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**Measuring Financial
Integration: Lessons from
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This paper evaluates and compares the dynamics of the financial integration process as described by different empirical approaches. To this end, a wide range of methods accounting for several dimensions of integration and a novel evaluation scheme – based on the positive association between financial integration and real exchange rate volatility – are employed. Using monthly equity market data running from April 1985 to December 2014 for two groups of countries, we find that (i) the degree of heterogeneity among the patterns generated by the proposed set of financial integration measures is rather low and (ii) the standard unconditional correlation – on average – captures equity market integration rather well and performs – in the worst case – as more sophisticated integration measures.

Keywords

Equity market integration, dynamic correlation, principal components, RER volatility

JEL Codes

F15, F44, G15

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Measuring Financial Integration: Lessons from the Correlation

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Abstract

This paper evaluates and compares the dynamics of the financial integration process as described by different empirical approaches. To this end, a wide range of methods accounting for several dimensions of integration and a novel evaluation scheme – based on the positive association between financial integration and real exchange rate volatility – are employed. Using monthly equity market data running from April 1985 to December 2014 for two groups of countries, we find that *(i)* the degree of heterogeneity among the patterns generated by the proposed set of financial integration measures is rather low and *(ii)* the standard unconditional correlation – on average – captures equity market integration rather well and performs – in the worst case – as more sophisticated integration measures.

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1 Introduction

International financial markets have become increasingly integrated over the last 30 years. An increasing degree of financial integration among countries tends to provide both advantages and disadvantages. On the one side, a higher level of integration increases risk-sharing opportunities allowing for larger insurance benefits and more efficient consumption smoothing (Jappelli and Pistaferri (2011); Suzuki (2014), among others). In this respect, financial integration may generate both short- and long-run welfare benefits (Colacito and Croce (2010), Yu (2015)).¹ On the other side, the increasing level of global financial integration has induced strong positive cross-country equity return correlations. As a result, international portfolio diversification benefits decreased (Kearney and Lucey (2004); Goetzmann, Li, and Rouwenhorst (2005); Donadelli and Paradiso (2014a)). Notice also that financial integration and frictionless international capital flows regime may also affect countries' specific policy targets. Blanchard, Dell'Ariccia, and Mauro (2010), for instance, point out that the policy targets of a specific country could not be well-suited with current international financial market dynamics.

Financial integration has received an enormous amount of attention over the last two decades. Needless to mention, it is still at the center of the policy debate. Agents tend to be forward-looking in their decisions. It is therefore relevant for them to get a better understanding of the level of integration. Of course, both policymakers and investors need an instrument able to measure integration and its evolution over time. A key step then consists in the choice of a proper measure. As there are many possible measures of financial integration it is natural to ask whether they all provide similar results in terms of financial integration levels and patterns. To this end, this paper examines the financial integration pattern produced by a battery of indicators proposed and employed in the international finance literature over the last decades to shape integration dynamics.

To account for all possible dimensions of financial integration a relatively large number

¹In particular, Yu (2015) argues that overall welfare benefits change along the financial integration process.

of existing indicators is considered. Table 1 (Panel A) presents a list of main measures considered by the literature of the last ten years (and in this study) along with their properties. Being largely accepted that integration is a dynamic concept, we employ methodologies allowing us to capture financial integration over time.

We rely first on the simplest measure of integration: the unconditional correlation. Since the correlation along with other correlation-based measures suffers from a co-movement bias (i.e. the correlation score is unable, in some circumstances, to summarize the real integration among stock returns (Pukthuanthong and Roll (2009))), two recently introduced PCA-based measures are implemented: (i) the percentage of variance explained by the first principal component used by Volosovych (2011) (hereinafter the **1st PC**) and (ii) the multi-factor adjusted R-square proposed by Pukthuanthong and Roll (2009) (hereinafter the **R-square**). To account for stochastic independence (i.e. the measured correlation between stock returns may be correlated with measured stock return volatilities), the methodology of Ball and Torous (2006) is also implemented. In addition, we rely on volatility- and heteroskedasticity-adjusted measures. In this respect, we employ the (i) volatility-adjusted correlation introduced by Forbes and Rigobon (2002); (ii) the dynamic conditional correlation model (DCC-GARCH) proposed by Engle and Sheppard (2001) and Engle (2002); (iii) the BEKK-GARCH along the lines of Engle and Kroner (1995); and (iv) a conditional time-varying beta. Based on the ongoing debate on whether or not the standard unconditional correlation represents a robust measure of integration (see Carrieri, Errunza, and Hogan (2007); Pukthuanthong and Roll (2009); Volosovych (2011)), this study uses the latter as a benchmark indicator of financial integration.

