Journal of
Risk and Financial Management

MDPI

Article

The Determinants of Credit Risk: An Evidence from ASEAN and GCC Islamic Banks

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Received: 24 December 2019; Accepted: 29 April 2020; Published: 6 May 2020

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Abstract: In less than a decade, the Islamic Banking (IB) industry has become an essential part of the global financial system. During the last ten years, the IB industry has witnessed changes in economic conditions and proved to be resilient during the periods of financial crisis. This paper aims to examine the important issues related to credit risk in selected Islamic banks in nine countries from Association of South East Asian Nations (ASEAN) and Gulf Cooperation Council (GCC) regions. It employs the generalized least squares panel data regression, to estimate the ratio of non-performance financing to total financing as dependent variables and bank specific variables (BSV) to determine the credit risk. It uses 12 years of unbalanced panel data from 40 different Islamic banks. The overall findings show that financing quality has a significant positive effect on credit risk. It is observed that the larger IBs owned more assets with lower credit risk compared to smaller banks. The bank's age is also an important factor influencing the credit risk level. Moreover, regulatory capital significantly reduces the credit risk exposure adherence to the minimum regulatory capital requirements which help IBs to manage their credit risk exposures. It was also observed that IBs were not affected by the global financial crisis due to less credit risk compared to the conventional banks.

Keywords: credit risk; Islamic Bank; financial crisis

JEL Classification: C1; G01; G21; G29

1. Introduction

The recent growth and development of the Islamic banking (IB) industry has prompted attention and further investigation towards the management of IBs, specifically risk management. At present, the total assets of Islamic banks have amounted to more than USD 3.2 trillion[1], holding the largest share of total Islamic finance assets and owning approximately 76%. This highlights the importance of comprehensive risk management, as the IB business model significantly differs from conventional banks (CB). Islamic Banks must also adhere to regulatory requirements, such as, *Shari'ah* compliance (see Akkizidis and Khandelwal 2008; Cihák and Hesse 2008), thus resulting in an additional element of risk when compared to conventional banks. Amongst the various types of risk faced by banks, credit risk serves as the primary threat to financial stability in the banking industry (Basel 1999). For IBs, credit risk may be more essential to handle due to the nature of the financing model (modes) itself (Cihák and Hesse 2008; İncekara and Çetinkaya 2019). It offers financing with several different models;

[1] https://www.arabianbusiness.com/islamic-finance-assets-forecast-be-worth-3-2trn-by-2020-641156.html.

for example, some financing modes are based on profit and loss sharing (PLS) while others are based on debt or trading financing modes (non-PLS). As a result, credit risk may arise in different circumstances according to various PLS vis-à-vis non-PLS financing modes. Credit risk is measured by referring to the size of non-performing loans (NPL). According to Reinhart and Rogoff (2011), the size of NPL is an important benchmark in evaluating a banking crisis. Therefore, the need to understand the determinants of credit risk is essential.

Compared to the extensive literature published on conventional banking (CB), there are limited studies regarding the credit risk in IBs[2]. The number of empirical studies on Islamic banks' credit risk are minimal and very few attempted to address the issues related to this specific kind of risk[3] (Al-Tamimi and Al-Mazrooei 2007; Hassan 2009). Researchers have addressed various risk management issues including credit risk without due regards being given to the study of credit risk in member countries of the Association of South East Asian Nations (ASEAN) and the Gulf Cooperation Council (GCC) which contribute more than 50% of IBs size.

This paper attempts to fill this gap in the literature. It investigates the key determinants of credit risk in IBs in the ASEAN and the GCC regions, as these two regions are at the forefront of global Islamic banking industry. IB in the GCC started its journey in 1975 with the establishment of the Islamic Development Bank (IDB). Since then, other gulf countries have gradually implemented Islamic banking in collaboration with the conventional system with a similar trend being seen in ASEAN countries. Acknowledging the difference in market structure and regulations among ASEAN and GCC countries, it is appreciated to examine the determinants of credit risk using seven (financing, financing quality, capital buffer, capital ratio, net interest margin, management efficiency and age) bank specific variables (BSV) in selected IBs. To this end, this paper seeks to answer the following four research questions (RQ) related to the credit risk associated with BSV in IBs.

RQ1. Are the BSVs used as exploratory variables, the key determinant of credit risk?
RQ2. Is there a significant different between IBs credit risk level of the two regions; ASEAN and GCC?
RQ3. Does the age of the banks also influence the credit risk?
RQ4. What are the effects of the global financial crisis (GFC) on credit risk across various countries?

This paper employs an unbalanced panel data regression model to examine the determinants of credit risk in Islamic banks across GCC and ASEAN regions. It estimates the fixed effects (FE) and random effects (RE) using generalized least square (GLS) estimation method. It computes the ratio of non-performance financing (NPF) to total financing as dependent variables and bank specific variables to determine the credit risk determinants.

This paper contributes to the Islamic banking and finance industry literature in three ways. Firstly, it examines the determinants of credit risk across different regions rather than focusing on a single country or region. Bank level data was used rather than an aggregate data, capturing different characteristics amongst banks (IBs) in both regions. It also addresses the research question of whether there are significant differences in credit risk between the two regions. This is important as it can be utilized by policy makers in the process of structuring a better credit risk management framework.

Secondly, it focuses on the impact of age on the credit risk level. There is a notable difference in years of establishment between ASEAN and GCC, and IB poses a question on the significance of this factor in influencing credit risk levels. With different levels of experience in the industry, we may or may not see a relative deviation in credit risk. Finally, this study examines whether the global financial crisis (GFC) had a significant impact on the credit risk level of Islamic banks in ASEAN and GCC regions. This will help to identify whether the two regions were impacted differently. The motivation to examine the GFC impact is to determine if the IB structure reacts differently to the crisis as compared

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[2] Most studies include the Islamic window which is embedded in conventional banking institutions.
[3] An extensive recent literature review is done by Al Rahahleh et al. (2019) on the developments in risk management in Islamic Finance.

to the conventional system. This is an important and timely research question in the presence of COVID-19 financial crises (see McKibbin and Fernando 2020).

The rest of this paper is organized as follows. In the preceding sections, the research question is introduced and the brief literature review relevant to the study is given by incorporating important existing research in this area. Section 3 describes the selected data used, sample selection procedure of unbalanced data over time and countries and the research methodology adopted to conduct empirical research using complex unbalanced clustered panel data. Section 4 examines the results on credit risk in the IB industry along with the effect of GFC which enable to make analogue discussion about the COVID-19 effects on financial portfolios. The final section summarizes the main findings and elaborate on limitations of the study.

2. Literature Review

Understanding financial stability in the banking sector, particularly in managing credit risk, is increasingly important especially when industry faces extreme events; like GFC and/or COVID 19 types of uncertain events. Research on credit risk management have attracted the attention of many academician and financiers, from developed and developing countries. Moreover, Investigating the factors that drive the credit risk in the banking sector is vital to the bank's management, finance industry and their regulatory bodies. Most of the studies about the credit risk of commercial banks focus on developed countries, ignoring due research on banks from developing countries. For example, (Bonfim 2009; İncekara and Çetinkaya 2019; Louzis et al. 2012) are among others who worked on developed country's data. They investigated various issues of credit risk, such as the effect of macroeconomic and banks specific variables on credit risk, the relationship of credit risk and liquidity risk, and gave evidence from the latest financial crisis like AFC and GFC.

Some prior studies have measured credit risk by using the ratio of non-performing loans (NPL). Among these are the work of (Alandejani and Asutay 2017; Bonfim 2009; Misman et al. 2015; Rahman and Shahimi 2010). Moreover, recent literature reviews were completed by Bhatti et al. (2019) and Al Rahahleh et al. (2019). In banking studies, the loan is classified as NPL when the payment of interest and principal are overdue by 90 days or more. Higher NPL causes the banks to experience lower profit margins and if the problem increases, it can lead to a crisis. Potential influences on the NPL include the types of borrower, bank management and adverse changes in the economic situation. The importance of efficient credit risk management invites many parties especially researchers, regulators and banks' management to investigate the determinants of credit risk in banking. This will help them to understand and propose a comprehensive credit risk management framework. The level of credit risk is found to be a significant influence in the performance of banks (Ahmadyan 2018). Therefore, examining the key drivers of credit risk is important for the banks to manage its function in an efficient way.

This study links the two main areas of credit risk research. Firstly, it aims to discuss the significance of bank specific variables (BSV) or microeconomics and their impact on credit risk level for the selected data in our empirical study. Secondly, it intends to examine the effect of the changes in macroeconomic variables on credit risk. A dummy variable to represent GFC was used to examine the impact of financial crisis on credit risk management.

Bank-Specific Variables and Credit Risk

Current literature related to credit risk management suggests two important determinants of credit risk, namely systematic factors and unsystematic factors. Systematic risk refers to risk that cannot be eliminated and controlled by the bank itself. For example, (i) macroeconomic factors like inflation, changes in interest rate and unemployment rate; (ii) changes in economic cycle like a recession and financial crisis; (iii) political factors. All these factors will influence the capacity of the borrower to repay back the loans and a failure to do so will classify the loan as an NPL. Despite the importance of systematic risk in influencing the credit risk, the unsystematic risk should not be ignored. Louzis et al. (2012) claim in their study that a distinctive structure of banking industry across different countries and the individual bank management will vary the impact of unsystematic risk on credit risk level.

