014	0.610	0.638	0.179	0.604	0.696	0.258	0.612	0.630	0.149	0.838
Global mean	**0.755**	**0.778**	**0.130**	**0.685**	**0.709**	**0.137**	**0.776**	**0.799**	**0.120**	–

output by (1-0.778) = 22,2 %, holding inputs fixed. On the other hand, the results from Model (B) exhibit an overall mean technical efficiency score equal to 75.5 %. Thus, banks should concurrently expand their desirable outputs and contract bad loans by (1 − 0.755) = 24.5 %, while maintaining inputs fixed.

Within each banking business model, both conventional and Islamic banks' technical efficiency scores generally have a falling tendency. Based on Model (A), the scores of conventional banks dropped after rising in 2009, while those of Islamic banks climbed from 67.3 % in 2007 to over 70 % in 2008 and 2009. However, since 2010, the scores witnessed a decreasing trend suggesting a remarkable deterioration. An inter-temporal analysis reveals that conventional banks surpass Islamic banks all the time with an average technical efficiency of 81.2 % compared to 67.2 % for Islamic banks. These outcomes provide clear evidence that the Islamic banking system is less efficient than the conventional one. Our results are supported by some previous studies such as Abdul-Majid et al. (2011) and Johnes et al. (2014). The latter relate the lower Islamic banking efficiency to the fact that these banks support additional costs and higher operational risk than their conventional counterparts. It should be noted that nearly the same time-varying trend in efficiency scores is still observed in Model (B).

After measuring efficiency scores for all banks, Islamic and conventional ones, we carried out a mean comparison test. We used the non-parametric Wilcoxon rank-sum (WRS) test to compare the levels of efficiency of Islamic and conventional banks. The results strongly confirm the large difference between conventional and Islamic banks.

Predominantly, Islamic banks are expected to exhibit lower technical efficiency in respect to conventional banks for several reasons. First, the strict application of Sharia rules means that several Islamic banking products are bespoke, therefore increasing operational costs. Second, Islamic banks are relatively small in size in relation to conventional ones (Chapra, 2007), and it is generally assumed that technical efficiency tends to increase remarkably with size within the banking industry (see, for instance, Miller and Noulas, 1996; Abdul-Majid et al., 2005; Chen et al., 2005; Drake et al., 2006). Additionally, Islamic banks are usually characterized as being domestically owned, and there is evidence that foreign-owned banks tend to be more technically efficient than domestically-owned ones (Sturm and Williams, 2004; Matthews and Ismail, 2006).

The evaluation of the technical efficiency scores by country reveals that technical efficiency varies considerably across countries. Based on the results depicted in Fig. 2, which displays efficiency scores from our basic model (i.e., Model A), it appears that Asian banks exhibited higher technical efficiency, with global mean scores of 83.96 % and 81.66 % for Bangladesh and Indonesia, respectively. It is also notable that the GCC[6] banks display the lowest average scores.

As regards the difference between Islamic and conventional banks, Fig. 2 gives further insights about the differences between countries. Asian conventional banks still lead (86.21 % and 85.41 %, respectively, for Bangladesh and Indonesia), closely followed by Turkey (83.53 %) and Jordan (82.92 %). Then comes Qatar (81.72 %), which takes the first position of the GCC countries. On the other hand, the Islamic banks of Bangladesh demonstrate the highest mean efficiency (73.71 %). Bangladesh is closely followed by

[6] The Gulf Cooperation Countries comprise six countries: The United Arab Emirates (UAE), Bahrain, Kuwait, Saudi Arabia, Qatar and Oman. This latter is not considered within our study because Oman's Islamic banking and finance sector can only be traced back three years.

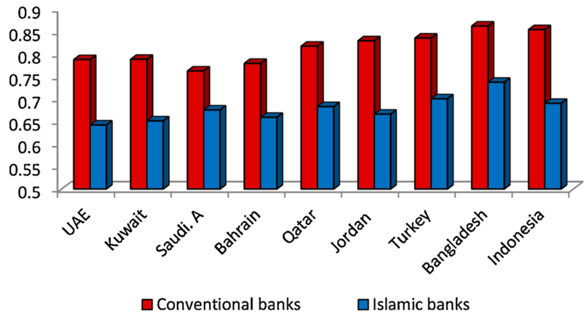

Fig. 2. Technical efficiency by country and bank type (model A).

Turkey and Indonesia with 69.03 % and 70.05 %, respectively. Islamic banks in the UAE come in the last position with average efficiency scores of 64.21 %. This outcome corroborates with that in Abdul-Majid et al. (2010) suggesting that banks in Bangladesh recorded high levels of efficiency compared to other OIC countries. The result is indeed not surprising, since several studies show that Bangladesh's banking industry is expanding and showed high profitability and stability levels even during the 2008 global financial crisis (Islm and Kassim, 2015).

5.2. The price of bad loans

The second part of our analysis deals with the pricing of banking credit risk. NPLs constitute the undesirable output in our applied directional distance function. Their perceived prices, called shadow prices, are derived as a measure of the "*opportunity cost of reducing the bad output by one unit in terms of the foregone production of desirable output once inefficient production has been eliminated*" (Assaf et al., 2013). Moreover, we consider adopting the methodology of Färe et al. (2006) to estimate the undesirable outputs' negative value. The NPLs' costs (or shadow values) are measured through multiplying the NPLs by the estimated shadow prices. In fact, such costs would help measure revenue loss incurred by credit risk management. Table 5 below depicts the NPLs' estimated shadow prices together with their related costs.

The estimations in Model (A) indicate that prices are oscillating between 61 dollars and 169 dollars with an average value of 137 dollars. This price suggests that a one thousand dollars reduction in bad loans reduces revenues by 137 dollars. In other words, exhibiting these levels, bankers need to scarify, on average, 137 dollars of their revenues to reduce NPLs by one thousand dollars.