Improvements with respect to existing studies are also carried out (see Table 1, Panel B). The volatility-adjustment in the standard unconditional correlation measure is implemented by relying on the key events embedded in the US and EU economic policy uncertainty indexes developed by Baker, Bloom, and Davis (2013). This allows us to account for multiple

changes in volatility, which correspond to major political and financial markets events.² For robustness, the **R-square** and **1st PC** are re-computed by accounting for stochastic interdependence. In other words, in both PCA-based measures, the sample correlation is substituted with the correlation obtained via the [Ball and Torous \(2006\)](#)’s procedure. This may better capture the integration in tranquil time periods (see [Ball and Torous \(2006\)](#)).

To make sure that our results are general and do not strictly depend on the chosen sample (i.e. sample bias), we implement all the measures listed in [Table 1](#) by using data for two groups of countries: (i) the G7, which we classify as an homogeneous group in terms of volatility patterns and average returns; (ii) the non-G7 (i.e., Australia, Belgium, Denmark, Ireland, Sweden, Switzerland and South Africa), which includes economies with a large variety of sizes, degrees of openness and financial market characteristics.

A natural question is then the following: How can we evaluate the effectiveness of these indicators in measuring integration? To some extent financial integration is an abstract concept and measuring it realistically may be challenging. From a quantitative point of view, it is therefore difficult to state that one measure is better than another one. In this respect, a suggestion to build an evaluation scheme comes from the international business cycle (IBC) literature. IBC studies show that a relatively high level of integration (i.e. the presence of international complete and frictionless financial markets) can re-produce the real exchange rate (RER) volatility observed in the data (see [Kollmann \(2009\)](#); [Colacito and Croce \(2010\)](#); [Colacito and Croce \(2013\)](#); [Gourio, Siemer, and Verdelhan \(2013\)](#); [Donadelli and Paradiso \(2014a\)](#); [Caporale, Donadelli, and Varani \(2015\)](#); [Kollmann \(2015\)](#)). In other words, full risk-sharing is associated with high RER volatilities. Of course, this result suggests a positive relationship between financial integration and RER volatility. Based on this IBC evidence, we are able to evaluate the proposed integration measures by computing their average correlation with the observed RER volatility. To the best of our knowledge this is the first study aimed at comparing the financial integration pattern generated by different

²This differs from [Forbes and Rigobon \(2002\)](#) who focus on a single shift in the variance level.

measures as well as evaluating their performances by relying on a well established theoretical concept.

Our main results are as follows. First, we observe that (i) the unconditional correlation, 1st PC and R-square give rise to almost identical equity market integration patterns; (ii) volatility-adjusted measures tend to produce highly volatile integration patterns. Second, by relying on the novel proposed evaluation criterion, we find that the performance of the unconditional correlation is not far from the one provided by more sophisticated integration measure. Differently, those measures accounting for changes in volatility and heteroskedasticity (i.e., Forbes-Rigobon correlation, DCC-GARCH, BEKK, Conditional Beta) do not perform very well.

The remainder of this paper is organized as follows. Section 2 reviews the literature on financial integration and examines the pros and cons of different measures adopted in the literature. Section 3 describes all the methodologies in details. Section 4 presents the data and summary statistics. Section 5 presents the estimation results from the integration indicators and compares their behaviors. Section 6 employs a novel and simple approach to evaluate the performance of the proposed measures. Section 7 concludes.

Table 1: LIST OF FINANCIAL INTEGRATION MEASURES: EXISTING STUDIES, EMPIRICAL METHODS AND MEASURES' CHARACTERISTICS

PANEL A:						
Measure	Studies on Financial Integration	Dynamic	Comov. Bias	Volatility	Heterosk.	Stochastic Interdep.
Unc. Corr.	Goetzmann, Li, and Rouwenhorst (2005); Quinn and Voth (2008)	X				
R-square	Pukthuanthong and Roll (2009)	X	X			
1st PC	Volosovych (2011); Volosovych (2013)	X	X			
Corr. (ASI)	Ball and Torous (2006)	X				X
Forbes-Rigobon Corr.	Connolly, Stivers, and Sunc (2007)	X		X		
DCC-GARCH	Chiang, Jeon, and H (2007); Wang and Moore (2008); Egert and Kocenda (2011)	X			X	
BEKK-GARCH	Caporale and Spagnolo (2011); Bekiros (2013)	X			X	
Cond. Beta	Choudhry and Jayasekera (2013); Jayasinghe, Tsui, and Zhang (2014)	X			X	
PANEL B:						
Measure						
R-square (ASI)	This paper	X	X			X
1st PC (ASI)	This paper	X	X			X
Forbes-Rigobon Corr.	This paper	X		X*		

