Default and Recovery Rates on Islamic Banks Financing: Implications for the New Capital Adequacy Standard

Abdul Ghafar Ismail and *Ahmad Azam Sulaiman*

Abstract: This paper analyses the association between aggregate default and recovery rates on bank financing, and seeks empirically to explain this relationship. We examine recovery rates on Islamic banks, over the period 1994-2004. Our results show a significant increase in both expected and unexpected losses when recovery rates are stochastic and negatively correlated with default probabilities. We attempt to explain recovery rates by specifying a statistical least squares regression model applied to 15 Islamic banks in Malaysia. The central thesis is that aggregate recovery rates are basically a function of supply and demand for the securities. Our econometric univariate and multivariate panel models explain a significant portion of the variance in banks recovery rates aggregated across all seniority and collateral levels. We analyse how the link between default probability and recovery risk would affect the procyclicality effects of the New Basel Capital Accord. We see that, if banks use their own estimates of loss given default (as in the 'advanced' internal rating based approach), an increase in the sensitivity of banks' loss given default due to the variation in default probability over economic cycles is likely to follow.

I. Introduction

The new Basel Capital Adequacy Standard (Basel II) introduces a standardized and also an internal ratings-based (*IRB*) approach for assessing credit risk.

Abdul Ghafar Ismail, Professor of Banking and Financial Economics, Universiti Kebangsaan, Bangi, Selangor, Malaysia.

Ahmad Azam Sulaiman, Post-graduate Student, Universiti Kebangsaan, Bangi, Selangor, Malaysia.

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This rule-based approach is designed to address some of the most blatant shortcomings of the current Accord. Compared to the present Accord, the *IRB* approach is fundamentally different in concept, design, and implementation and is intended to produce a capital requirement more closely linked to each bank's actual credit risks – a lower-quality portfolio will face a higher capital charge, and a higher-quality portfolio a lower capital charge. Such an approach is essential to creating the correct incentives for both banks and supervisors.

The *IRB* at heart provides a continuous mapping from the basic set of four input parameters (probability of default *(PD)*, loss given default *(LGD)*, exposure at default *(EAD)* and Maturity *(M)*, plus some other observables such as borrower type, to a minimum capital requirement. A critical issue with respect to the *IRB* approach is the reliability of the credit risk parameters supplied by banks, upon which the capital charges are based. This mapping is based on the same analytical framework as most credit portfolio models.

However, in the credit risk literature significant attention has been devoted only to the estimation of the first parameter; far less attention has been given to the estimation of recovery rate (*RR*) and especially to the relationship between *RR* and *PD*. This is mainly a consequence of two related factors. First, credit pricing models and risk management applications tend to focus on the systematic risk components of credit risk, as these are the only ones that attract risk-premia. Second, credit risk models traditionally assumed *RR* to be dependent on individual features (*e.g.* collateral or seniority) that do not respond to systematic factors, and to be independent of *PD*. The aim of this study therefore is to produce empirical evidence on the link between probability of default and recovery rate. A better understanding of how the two variables are related, and how they vary across banks and over time, may help us to understand the need for and effect of provisioning regulation.

The remainder of this paper is divided into six sections. In the second section, we review the modelling of credit risk. In the third section, we build the univariate and multivariate model aimed at providing the basis for an empirical estimation. The data sources and descriptions are given in the fourth section. The fifth section presents the results, and the final section summarizes the conclusions.

II. Literature Review

The literature on credit risk modelling is extensive and starts with the research by Altman (1971). Following Altman, a number of authors have estimated various types of default risk models on cross-sectional data sets. See, for example: Altman (1973 and 1984), Frydman *et al.* (1985), Li (1999), and Shumway (2001). These papers all have a single focus on the analysis of (credit) risk and the prediction of bankruptcy at the firm level.

In the last decade, a whole range of modelling techniques has been developed to analyse portfolio credit risk. Broadly considered, there are three groups of portfolio credit risk models. The first group is 'structural' and based on Merton's (1974) model of firm capital structure in which individual firms default when their assets' value falls below the value of their (non-equity) liabilities. Examples of such a microeconomic causal model are *CreditMetrics* and *KMV's PortfolioManager*. The second group consists of econometric factor risk models, like McKinsey's *CreditPortfolioView*. McKinsey's model is basically a logistic model where default risk in 'homogeneous' subgroups is determined by a macroeconomic index and a number of idiosyncratic factors. These two model types apply basically similar Monte Carlo simulations to calculate portfolio risk, as both are 'bottom-up' models that compute default rates at either the individual firm level or at sub-portfolio level. Both thus require a similar kind of aggregation. The third group contains 'top-down' actuarial models, like Credit Suisse's CreditRisk+, that make no assumptions with regard to causality.