Moreover, the literature revealed that unsystematic risk or bank specific variables (BSV) are hypothesized to have either a positive or negative relationship with the level of NPL. The important BSV discussed in previous studies included financing variables, capital, cost of fund, management quality, and efficiency. Some of these studies examine the link between BSV and credit risk by focusing on the efficiency and problem loans matter. For example an early study by Berger and DeYoung (1997) focuses on bad management, skimming and moral hazard issues. These issues are related to the relationship between loan quality, cost efficiency, bank capital and credit risk. Evidence from the US banking sector (for example, Angbazo 1997; Berger and DeYoung 1997; Cebenoyan and Strahan 2004; Gallo et al. 1996) indicates that BSV have a significant effect on credit risk of commercial banks. Moreover, Cebenoyan and Strahan (2004) in their study on US commercial banks from 1987 to 1994 find that the type of loan has a positive and significant influence on credit risk. Another study using a dataset from developing countries conducted by Eng and Nabar (2007) also concludes that a few BSV did significantly influence bank risk using data from 1993 to 2000.

Furthermore, previous studies have also discussed the effect of lending or financing variables on various risks faced by commercial and/or Islamic banks. To empirically test this, the authors used two financing variables against credit risk, namely financing quality and financing expansion. Financing quality is measured using a ratio of loan loss provision[4] to total assets. Banks make a provision for losses in order to adjust loan loss reserves to reflect expected future losses. This provision does not involve direct cash outflows. It is instead decreased as reported net income, retained earnings and shareholders' equity. In the case of IBs, this provision is made in order to anticipate future losses for financing and investment accounts such as Mudharabah, Murabahah and Musharakah (see Zoubi and Al-Khazali 2007, for sukuk see Azmat et al. 2020; Khawaja et al. 2020). Previous studies found that financing quality has a positive-significant relationship with credit risk (Ahmed et al. 1999; Eng and Nabar 2007). When banks make a higher provision for loss, the loans or financing is argued to be of low quality or carry a higher risk of default, leading to an increase in credit risk exposure.

The second variable related to credit risk is the proportion of loans or financing to the total bank assets. Financing item is generally perceived to be a higher risk compared to other asset items. Holding a larger amount of financing (loan) relative to total assets, exposes banks to high default risk and less liquidity compared to other asset components, in addition to creating a credit and liquidity risk conflict (Hassan et al. 2018; Imbierowicz and Rauch 2014; Zarei et al. 2019). However, as loans or financing are major services provided by banks, this problem cannot be avoided. Therefore, a higher proportion of total financing to total assets will potentially increase NPL and create a credit risk for banks. Love and Turk Ariss (2014) claim that a rapid growth in financing will give an adverse impact on credit risk. A positive coefficient is commonly assumed between financing expansion and credit risk. However, a negative coefficient might also appear when the banks have better credit risk management strategies. Gallo et al. (1996) and Madura et al. (1994) document mixed results on composition relative to total assets. Madura et al. (1994) demonstrate a negative relationship between the proportion of loans to total assets and bank risk but when considering only on real estate loans, a positive significant relationship exists.

Recently, Louhichi and Boujelbene (2016) claimed that capital plays an important role in the banks' management of credit risk. Banks' capital consists of ordinary shares and retained earnings. Traditionally, banks hold larger amounts of capital to reduce the risk of insolvency and to buffer losses from unexpected circumstances. Cebenoyan and Strahan (2004) noted in their study that banks can reduce the possibility of failure by holding appropriate amounts of capital buffer, liquid assets and employing an active risk management system. Banks with active risk management strategies can retain less capital and invest in

[4] IFRS-9 standard on expected credit losses (ECL) in three different stages, Stage 1, Stage 2, and Stage 3, which is different from the existing loan loss provisions and has been in the industry and IBs are yet to implement that standards and the implications will be different which are not captured in this study.

more risky assets and illiquid loans (see Froot et al. 1993). In bank management, the amount of capital required to be maintained by the banks is monitored by bank regulators. In practice, bank regulators require banks to hold minimum amounts of capital to promote safety and soundness. The Basel committee on banking supervision (BCBS) introduced in June 2006 represents a capital adequacy requirement under Basel II with the intention of controlling or reducing risk-taking by the banks.

The BCBS provides a guideline for all commercial banks regarding minimum capital requirements. This regulatory capital consists of Tier I and Tier II capital. All commercial banks must maintain a minimum total capital of 8% from risk weighted assets (RWAs) of the bank (Basel 2001). Under this arrangement, Tier I percent must exceed at least 4% of the risk weighted assets and 3% of total assets. In Tier II, the amount must not exceed the amount of Tier I. This system therefore requires at least 50% of the amount of total capital to be supplied by TIER 1 capital. In November 2010, the capital ratio (CR) definition was changed based on the Basel-III Capital Framework. Under Basel-III, the calculation of CR is stricter in regard to the definition of capital (Hannoun 2010)[5].

Empirical studies provide mixed evidence on the relationship between regulatory capital ratio and credit risk. Berger and DeYoung (1997) suggest that CR has a negative relationship with credit risk whereas Ahmad and Ariff (2007) found a positive relationship between regulatory capital and credit risk in Japan, Malaysia and Mexico. Godlewski (2005) discussed CR in a different perspective and noted that banks with different levels of regulatory capitals react differently to credit risk. Banks with low regulatory capital will have a significant negative relationship with credit risk. This explains why undercapitalized banks may not be able to deal with risky loans and in turn will face the problem of higher credit risk.

The other important variable is capital buffer. In previous studies, capital buffer is a proxy for the ratio of total equity to total assets ratio. Capital buffer is expected to have a negative relationship with credit risk level. Cebenoyan and Strahan (2004) found a negative relationship between capital buffer and credit risk in United States (US) commercial banks for 1988 to 1993. Berger and DeYoung (1997) documented mixed results regarding the relationship between CR and non-performance loans. They suggested that banks with a low CR will have a negative relationship between the capital and credit risk. This situation may happen due to moral hazard issues. With regard to Islamic banks, Abedifar et al. (2013) in their study reported a negative relationship between capital asset ratio and credit risk. However, they failed to prove any significant relationship between the understudy variables. Rahman and Shahimi (2010) used data from the Malaysian Islamic banks and windows[6] and observed a significant negative relationship between capital buffer and credit risk. Most Islamic banks in Malaysia are new as they began their operation between 2005 and 2010 and consequently IBs may only have small amounts of capital as compared to CBs.

The ability to generate income based on given assets is one of the important factors when measuring efficiency. Net interest margin (NIM)[7] is one of the indicators that can be used to proxy efficiency in credit risk analysis for CBs. NIM is defined as the spread between interest income and expenses over the total assets invested by the bank. Angbazo (1997) explained that when a bank's NIM decreases, the bank may change its credit risk policy by accepting more risky loans and indirectly increase credit risk. It means that banks with a smaller NIM tend to have higher credit risk levels. This may be due to a bank's decision to increase the margin and practice a more liberal credit policy. In a study by Maudos and De Guevara (2004), NIM had a positive significant effect on credit risk. As IBs are free from interest provisions, the effect of NIM on credit risk may be different. Rahman and Shahimi (2010) used interest expenses instead of the NIM and found a positive and significant relationship between interest expenses and credit risk.

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5 Under Basel III, the minimum capital adequacy ratio that banks must maintain is 8%. The capital adequacy ratio measures a bank's capital in relation to its risk-weighted assets.

6 The Bank Negara Malaysia introduced the IB system when it launched the Skim Perbankan Tanpa Faedah (Interest–free banking Scheme) in 1993. Since then, commercial banks have offered IB products through a specialized service called the 'Islamic window'.

7 In IB it's called Net Profit Margin (NPM), hereafter we assume that NIM for CBs and NPM for IBs.

Louzis et al. (2012) suggested that the too-big-to-fail theory is important in determining credit risk. They claim that banks which believe in such a theory have a higher propensity to expose themselves to excessive risk-taking activities, for example, by giving loans to lower quality of borrowers and having a high leverage ratio. Theoretically, larger banks can absorb more risk-taking activities compared to smaller banks. Saunders et al. (1990) concluded that size and risk should be negatively related, as larger banks have more diversification in assets to mitigate risk. A similar result was observed by How et al. (2005) in their study of analysing Islamic financing and risk in Malaysia. They concluded that the larger banks have significantly less credit risk compared to smaller banks. Other studies which support this finding of similar bank's size and credit risk relationship are Rahman and Shahimi (2010); Ahmad and Ahmad (2004); Konishi and Yasuda (2004); Gulati et al. (2019) among others. Gulati et al.'s (2019) paper empirically showed that the size of banks in India influence their credit risk. The authors indicated that larger banks in the industry are exposed to greater credit risk. Additional to large volumes of financing, these banks also provide financing to various types of businesses, resulting in an increased exposure to individual business risks.

Moreover, size also helps banks contain adverse effects of a financial crisis. Abdelrahim (2013) found that the size of Saudi banks during the GFC had a significant negative relationship with their credit risk. This implies that the larger the bank, the lower the credit risk. Beck et al. (2013) also reported a similar finding where size was significantly and negatively related to the NPL of CBs and Islamic banks during the GFC.

3. Data and Methodology

This section explains the details of the data selection from ASEAN and GCC regions, research methodology employed, importance of the variables used to interpret the data set and an appropriate model used to conduct empirical study. Let us begin with the data selection.