Notes: Panel A reports the list of financial integration indicators employed by the international finance literature over the last ten years with their respective technical features. Panel B reports the main improvements carried out in this study. * The volatility-adjustment is implemented by relying on the set of relevant political and financial events indicated in the US and EU economic policy uncertainty indexes developed by [Baker, Bloom, and Davis \(2013\)](#).

2 On the selection of proper financial integration measures

Most broadly, the existing financial integration indicators can be classified in three categories: (i) price-based indicators; (ii) quantity-based indicators; and (iii) regulatory (or institutional) measures. Generally, four criteria are used to evaluate the usefulness of the above indicators (see [Adam, Jappelli, Menichini, Padula, and Pagano \(2002\)](#)): (i) data availability; (ii) reliability of the data on which the indicators are based; (iii) economic meaning of the indicators and (iv) the ease of building and updating the indicators. Based on these criteria, price-based indicators – classified also as direct measures of integration – have attracted more attention than quantity-based indicators (i.e., stock or flow data). Stock market returns, of course, satisfy the above conditions. Since price-based indicators invoke the law of one price, they also have a clear-cut interpretation, which is often lacking for those quantity indicators relying on flow data (see [Volosovych \(2011\)](#)). For these reasons, the simple analysis of the co-movement between asset prices has gained most of the scholars’ attention (see, among many others, [Kim, Moshirian, and Wu \(2006\)](#); [Bekaert, Hodrick, and Zhang \(2009\)](#); [Pukthuanthong and Roll \(2009\)](#); [Volosovych \(2011\)](#)). Hence, although financial integration encompasses many different aspects of complex interrelationships across various financial markets, this study follows this strand of the literature and relies on cross-country equity prices convergence.

From a methodological viewpoint, the empirical literature has proposed different measurement frameworks relying on price-based indicators: Vector Auto-Regression (VAR) models ([Khalid and Kawai \(2003\)](#); [Elyasiani and Wanli \(2008\)](#); [Jayasuriya \(2011\)](#)), unconditional cross-country correlation ([Watson \(1980\)](#); [Meric and Meric \(1989\)](#); [Goetzmann, Li, and Rouwenhorst \(2005\)](#)), cointegration and error-correction models ([Laopodis \(2011\)](#); [Gupta and Guidi \(2012\)](#)), GARCH-based models ([Billio and Pelizzon \(2003\)](#); [Kim, Moshirian, and Wu \(2006\)](#); [Carrieri, Errunza, and Hogan \(2007\)](#); [Wang and Moore \(2008\)](#); [Egert and Ko-](#)

cenda (2011)), asset pricing models (de Jong and de Roon (2005); Barr and Priestley (2009); Abad, Chuliá, and Gómez-Puig (2010)), PCA (Nellis (1982); Mauro, Sussman, and Yafeh (2002); Volosovych (2011); Donadelli and Paradiso (2014b)), common component approach (Carrieri, Errunza, and Hogan (2007); Pukthuanthong and Roll (2009); Yu, Fung, and Tam (2010)). VAR based studies make use of impulse response analysis to investigate the effects of contagion and the degree of interdependencies (i.e., an indirect measure of the integration between markets), whereas cointegration based studies aim to assess the presence of a long-run equilibrium among the financial variables (for instance, stock prices) of various countries. Asset pricing models usually rely on a standard CAPM framework and assume that the excess return of a country is generated by global factors (with a coefficient ξ) and idiosyncratic factors (with a coefficient $(1-\xi)$). The parameter ξ is meant to capture equity market segmentation. Cointegration methods, VAR and asset pricing models tend to have major drawbacks that do not really fit the agenda of this paper. For examples, cointegration and VAR models are not able to reproduce a numerical measure of financial integration.³ In addition cointegration methods have been criticized for being static approaches and unable to capture the dynamic evolution of a process (see, among others, Kearney and Lucey (2004), Kim, Moshirian, and Wu (2006), Wang and Moore (2008)).⁴