Koyluoglu and Hickman (1998) provide an elaborate description of the above-mentioned types of portfolio credit risk models. They note that all model types, despite their differences, are built on three more or less general components to calculate portfolio loss distributions. First, they contain some process that generates conditional default rates for each borrower in each state of nature and a measure of co-variation between borrowers in different states of nature. Second, their set-up allows for the calculation of conditional default rate distributions for sets of homogeneous sub-portfolios (*e.g.*, rating classes) as if individual borrower defaults are independent, since all joint behaviour is accounted for in generating conditional default rates. Third, unconditional portfolio default distributions are obtained by aggregating homogeneous sub-portfolios' conditional distributions in each state of nature; then conditional distributions are averaged using the probability of a state of nature as the weighting factor.

Gordy (2000) confirms the general insights of Koyluoglu and Hickman in a thorough comparison of two influential benchmarks for credit risk models, *CreditMetrics* and *CreditRisk+*. He concludes that they have very similar mathematical structures and that the prime sources of discrepancies in predictions are differences in distributional assumptions and functional forms. Gordy's findings suggest some general insights into the workings of these credit risk models. Among other things, he concludes that the models are highly sensitive to both the average default correlations in the model – that in turn determine default rate volatility – and the shape of the implied distribution of default probabilities. Since the work on the reform of the Basel Accord began, a number of efforts have been made to apply credit risk models to the ultimate goal of calculating capital requirements under a variety of alternative systems. Estrella (2001), for example, contains a theoretical model of optimal bank capital. He finds that a regulatory minimum capital requirement based on value at risk (*VaR*) is likely to be procyclical and suggests some ways to remedy this procyclicality.

Gordy (2000) examines the relation between portfolio models of credit *VaR* and ratings-based 'bucket' models. He concludes that the latter can be reconciled with the general class of credit *VaR* models and that even portfolio credit VaR models imply marginal capital charges that depend only on an asset's own characteristics under some very general assumptions. Carey (1998) contains a new non-parametric methodology to estimate loss rates in the bad tail of the credit loss distribution. Calem and LaCour-Little (2001) estimate a survival time model for mortgage loan data and apply Carey's method to simulate *PD* distributions. They find that capital charges vary substantially with loan or borrower characteristics. They also conclude that capital charges are generally below the current standard and thereby provide some empirical support for the occurrence of securitization.

Hamerle *et al.* (2002) follow another approach and model the (unconditional) *PD*s by means of a non-linear random effects probit and logit model. Carey and Hrycay (2001) empirically examine the properties of the most commonly used methods to estimate average *PD*s by rating class. They find that the mapping and scoring-model methods are potentially subject to bias, instability and gaming. As a result of the interest that the reform of the Basel rules has generated, a number of authors have also examined the design of banks' internal ratings systems and the consequences that their design have for the functioning of Basel II. Treacy and Carey (1998), for example, describe the ratings systems of large US banks and collect some statistics on the distribution of loans over rating classes and the related loss rates and risk profiles. Carey (2000) finds, based on simulated data, that the success of the *IRB* approach will depend on the extent to which it will take into account differences in assets and portfolio properties, such as granularity, risk properties and remaining maturities.

III. The Model

During the last three years, new approaches explicitly modelling and empirically investigating the relationship between *PD* and *RR* have been developed. These models include Frye (2000a and 2000b), Jarrow (2001), Hu and Perraudin (2002), Jokivuolle and Peura (2003), Carey and Gordy (2003), Bakshi *et al.* (2001), Altman *et al.* (2001 and 2005), and Acharya *et al.* (2003). The model proposed by Frye (2000a and 2000b) draws on the conditional approach suggested by Finger (1999) and Gordy (2000). In these models, defaults are driven by a single systematic factor – the state of the economy – rather than by a multitude of correlation parameters. These models are based on the assumption that the same economic conditions that cause defaults to rise might cause recoveries to decline, *i.e.* that the distribution of recovery is different in high-default periods from low-default ones. In Frye's model, both *PD* and *RR* depend on the state of the systematic factor. The correlation between these two variables can, therefore, be derived from the following univariate equation:

$$RR = f(PD) \tag{1}$$

The intuition behind Frye's theoretical model is relatively simple, namely that if a borrower defaults on a loan, a bank's recovery will likely depend on the value of the loan collateral. The value of the collateral, like the value of other assets, depends on economic conditions. If the economy experiences a recession, recoveries may decrease just as default rates tend to increase. Therefore, equation (1) can be written as the following multivariate equation:

$$RR = f(PD, M3, ROA, GDP) \tag{2}$$

Equations (1) and (2) give rise to a negative correlation between default rates and recoveries. Loans have a positive influence on profitability (*ROA*), because as a bank's core business, they are a major generator of interest income. While both models originally developed by Frye (2000a) implied recovery be taken from an equation that determines collateral, Frye (2000b) modelled recovery directly. This allowed him to test his model empirically using data on defaults and recoveries from US corporate bond data. More precisely, data from *Moody's Default Risk Service* database for the 1982–1997 periods were used for the empirical analysis. Results show a strong negative correlation between default rates and recoveries for corporate bonds. Frye's (2000b and 2000c) empirical analysis allows him to conclude that in a severe economic downturn bond recoveries might decline 20–25 percentage points from their normal-year average. Loan recoveries may decline by a similar amount, but from a higher level.

While in the original Merton (1974) framework an inverse relationship between *PD* and *RR* exists, the credit risk models developed during the 1990s treat these two variables as independent. The currently available and most used credit pricing and credit *VaR* models are indeed based on this independence assumption and treat *RR* either as a constant parameter or as a stochastic variable independent from *PD*. In the latter case, *RR* volatility is assumed to represent an idiosyncratic risk, which can be eliminated through adequate portfolio diversification. This assumption strongly contrasts with the growing empirical evidence – showing a negative correlation between default and recovery rates –that has been reported in the previous section of this paper and in other empirical studies (Frye, 2000b and 2000c; Altman 2001; Carey and Gordy, 2003; Hamilton *et al.*, 2001; Altman *et al.*, 2001 and 2005). This evidence indicates that recovery risk is a systematic risk component. As such, it should attract risk premia and should be adequately considered in credit risk management applications. The potential consequences – in terms of credit risk underestimation – of the *PD* and *RR* independence assumption when these two variables are instead correlated are shown by Altman *et al.* (2005).

Finally, we consider the *RR/PD* link and procyclicality effects. Procyclicality involves the sensitivity of *RR* to economic and financial market cycles. Since ratings and default rates respond to the cycle, the new internal ratings-based (*IRB*) approach proposed by the Basel Committee risks increasing capital charges, and limiting credit supply, when the economy is slowing (the reverse being true when the economy is growing at a fast rate). As we saw in the previous paragraph, the original inverse relationship between *PD* and *RR* hypothesized has been replaced by one that treats these two variables as independent. The currently available and most used credit pricing and credit *VaR* models are indeed based on this independence assumption and treat *RR* either as a constant parameter or as a stochastic variable independent from *PD*. In the latter case, *RR* volatility is assumed to represent an idiosyncratic risk which can be eliminated through adequate portfolio diversification.

IV. Data Sources and Descriptions

In order to estimate equations (1) and (2), we use an unbalanced bank-level panel data set for 15 Malaysian Islamic banks (comprising two full-fledged

Islamic banks and thirteen Islamic windows). The data are annual and span the period from 1994 to 2004. In this manner a full cycle of the Malaysia economy is included, a point of particular importance given that the aim of this paper is, as mentioned, to analyse whether there is a relationship between the business cycle and recovery rate. Recovery rate is defined as the total recovery over lagged values of total provisions.

We proceed by listing several explanatory variables that we believe to be correlated with aggregate recovery rates. The exact definitions of the variables are as follows. The *GDP* variable is included to capture economic growth effects. The total of specific and general provisions over total loans is used as proxy for default rates (PD). The total financing *(as a share of total assets), L* represents the (relative) size of financing. Generally speaking, total financings have a positive influence on profitability, because as a bank's core business, they are a major generator of income. But, total financing also entails operational costs and credit losses. If costs and risks are not expressed adequately in the price of credit (*i.e.* the mark-up rate for Islamic debt financing), for instance, as a result of cross subsidization, then financing becomes a loss-making business. In any case, this variable serves to characterize a bank's balance sheet. Like the variables that follow below, the financing variable is divided by total assets (*ROA*) in order to standardize it and allow comparisons across banks and years.