3.1. Data

The dataset in this empirical study consists of nine panels; four from ASEAN region and five from GCC countries, for a 12-year time period between 2000 to 2011. These sample countries are selected because they practice a dual banking system; conventional and Islamic banking. In total there are 72 IBs from nine selected countries of both regions. We face two complication in choosing unbalanced panel data model. Firstly, some IBs started operation in different years rather than the sampled period (i.e., 2000 to 2011) which resulted unequal operational periods. Secondly, some of the banks, 'bank characteristics' such as NPL, CR and loan loss provision (LLP) were missing. To overcome on this problem, we used unbalanced time and unbalanced panels in our model. So, the total number of observations used in the regression analysis is turned out to be 180, representing only 40 full-fledge Islamic banks out of 72 banks. The sample selection details of 180 observation with sampling distribution of time periods and the number of selected banks from 9 countries are given in Table A3 in Appendix B. All the data has been converted into the US dollar (US$) to maintain consistency for comparison purposes. The data were collected from the BankScope[8] database and other information sourced from each bank's website and respective country's Central Bank reports and website. Table 1 reports the details sample frame of the number of banks selected for specific country and regions.

In our empirical study, the credit risk is measured as the ratio of non-performance financing (loans) to the total financing outstanding. The credit risk is modelled at the microeconomic or BSV level from the consolidated financial statement of each selected bank. Several BSV are considered and are categorize into few groups to represent the financing quality, moral hazard, management efficiency

8 The total number of Islamic banks operating in each country is listed in Appendix A and the sampling ddistribution of the number of oobservations by years and ccountry are given in Tables A2 and A3 in Appendix B.
9 Just recently, this bank is closed in 2019 by the MAS.

and capital. We first used the proportion of loan loss provision to measure the quality of the loan. With regards to banks, increases in provision for loss justify the deterioration of the quality of loan in their banking book. This may lead to the higher NPL value resulting higher credit risk level. In early section, we noted some studies have confirmed that capital plays important role in managing credit risk in banks. Two variables are used to examine the effect of capital on credit risk. First is 'total equity to total assets' and the second is 'total capital to total risk weighted assets. We expected these two variables may show a positive or a negative effect on credit risk, as different level of regulatory capital reacts differently to the underlying credit risk.

The 'net interest margin' and 'earnings ratio' are another important aspect which need to be considered in examining the determinants of credit risk. Both variables will measure the efficiency of the bank in their daily operation. The inclusion of these variables is to see 'how bank decision on generating income will affect credit risk?'.

Table 1. Number of Sampled Islamic Banks (IBs) in Association of South East Asian Nations (ASEAN) and Gulf Cooperation Council (GCC).

No.	Country	Group	No. of IBs
1	Brunei	ASEAN	1
2	Indonesia	ASEAN	1
3	Malaysia	ASEAN	17
4	Singapore[9]	ASEAN	1
5	Bahrain	GCC	5
6	Kuwait	GCC	3
7	Qatar	GCC	3
8	UAE	GCC	6
9	Saudi Arabia	GCC	3
	Total		40

3.2. Research Methodology

This paper employs the unbalanced panel data technique to examine the determinants of credit risk of IBs from nine countries of ASEAN and the GCC regions. Unbalanced panel data is a technique that pools the unequal sample observations in the cross-section over a certain period. In panel data the observations are indexed through ($N \times T$) dimension. N is the number of firms (panels) and T is the dimension of a time series, such as years, months or daily data series; $t = 1, 2, \ldots, T$ of each $i = 1, 2, \ldots, N$ cross-section observations in the sample. The unbalanced panel data regression model fits this study because it can analyze changes at the bank level which cannot be done in either cross-section or time series models.

The panel data model is expressed as:

$$y_{it} = \beta_0 + \beta_{it}\, X_{it} + u_{it}\; j = 1, \ldots, m(i); t = 1, \ldots, T, i = 1, \ldots, n. \tag{1}$$

where in (1) above, the sample size consists of unbalanced panels such that $N = \sum_{i=1}^{n} m(i)$, where $m(i)$ is the number of banks in the ith country, y_{it}, u_{it} are $N \times 1$ vectors, X is $N \times k$ matrix, β is $k \times 1$ vector and β_0 is an unknown constant coefficient to be estimated, and X_{it} refers to the set of explanatory variable with $N \times k$ dimension representing selected Islamic bank.

The panel data model controls for the unobserved individual heterogeneity of firms (IBs) by incorporating firm-specific effects, which may be fixed or random. In this case u_{it} is a time-varying error term that can be written as $u_{it} = \alpha_i + v_{it}$. The α_i denotes the unobservable effects of the individual IB that are constant overtime and v_{it} is the remaining disturbance with a usual assumption that it is not correlated to the dependent variable. Therefore, the Equation (1) can be expressed as follows:

$$y_{it} = \beta_0 + \beta_{it}\, X_{it} + \alpha_i + v_{it} \tag{2}$$

The model (2) is based on the following set of assumptions:

i. α_i and v_{it} are normally distributed and they are mutually independent,
ii. $E(\alpha_i) = E(v_{ij}) = 0$, for $i = 1, \ldots, m, j = 1, 2, \ldots, m(i)$,
iii. $E(\alpha_j \alpha_{i'}) = \begin{cases} \sigma_1^2, & i = i' \\ 0, & otherwise, \end{cases}$
iv. $E(v_{ij} v_{i'j'}) = \begin{cases} \sigma_2^2, & i = i', j = j' \\ 0, & otherwise. \end{cases}$

In the scenario where the unobserved effects α_i is correlated with the explanatory variables, the fixed effects panel data is used. Alternatively, if it is proven that all explanatory variables are truly random, then random effects should be employed. Due to the nature of bank characteristics such as size of assets, risk and capital and market timing, the employment of unbalanced panel data regression assuming fixed effects is appropriated, and this choice can be tested using the Hausman test.

The estimated model of credit risk, under (1) and (2) can be expressed as:

$$\mathrm{CR}_{it} = \beta_0 + \beta_{it} X_{it} + \alpha_i + \nu_{it} \tag{3}$$

For $i = 1, \ldots, 15 = N$, $t = 1, \ldots, 12 = T$, $k = 1, \ldots, 7 =$ BSV's.

Where in (3) above, CR_{it} is the dependent variable of which represents credit risk of the ith IBs. X_{it} is a set of explanatory variables measured at time t, α_i is unobserved in all periods but constant over time i, ν_{it} is a time-varying idiosyncratic error and the total number of selected observations in our sample are 180. The detail sample selection is given in Tables A2 and A3 in Appendix B at the end of the paper.

Note that in Equation (3), CR_{it}—credit risk is proxy by the ratio of non-performance financing to the total financing outstanding. This is due to Lassoued (2018) approach to determine the key factors of credit risk in ASEAN and GCC Islamic banks. These are seven BSV's used as exploratory variables of credit risk. The BSV includes are financing, financing quality, capital buffer, capital ratio, net interest margin, management efficiency and log of total assets (SIZE). We test the following four hypotheses associated with RQ1 to RQ4, as discussed in Section 1.

Hypothesis 1 (H1). *Bank specific variables (BSV) are the key determinant of credit risk.*

Further, this current study also investigates if there is any significant different between two regions, the ASEAN and the GCC's Islamic banks in term of their credit risk level. To answer this question, a dummy variable is used to represent regional countries group. Group dummy is equal to '1' for GCC and '0' for the ASEAN. This study also controls for age factor in regard to the credit risk level. The objective is to examine if age of the banks also influences the IB's credit risk. We assume that older Islamic banks are likely to have more experience, knowledge and better operating systems for managing credit risk exposures. Thus, age is expected to have a negative relationship with the dependent variable.

Hypothesis 2 (H2). *Credit risk level is significantly different for ASEAN and GCC Islamic banks.*

Hypothesis 3 (H3). *Age factor gives impact on the credit risk.*

To capture the effects of macroeconomic factors, the models are controlled by some important dummy variables. A set of time dummy for each year of the observation is included, examining the changes in economic conditions and regulations concerning the Islamic banks over that time. The dummy for the base year (year = 2000) is excluded from the estimation model to avoid multicollinearity.[10] In addition, the analysis also investigates the effects of the global financial

[10] Berger and DeYoung (1997) suggest that the dummy for base year should be excluded from the estimation model.

crisis (GFC) on credit risk across various countries. To achieve this objective, the dummy representing crisis period is introduced and the years 2008, 2009, and 2010 are defined as the crisis period. The GFC wrecked the financial system from mid-2008 to mid-2009. However, this study also included 2010 as crisis year to capture the delayed effect across countries. Crisis is a time period dummy variable representing 1 for 2008, 2009, and 2010 and zero for non-crisis period.

Hypothesis 4 (H4). *GFC do affects the credit risk of Islamic banks.*

The details of variables and their definitions are included in Table 2 below.

Table 2. Empirical Model Variables and Definitions.