The standard unconditional correlation is simple to implement and have a straightforward interpretation. To summarize comovement in a group of markets, the usual practice is to compute the average of the correlation coefficients across country-pairs (Mauro, Sussman, and Yafeh (2002); Quinn and Voth (2008)). Some studies employ unconditional correlation over different subperiods (Goetzmann, Li, and Rouwenhorst (2005); Quinn and Voth (2008)). Traditionally, however, the unconditional correlation implicitly assumes that the relationship between assets does not change over time. Hence, they do not track down the dynamics of

³In a cointegrating framework, an error correction representation contains information about the speed of adjustment of corrections respect to deviations from long-run equilibrium. This information has not a linkage with a measure of integration.

⁴Exceptions are the studies of Pascual (2003) and Laopodis (2011) that conduct rolling cointegration tests, but the flaw of the lack of a direct measure of integration remains.

the relationships, in particular of the volatility. To capture changes in the volatility across equity markets, some authors adopt GARCH-based dynamic conditional correlation models (Wang and Moore (2008); Egert and Kocenda (2011)). Two problems are connected with these models: (i) Longin and Solnik (2001) show that correlation is not related to market volatility per se but it is mainly affected by the market trend; correlation seems to rise only when asset prices fall (bear markets) and not when they are expected to rise (bull markets); (ii) Forbes and Rigobon (2002) argue that conditional correlation is subject to volatility bias; the coefficient would increase in periods of high volatility (during crisis or shocks) and, as a consequence, may lead to wrong conclusion that there is contagion effect during a crisis. The unconditional correlation is thus relatively less affected by the volatility and may represent a better measure. In summary, the literature on conditional correlation has not reached a general consensus on how to correct the problem of conditional heteroskedasticity (Volosovych (2013)).

Still, the standard unconditional correlation along with other correlation-based metrics have been subject to a severe criticism. Bekaert, Hodrick, and Zhang (2009) conclude that *“Correlations are an important ingredient in the analysis of international diversification benefits and international financial market integration. Of course, correlations are not a perfect measure of either concept”*. More specifically, Pukthuanthong and Roll (2009) write: *“The simple correlation between broad financial market index returns from two countries can be a poor measure of their economic integration”*. Similarly, Volosovych (2011): *“I argue that a conventional measure of co-movement, the coefficient of correlation, has limited applicability as a measure of economic integration”*. Based on these arguments, Pukthuanthong and Roll (2009) and Volosovych (2011) propose two PCA-based integration measures, which, according to their view, are more robust than the standard correlation. Pukthuanthong and Roll (2009) introduce a novel measure based on the explanatory power of a multi-factor model. In their setting, the first ten principal components – which explain almost 90% of the variation across equity market returns – are employed as global factors. The adjusted R-square is then

computed in each calendar year for each country. The cross-country average R-square represents then their alternative integration measure. In the spirit of [Nellis \(1982\)](#) and [Mauro, Sussman, and Yafeh \(2002\)](#), [Volosovych \(2011\)](#) instead uses the proportion of total variation in individual returns explained by the first principal component to measure the degree of financial integration.⁵ He focuses on the bond market of 15 industrialized economies from 1875 to 2009 and computes the integration dynamics using a rolling window of 156 months. Of course, PCA-based measures may also rise some concerns. For example, among others, the PCA is usually subject to a trade-off between the covariance and the correlation matrix used to derive the components. In the correlation matrix the variables are standardized. The goal of this simple transformation is to give to all variables an equal weight, even if they exhibit huge variance differences. In general, such transformation is not required when variables have the same unit. To be sure that a high variance variable will not dominate the principal components this transformation is often implemented. Of course, this may represent a non-negligible drawback. Therefore, by using the covariance matrix there can be the risk that variables with high variance will influence the overall analysis.