Table 5 also provides a comparison between the average shadow prices of both Islamic and conventional banks. The results indicate that, on average, Islamic banks have a higher shadow price than their conventional peers. Particularly, to dispose of one thousand dollars of NPLs, Islamic banks must forgo 143 dollars of their desirable outputs versus 136 dollars in the case of conventional banks. The difference between the two types of banks appears not to be considerable, which is in line with the results of the Wilcoxon rank-sum test that achieve a significant difference only in 2008. Overall, it is evident that both groups pursue the same tendency over the entire period; a permanent upward trend. Nevertheless, when investigating each individual year, we notice that conventional banks' prices surpassed those of Islamic banks significantly during the 2007–2008 period and in 2012. In contrast, during the other study years, Islamic banks' costs become notably higher compared to their conventional counterparts.

Turning to the results from Model (B), Table 5 shows that the average shadow price for all sample banks is equal to 453 dollars. In fact, the prices show a steady upward trend during the overall study period with a lowest value equal to 265 dollars in 2005 and a highest value of 674 dollars in 2014. Comparing Islamic versus conventional banking systems, the results demonstrate that Islamic banks constantly have higher shadow prices than conventional banks.

Actually, by applying higher shadow prices (Model A and Model B), Islamic banks appear to be less risky than their conventional peers. Effectively, the Islamic banks in our study already reveal lower NPL ratios compared to their conventional counterparts (see Table 3). This result is consistent with that in Chaffai and Lassoued (2013), who noted that "*banks with relatively high NPLs shadow prices have the lowest level of NPLs, while the less risky banks (low levels of NPLs) have greater shadow prices*".

Table 5 reveals additional indications about the attitude of conventional and Islamic banks towards risk. In fact, the previous empirical literature showed that shadow prices are negatively correlated to banks' risk-taking behavior. Hence, by perceiving higher shadow prices, Islamic banks are considered to have a lower attitude toward risk (i.e., they are risk-averse). This outcome is to some extent evident given that Islamic banks are mainly exposed to higher credit risk, which entails prudent behavior towards risk.

In essence, Islamic banks' exposure to credit risk relies on a variety of factors, such as the complexity of Islamic loan contracts (Abedifar et al., 2013; Kammer et al., 2015), limited default penalties (Yaakub et al., 2014; Hatta et al., 2015) and moral hazard incentives caused by profit and loss sharing contracts (i.e., Musharakah and Mudarabah) (Dakhlallah and Miniaoui, 2011; Sundararajan and Erico, 2002).

Fundamentally, Shariah promotes the concepts of brotherhood, equal treatment and mutual trust. Indeed, in the participatory (PLS) contracts, a party that has no capital invested does not have to share the losses. That is, the losses are entirely borne by the Islamic bank if this occurs. Still, Islamic banks are not allowed to charge penalties due to the default of payments by the customer. Besides, they can't require collateral to reduce risks as practiced by the conventional banking industry.

As a consequence, and principally due to a high level of moral hazard, adverse selection and insufficient expertise in project

Table 5
Shadow prices and costs of bad loans: $(g_y,g_b) = (1, -1)$.

	NPLs' shadow prices (USD'000)				NPLs' costs (USD'000)			
	All	Islamic	Conventional	WRS	All	Islamic	Conventional	WRS
Model A (y_1 = interest income, y_2 = non interest income, x_1 = fixed assets, x_2 = interest expenses, x_3 = non-interest expenses, b = nonperforming loans)								
2005	0.061	0.067	0.059	1.126	147.16	122.07	152.69	−0.271
2006	0.097	0.098	0.098	−0.941	222.91	188.97	231.27	0.396
2007	0.132	0.120	0.136	−1.629	335.94	300.72	344.87	0.541
2008	0.143	0.129	0.148	−2.479**	466.95	387.66	491.17	1.393
2009	0.141	0.142	0.140	1.251	623.64	424.52	688.22	2.074**
2010	0.141	0.159	0.135	1.912*	664.74	468.52	729.28	1.920*
2011	0.153	0.163	0.149	1.585	633.27	500.91	679.16	2.136**
2012	0.172	0.169	0.173	−0.246	706.46	573.62	753.78	1.869*
2013	0.161	0.178	0.155	1.223	710.66	718.36	708.16	1.909*
2014	0.169	0.181	0.166	0.637	769.54	626.49	809.60	1.673*
Global mean	**0.137**	**0.143**	**0.136**	–	**529.84**	**440.63**	**556.67**	–
Model B (y_1 = total loans, y_2 = other earning assets, x_1 = personal expenses, x_2 = fixed assets, x_3 = total deposits, b = nonperforming loans)								
2005	0.265	0.322	0.252	3.685***	573.12	593.01	568.48	0.069
2006	0.307	0.364	0.293	3.538***	647.40	667.76	642.17	−0.083
2007	0.339	0.400	0.324	3.493***	809.76	966.86	772.14	0.386
2008	0.391	0.447	0.374	2.929***	1152.02	1155.32	1151.02	−0.759
2009	0.427	0.483	0.409	3.212***	1775.30	1351.23	1909.22	−1.800*
2010	0.476	0.504	0.466	1.382	2136.56	1638.19	2307.06	−2.042**
2011	0.511	0.493	0.518	−0.823	2192.30	1797.94	2334.27	−2.264**
2012	0.548	0.498	0.566	−2.497**	2411.90	1636.39	2688.11	−2.314**
2013	0.637	0.581	0.656	−1.880*	3226.70	2295.24	3531.21	−2.117**
2014	0.674	0.578	0.704	−2.154**	3706.93	2571.36	4056.34	−1.822*
Global mean	**0.453**	**0.472**	**0.447**	–	**1822.20**	**1490.09**	**1923.60**	–

evaluation and related techniques, Islamic financial institutions rely more on non-PLS rather than on PLS modes. Hereof, Aggarwal and Yousef (2000) admit that Islamic banks mainly use non-PLS instruments to avoid the moral hazard problems associated with PLS financing. Chong and Liu (2009) show that in Malaysia only 0.5 % of Islamic bank finance is based on PLS principles. Dar and Presley (2000) claim that even Mudharabah companies in Pakistan, which are supposed to operate in the form of PLS, mainly follow non-PLS modes of finance.