Variables	Abbreviation	Proxy Measurement
Credit Risk	CR	Non-performing financing to total financing outstanding
Financing Expansion	Fin. Exp	Total financing to total assets
Quadratic Term of Financing Expansion	Fin. Exp^2	The squared value of Fin. expansion
Financing Quality	FLP	Financing loss provisions to total assets
Capital Buffer	Cap Buffer	Total equity to total assets
Capital Ratio	CAPR	Total capital (TIER 1 and TIER 2 capital) to Total RWA
Net Interest Margin	NIM	(Profit-Cost)/Average Invested Assets
Management efficiency	MGT	Total earning assets to total assets
Total Assets	SIZE	Natural logarithm of total assets
Group dummy	GROUP	Dummy variables; '1' for Islamic banks in GCC group and '0' for Islamic banks in ASEAN group.
Crisis Period	Crisis	Dummy variable; '1' for crisis period 2008, 2009, 2010 and '0' for other years.
Age of Banks	Age	How long the banks were established

4. Empirical Results

As discussed earlier that the aim of this paper is to examine the determinants of credit risk by examining a few bank specific variables and dummy variables. So, to this end we considered ten (10) explanatory variables and three (3) dummy variables representing countries group, age and financial crisis in a similar manner as Mansor et al. (2019) did for the case of Islamic Mutual fund[11]. The results are tabulated in Table 3 which summarize the summary statistics regarding credit risk and bank-specific characteristic variables for all 40 banks. It includes 20 Islamic banks from ASEAN member countries and the other 20 Islamic banks from GCC member countries. The average value of credit risk[12] for the 12-year period is 5.2% and the median is 3.5%. This figure indicates that about half of the Islamic banks in the study have a credit risk of less than 3.5%. This situation suggests that there are a few Islamic banks with higher credit risk which is increasing the average value of credit risk. The bank level average credit risk between Islamic banks differs dramatically, ranging from a minimum of 0.04% to a maximum of 22.11%.

For the composition of the Islamic banks' total assets, on average, 56.15% of assets are contributed by financing (loan) activities. Some banks that are exposed to a higher risk profile, have found rely heavily on financing activities with a maximum amount of 88.23% of ratio between total financing to total assets. More than 50% of the sample banks are exposed to this situation as the median value of the ratio of financing to total assets is 58.06%.

Capital is very important to buffer risk exposure faced by banks. The mean of the 40 banks' capital buffer is 13.16%. This variable ranges from a minimum of negative 1.7% to a maximum of 73.17%.

[11] Just recently, Mansor et al. (2019) studied the return performance and persistence of Islamic and conventional mutual funds during financial crises periods in the presence of spurious regression and noted misleading and controversial conclusions on the performance of funds.
[12] Credit risk is the ratio of non-performance financing to total financing.

A similar situation involves the important capital indicator called CR (capital ratio). The mean value for CR is 19.53% ranging from a negative 2.47% to 92.02%. After further investigation of the dataset, the biggest negative value of capital buffer and CR derives from Malaysian Islamic banks[13].

To evaluate the efficiency of Islamic banks in generating profits, two bank-specific characteristics are included in the analysis. The NIM which is referring to margin between cost and profit of financing activities shows a mean value of 4%. The most efficient Islamic banks can generate a margin of 13.53% and the smallest ones are able to generate 0.52%. This very low margin is due to some sample banks in the dataset being very new and only have observations for one or two years[14]. The ratio of total earning assets to total assets is used to indicate management efficiency. On average, Islamic banks in ASEAN and GCC have a very high percentage of total earning assets with a mean value of 82.16%. The higher proportion of total earning assets to total assets is a good sign in that most Islamic banks have high earning assets rather than non-earning assets. Bank size is another important factor that should be included in the analysis of credit risk determinants. On average about 50% of the total assets is made up of financing amounts, and larger banks can afford higher levels of credit risk. The observations reveal that the average total assets are US$7,814,832. It is worth noting here that the size differs markedly ranging from a minimum of US$353,507 to a maximum of US$58,900,000. The huge variation may be caused by sampled banks having started at different times.

Table 3. Summary Statistics of Bank specific variables.

Variable	Mean	Median	Min	Max	Std. Dev	Kurtosis	Skewness
Cr	5.219	3.497	0.040	22.113	4.946	4.242	1.335
Fin. Exp	56.153	58.060	13.691	88.233	13.828	2.750	−0.320
FLP	1.380	0.926	−0.610	25.120	2.400	60.946	6.800
Cap. Buffer	13.161	11.296	−1.699	73.168	8.279	17.488	2.626
CAPR	19.530	17.405	−2.470	92.020	9.991	21.941	3.415
NIM	4.005	3.691	0.520	13.529	1.769	7.079	1.238
MGT	82.166	86.597	18.031	99.342	13.941	5.968	−1.598
SIZE (US$)	7,814,832	3,988,425	353,507	58,900,000	10,500,000	9.853	2.607

Notes: (i). Sample consists of 180 observations on fully-fledged Islamic banks (unbalanced data selected from 40 banks for 2000 to 2011). Sample data are not the same for all years due to banks being established in different years. The table presents the mean, median, minimum, maximum, standard deviation, kurtosis and skewness value of each variable. All the data are in ratio percentage value except for SIZE which is in thousand US$. (ii). CR is the ratio of non-performance financing to total financing; Fin. Exp, the ratio of total financing to total assets; FLP, the ratio of loan loss provision to total assets; Cap Buffer, the ratio of total equity to total assets; CAPR, the ratio of TIER 1 & TIER 2 to total risk-weighted assets; NIM, net interest margin; MGT, the ratio of total earning assets to total assets; size is the natural logarithm of borrowers' total assets.

4.1. Correlation Analysis

Pairwise correlation testing is conducted to provide statistical measures on the relationship between two variables. This test is also calculated to detect multicollinearity, which arises when two or more independent variables interact to a high degree. A high level of interaction may increase the standard errors of the estimated regression coefficients, thus resulting in bias in the empirical findings. Table 4 reports the correlation coefficient between the dependent and independent variables. The correlation coefficient indicates the magnitude and direction of the relationship. The correlation matrix reveals that there are two variables that have high inter-correlation with the correlation value above 0.5. Those variables are CAPR and Cap Buffer (0.725) and GROUP and MGT (0.526). To further test the high inter-correlations, the variance inflation test (VIF) is conducted. This test suggests that there is no serious multicollinearity occurring in the variables used.

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13 This negative value of capital buffer and capital ratio was experienced by the Bank Islam Malaysia Berhad and resulted from a huge loss incurred in 2005.

14 Refer to Table A2 in Appendix B for details on how old each bank is and Table A3 in Appendix B show number of years and number of banks included in our sample of 180 observations.

Table 4. Pairwise Correlation Matrix of Bank-specific Variables.

	CR	Fin. Exp	FLP	Cap Buffer	CAPR	NIM	MGT	SIZE	Age	GROUP	Crisis
CR	1										
Fin. Exp	−0.224 ***	1									
FLP	0.329 ***	−0.046	1								
Cap. Buffer	−0.054	0.069	0.098	1							
CAPR	−0.049	−0.195 ***	0.132 *	0.725 ***	1						
NIM	−0.110	0.151 **	0.077	0.207 ***	0.247 ***	1					
MGT	−0.014	0.388 ***	−0.086	0.193 ***	−0.208 ***	−0.105	1				
SIZE	0.043	0.219 ***	−0.083	−0.012	−0.183 **	−0.003	0.181 **	1			
Age	−0.074	0.048	−0.085	−0.165 **	−0.114	−0.067	0.046	0.095	1		
GROUP	−0.147	0.175 **	−0.171	0.481 ***	0.217 ***	0.123	0.526 ***	0.415 ***	0.000	1	
Crisis	−0.179 **	0.069	0.105	0.088	0.107	0.067	−0.247 ***	0.047	−0.009	−0.075	1

Notes: CR is the ratio of non-performance financing to total financing; Fin. Exp, the ratio of total financing to total assets; FLP, the ratio of loan loss provision to total assets; Cap Buffer, the ratio of total equity to total assets; CAPR, the ratio of TIER 1 & TIER 2 to total assets; NIM, net interest margin; MGT, the ratio of total earning assets to total assets; SIZE, the natural logarithm of total assets; GROUP is a dummy '1' for GCC countries Islamic banks, '0' otherwise; Age refers to the age of the bank at time *t*; Crisis is equal '1' for 2008,2009 & 2010, '0' for other years. Note that ***, ** and * denotes significance at 1%, 5% and 10% levels, respectively.

4.2. Estimated Results of Whole Sample Islamic Banks

Table 5 reports the regression results for credit risk model about all possible samples. We used fixed effects and the random effect models to do the estimation. The decision to use these two models is based on a few econometric tests for panel data. We conducted the BPLM test to decide which model is appropriate for the estimation model. Based on results of the BPLM test, we reject the null hypothesis, and this indicates that significant differences exist between these banks. Therefore, simple OLS regression is not suitable for analyzing the data. Further, using the random effects generalized least square (RE-GLS) model, we estimate the determinants of credit risk of all samples. However, to acknowledge the variability in Islamic banks across the sample countries, we also run a fixed effects (FE) model. In using the FE model, we can control for all time-invariant differences between the individual Islamic banks which had not been observed by the model equation. Therefore, the FE model is expected to produce unbiased estimated coefficients.

To evaluate why the results between RE-GLS and FE models conflict, the Hausman test is used. This test has rejected the null hypothesis and suggests that the difference in coefficients is systematic, and therefore the FE model should be used to estimate the determinants of credit risk for whole samples Islamic banks. Column 1 of Table 5 presents the results of the FE model. It is important to note that we were unable to use the FE model for the column 2 estimation. A group dummy is included in this particular estimation to compare credit risk determinants across the ASEAN and GCC groups. GROUP dummy takes a value of '1' for GCC countries' Islamic banks and this dummy is time-invariant. In this case the RE-GLS model is used because it can estimate time invariant variables, whereas the FE model cannot. Note that dummies were included in both models and standard errors were calculated and adjusted for 40 clusters in the bank.