V. The Results

Table 1 shows the descriptive statistics of different variables to examine the bivariate relationship by comparing the average (mean) for each variable. The reported results in the table show that the values of each variable deviate slightly from the standard deviation. Therefore, they are very volatile.

Table 1: Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
RR_{it}	1.332	5.130	7.252	59.561	15058.620*
PD_{it}	3.941	28.739	8.135	70.782	21663.530*
$M3_{it}$	5.598	0.129	−0.672	2.530	13.930*
ROA_{it}	2.158	2.926	7.042	64.537	19593.640*
GDP_{it}	4.701	0.062	−0.217	2.572	2.548

Note: '*' indicates statistical significance at 1% level

To verify whether the sample data is normally distributed, the data are tested using several techniques such as the skewness test, kurtosis, the Jarque-Bera as well as the value of mean and median. If a sample is normally distributed, then the value of skewness will be equal to zero, the value of kurtosis should be three and the value of mean should be the same as the value of its median while the value of Jarque Bera should not be significant or with high value of probability. A sample of data that is normally distributed should be an efficient estimator, unbiased and consistent.

Based on the descriptive statistics, GDP_{it} is not normally distributed because the Jarque-Bera is not significant with a high value of probability. The kurtosis value for *GDP* is 2.572. The value of mean and median for all the variables is not the same, while their skewness is not equal to zero. The values of kurtosis are not equal to three and the values of Jarque-Bera are significant. Therefore it can be concluded that, based on the above, the Ordinary Least Squares estimation method is not the best estimation method to use. Hence, the Generalized Least Squares method is more appropriate and expected to yield a much better result.

Table 2: Correlation Matrix

	RR_{it}	PD_{it}	$M3_{it}$	ROA_{it}	GDP_{it}
RR_{it}	1				
PD_{it}	−0.03318	1			
$M3_{it}$	−0.06292	−0.14108	1		
ROA_{it}	0.144482	0.035868	0.101373	1	
GDP_{it}	−0.14108	−0.0553	0.942599	0.102013	1

The correlation matrix reported in Table 2 shows that there is a negative correlation coefficient between recovery and all variable except ROA_{it}. The negative correlation between *RR* and *PD* might lead to insufficient bank reserves and cause unnecessary shocks to financial markets. As far as procyclicality is concerned, this effect tends to be exacerbated by the correlation between RR_{it} and PD_{it}, and low recovery rates when defaults are high would amplify cyclical effects. This would be especially true under the so-called 'advanced' *IRB* approach, where banks are free to estimate their own recovery rates and might tend to revise them downwards when defaults increase and ratings worsen.

Table 3: Panel Unit Roots Test

Variable	ADF-Fisher Chi-Square		Levin, Lin & Chu t^*	
	At level	First Difference	At level	First Difference
RR_{it}	33.168**	22.6912	–13.593*	–4.199*
PD_{it}	48.281*	36.832*	–5.581*	–7.458*
$M3_{it}$	21.453	46.158**	–3.769*	–5.709*
ROA_{it}	33.223**	42.818*	–10.712*	–17.543*
GDP_{it}	4.882*	83.982*	–0.361	–10.618*

Notes: (i) '*' indicates statistical significance at 1% level; '**' indicates statistical significance at 5% level; (ii) Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution; (iii) All other tests assume asymptotic normality.

The standard unit root test has to be performed to check the stationarity of our data. However, it is often argued that the commonly used unit root tests such as the augmented Dickey-Fuller (ADF) test and the Phillips-Perron test are not very powerful. As a response, panel unit root tests are developed. These tests are in essence motivated to increase the power through pooling information across units. ADF-Fisher assumes individual unit root process and uses *Chi-square test* statistics. Table 3 presents all variables except $M3_{it}$ stationary at level and significant at difference percentages. In the first difference, $M3_{it}$ is stationary at 10% but RR_{it} is not stationary. Levin *et al.* (1993) assume common unit root process and use t-test. Based on the figures reported in Table 3, we find the coefficient GDP_{it} not stationary in levels. In the first difference, all variables are stationary at 1%.

Tables 4 and 5 shows the result from estimation for GLS model without effect (Model 1), random effect model (Model 2), fixed effect model (Model 3) and time effect model (Model 4). As reported in column two of Table 4, the model explains the relationship between recovery and default rates. We find that the default rate is not significant and negatively related to recovery. This result is similar to the correlation matrix result.