Nonetheless, while Islamic banks appear to refrain from practicing PLS modes of finance, they still face possible withdrawal risks compared to conventional banks (Khan and Ahmed, 2001; Sundararajan and Erico, 2002; Obaidullah, 2005). In this regard, the previous literature claims that religious people are more risk-averse (Hilary and Hui, 2009), implying that Islamic bank depositors could be more sensitive to bank performance and demonstrate greater withdrawal risk compared to conventional banks' depositors. As a consequence, Islamic banks might be in danger of transferring part of their profits to investment account holders to reduce withdrawal risk. Such a risk is known as displaced commercial risk (AAOIFI, 1999).

It is worth highlighting that the magnitude of the estimated shadow prices is somewhat higher than previous results provided by Assaf et al. (2013) in the context of Turkish banks and Chaffai et al. (2007) in the context of 29 emerging countries. However, the perceived prices are very close to the costs estimated by Chaffai and Lassoued (2013) when exploring the Tunisian banking industry. In this study, the authors find that Tunisian banks need to forgo 130 Tunisian Dinars to reduce NPLs by one thousand Dinars. Moreover, our outcomes are somewhat consistent with those reached by Huang and Chung (2016) when exploring Taiwan's banking industry efficiency. In their study, the shadow prices are found to be variable across time with an average value of 204 dollars.

Moving to the NPLs' costs displaying the cost that the bank has disposed to deal with toxic loans, Table 5 presents the testing results for the differences in NPLs' costs between Islamic and conventional banks. The average scores suggest that the conventional banks' mean costs have been considerably higher than those of the Islamic banks both in Model (A) and Model (B). This outcome is expected since conventional banks have higher NPL levels compared to Islamic banks (see Table 3).

Otherwise, we note the existence of a negative association between the shadow price of the undesirable output and its level. That is, banks with relatively high NPLs' shadow prices have the lowest NPL levels, while the less risky banks (low levels of NPLs) have higher shadow prices. This result is in line with that of Chaffai et al. (2007), who provide further evidence that banks with a low level of NPLs have higher NPLs' shadow prices.

5.3. Risk preference assumption

Wei et al. (2013) and Molinos-Senante et al. (2015) admitted that *"when estimating a directional distance function, the specification of the directional vector plays an essential role"*. That is, within the banking industry vectors deviate according to the assumption of risk preference and particularly the behavior of the bank towards risk. For example, the directional vector $(g_y,g_b) = (1,-1)$ is considered as the classic behavior of equal sensitivity to risk, namely the "*preference for risk balance*" as in Zhu et al. (2016). We follow these authors in identifying three distinguishing directional vectors that are different from the standard choice $(g_y,g_b) = (1,-1)$. Fig. 3 below

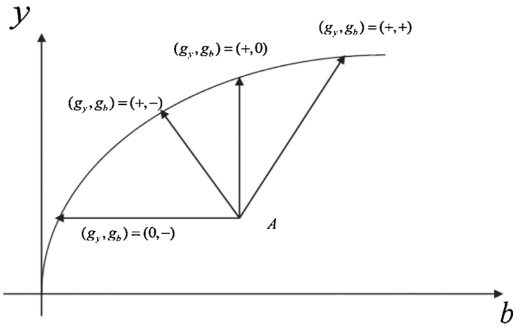

Fig. 3. Adjusting directional vectors.
(Source: Ning Zhu et al., 2016*)*

demonstrates the direction vector adjustment within each directional vector or each risk preference.

Given that NPLs represent the undesirable output, they are also a measure of banking credit risk. That is, credit risk rises when NPLs increase. Accordingly, bank behavior is related to its risk preference. These preferences are illustrated in four directions adjusted between desirable output (y) and undesirable output (b). For instance, when the bank (decision-making unit: DMU) has the sole objective of minimizing risk (or contracting NPLs), it is considered strongly sensitive to risk, this is the "*preference for risk aversion.*" On the contrary, when the DMU doesn't care about risk, it is considered as indifferent to risk. This case is called the "*preference for risk neutral.*" Finally, if the DMU enjoys assuming risk, that is to say, it is a strong risk-taker, it has a "*preference for risk-taking.*" We further illustrate each risk preference assumption in Table 6 below.

Table 7 reports the estimated results. It appears clear that the shadow prices of all sample banks are variable according to the bank's risk preference. Principally, the perceived cost of credit risk increases when the bank accords more importance to risk, i.e., is more sensitive to risk. For instance, the upper shadow prices are marked under the preference for risk aversion assumption, that is, when bankers have the reduction of NPLs as a primary objective. In this context, Chaffai et al. (2007) found the same results and argued that risk-averse bankers have a high proportion of NPLs. Therefore, they search primarily for a maximum reduction of these toxic loans. To do this, they usually apply high prices when according credits.

Moving now to a differentiation between Islamic and conventional banks regarding their sensitivity toward risk, it is worth noting that the Islamic and conventional subsamples witnessed broadly the same trends. Islamic banks surpass their conventional peers on average values under the four assumptions, but not consistently. Indeed, in Fig. 4 we present additional interesting results from comparing the time-varying shadow prices between the two banking types.

Fig. 4a indicates that Islamic and conventional banks' prices witnessed almost the same trends. The costs relevant to the two bank sets saw a declining trend over the study period. This outcome demonstrates that, over time, both bank sets are holding more risk.

Otherwise, Fig. 4b–d indicate divergent outcomes. Here conventional bank prices mostly exceed Islamic bank prices in the 2006–2008 period and 2012, i.e., at the onset of the subprime crisis and the European sovereign debt crisis. Otherwise, Islamic bank prices become higher.

5.4. Assessment of the main drivers of the perceived price of credit risk

In this section, we investigate the determinants of the perceived price of NPLs. We regress the shadow prices on a number of explanatory variables. Using Simar and Wilson's (2007) truncated regression model combined with bootstrapped confidence intervals, we explore the possibility that this may be affected by some factors including bank characteristics, macroeconomic indicators and economic freedom measures. A brief description of the variables used, the summary statistics and the correlation among them are reported successively in Tables 8–10.