Table 5. Full Sample Regression Results.

Independent Variables	Dependent Variable: Credit Risk			
	(1) FE		(2) RE-GLS	
	Coefficient	S.E.	Coefficient	S.E.
C	69.550 ***	21.775	13.385	10.006
Fin. Exp	−0.007	0.037	−0.026	0.025
FLP	0.280 *	0.159	0.469 *	0.249
Cap. Buffer	0.080	0.097	0.108	0.086
CAPR	−0.057	0.047	−0.067	0.060
NIM	0.156	0.167	0.134	0.181
MGT	−0.057	0.053	−0.075	0.046
SIZE	−3.966 **	1.645	0.200	0.701
GROUP			0.169	1.640
R-squared	0.275		0.232	
No. of observation	180		180	
Time Dummy	Yes		Yes	

Notes: (i) The table presents estimation results using fixed effects and random effect GLS. Column (1) reports estimated results for firm and time FE. Column (2) reports estimated results for RE-GLS with time dummy. All column results report robust standard errors are adjusted for heteroskedasticity and covariance using White's cross-sections. ***, ** and * denotes significance at 1%, 5% and 10% levels, respectively. The estimations are conducted on unbalanced panel data of 180 observations from 2000–2011 for 40 Islamic banks of 9 countries. (ii) Dependent variable is the ratio of non-performance financing to total financing. The independent variables are Fin. Exp, the ratio of total financing to total assets; FLP, the ratio of loan loss provision to total assets; Cap Buffer, the ratio of total equity to total assets; CAPR, the ratio of TIER 1 & TIER 2 to total assets; NIM, net interest margin; MGT, the ratio of total earning assets to total assets; SIZE, the natural logarithm of total assets; GROUP is a dummy '1' for GCC countries Islamic banks, '0' otherwise.

The results of the financing expansion appear to have a negative sign in both models in columns 1 and 2 in Tables 4 and 5. This suggests that a higher ratio of financing to total assets reduces the credit risk level of Islamic banks. The negative coefficient between credit risk and financing expansion signals that Islamic financing types offer a low risk of default since this result contradicts that generally found in the literature. However, we failed to find any significant relationship between financing expansion and credit risk in all sample Islamic banks.

The coefficients for FLP are positive and statistically significant regardless of specification and estimation method used for all sample Islamic banks in Table 5. This demonstrates that the larger the provision allocated by the banks, then the credit risk will be higher. Theoretically, banks normally make a higher provision for loss to signal that the quality of financing portfolio held by the banks will deteriorate. Banks will make a larger provision to anticipate future losses reflected by the high-risk financing portfolio and any adverse external events. The results suggest that Islamic banks make higher provision to anticipate increases in future credit risk levels. It is consistent with studies by Eng and Nabar (2007) and Ahmad and Ariff (2007). Louhichi and Boujelbene (2016) claim that high quality loan will contribute to lower credit risk. As FLP proxy by the amount of loss provision made by the banks, the positive results signaling that the bank management should have better policy in giving loan or financing to control the quality of financing.

The results concerning the two capital variables illustrate the effects of capital composition on banks' credit risk levels. Capital buffer (Cap buffer) represents the leverage effect and CAPR represents how specific regulatory standard affects banks' credit risk exposures. Cap buffer is statistically insignificant, suggesting that leverage has little influence on credit risk behavior of all sample's Islamic banks. CAPR has a negative coefficient in all estimations and does not demonstrate any significant influence on credit risk. The objective of having high leverage and CAR is to reduce the level of problem loans. The descriptive statistics of all sample Islamic banks in the ASEAN and the GCC reveal that on average Islamic banks have large amounts of regulatory capital (CAPR).[15] Even under-capitalized banks held more than the regulatory minimum requirement. Therefore, the CAPR is insignificant in driving the credit risk level of all Islamic banks.

Regarding the relationship between credit risk and earnings, NIM appears to have a positive coefficient as expected. However, both models fail to find any statistically significant relationship between NIM and credit risk. Another measure of earning (the ratio of total earning assets to total assets) is also related to banks' management efficiency. MGT also appears to have no statistically significant effect on Islamic banks' credit risk. These findings are inconsistent with previous empirical findings on banks in the US and Europe. It is argued that better management efficiency should provide banks with less credit risk. We further investigate this issue by looking at a specific country or sub-group of country in the next section.

Examining the coefficients on assets size and credit risk shows that a negative and statistical significance at 5% appears when using the fixed effects model. This suggests an inverse relationship between bank size and credit risk. Larger banks can absorb more risk-taking activities because they are more diverse. Saunders et al. (1990) contend that size and risk should be negatively related because the larger the bank, the greater its ability to diversify assets risk. This conclusion is consistent with the studies on Malaysia and Japan (How et al. 2005; Konishi and Yasuda 2004; Rahman and Shahimi 2010).

The GROUP dummy takes on a value of 1 for Islamic banks in GCC countries. As observed from Table 1 that there are total 20 Islamic banks in 5 GCC countries and 20 Islamic banks from 4 ASEAN countries. The GROUP dummy was only included in the RE effect model.[16] Using the RE estimation, the GROUP dummy has demonstrated a positive coefficient. This indicates that Islamic banks in GCC countries are exposed to slightly higher credit risk compared to the Islamic banks in the ASEAN group. However, we fail to find statistically significant relationship between GROUP dummy and credit risk.

Time fixed effects are included in both models to control for macroeconomic changes. The inclusion of time FE is necessary after considering the result of the joint test. The joint test is conducted to see if

[15] On average the Islamic banks in both ASEAN and the GCC countries have the CAPR above the standard as suggested by Basel-II. The suggested CAPR based on Basel-II is 8percent.

[16] Note that FE regression is not able to derive the coefficient for the GROUP dummy. The GROUP variable will be omitted due to collinearity of the dummy variable.

the dummies of all years are equal to zero, if they are then no time fixed effects are needed. We have rejected the null hypothesis that all years' coefficients are jointly equal to zero. Therefore, time FE is required in the estimation.

4.3. Examination of the Quadratic Specification

The model specifications include financing expansion as a possible explanatory variable. In the previous estimation we found a negative coefficient between financing expansion and credit risk. We further investigate whether there is a non-linear relationship between financing expansion and credit risk and plotted the residual of the model without square term against financing expansion. The scatter plot shows a pattern of curving, a sign that the error term does correlate with financing expansion quadratically. We also examine linear fit and quadratic fit between credit risk and financing expansion. Comparing these two graphs suggests that quadratic seems to be the better fit. Therefore, we include quadratic specification for financing expansion in the next estimated model. The following equations were used to estimate the model:

$$\begin{aligned}\mathrm{CR}_{it} = \beta_0 + \beta_1\mathrm{Fin\ Exp}_{it} + \beta_2\mathrm{Fin\ Exp^2}_{it} + \beta_3\mathrm{FLP}_{it} + \beta_4\mathrm{Cap\ Buffer}_{it} + \beta_5\mathrm{CAPR}_{it} + \beta_6\mathrm{NIM}_{it} \\ + \beta_7\mathrm{MGT}_{it} + \beta_8\mathrm{SIZE}_{it} + \alpha_{it} + \nu_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}\mathrm{CR}_{it} = \beta_0 + \beta_1\mathrm{Fin\ Exp}_{it} + \beta_2\mathrm{Fin\ Exp^2}_{\mathrm{it}} + \beta_3\mathrm{FLP}_{it} + \beta_4\mathrm{Cap\ Buffer}_{it} + \beta_5\mathrm{CAPR}_{it} + \beta_6\mathrm{NIM}_{it} \\ + \beta_7\mathrm{MGT}_{it} + \beta_8\mathrm{SIZE}_{it} + \beta_9\mathrm{GROUP}_{it} + u_{it}\end{aligned} \tag{5}$$

Table 6 reports the estimation results for the FE and RE-GLS with the quadratic term of financing expansion. The robust errors are reported. The negative coefficient of financing expansion^2 indicates that an inverted U-shaped quadratic relationship exists between financing expansion and credit risk. However, we find an insignificant relationship between financing expansion and credit risk for both models. This outcome suggests that financing activities do not statistically significantly influence the level of credit risk in all sample Islamic banks. The other explanatory variables' results are like the previous estimation results reported in Table 5. The quadratic specification for financing expansion will be used for the other estimation model in the next subsection.

Table 6. Estimated Results with Quadratic Term.