Table 4: Univariate Result

Specification	Parameter Estimates			
	Non Effect	Fixed Effect	Random Effect	Time Effect
	MODEL 1	MODEL 2	MODEL 3	MODEL 4
Constant	1.676* (2.683)		1.677* (2.596)	
PD_{it}	−0.130 (−0.302)	−0.306E-03 (−0.007)	0.012 (−0.285)	−0.991 (−0.217)
R^2	0.0011	0.180	0.0010	0.101
Adj R^2	−0.0109	0.002	−0.0109	−0.034
DW-test	2.556	3.112	2.611	2.418

Notes: '*' indicates statistical significance at 1% level.

Table 5: Multivariate Result

Specification	Parameter Estimates			
	Non Effect	Fixed Effect	Random Effect	Time Effect
	MODEL 1	MODEL 2	MODEL 3	MODEL 4
Constant	161.984** (2.322)		137.773** (2.015)	
PD_{it}	−0.215 (0.512)	−0.092 (−0.191)	−0.174 (−0.438)	−0.714 (−0.153)
$M3_{it}$	44.639** (1.961)	24.207 (0.918)	36.279*** (1.665)	94.251 (0.647)
ROA_{it}	0.282 (1.488)	0.159 (0.720)	0.228 (1.260)	0.255 (1.228)
GDP_{it}	−87.507** (−2.349)	−48.046 (−1.075)	−72.347** (−2.014)	−103.664 (−0.832)
R^2	0.091	0.199	0.091	0.129
Adj R^2	0.046	−0.019	0.046	−0.046
DW-test	2.587	3.014	2.587	2.484

Notes: '*' indicates statistical significance at 1% level; '**' indicates statistical significance at 5% level; '**' indicates statistical significance at 10% level; Figures in parentheses are t-test statistics.

In column two Table 5, the figures explain the relationship between recovery and business cycles. We find the estimated coefficient of the macroeconomics indicator *GDP* and $M3_{it}$ are significant at 5% in model non effect and random effect. *GDP* is negatively related with *RR* or anticyclical but $M3_{it}$ has a positive sign. The coefficient of *PD* is negatively related to recovery in all models but not significant in all models. This finding is similar in univariate model. The coefficients of *ROA* have a negative sign and are not significant.

Table 6: Diagnostic Tests

Test	Statistic	Stat.	P-value
LM test for a pooled OLS model versus a random-effects model	χ^2	1.04	0.307
Hausman test for a random-effects model versus a fixed-effects model	χ^2	1.02	0.907
Breusch-Pagan test for heteroscedasticity	χ^2	9.0656	0.000

In terms of the diagnostic tests reported in Table 6, first, we conducted Lagrange Multiplier (LM) tests to examine the relative efficiency of the heterogeneous fixed/random-effects estimation against the homogeneous pooled OLS model. The LM *Chi-square* ($\chi 2$) values are not significant in the models (one-tailed). This suggests the pooled cross-sectional OLS model is more efficient than that fixed/random-effects model. Second, we performed a Hausman specification test, which is based on the differences between the coefficients estimated from fixed or random-effects models, to determine which kind of panel model would be most appropriate in this study. The computed Chi-square statistic was also found to be not significant in the model, indicating that the null hypothesis of zero correlation between the unobservable company-specific effects and the explanatory variables in the model can be rejected. In this case, the random-effects model can still derive consistent estimates but the fixed effects model cannot. Hence, the random-effects model is much better than the fixed effect in this study. Finally, Breusch-Pagan tests were conducted to test for the presence of heteroscedasticity in the model. The computed $\chi 2$ values were statistically significant in the estimation ($p \leq 0.05$, one-tailed), indicating the presence of heteroscedasticity problem in the volume decision models.

VI. Conclusions

This paper analysed the link between recovery rates and default rates for Islamic banks, both from a theoretical and an empirical standpoint. As far as the theoretical aspects are concerned, most of the literature on credit risk management models treats the recovery rate variable as a function of historic average default recovery rates (conditioned perhaps on seniority and collateral factors), but in almost all cases as independent of expected or actual default rates. This appears rather simplistic and unrealistic in the light of our empirical evidence. In this study, we modelled the recovery rates on defaults rates, over the period 1994-2004. These statistical models assign a key role to the supply of defaulted paper (default rates) and explain a substantial proportion of the variance in recovery rates aggregated. These results have important implications for portfolio credit risk models, for markets which depend on recovery rates as a key variable (*e.g.*, securitizations, credit derivatives, *etc.*), and for the current debate on the new standard guidelines for capital requirements on Islamic bank assets. This paper finds a negative correlation between default and recovery rates – that has been reported in other empirical studies (Frye, 2000b and 2000c; Carey and Gordy, 2003; Hamilton *et al.*, 2001; Altman, 2001 and 2005). This evidence indicates that recovery risk is a systematic risk component. As such, it should attract risk premiums and should be adequately considered in credit risk management applications.