Briefly, we used four bank-specific factors, namely capitalization (*CAP*), profitability (*PROF), size (SIZE)* and liquidity (*LIQ)*. We measure bank capitalization by the ratio of equity to total assets. CAP is expected to be negatively related to the perceived prices since

Table 6
Bank behavior toward risk and risk preference assumptions.

	Bank behavior	Directional vector	Description
Pref (1)	*A preference for risk aversion*	$(g_y, g_b) = (0, -1)$	Reducing the bad output is the bank's fundamental objective; reduction of undesirable output while maintaining the desirable output constant.
Pref (2)	*A preference for risk balance*	$(g_y, g_b) = (1, -1)$	Simultaneously reducing bad output and increasing desirable outputs with the same weight.
Pref (3)	*A preference for risk neutral*	$(g_y, g_b) = (1, 0)$	The bank focuses solely on increasing desirable outputs while keeping the undesirable output constant.
Pref (4)	*A preference for risk-taking*	$(g_y, g_b) = (1, 1)$	Simultaneously increasing undesirable and desirable outputs.

Table 7
Shadow price of bad loans under different risk preferences.

	All sample banks				Islamic				Conventional			
	(0,-1)	(1,-1)	(1,0)	(1,1)	(0,-1)	(1,-1)	(1,0)	(1,1)	(0,-1)	(1,-1)	(1,0)	(1,1)
Model A	0.246	0.137	0.124	0.121	0.252	0,143	0.127	0.126	0.244	0.136	0.122	0.119
Model B	0.761	0.453	0.425	0.363	0.744	0.472	0.445	0.376	0.766	0.447	0.418	0.359

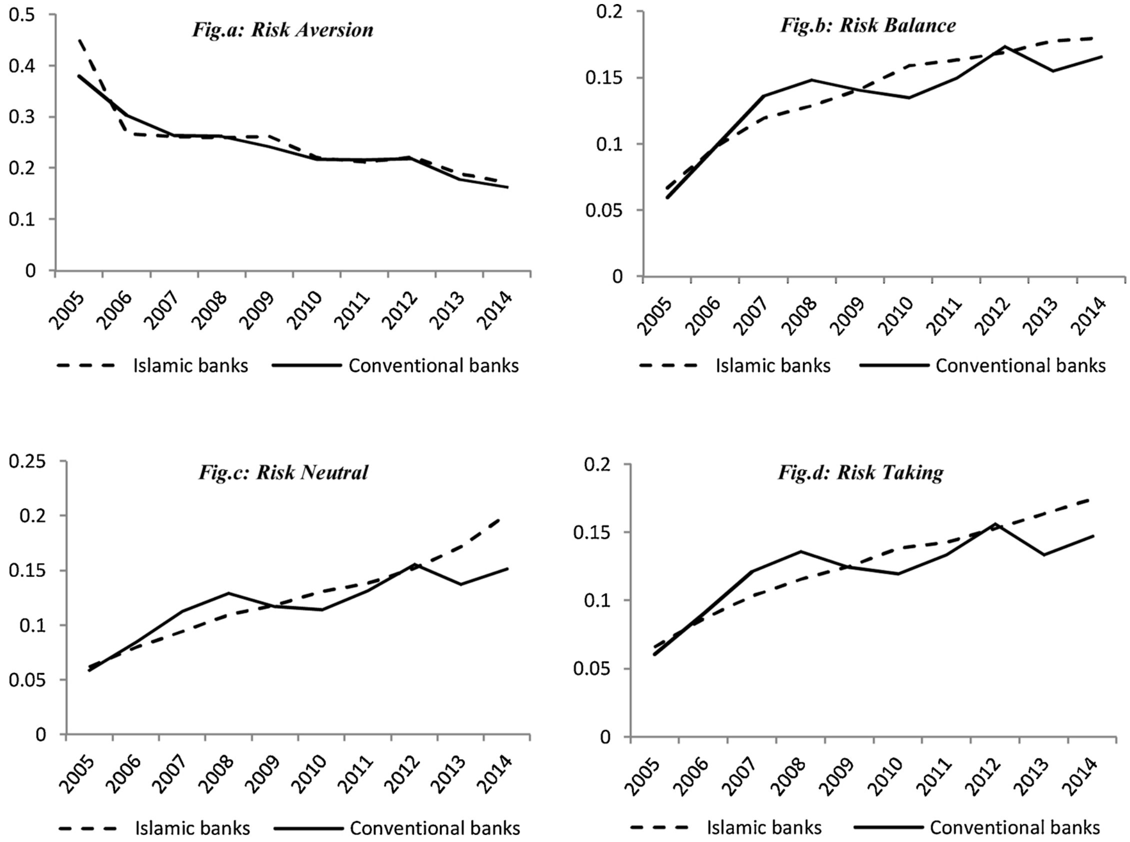

Fig. 4. NPLs' shadow prices averaged by year and bank type (Model A).

high levels of capital usually serve as a buffer against any possible losses (Kosak et al., 2015; Brei and Schclarek, 2013; Jokipii and Milne, 2008), which can therefore reinforce banks' ability to take risk. Profitability is captured by the return on average assets. We believe that improved profitability can induce risk-taking (Ibrahim and Rizvi, 2017; Bokpin, 2016) and hence expect a negative effect on the perceived prices. Regarding bank size, it is believed that large banks are riskier than small banks, especially when they have inadequate capital or unstable funding (Laeven et al., 2016). We hence expect size to have a positive effect on the perceived prices.

As regards the bank liquidity proxy, we employ the net loans to total assets ratio, which reflects banks' liquidity management. According to Alandejani et al. (2017), a raised liquidity ratio denotes a critical position, which may increase the risk of bank failure. In view of that, we expect *LIQ* to affect the perceived costs of credit risk positively.