Given that there is no a general consensus on the proper measure of integration, this study provides a survey of the indicators employed in the international finance literature to monitor the degree of integration across equity markets over time. Our contribution is twofold. First, this paper represents a first attempt to examine the degree of heterogeneity in the information provided by different metrics. Loosely speaking, do these measures provide similar integration patterns? Second, we relate each specific integration pattern with the RER volatility, which is well known to be high in the presence of highly integrated equity markets and relatively low in the presence of segmented markets (see [Colacito and Croce \(2013\)](#), [Donadelli and Paradiso \(2014a\)](#), [Caporale, Donadelli, and Varani \(2015\)](#), [Kollmann \(2015\)](#)). We stress that this allows us to evaluate the proposed measures quantitatively.

⁵[Mauro, Sussman, and Yafeh \(2002\)](#) find that the first principal component explains a large proportion of variation of sovereign bond spreads for a group of emerging market countries from 1877 to 1913 and an even larger proportion in the 1990s. Earlier, [Nellis \(1982\)](#) used PCA to compare interest rate comovement among industrialized countries before and after the move to a floating exchange rate regime in the early 1970s.

3 Measuring integration

This section provides the methodologies of constructing different indicators for capturing the dynamics of equity market integration among countries. Specifically, we present in details all the measures listed in Table 1. Section 3.1 introduces the standard unconditional correlation. In Section 3.2 we present the two PCA-based measures that correct for the the co-movement bias (i.e. R-square and 1st PC). In the spirit of [Ball and Torous \(2006\)](#), section 3.3 introduces the concept of stochastic interdependence and apply it to the standard correlation, R-square and 1st PC. Section 3.4 relies on well-known volatility- and heteroskedasticity-adjusted measures (i.e. Forbes-Rigobon, DCC-GARCH, BEKK-GARCH, conditional beta).

3.1 The dynamic unconditional correlation

The unconditional correlation coefficient is one of the most widespread proxies for measuring international financial integration, as pointed out by [Kearney and Lucey \(2004\)](#).⁶ In order to assess the co-movement similarities of a group of countries, it is usually convenient to compute bilateral correlations and investigate their first and second moments.⁷ In particular, a rise in the mean of the correlations calculated over rolling windows coupled with a simultaneous decrease in the variance of the correlations indicate increased market integration. We compute average correlations for both groups of countries as follows:

$$\bar{\rho} = \frac{2}{N(N-1)} \sum_{i=1}^N \sum_{j=i+1}^N \rho_{ij}$$

where $\rho_{ij} = \sigma_{ij}/\sigma_i\sigma_j$, σ_{ij} is the covariance of returns between asset i and asset j , and σ_i is the respective standard deviation, $i, j \in \{1, \dots, N\}$. The estimated correlations refer to the end points of the windows, i.e. they represent the average correlation over the past window

⁶Examples of studies using simple correlation include [Panton, Lessig, and Joy \(1976\)](#) and [Hilliard \(1979\)](#).

⁷We focus on unweighted correlations and do not consider a weighting of correlation coefficients by country size as this would bias outcomes mostly to the largest economies (i.e. US, Japan and Germany). However, [Gayer \(2007\)](#) reports that the weighting of countries does not qualitatively alter findings.

length. The length of the rolling window is fixed at 60 months which is an approximate length of a full business cycle.⁸

3.2 Adding robustness

From an asset pricing point of view, two markets can be fully integrated even if their equity returns are not correlated. In such a special case, the conventional measure of co-movement presented in the previous section fails as a market integration proxy (see, among others, [Pukthuanthong and Roll \(2009\)](#)). In the following, we present two PCA-based measures that have been recently developed to overcome this particular problem.

I. THE R-SQUARE

[Pukthuanthong and Roll \(2009\)](#) argue that the correlation coefficient may represent an unsuitable measure of integration and show that two countries could be perfectly integrated while displaying no correlation between their returns. As an alternative, they propose a measure based on the explanatory power of a multi-factor linear model. This approach does not rely on any particular asset pricing model but merely requires globally common factors which can be interpreted as non-traded risk factors that are driving global financial markets. In this setting, the global factors are represented by the principal component scores obtained from applying the PCA to normalized returns:

$$f_{i,t} = v_{i,1}r_{1,t} + v_{i,2}r_{2,t} + \dots v_{i,N}r_{N,t}, \quad (1)$$

where $r_{n,t}$ is the country index n th return at time t and v_{ij} is the j th element of i th PC, also called scoring coefficient or loading.

⁸The rolling window length over which correlations are computed can affect the outcome. The window should be wide enough to leave sufficient observations to compute precise correlation coefficients but short enough in order to avoid smoothing out important medium-term changes in integration. In general, the optimal window size cannot be determined analytically but has to be determined from the outset. In any case our results are robust to varying window lengths (see [Figure B.1](#)).