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Appendix: **Unit Root Test**

(i) The ADF-Fisher test

Maddala and Wu (1999) propose the test statistic, which is based on combining the *P*-values of the test statistics (of β_i) of *N* independent ADF regressions from

$$\Delta q_{it}^{k} = \alpha_i + \beta_i q_{it-1}^{k} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta q_{it-j}^{k} + e_{it} \tag{1}$$

$$i = 1 \ldots\ldots\ldots N \qquad t = 1 \ldots\ldots\ldots T$$

The test is non-parametric and is based on Fisher (1932). Similar to Im et al (1997), this test allows for different first-order autoregressive coefficients and has the same null and alternative hypothesis in the estimation procedure. The test statistic (the Fisher test $P(\lambda)$ is as follows:

$$P(\lambda) = -2\sum_{i=1}^{N} \ln(\pi_i) \tag{2}$$

where π_i is the *P*-value of the test statistic for unit *i*. The Fisher test statistic $P(\lambda)$ is distributed as a chi-squared distribution with $2N$ d.f. Maddala and Wu show that the Fisher test achieves more accurate size and high power relative to the LL test. The advantage of this test is that it can use different lag lengths in the individual ADF regressions, although the IPS test must use the same lag length in all the individual ADF regressions. The Fisher test does not require a balanced panel as in the case of the IPS test. Therefore, in practice, the Fisher test is straightforward to use and may decrease the bias which is caused by the lag selection (Banerjee (1999) and Maddala and Wu (1999)).

(ii) Levin and Lin test

Levin and Lin (1993) developed a panel unit root test that has more power than univariate unit root tests by imposing the same first order autoregressive coefficient and intercept on all series. This approach jointly tests if all series in the panel follow a unit root process. Evans and Karras (1996) enhance the panel approach by allowing for different intercepts and testing for both stochastic and absolute convergence. Stochastic convergence implies that innovations are transmitted one-for-one to all series in the panel, so that the variables are stationary. The panel procedure requires the following steps.

$$\Delta q_{it} = \alpha_i + \rho_i q_{i,j-1} + \sum_{j=1}^{p} \theta_{ij} \Delta q_{i,t-j} + e_{it} \quad \text{t=1,2...T} \tag{3}$$

The cross-sectional means for the panel are first subtracted from each series.

$$\Delta z_{it} = \delta_i + \rho z_{i,j-1} + \sum_{j=1}^{p} \theta_{ij} \Delta z_{i,j-1} + \mu_{it} \tag{4}$$

where $u_{it}=e_{it}/\ \sigma_i/F$ and $F\delta_i = \alpha_i/\sigma_i$ If the *t*-ratio for the estimated ρ, $\tau(\rho)$, exceeds a critical value from a Monte Carlo simulation, then we reject the null hypothesis of a unit root, H_0: $\rho = 0$, for all *N* economies in favor of a mean reverting process, H_1: $\rho > 0$. If PPP holds, one can then test if the constants are significantly different from zero for all economies by calculating the *F*-ratio, $\phi(\delta) = \sum_{i=1}^{N} [\tau(\delta)]^2 / (N-1)$ Here, τ (δ_i) is the *t*-ratio from the OLS estimate of i from the standard ADF regression given by equation (10). If the statistic exceeds the Monte Carlo critical value, then we reject a common intercept of zero for all economies. The Monte Carlo experiment is calculated following the steps of Evans and Karras (1996). Ordinary least squares estimates the parameters under the two nulls:

$$\Delta q_{it} = \alpha_i + \sum_{j=1}^{p} \theta_{ij} \Delta q_{i,t-j} + v_{it} \tag{5}$$

$$\Delta q_{it} = \rho_i q_{i,t-1} + \sum_{j=1}^{p} \theta_{ij} \Delta q_{i,t-j} + v_{it} \tag{6}$$