Furthermore, to control the macroeconomic environment, we incorporate the growth rate of the gross domestic product (*GDPgr*) and the inflation rate (*INF*) into the regression. Representing healthier economic conditions, GDPgr is expected to raise banks' incentives for risk-taking (Bikker and Vervliet, 2017; Bitar et al., 2017). We therefore expect a negative influence on the perceived credit risk costs. Inflation, which usually serves as a measure of macroeconomic uncertainty (Ibrahim and Rizvi, 2017), is expected to exert an adverse effect on banks' risk-taking behavior in that banks turn out to be extremely cautious when facing heightened uncertainty. Thus, we expect its impact on the perceived prices to be positive. It is worth highlighting that, in addition to these macroeconomic variables, we also control for the 2008 global financial crisis.

Furthermore, we introduce three indicators of economic freedom to control for the institutional environment. In particular, we use the overall freedom index (*OVFR)* as an aggregate measure of a country's overall economic freedom. Then, we use the financial freedom index (FINFR), which represents an overall indicator of financial and banking freedom. Put simply, it measures the degree of openness of the banking industry (Demiguc-kunt et al., 2004; Chortareas et al., 2011, 2013). Against this background, Ghosh and

Table 8
Description of the regression variables and sources.

Variable	Notation	Description	Sources
Bank-Specific Factors			
Bank Capitalization	*CAP*	Equity over total Assets	Datastream (2015)
Bank Profitability	*PROF*	Return on assets ratio	Datastream (2015)
Bank Size	*Size*	Natural logarithm of total assets	Datastream (2015)
Bank Liquidity	*LIQ*	Total loans over total assets	Datastream (2015)
Country-Specific Factors			
GDP growth	*ΔGDP*	Annual growth rate of GDP	World Bank (2015)
Inflation	*INF*	Inflation rate	World Bank (2015)
Subprime Crisis Period	*Crisis*	Dummy variable taking the value of one in 2008 and 2009 years and zero otherwise	–
Economic Freedom Indexes			
Overall Economic Freedom Index	*OVF*	A measure of the degree of a country's economic freedom. The index is composed of 10 economic measurements, namely business freedom, trade freedom, fiscal freedom, government size, monetary freedom, investment freedom, financial freedom, property rights, labor freedom and freedom from corruption.	Heritage Foundation (2015)
Financial Freedom Index	*FINF*	A measure of a country's independence from government control and interference in the financial sector, including banks	
Freedom from Corruption Index	*CORF*	A measure of the non-prevalence of political corruption within a country, as reported by the Corruption Perception Index for 2011.	

Table 9
Summary statistics of the regression variables.

	All Banks				Islamic Banks				Conventional Banks			
Symbol	Obs.	Mean	Median	Std.D	Obs.	Mean	Median	Std.D	Obs.	Mean	Median	Std.D
CAP	**889**	0.134	0.123	0.060	**209**	0.162	0.139	0.097	**680**	0.125	0.121	0.038
PROF	**889**	0.021	0.018	0.030	**209**	0.026	0.017	0.057	**680**	0.019	0.018	0.012
SIZE	**889**	15.98	16.09	1.351	**209**	15.49	15.42	1.22	**680**	16.13	16.34	1.35
LIQ	**885**	0.609	0.629	0.151	**209**	0.664	0.687	0.197	**676**	0.584	0.612	0.130
GDPgr	**889**	0.054	0.055	0.045	–	–	–	–	–	–	–	–
INF	**889**	0.052	0.049	0.038	–	–	–	–	–	–	–	–
OVFR	**889**	64.01	64.2	7.280	–	–	–	–	–	–	–	–
FINFR	**889**	52.54	50	18.01	–	–	–	–	–	–	–	–
CORFR	**889**	44.73	46	13.43	–	–	–	–	–	–	–	–

Table 10
Correlation coefficient matrix of main regression variables.

	CAP	*PROF*	*SIZE*	*LIQ*	*GDPgr*	*INF*	*OVFR*	*FINF*	*CORFR*
CAP	1								
PROF	0.3902***	1							
SIZE	−0.1610***	−0.0411	1						
LIQ	0.0326	0.0273	−0.1505***	1					
GDPgr	0.1099***	0.1685***	−0.1044***	−0.0642*	1				
INF	−0.1554***	−0.0211	−0.1250***	0.0761**	0.1556***	1			
OVFR	0.3242***	0.0004	0.2500***	−0.2213***	0.1036***	−0.4498***	1		
FINFR	0.2356***	−0.0391	0.1582***	−0.2907***	0.2287***	−0.1746***	0.8215***	1	
CORFR	0.3481***	0.0934***	0.2322***	−0.1056***	0.0548	−0.3846***	0.7874***	0.5521***	1

Ghosh (2016) states that less government interference (i.e., freedom from various controls) plays an important role in affecting banks' risk-taking. The author further explains that "*excessive government interference can restrict the free play of market forces and curb bank innovative activity (new product and services)*". Accordingly, banks might be forced to engage in excessively risky lending strategies so as to compensate for potential revenue losses.

Finally, we include the freedom from corruption index (CORFR) to assess the perception of corruption in the business environment. Chortareas et al. (2013) demonstrate that this index "*captures the failure of integrity in the system, a distortion by which individuals are able to gain at the expense of the whole*." In the literature, corruption is widely believed to hamper bank lending since it acts as a tax that heightens the cost of lending (Weill, 2011). Therefore, CORFR is expected to affect the perceived credit risk costs negatively.

Accordingly, the shadow price (SHDW) serves as the dependent variable in the estimation of the following equation:

$$SHDW_{it} = \beta_0 + \beta_1 CAP_{it} + \beta_2 PROF_{it} + \beta_3 SIZE_{it} + \beta_4 LIQ_{it} + \beta_5 GDPgr_{it} + \beta_6 INF_{it} + \beta_7 FREE_{it} + \varepsilon_{it} \tag{11}$$

Table 11
Correlates of the shadow prices: Bootstrapping regression model.