The first $f_1, \dots, f_K$, $K < N$, global factors serve as explanatory variables in a multivariate regression for all N country index return series:

$$r_{n,t} = \beta_{n,0} + \beta_{n,1}f_{1,t} + \dots + \beta_{n,K}f_{K,t} + \epsilon_{n,t}, \quad n \in \{1, \dots, N\}, \quad (2)$$

where $\beta_{n,k}$ measures country's index n th exposure to k th global factor. The cross-country average of the adjusted R-square obtained from the above regressions serves as a robust measure of financial integration.⁹

We acknowledge that our estimation procedure deviates slightly from the original approach. [Pukthuanthong and Roll \(2009\)](#) use daily returns and estimate the eigenvectors for each calendar year separately and apply them to returns in the following calendar year. In doing so, they produce out-of-sample global factors which are then used as explanatory variables in the regressions. Differently, we estimate the **R-square** using five-year rolling windows and by retaining $K = 3$ in-sample global factors.¹⁰

II. THE 1ST PC

[Volosovych \(2011\)](#) proposes an alternative PCA-based measures where the proportion of total variation in individual equity returns explained by the 1st PC is meant to capture integration levels. He argues that this approach have several advantages: (i) it accounts for several dimensions of integration including co-movement and segmentation; (ii) it is robust to the presence of outliers or heavy-tailed distributions and to the choice of a reference country; and (iii) it has a clear theory-based interpretation.

⁹The **R-square** as a potential measure of integration has been used also by [Yu, Fung, and Tam \(2010\)](#). However, their common component approach differs from the one developed by [Pukthuanthong and Roll \(2009\)](#) in several dimensions: (i) the adjusted R-square is obtained using a 3-year rolling OLS estimation; (ii) the employed factors are not represented by extracted principal components (i.e. artificial risk factors) but by four traded factors (i.e. currency returns, excess equity returns, dividend yields and forward premia).

¹⁰For robustness, we also computed out-of-sample global factors for each rolling window. The main results were not affected and are available upon request. The first three PCs generally account for close to 90% of the cumulative return variation. Notice that by using less than three global factors our main results are unaffected.

The estimation procedure is straightforward. The initial steps correspond to the ones needed for computing the **R-square**. What is different here is that instead of performing a PCA-based regression, [Volosovych \(2011\)](#) assumes that the variation explained by the **1st PC** – estimated via rolling windows – can serve as a measure of financial integration. Formally,

$$\text{Variation explained by 1st PC} = \frac{\lambda_1}{\sum_{i=1}^N \lambda_i}, \quad (3)$$

where λ_i is the eigenvalue of i th PC. The intuition behind this approach is that financial market integration can be captured by the proportion of countries' returns explained by an unobserved factor. [Volosovych \(2011\)](#) interprets it as the unobserved “world return”.¹¹

3.3 Accounting for Stochastic Interdependence

I. THE CORRELATION IN PRESENCE OF STOCHASTIC INTERDEPENDENCE

[Ball and Torous \(2006\)](#) introduce a multivariate stochastic covariance model that accounts for the fact that measured correlation between stock returns is correlated with measured stock return volatilities. In particular, they propose a linear state-space framework in which measured variables explicitly differ from their population counterparts by observation errors. The model – originally developed for measuring contagion among countries – takes the following form:

$$y_t = \alpha_t + \epsilon_t, \quad \text{var}(\epsilon_t) = H, \quad (4)$$

$$\alpha_t = T\alpha_t + \eta_t, \quad \text{var}(\eta_t) = Q, \quad (5)$$

where $y_t = \{\log \sigma_{i,t}^2, \log \sigma_{j,t}^2, z_{i,j,t}\}$ is the observation vector of log country variances σ_t^2 and Fisher transform $z_{i,j} = \frac{1}{2} \log \frac{1+\rho_{ij}}{1-\rho_{ij}}$ of the sample correlation ρ_{ij} . α_t is the population coun-

¹¹This approach to measuring financial integration was also employed by [Nellis \(1982\)](#) and [Mauro, Sussman, and Yafeh \(2002\)](#). We stress that the measures proposed by [Pukthuanthong and Roll \(2009\)](#) and [Volosovych \(2011\)](#) are very similar. Moreover, under certain assumptions, they generate identical numbers. This relation is shown in [Jong and Kotz \(1999\)](#). In [Appendix C](#), we formally prove this by using a toy example.