Independent Variables	Dependent Variable: Credit Risk			
	FE		RE-GLS	
	Coefficient	S.E.	Coefficient	S.E.
C	69.286 ***	23.960	11.996	10.376
Fin. Exp	0.002	0.185	0.062	0.152
Fin. Exp^2	−0.00008	0.001	−0.001	0.001
FLP	0.280 *	0.159	0.466 *	0.249
Cap. Buffer	0.079	0.100	0.096	0.092
CAPR	−0.056	0.041	−0.058	0.057
NIM	0.157	0.171	0.144	0.186
MGT	−0.057	0.055	−0.076	0.047
SIZE	−3.963 **	1.670	0.145	0.691
GROUP			0.218	1.648
R-squared	0.275		0.236	
No. of observation	180		180	
Time Dummy	Yes		Yes	

Notes: (i). The table presents estimation results using fixed effects and random effect GLS. Column (1) reports estimated results with firm and time FE. Column (2) reports estimated results for RE-GLS with time dummy. All column results robust the Standard errors are adjusted for40 clusters of banks. Note that ***, ** and * denotes significance at 1%, 5% and 10% level, respectively. The estimations are conducted on unbalanced panel data of 180 observations for 40 IB of ASEAN and GCC countries from 2000–2011. (ii). Dependent variable is the ratio of non-performance financing to total financing. The independent variables are Fin. Exp, the ratio of total financing to total assets; FLP, the ratio of loan loss provision to total assets; Cap Buffer, the ratio of total equity to total assets; CAPR, the ratio of TIER 1 & TIER 2 to total assets; NIM, net interest margin; MGT, the ratio of total earning assets to total assets; SIZE, the natural logarithm of total assets; GROUP is a dummy '1' for GCC countries IB, '0' otherwise; Age refers to the age of the bank up to the year 2011; Fin. Exp^2 is the squared value of Fin. Exp.

4.4. The Robustness Test on Age Specification

To accommodate the effect of Islamic banks longevity or age in determining level of credit risk, the age variable was added into the model estimations. The age variable is defined as the number of years since a bank's establishment. The ASEAN and GCC have a range of age value from 1 to 37 years. With different experiences in the industry, it is possible that age will influence the credit risk level of the sample Islamic banks.

Table 7 reports results from the FE and RE using GLS estimations with a robust standard error adjusted for 40 clusters banks. It is observed from the above table that age appears to have a positive relationship with credit risk. The FE estimation find an insignificant relationship between age and credit risk which is contradict with the RE-GLS model. The RE-GLS model suggests that the older the Islamic banks operating in terms of number of years, the more credit risk exposures they are likely to experience. This section also tests for a quadratic relationship between age and credit risk. However, the result failed to find significant effects when all sample Islamic banks in the dataset are included.

Table 7. Estimated Results for Model with Age Variable.

Independent Variables	Dependent Variable: Credit Risk			
	FE		RE-GLS	
	Coefficient	S.E.	Coefficient	S.E.
C	68.434 ***	22.908	23.832 **	11.509
Fin. Exp	0.002	0.185	0.064	0.161
Fin. Exp^2	−0.00008	0.001	−0.001	0.001
FLP	0.280 *	0.159	0.424 *	0.228
Cap. Buffer	0.079	0.100	0.082	0.089
CAPR	−0.056	0.041	−0.044	0.057
NIM	0.157	0.171	0.085	0.163
MGT	−0.057	0.055	−0.067	0.047
SIZE	−3.963 **	1.670	−0.800	0.722
GROUP			−0.715	1.720
Age	0.258	0.363	0.197 **	0.083
R-squared	0.274		0.259	
No. of observation	180		180	
Time Dummy	Yes		Yes	

Notes: (i). The table presents estimation results using fixed effects and random effect GLS. Column (1) reports estimated results with firm and time FE. Column (2) reports estimated results for RE-GLS with time dummy. All column results robust the Standard errors are adjusted for heteroskedasticity and covariance using White's cross-sections. ***, ** and * denotes significance at 1-percent, 5-percent and 10-percent level, respectively. The estimations are conducted on unbalanced panel data of 180 observations for 40 Islamic banks of ASEAN and GCC countries from 2000–2011. (ii). Dependent variable is the ratio of non-performance financing to total financing. The independent variables are Fin. Exp, the ratio of total financing to total assets; FLP, the ratio of loan loss provision to total assets; Cap Buffer, the ratio of total equity to total assets; CAPR, the ratio of TIER 1 & TIER 2 to total assets; NIM, net interest margin; MGT, the ratio of total earning assets to total assets; SIZE, the natural logarithm of total assets; GROUP is a dummy '1' for GCC countries Islamic banks, '0' otherwise; Age refers to the age of the bank up to the year 2011; Fin. Exp^2 is the squared value of Fin. Exp; Age is the number of years since the banks' establishment.

4.5. The Global Financial Crisis (GFC) and Credit Risk

This section investigates the effects of the GFC on credit risk of Islamic banks in the ASEAN and GCC countries. The GFC caused much harm to the banking industry. It is believed that the CBs were much more affected than the Islamic banks. Table 8 reports the regression results for the impact of the GFC on all sample Islamic banks for their credit risk in six separate estimation models. We use panel data FE and RE-GLS specifications, and the six separate estimations are calculated using different set of explanatory variables, for example, with or without group dummy and bank age. It is worth mentioning that we do not include the quadratic term of age for all sample estimations.

From Table 8; column 2, we see that the coefficients of crisis dummy are negative and only statistically significant when the group dummy is included in the estimation model. This variable is added in column 2 is RE-GLS model.

Table 8. Estimated Results for the global financial crisis (GFC).

Independent Variables	Dependent Variable: Credit Risk											
	FE(1)		RE-GLS(2)		RE-GLS(3)		FE(4)		RE-GLS(5)		RE-GLS(6)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
C	73.521 ***	21.110	14.117	9.838	16.794 *	9.956	72.496 ***	20.155	25.676 **	11.357	27.646 **	11.013
Fin. Exp	0.044	0.171	0.106	0.136	0.106	0.138	0.044	0.171	0.110	0.144	0.110	0.145
Fin Exp^2	−0.0004	0.001	−0.001	0.001	−0.001	0.001	−0.0004	0.001	−0.001	0.001	−0.001	0.001
FLP	0.283 **	0.134	0.463 **	0.221	0.464 **	0.222	0.283 **	0.134	0.424 **	0.200	0.427 **	0.202
Cap. Buffer	0.061	0.100	0.067	0.085	0.056	0.089	0.061	0.100	0.052	0.083	0.049	0.088
CAPR	−0.045	0.038	−0.046	0.054	−0.047	0.054	−0.045	0.038	−0.031	0.055	−0.035	0.054
NIM	0.189	0.196	0.157	0.197	0.134	0.207	0.189	0.196	0.094	0.172	0.092	0.182
MGT	−0.069	0.056	−0.089 *	0.047	−0.094 **	0.047	−0.069	0.056	−0.080 *	0.047	−0.087 *	0.047
SIZE	−4.279 ***	1.533	0.018	0.671	−0.129	0.647	−4.279 ***	1.533	−0.910	0.719	−1.067	0.701
Crisis	−2.214	1.470	−2.387 *	1.348	−2.172	1.462	−2.214	1.470	−2.443	1.368	−2.290	1.478
Group			−0.631	1.719					−1.619	1.780		
Age							0.310	0.330	0.199 **	0.084	0.189 **	0.090
R-squared	0.306		0.271		0.240		0.306		0.303		0.269	
No. of observation	180		180		180		180		180		180	
Time Dummy	Yes		Yes		Yes		Yes		Yes		Yes	

Notes: (i) The table presents estimation results using the RE-GLS and FE regression models. All column results the Standard errors are adjusted for heteroskedasticity and covariance using White's cross-sections. ***, ** and * denotes significance at 1-percent, 5-percent and 10-percent level, respectively. The estimations are conducted on unbalanced panel data of 180 observations for 40 Islamic banks of ASEAN and GCC countries from 2000–2011. (ii) Dependent variable is the ratio of non-performance financing to total financing. The independent variables are Fin. Exp, the ratio of total financing to total assets; FLP, the ratio of loan loss provision to total assets; Cap Buffer, the ratio of total equity to total assets; CAPR, the ratio of TIER 1 & TIER 2 to total assets; NIM, net interest margin; MGT, the ratio of total earning assets to total assets; SIZE, the natural logarithm of total assets; REGION is a dummy '1' for GCC countries' IB, '0' otherwise; Crisis is a dummy '1' for 2008,2009,2010, '0' otherwise; DBM is a dummy '1' for Malaysian Islamic banks, '0' otherwise; Fin. Exp^2 is the squared value of Fin. Exp; Age refers to the age of banks since their establishment.

The group dummy for this purpose value of one for the GCC countries' Islamic banks. Islamic banks in the GCC had lower credit risk than those of the ASEAN during the crisis period of 2008 to 2010. This situation might be due to several factors: (i) strong economic and financial state of GCC countries during the GFC, (ii) Islamic banks in the GCC did not engage in high risk financing portfolios, and (iii) different financing contracts offered by the Islamic banks in the GCC. Overall, the results suggest that Islamic banks carry lower credit risk during crisis periods. Hasan and Dridi (2010) claim that the uniqueness of the IB business model helped nullify the GFC's severe impact on profitability and credit performance.

The coefficient of financing expansion has a negative insignificant coefficient relationship with credit risk. This is consistent with results explained in the previous section. It also explains that higher growth in financing does not cause an increase in credit risk level during the crisis period. This finding agrees with the one achieved by Abedifar et al. (2013). Regarding financing quality, the FLP coefficient shows a positive and significant result regardless of specification and estimation methods.

The management efficiency of Islamic banks was not significantly affected by the GFC. MGT had a negative and statistically significant effect on credit risk when the models are controlled for the group dummy. As for the size of the banks, it only appears to have a negative and significant relationship when the model uses the FE specification. Using RE-GLS, size is insignificant in all samples.

The dummy to proxy Malaysian Islamic banks is introduced in the model estimation. The DBM dummy takes the value of one for Islamic banks. The estimation results for columns 3 and 6 report that Islamic banks' credit risk did not act differently from the other 8 countries' Islamic banks during the GFC.