	All Banks				Conventional Banks				Islamic Banks			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Constant	0.041	−0.048*	0.027	0.040	0.002	−0.064**	−0.006	0.001	0.149**	0.018	0.124**	0.153**
CAP	−0.006	−0.090***	−0.060*	−0.026	−0.016	−0.106**	−0.062	−0.053	−0.027	−0.159***	−0.111**	−0.037
PROF	−0.244*	−0.168	−0.174	−0.238	−0.602***	−0.391**	−0.418**	−0.555***	−0.204	−0.124	−0.127	−0.205
SIZE	0.005***	0.003**	0.004***	0.004***	0.007***	0.005***	0.006***	0.006***	0.001	−0.006	−0.001	0.0006
LIQ	0.042***	0.056***	0.060***	0.043***	0.062***	0.072***	0.076***	0.062***	0.002	0.031*	0.031*	0.003
GDPgr	−0.088**	−0.143***	−0.152***	−0.096***	−0.079**	−0.129***	−0.129***	−0.091**	−0.031	−0.124	−0.157*	−0.033
INF	−0.147***	−0.003	−0.110**	−0.119**	−0.075	0.036	−0.044	−0.042	−0.375***	−0.171*	−0.338***	−0.364***
OVFR	–	0.002***	–	–	–	0.001***	–	–	–	0.003***	–	–
FINFR	–	–	0.0006***	–	–	–	0.0004***	–	–	–	0.001***	–
CORFR	–	–	–	0.0002*	–	–	–	0.0002*	–	–	–	0.0001
No. Of Obs.	874	874	874	874	665	665	665	665	209	209	209	209
Khi^2	83.50***	133.46***	113.65***	89.42***	81.73***	102.69***	92.47***	82.87***	38.47***	70.23***	52.85***	42.65***
R-sq	0.082	0.122	0.117	0.085	0.100	0.129	0.119	0.104	0.129	0.243	0.219	0.130

where i indexes the bank and t indexes the year. CAP, PROF, SIZE, LIQ, GDPgr, and INF are already defined above. As for $\mathbf{FREE_{i,t}}$, it is a vector of economic freedom indexes that include OVFR, FINF and CORF. The data for the variables accounting for economic freedom are obtained from the Heritage Foundation's 2015 database.

Table 9 further reports the summary statistics relevant to the entirety of applied variables. We propose to demonstrate the major distinctive differences between Islamic and conventional banks to further give justification for their different behavior towards risk.

Banking capitalization, as measured by the equity to assets ratio, is higher for Islamic banks, suggesting that they are significantly better capitalized compared to their conventional peers. Regarding the banking profitability indicator, PROF also appears to be considerably higher for Islamic banks as compared to conventional ones. An averaged bank size measure of Islamic banks stands at 15.49, while it is 16.13 for conventional banks. Finally, we find that Islamic banks have higher liquid assets compared to their conventional peers.

Table 10 provides information on the degree of interdependence between the variables used in the regression analysis. We notice a moderate correlation between the bank-specific variables, which implies that multicollinearity problems are not serious. In fact, Kennedy (2008) points out that multicollinearity is a problem when the correlation is above 0.8. It is worth highlighting that there is a high correlation between the economic freedom variables and the regression models are therefore estimated including one economic freedom indicator at a time, rather than estimating all economic freedom variables simultaneously.

5.4.1. *Truncated regression results*

We display the regression results in Table 11. Each model presents the results derived from economic freedom variables while controlling for a selected set of relevant bank-specific and macroeconomic ones. In particular, the first column in Table 11 reports the basic regression model that includes the bank-specific and macroeconomic control variables (model 1). The next three columns include alternative economic freedom control variables one at a time (models 2–4).

Once we control for the bank-level characteristics, we find that capitalization has an adverse significant effect on the shadow price in several models, suggesting that well-capitalized banks lower the risk premium. This result disproves the conclusion that bankers perceiving a higher credit risk price try to cover less risk by building more economic capital (Chaffai et al., 2007). Nevertheless, it provides support to the argument that well-capitalized banks face lower costs of going bankrupt, which in turn results in lower costs of findings (Kosmidou, 2008). In other words, a strong capital structure provides support to withstand financial turbulences and increase depositors' security; the bank operates in a safe situation which allows acquiring risky portfolios and thus applying lower risk premiums when according loans.

The proxy of profitability (ROA) reveals a negative relation with NPLs' shadow prices. Nevertheless, this relationship is significant only in the case of conventional banks. The results imply that banks exhibiting high profitability levels enjoy high-quality monitoring and management support. In this case, the bank could take on risky activities without a sturdy doubt of failure. Thus, the perceived prices of risk are minor.

The results also document that bank size has a positive and significant relationship with shadow prices in almost all models except those of Islamic banks. This implies that the larger the bank, the higher is the perceived price of credit risk. In fact, large banks usually have a good management quality, which in turn could lead to a secure lending decision-making process. As a consequence, to stay away from default risk, bankers make cautious lending decisions, thus perceiving higher shadow prices.

Regarding bank liquidity, we find that LIQ has a positive and significant impact on shadow prices in several regressions shown in Table 11. This finding implies that holding more liquid assets spurs bankers to raise the cost of credit as a way to increase bank returns. Likewise, LIQ appears to have a positive effect on Islamic banks' credit risk perceived costs, yet with a low level of significance. This outcome may be explained by the fact that Islamic banks lack liquid securities on their asset side (Saeed and Izzeldin, 2016) mainly due to the complexities associated with PLS modes of financing, which require prudent behavior to capture good investment opportunities (Bourkhis and Nabi, 2013).

Regarding the influence of macroeconomic variables, GDP growth exhibits a negative and statistically significant coefficient, a finding that is robust across all sample banks and conventional banks. Therefore, an improved economic environment would encourage bankers to lend more and improve the quality of their assets. Banks behave as excessive risk-takers and thus lower the prices when according a loan. In the case of Islamic banks, however, we find that economic growth does not affect the perceived price of credit risk. Likewise, it can be observed from Table 11 that a rise in the inflation rate reduces the shadow prices in the cases of all banks and Islamic banks only.

Turning to the impact of the economic freedom control variables, we note that, given the strong correlation between the economic freedom indexes (see Table 10), the regression models are estimated by including each economic freedom indicator at a time instead of estimating them concurrently. As expected, the results show that both the overall freedom and the financial freedom indexes consistently exhibit a positive and highly significant correlation with the perceived prices of credit risk. Finally, it is notable that the freedom from corruption index is positively associated with the perceived cost, but with low significant levels.