terpart of y_t with independent error terms η_t . ϵ_t denotes the measurement errors with non-diagonal covariance matrix H . Following [Ball and Torous \(2006\)](#), the covariance matrices H and Q as well as the transition matrix T are estimated by applying the Kalman filter in combination with the EM Algorithm.¹²

Notice that the estimation procedure used in this paper differs from the one originally proposed by [Ball and Torous \(2006\)](#) where they measure volatilities and correlations by dividing the whole time series sample of daily returns into sequential non-overlapping intervals. The countries' return volatilities and the respective bilateral return correlations are assumed to be constant within each interval but are allowed to vary across the resultant intervals. Differently, we estimate volatilities and correlations using monthly returns with overlapping intervals (i.e. rolling windows) of length 60 months. Within each window, the moments are assumed to be constant but allowed to vary across the rolling windows.¹³ The inverse of the estimated Fisher transform that is obtained from the state equation (5) is, in the context of the model, the rolling population correlation between two countries. The cross-country average of this estimate serves us as a new measure of financial market integration that accounts for the dependence between measured correlations and measured volatilities.

II. THE R-SQUARE AND 1ST PC

Given the fact that measured volatilities correlate with measured correlations, it is reasonable to recalculate **R-square** and **1st PC** by accounting for this stochastic interdependence. Since both measures rely on the PCA, which in turn uses the return correlation matrix as input, we simply substitute the sample correlations (more precisely, measured correlations) by

¹²The estimation methodology follows the steps described in the Appendix of [Ball and Torous \(2006\)](#). First, we fit univariate linear state space models for each of the three series. Using the estimated coefficients, we run the EM algorithm with 150 iterations in the multivariate case. Next, the EM estimates are used as starting values in the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. Similar to the original paper, we work the Choleski factorization of H and Q to ensure positive definiteness. The population correlation is then obtained from the Fisher transforms by employing Broyden's Method.

¹³In our view, this can be interpreted as a low-frequency long-run mean estimation of volatilities and correlations across a cycle. For robustness, we also apply the original approach using five month non-overlapping intervals. Results generate similar equity market integration dynamics. Results are available upon request.

population correlations obtained from the multivariate stochastic covariance model described in the previous sub-section. This procedure is repeated for each rolling window while all other calculation steps remain unaffected. We refer to these adjusted measures as: the **R-square (ASI)** and the **1st PC (ASI)**.

3.4 Accounting for Volatility and Heteroskedasticity

I. FORBES-RIGOBON AND MULTIPLE VOLATILITY ADJUSTMENT CORRELATION

Previous studies document a positive linkage between correlation and volatility (see, among others, [King, Sentana, and Wadhwani \(1994\)](#), [Ramchand and Susmel \(1998\)](#) and [Morana and Beltratti \(2008\)](#)). [Longin and Solnik \(1995\)](#), for instance, provide evidence of instability in the correlation patterns characterizing international stock markets, with both volatility and correlation increasing in correspondence of the October 1987 stock market crash, and correlation remaining higher afterwards, also when volatility reverted to pre-crash levels. When studying contagion in financial markets, [Forbes and Rigobon \(2002\)](#) find larger cross-country correlation when common volatility is high. Then, they argue that correlations are biased by heteroscedasticity. In particular, volatilities rise during crises which leads to an artificial upward-bias in correlations. The authors propose a volatility-adjusted correlation coefficient which takes the following form:

$$\rho_t^{FB} = \frac{\rho_t}{\sqrt{1 + \delta_t[1 - (\rho_t)^2]}}, \quad (6)$$

where ρ_t is the unconditional Pearson correlation, and δ_t is the increase in the variance of the returns in any two-year interval relative to the period with the minimum variance.