The inclusion of age as the explanatory variable together with the group dummy and crisis implies that older Islamic banks were exposed to higher credit risk than newer Islamic banks during the GFC. The coefficients of age are positive and statistically significant. This suggests that the GFC did affect the older Islamic banks.

5. Conclusions and Limitation

This paper analyses the determinants of credit risk in Islamic banks within the ASEAN and GCC regions. It uses financial data—consisting of 180 observations—from five GCC countries and four ASEAN countries, during the period 2000 to 2011. Previous studies argue that BSV significantly influences the credit risk level of commercial banks. However, only a few studies have focused so far on the credit risk determinants of Islamic banks. Therefore, this paper aims to compare the credit risk profiles of these countries, the main determinants of credit risk and uses subsample periods to assess the impact of the GFC on credit risk. Statistical and econometric methods such as descriptive statistics, mean difference t-test and panel data models were applied to achieve these objectives. The study did not control for country-specific environmental issues. Instead, the analysis was conducted using firm, country-specific samples for the ASEAN and GCC countries, and macroeconomic changes that were controlled through a time and crisis dummy.

The most important evidence arising from this paper concerns the main determinants of credit risk and how changing economic conditions affect the credit risk level of Islamic banks. The FE and RE-GLS panel data analysis models were applied to the unbalanced dataset for the whole sample and subsample Islamic banks. Regarding credit risk determinants in Islamic banks in the ASEAN and GCC, it can be concluded that financing quality demonstrates a positive significant relationship with credit risk level regardless of specification models and datasets. Similar results appear for the comparison of determinants in Islamic banks in the ASEAN and GCC groups. This result implies that Islamic banks should scrutinize their financing policy to ensure they can reduce the probability of default, and therefore mitigate provisions for loss.

The descriptive statistics indicate a significant difference in sizes between countries and sub-sample groups. Using the FE model specification, asset sizes appear to have a negative and statistically significant influence on credit risk across different countries and groups. This suggests that large banks have an advantage in terms of portfolio diversification and managerial skill to generate more finance with a lower credit risk than smaller banks. A large asset size is normally associated with how long a bank has operated. Older banks tend to have larger assets compared to newer banks. Therefore, bank age was included in the estimation models.

Macroeconomic condition changes, particularly the recent GFC, provide important evidence for the study. It is suggested that Islamic banks were not greatly affected by the GFC and performed better because they had lower credit risk during 2008 to 2010. The resilience of Islamic banks during crises implies that the Islamic banking is relatively safer compared to conventional banking. These results are consistent with the findings of Bhatti and Nguyen (2012) and Al Rahahleh et al. (2019). These findings are essential for policy makers, investors and other stakeholders including banks and central banks.

The findings of this study imply several policy and regulation implications. Firstly, this study suggests that there is a significant difference in terms of asset size between banks in ASEAN and GCC regions. This indicates that the regulators might consider suggesting Islamic banks which are smaller in size to have a strategic merger in order to become stronger and larger. In addition, the regulators may also emphasize that the bank's management maintain an adequate level of capital level, which plays an important role in managing credit risk. Secondly, there is evidence that Islamic banks are more resilient during the financial crisis. Therefore, policy makers can increase awareness and promote the advantages of Islamic banking in creating a sustainable and stable financial system.

This study concentrates only on a few Islamic banks in ASEAN and GCC countries. As the sample was selective, it imposes several limitations especially in terms of the choice of econometric models and model specifications. Employing a mixed methods analysis approach to examine the main issues of this proposition has enhanced the robustness of the investigation. The study only uses bank-specific characteristics as explanatory variables for the credit risk of Islamic banks. Therefore, the effects of macroeconomic variables on credit risk were not discussed except for the impact of the GFC. In summary, it can be concluded that the finding of this study may be interpreted as a policy paper for financiers, investors and other stakeholders including banks and central banks, identifying that Islamic banks may be better risk-protected during periods of financial distress and crises.

Author Contributions: Both authors are participated in this research as F.N.M. is the main investigator and M.I.B. is her supervisor. F.N.M. initiated the original manuscript, and then the revised draft and its changes into model specification, rewriting, updating literature review was incorporated by M.I.B. All authors have read and agreed to the published final revised version of the manuscript.

Funding: This research received to external funding.

Acknowledgments: We are thankful to three anonymous reviewers for their constructive comments which have improved the paper and Taha Bhatti and Esha Zahid for valuable comments in proofreading the paper.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Total Number of Islamic banks in ASEAN and GCC Countries.

No.	Country	Group	No. of Islamic Banks
1	Brunei	ASEAN	3
2	Indonesia	ASEAN	1
3	Malaysia	ASEAN	17
4	Singapore	ASEAN	1
5	Bahrain	GCC	22
6	Kuwait	GCC	9
7	Qatar	GCC	5
8	UAE	GCC	10
9	Saudi Arabia	GCC	4
	Total		72

Source: BankScope database.

Appendix B

Table A2. Details of the Sample Islamic banks.

No.	Bank Name	Country	Date of Establishment
1	Al-Salam Bank-Bahrain B.S.C.	Bahrain	3-May-2005
2	Albaraka Banking Group B.S.C.	Bahrain	6-Jan-1998
3	Khaleeji Commercial Bank B.S.C.	Bahrain	20-Oct-2003
4	Kuwait Finance House	Bahrain	9-Dec-2001
5	Shamil Bank of Bahrain B.S.C.	Bahrain	1982
6	Bank Islam Brunei	Brunei	2005
7	Bank Syariah Mandiri	Indonesia	1999
8	Boubyan Bank KSC	Kuwait	2004
9	Kuwait Finance House	Kuwait	1977
10	Kuwait International Bank	Kuwait	Jul-2007
11	Affin Islamic Bank Berhad	Malaysia	2006
12	Al Rajhi Banking & Inv Corp (Malaysia) Berhad	Malaysia	2006
13	Alliance Islamic Bank Berhad	Malaysia	2008
14	AmIslamic Bank Berhad	Malaysia	2006
15	Asian Finance Bank Berhad	Malaysia	2005
16	Bank Islam Malaysia Berhad	Malaysia	1983
17	Bank Muamalat Malaysia Berhad	Malaysia	1999
18	CIMB Islamic Bank Berhad	Malaysia	2006
19	EONCAP Islamic Bank Berhad	Malaysia	2006
20	HSBC Amanah Malaysia Berhad	Malaysia	2004
21	Hong Leong Islamic Bank Berhad	Malaysia	2005
22	Kuwait Finance House (Malaysia) Berhad	Malaysia	2005
23	Maybank Islamic Berhad	Malaysia	2008
24	OCBC Al-Amin Bank Berhad	Malaysia	2008
25	Public Islamic Bank Berhad	Malaysia	2008
26	RHB Islamic Bank Berhad	Malaysia	2005
27	Standard Chartered Saadiq Berhad	Malaysia	2008
28	Masraf Al Rayan (Q.S.C.)	Qatar	10-Sep-2006
29	Qatar International Islamic Bank	Qatar	1-Jan-1991
30	Qatar Islamic Bank SAQ	Qatar	7-Jan-1983
31	Al Rajhi Bank	Saudi Arabia	1978
32	Alinma Bank	Saudi Arabia	28-Mar-2006
33	Bank AlBilad	Saudi Arabia	4-Nov-2004
34	The Islamic Bank of Asia	Singapore	7-May-2007
35	Abu Dhabi Islamic Bank	UAE	20-May-1997
36	Ajman Bank	UAE	Feb-2008
37	Dubai Bank	UAE	2-Aug-2002
38	Dubai Islamic Bank	UAE	1975
39	Emirates Islamic Bank	UAE	2004
40	Sharjah Islamic Bank	UAE	2002

Table A3. The sampling Distribution of Observations by years and Country.

Banks/Years	Periods	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Total
Bahrain	6							2	2	4	3	1	1	13
Kuwait	6							1	2	3	3	3	2	14
Qatar	11		1	2	2	2	2	2	2	1	3	3	3	23
Saudi Arabia	8					1	1	1	1	2	2	2	3	13
UAE	6							1	4	4	5	5	5	24
Malaysia	12	2	2	2	1	2	2	6	8	15	17	17	8	82
Brunei	4									1	1	1	1	4
Indonesia	6				1	1	1	1	1	1				6
Singapore	1											1		1
Total		2	3	4	4	6	6	14	20	31	34	33	23	180

Note: This table show that the selected banks in unbalanced time and panels from each country.

References

Abdelrahim, Khalil Elian. 2013. Effectiveness of Credit Risk Management of Saudi Banks in the Light of Global Financial Crisis: A Qualitative Study. *Asian Transaction on Basic and Applied Sciences* 3: 73–91.

Abedifar, Pejman, Philip Molyneux, and Amine Tarazi. 2013. Risk in Islamic Banking. *Review of Finance* 17: 2035–96. [CrossRef]

Ahmad, Nor Hayati, and Mohamed Ariff. 2007. Multi-Country Study of Bank Credit Risk Determinants. *The International Journal of Banking and Finance* 5: 135–52.

Ahmad, Nor Hayati, and Shahrul Nizam Ahmad. 2004. Key Factors Influencing Credit Risk of Islamic Bank: A Malaysian Case. *The Journal of Muamalat and Islamic Finance Research* 1: 65–80.