5.4.2. *Robustness checks*

To check the validity of our results, we apply the fixed effects panel model[7] as another approach to examining the correlates of credit risk cost. Table 12 presents the results that describe the relationship between NPLs' shadow prices and explanatory variables in

[7] Actually, we initially applied both fixed (FE) and random effects (RE) models and our choice of the FE models is based on the Hausman specification test, which clearly and constantly rejected the null hypothesis.

Table 12
Correlates of the shadow prices: Fixed effects model.

	All Banks				Conventional Banks				Islamic Banks			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Constant	−0.787***	−0.812***	−0.754***	−0.857***	−0.905***	−0.906***	−0.874***	−0.964***	−0.513***	−0.624***	−0.510***	−0.591***
CAP	−0.083	−0.129**	−0.116**	−0.070	−0.173**	−0.219***	−0.192**	−0.167**	−0.050	−0.094	−0.096	−0.027
PROF	−0.077	−0.048	−0.046	−0.063	0.047	0.041	0.076	0.084	−0.119	−0.071	−0.074	−0.099
SIZE	0.056***	0.045***	0.052***	0.064***	0.062***	0.052***	0.058***	0.067***	0.042***	0.029***	0.038***	0.057***
LIQ	0.049***	0.042**	0.041**	0.051***	0.097***	0.083***	0.077**	0.107***	0.017	0.015	0.020	0.009
GDPgr	−0.025	−0.041	−0.055	0.001	−0.041	−0.052	−0.064	−0.020	0.023	−0.019	−0.026	0.066
INF	−0.024	0.026	−0.048	−0.001	0.035	0.075	0.020	0.048	−0.211**	−0.134	−0.245**	−0.129
OVFR	–	0.003***	–	–	–	0.002***	–		–	0.005***	–	–
FINFR	–	–	0.001***	–	–	–	0.0007***	–	–	–	0.001***	–
CORFR	–	–	–	−0.001***	–	–	–	−0.0009**	–	–	–	−0.003***
No. Of Obs	874	874	874	874	665	665	665	665	209	209	209	209
R-sq	0.280	0.305	0.299	0.293	0.307	0.325	0.319	0.314	0.270	0.311	0.298	0.342
Khi^2	49.64	47.98	46.72	45.41	43.22	40.10	39.03	38.06	10.87	11.3	10.66	13.03

Note: ***, ** and * indicate statistical significance at 1 %, 5 % and 10 % levels, respectively.

all sample banks, Islamic as well as conventional banks.

By looking at all sample banks, we can readily note that bank-specific variables are signed in a way that is consistent with the results of the previous table. Likewise, the coefficients of GDPgr and INF are signed in accordance with Table 11, yet their effect turns out to be insignificant.

As for conventional banks, the main findings remained unchanged except for CAP, PROF and GDPgr. In particular, the coefficient of the bank capitalization variable is negative, as previously stated, yet with high and consistent levels of significance. This supports the results reported in Table 11 and implies that holding high levels of capital can incur additional risk-taking for conventional banks. Elsewhere, the PROF and GDPgr variables lost their significance via the fixed effects model and then disprove previous results.

Turning to Islamic banks, the results remain approximately unchanged except for CAP and Size. CAP has a negative impact, but is statistically insignificant. Hence, we conclude that Islamic banks' capitalization is not very powerful regardless of their risk-taking incentives. At the same time, Size affects NPLs' costs positively with high levels of significance, which contradicts previous results and suggests that a larger bank size increases the perceived costs of credit risk. We have already found similar results for all sample banks and the conventional banks subsamples. All in all, our findings reinforce the standpoint that the scale of operations can exert an impact on bank risk.

Ultimately, Table 12 gives us a consistent result for OVFR and FINFR. That is, their coefficients are still positive and statistically significant in all the reported fixed effects models. These outcomes further strengthen our findings in the truncated regression estimation and confirm that a higher level of financial freedom raises the perceived costs of credit risk. On the other hand, the coefficients of the corruption freedom index (CORFR) appear to be negative with high levels of significance, which disproves previous results and implies that corruption is an important factor influencing banks' risk-taking and thus the perceived cost of credit risk. The results from regression (4) indicate that the corruption index has a significant negative relationship with the perceived costs, implying that greater freedom from corruption causes prices to decrease. That is, severe corruption increases the perceived costs by discouraging banks to engage in lending. This result is in line with Weill (2011) in that corruption may hamper lending expansion by raising the cost of loans.

6. Conclusion

The study provides an advanced model of a bank production function by incorporating risk preferences. We employed the directional distance function in its quadratic form. Indeed, this function allows an asymmetrical treatment of desirable and undesirable inputs or outputs. In other words, it permits the simultaneous adjustment of inputs used and outputs (desirable and undesirable) produced by a bank. In this survey, NPLs are incorporated into the production function as undesirable outputs.

Alternatively, the directional distance function enables us to extract the shadow prices of bad output (i.e., NPLs), a measure which helps to monitor lending decisions in the presence of risk. We further applied a bootstrap regression to link the perceived prices by some explanatory variables. Our sample comprises 103 banks, including 27 Islamic and 76 conventional banks, operating in the Middle East and Asia over the 2005–2014 period.

The empirical investigation was carried out over four stages. In the first step, we estimated and analyzed the technical efficiency of the individual banks while taking into account banking risk (measured by NPLs). The obtained scores indicated an apparent superiority of the conventional banks as compared to their Islamic peers. In a second step, we evaluated the shadow prices of NPLs as a measure of the opportunity cost in terms of foregone revenue to the banker to the amount of one unit of NPLs to be reduced. These shadow prices, which have, to our knowledge, not been reported in any previous study on Islamic banking, allow managers to determine the costs of operations that a reduction in bad outputs would entail. At this stage, the results postulated that Islamic banks perceive higher prices. Put differently, the evaluation of the toxic loans' shadow prices demonstrated that the Islamic banks seem to be more risk-averse compared to their conventional peers.

Perceiving the cost of bad loans also provides a measure of the risk sensitivity of the banker, which further enables us to study the attitude towards risk of Islamic compared to conventional banks, a framework constructed for the first time within the Islamic banking context. This essay has established that shadow prices are inversely related to managers' attitude toward risk. Put differently, banks in a position of excessive risk-taking perceive a very low price for NPLs. Nevertheless, banks that are strongly sensitive to risk perceive the high cost of risk and hence higher prices of NPLs. This result is validated within the two considered banking systems.

In the latter stage of analysis, when exploring factors related to the perceived price of credit risk, we report a clear negative association between shadow prices and bank capitalization. However, a positive interconnection with liquidity and size is shown. When considering economic freedom indexes, we argue for the existence of a positive and highly significant association between its financial component and the credit risk's perceived prices.

These results have significant implications for bankers asked to reduce the amount of impaired loans and correctly make provisions for them. The strategy of perceiving the price or cost of bank's credit risk to further make rational lending decisions is critical for every institution in every industry, and even more critical for financial institutions in terms of lending decisions. Banks must take into account all relevant factors to make short- and long-term decisions. Our findings are relevant for implementing credit risk management strategies and give valuable information that can help avoid future credit risk rising, essentially by making rational lending decisions. In particular, the results demonstrate that Islamic banks have a low attitude toward risk (risk-averse) compared to conventional banks. This usually leads to the rejection of profitable financing proposals. In fact, a low attitude towards risk might, in turn, lead to a lower quantity of profit-sharing financing because it faces higher risk compared to debt-based financing. Effectively, a review of the literature suggests that the current practice of Islamic banks depends heavily on the debt-based Murabaha mode of financing (approximately 80 %). Considering current socio-economic conditions, asymmetric information (adverse selection and moral hazard) and, more importantly, the lack of trust, we are far away from PLS or so-called risk-sharing contracts.

Fundamentally, there should be a balance between profit sharing and debt-based financing. Indeed, the quantity of profit sharing financing needs to be increased because it reflects the commitment of Islamic banks to community development and could become an important criterion for Islamic banks' performance. However, if banks are to perform effectively, a high quantity of profit sharing financing needs to be followed by a high quality of financing, that is, relatively little non-performing financing. Altogether, if the quantity of profit sharing financing is to be increased or a criterion of Islamic bank performance to be improved, the attitude of Islamic banks towards risk should change.

To achieve this will take a significant paradigm change for everyone when they have only financing structures in mind. In actual fact, such structures are already common in the consumer psyche as there are similar structures dealing in unit trusts, shares or other types of investments, where risks are taken. But to flip it into an "equity financing" concept will remain a challenge to Islamic banks that are serious in offering something truly "Islamic."

Appendix A

Table A1
Parameter estimates of the directional distance function (model A).

Parameters	Variables	Coefficients			
		g (y, b) = (0,-1)	g (y, b) = (1,-1)	g (y, b) = (1,0)	g (y, b) = (1,1)
α_0	Intercept term	0.0511	0.0771	0.1038	0.1078
β_1	y_1	−0.0237	−0.8476	−0.9518	−0.9865
β_2	y_2	−0.0190	−0.0417	−0.0481	−0.0475
γ	b	1.0000	0.1106	0.0395	0.0340
β_{11}	$0.5y_1^2$	0.3086	−0.0054	0.0199	0.0327
β_{12}	y_1y_2	−0.0572	−0.0088	−0.0199	−0.0287
μ_1	y_1y_3	0.0000	−0.0143	−0.0073	−0.0039
β_{22}	$0.5y_2^2$	0.0034	0.0142	0.0199	0.0173
μ_2	y_2y_3	0.0000	0.0053	0.0073	0.0114
γ_{11}	$0.5b^2$	0.0000	−0.0089	−0.0070	−0.0075
α_1	x_1	0.0227	0.1881	0.2130	0.1827
α_2	x_2	0.1016	0.5308	0.5663	0.5716
α_3	x_3	0.0189	0.1677	0.2103	0.2388
α_{11}	$0.5x_1^2$	0.0342	0.0000	0.0095	0.0095
α_{12}	x_1x_2	−0.0247	0.0000	0.0079	0.0013
α_{13}	x_1x_3	0.0001	0.0000	0.0413	0.0533
α_{22}	$0.5x_2^2$	0.1542	0.1327	0.0819	0.0440
α_{23}	x_2x_3	−0.0450	−0.0164	−0.0442	−0.0433
α_{33}	$0.5x_3^2$	0.0602	0.3039	0.1928	0.0699
δ_{11}	x_1y_1	0.0036	0.0000	0.0087	0.0356
δ_{12}	x_1y_2	−0.0008	0.0000	−0.0087	−0.0106
η_1	x_1b	0.0000	0.0000	−0.0211	−0.0249
δ_{21}	x_2y_1	−0.1652	0.0330	0.0482	0.0462
δ_{22}	x_2y_2	0.0108	−0.0693	−0.0482	−0.0330
η_2	x_2b	0.0000	−0.0362	−0.0159	−0.0132
δ_{31}	x_3y_1	0.0742	−0.1111	−0.0538	0.0090
δ_{32}	x_3y_2	0.0754	0.0875	0.0538	0.0448
η_3	x_3b	0.0000	−0.0235	−0.0488	−0.0539
ν_1	T	−0.0744	0.0018	0.0008	0.0049
ν_2	$0.5T^2$	0.0314	0.0119	0.0091	0.0075
ψ_1	x_1T	0.0007	−0.0188	−0.0237	−0.0240
ψ_2	x_2T	0.0286	−0.0370	−0.0433	−0.0432
ψ_3	x_3T	−0.0132	−0.0236	−0.0203	−0.0178
ϕ_1	y_1T	−0.0850	0.0303	0.0349	0.0331
ϕ_2	y_2T	−0.0149	−0.0173	−0.0089	−0.0066
λ	Tb	−0.1000	0.0130	0.0260	0.0265
τ	D	0.01632	0.1526	0.1332	0.1235

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