Ahmadyan, Azam. 2018. Measuring Credit Risk Management and Its Impact on Bank Performance in Iran. *Marketing and Branding Research* 5: 168–83. [CrossRef]

Ahmed, Anwer S., Carolyn Takeda, and Shawn Thomas. 1999. Bank Loan Loss Provisions: A Reexamination of Capital Management, Earning Management and Signalling Effects. *Journal of Accounting and Economics* 28: 1–25. [CrossRef]

Akkizidis, Ioannis, and Sunil Kumar Khandelwal. 2008. *Financial Risk Management for Islamic Banking and Finance*. New York: Palgrave Macmillan.

Al-Tamimi, Hussein A. Hassan, and Faris Mohammed Al-Mazrooei. 2007. Banks' Risk Management: A Comparison Study of UAE National and Forein Banks. *The Journal of Risk Finance* 8: 394–409. [CrossRef]

Alandejani, Maha, and Mehmet Asutay. 2017. Nonperforming loans in the GCC banking sectors: Does the Islamic finance matter? *Research in International Business and Finance* 42: 832–54. [CrossRef]

Al Rahahleh, Naseem, M. Ishaq Bhatti, and Faridah Najuna Misman. 2019. Developments in Risk Management in Islamic Finance: A Review. *Journal of Risk and Financial Management* 12: 37. [CrossRef]

Angbazo, Lazarus. 1997. Commercial Bank Net Interest Margins, Default Risk, Interest Rate Risk, and Off- Balance Sheet Banking. *Journal of Banking & Finance* 21: 55–87.

Azmat, Saad, ASM Sohel Azad, M. Ishaq Bhatti, and Hamza Ghaffar. 2020. Islamic Banking, Costly Religiosity and Competition. *Journal of Financial Research*. [CrossRef]

Basel. 1999. *Principles for The Management of Credit Risk*. Basel: Basel Committe on Banking Supervision.

Basel. 2001. *Basel II Consultative Document*. Basel: Basel Committee on Banking Supervision.

Beck, Thorsten, Asli Demirgüç-Kunt, and Ouarda Merrouche. 2013. Islamic vs. Conventional Banking: Business Model, Efficiency and Stability. *Journal of Banking & Finance* 37: 433–47. [CrossRef]

Berger, Allen N., and Robert DeYoung. 1997. Problem Loans and Cost Efficiency in Commercial Banks. *Journal of Banking & Finance* 21: 849–70.

Bhatti, M. Ishaq, and Cuong C. Nguyen. 2012. Diversification evidence from international equity markets using extreme values and stochastic copulas. *Journal of International Financial Markets Institutions & Money* 22: 622–46.

Bhatti, M. Ishaq, Naseem Al Rahahleh, and Hussain Mohi-ud-Din Qadri. 2019. Recent Development in Islamic Finance and financial products. In *The Growth of Islamic Finance and Banking: Innovation, Governance and Risk Mitigation*, 1st ed. Edited by Hussain Mohi-ud-Din Qadri and Ishaq Bhatti. Abingdon: Routledge, pp. 5–16.

Bonfim, Diana. 2009. Credit Risk Drivers: Evaluating the Contribution of Firm Level Information and of Macroeconomic Dynamics. *Journal of Banking & Finance* 33: 281–99.

Cebenoyan, A. Sinan, and Philip E. Strahan. 2004. Risk Management, Capital Structure and Lending at Banks. *Journal of Banking & Finance* 28: 19–43.

Cihák, Martin, and Heiko Hesse. 2008. *Islamic Banks and Financial Stability: An Empirical Analysis*. IMF Working Paper. WP 08/16. Washington, DC: International Monetary Fund, pp. 1–29.

Eng, Li Li, and Sandeep Nabar. 2007. Loan Loss Provisions by Banks in Hong Kong, Malaysia and Singapore. *Journal of International Financial Management & Accounting* 18: 18–38. [CrossRef]

Froot, Kenneth A., David S. Scharfstein, and Jeremy C. Stein. 1993. Risk Management: Coordinating Corporate Investment and Financing Policies. *The Journal of Finance* 48: 1629–58. [CrossRef]

Gallo, John G., Vincent P. Apilado, and James W. Kolari. 1996. Commercial Bank Mutual Fund Activities: Implications for Bank Risk and Profitability. *Journal of Banking & Finance* 20: 1775–91.

Godlewski, C. J. 2005. Bank Capital and Credit Risk Taking in Emerging Market Economies. *Journal of Banking Regulation* 6: 128–45. [CrossRef]

Gulati, Rachita, Anju Goswami, and Sunil Kumar. 2019. What drives credit risk in the Indian banking industry? An empirical investigation. *Economic Systems* 43: 42–62. [CrossRef]

Hannoun, Hervé. 2010. *The Basel III Capital Framework: A Decisive Breakthrough*. Basel: Bank for International Settlements.

Hasan, Maher, and Jemma Dridi. 2010. *The Effects of The Global Crisis on Islamic and Conventional Banks: A Comparative Study*. IMF Working Paper. Washington, DC: International Monetary Fund, pp. 1–46.

Hassan, Abul. 2009. Risk Management Practices of Islamic Banks of Brunei Darussalam. *The Journal of Risk Finance* 10: 23–37. [CrossRef]

Hassan, M. Kabir, Ashraf Khan, and Andrea Paltrinieri. 2018. Liquidity Risk, Credit Risk and Stability in Islamic and Conventional Banks. *Research in International Business and Finance* 48: 17–31. [CrossRef]

How, Janice C. Y., Melina Abdul Karim, and Peter Verhoeven. 2005. Islamic Financing and Bank Risks: The Case of Malaysia. *Thunderbird International Business Review* 47: 75–94. [CrossRef]

Imbierowicz, Björn, and Christian Rauch. 2014. The relationship between liquidity risk and credit risk in banks. *Journal of Banking & Finance* 40: 242–56.

İncekara, Ahmet, and Harun Çetinkaya. 2019. Credit Risk Management: A Panel Data Analysis on The Islamic Banks in Turkey. *Procedia Computer Science* 158: 947–54. [CrossRef]

Khawaja, Mohsin, M. Ishaq Bhatti, and Dawood Ashraf. 2020. Ownership and control in a double decision framework for raising capital. *Emerging Markets Review* 41: 100657. [CrossRef]

Konishi, Masaru, and Yukihiro Yasuda. 2004. Factors Affecting Bank Risk Taking: Evidence From Japan. *Journal of Banking & Finance* 28: 215–32.

Lassoued, Mongi. 2018. Comparative study on credit risk in Islamic banking institutions: The case of Malaysia. *The Quarterly Review of Economics and Finance* 70: 267–78. [CrossRef]

Louhichi, Awatef, and Younes Boujelbene. 2016. Credit risk, managerial behaviour and macroeconomic equilibrium within dual banking systems: Interest-free vs. interest-based banking industries. *Research in International Business and Finance* 38: 104–21. [CrossRef]

Louzis, Dimitrios P., Angelos T. Vouldis, and Vasilios L. Metaxas. 2012. Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance* 36: 1012–27.

Love, Inessa, and Rima Turk Ariss. 2014. Macro-financial linkages in Egypt: A panel analysis of economic shocks and loan portfolio quality. *Journal of International Financial Markets, Institutions and Money* 28: 158–81. [CrossRef]

Madura, Jeff, Anna D. Martin, and Don A. Taylor. 1994. Determinants of Implied Risk at Depository Institutions. *Applied Financial Economics* 4: 363–70. [CrossRef]

Mansor, Fadillah, Naseem Al Rahahleh, and M. Ishaq Bhatti. 2019. New Evidence on Fund Performance in Extreme Events. *International Journal of Managerial Finance* 15: 511–32. [CrossRef]

Maudos, Joaquín, and Juan Fernandez De Guevara. 2004. Factors Explaining the Interest Margin in the Banking Sectors of the European Union. *Journal of Banking and Finance* 28: 2259–81. [CrossRef]

McKibbin, Warwick J., and Roshen Fernando. 2020. *The Global Macroeconomic Impacts of COVID-19: Seven Scenarios*. CAMA Working Paper. Canberra: The Centre for Applied Macroeconomic Analysis (CAMA).

Misman, Faridah Najuna, Ishaq Bhatti, Weifang Lou, Syamsyul Samsudin, and Nor Hadaliza Abd Rahman. 2015. Islamic Banks Credit Risk: A Panel study. *Procedia Economics and Financec* 31: 75–82. [CrossRef]

Rahman, Aisyah Abdul, and Shahida Shahimi. 2010. Credit Risk and Financing Structure of Malaysian Islamic Banks. *Journal of Economic Cooperation and Development* 31: 83–105.

Reinhart, Carmen M, and Kenneth S Rogoff. 2011. From financial crash to debt crisis. *American Economic Review* 101: 1676–706. [CrossRef]

Saunders, Anthony, Elizabeth Strock, and Nickolaos G. Travlos. 1990. Ownership Structure, Deregulation, and Bank Risk Taking. *Journal of Finance* 45: 643–54. [CrossRef]

Zoubi, Taisier A., and Osamah Al-Khazali. 2007. Empirical Testing of the Loss Provisions of Banks in the GCC Region. *Managerial Finance* 33: 200–511. [CrossRef]

Zarei, Alireza, Mohamed Ariff, and M. Ishaq Bhatti. 2019. The impact of exchange rates on stock market returns: New evidence from seven free-floating currencies. *The European Journal of Finance* 25: 1277–88. [CrossRef]