Our estimation procedure goes as follows. Analogous to the unconditional correlation, we fix the rolling windows at 60 months and compute the average volatility across all countries. Within each rolling window, we obtain the variance correction δ using 24 month intervals. Finally, we correct the mean correlation $\bar{\rho}$ using δ and plot the resulting volatility-corrected

correlation ρ^{FB} for the G7 and non-G7 countries. In line with the original argument of [Forbes and Rigobon \(2002\)](#), we account for this volatility adjustment only in the presence of major international financial and political events. To this end, we rely on the US and EU economic policy uncertainty indices developed by [Baker, Bloom, and Davis \(2013\)](#) and consider the following events: Black Monday (October 1987); 1st Gulf War (December 1990); Clinton Election (September 1992); Stability and growth pact (May 1997); Russian Crisis (August 1998); Bush election controversy (October 2000); 9/11 (September 2001); 2nd Gulf War (February 2003); European Constitutional Crisis (August 2005); Norther Rock support (August 2007); Large interest rate cuts (December 2007); subprime and EU sovereign debt crises (2008-2014).

II. DCC-GARCH

The DCC-GARCH proposed by [Engle and Sheppard \(2001\)](#) and [Engle \(2002\)](#), is another well suited model to examine correlation dynamics among assets. It belongs to the family of multivariate GARCH models and represents an extension of the Constant Conditional Correlations model (CCC) proposed by [Bollerslev \(1990\)](#). The DCC approach calculates the current correlation between variables as a function of past realizations of volatility within the variables as well as the correlations between the variables. The model is designed to allow for two stage estimation, where in the first stage univariate GARCH models are estimated for each residual series. In the second stage, residuals, transformed by their standard deviation estimated during the first stage, are used to estimate the parameters of the dynamic correlation. The model requires standardized residuals from the mean-variance specification of each return series. For stationary return series, ARMA models can be used to model the mean while GARCH models can be used to capture the time-varying volatilities of each return series $i \in \{1, \dots, N\}$. In the following, we assume that the conditional means of all

returns $r_{i,t}$ follow an ARMA(1,1) process:¹⁴

$$r_{i,t} = \mu_i + \phi_i r_{i,t-1} + \theta_i e_{i,t-1} + e_{i,t}. \quad (7)$$

The error vector $e_t = (e_{1,t} \dots e_{N,t})'$ is assumed to be conditionally normal with mean zero and covariance matrix H_t .¹⁵

$$e_t | \mathcal{F}_{t-1} \sim \mathcal{N}(0, H_t), \quad (8)$$

where $\mathcal{F}_{t-1}$ is the information set at time $t - 1$.

The DCC model assumes H_t can be decomposed as

$$H_t = D_t R_t D_t, \quad (9)$$

where D_t is a $N \times N$ diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{ii,t}}$ for the i th return series on the i th diagonal. R_t is a time-varying correlation matrix.

The variance term $h_{ii,t}$ for each market is assumed to be a function of the past innovation and conditional variance of this market: A univariate GARCH(1,1) process is assumed:

$$h_{i,t} = \omega_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,t-1} \quad (10)$$

After estimation of the GARCH models, we standardize the residuals as:

$$\epsilon_{i,t} = \frac{e_{i,t}}{\sqrt{h_{i,t}}} \quad (11)$$

¹⁴The estimation was also conducted using the BIC criterion to determine optimal p and q for an ARMA(p,q) process. The results did not yield any qualitative improvement and are included in the robustness section in the appendix.

¹⁵The Ljung-Box Q-test indicates little evidence for serial correlation of the residuals.

Then, the DCC correlation specification is as follows:

$$R_t = \text{diag}\{Q_t\}^{-1/2} Q_t \text{diag}\{Q_t\}^{-1/2}, \quad (12)$$

where $Q_t = [q_{ij,t}]$ is a symmetric positive definite variance-covariance matrix of the residual vector $\epsilon_t = (\epsilon_{1,t}, \dots, \epsilon_{N,t})'$. In particular,

$$Q_t = (1 - a - b)\bar{Q} + a\epsilon_t\epsilon_t' + bQ_{t-1}, \quad (13)$$

where $\bar{Q} = [\bar{q}_{ij}]$ denotes the unconditional covariance matrix of ϵ_t , and a and b are parameters to be estimated. The conditional correlation coefficient $\rho_{ij,t}$ between two local markets i and j is expressed by the following equation:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}. \quad (14)$$

As for the standard correlation, our GARCH-based indicator of financial integration is computed by averaging all the dynamic conditional country pair-correlations (estimated as in 14).

III. BEKK

An alternative approach to measuring the extent of market integration in terms of volatility is the application of the multivariate Baba-Engle-Kraft-Kroner (BEKK) model proposed by Engle and Kroner (1995). Assuming that the conditional mean return series follow a ARMA(1,1) process, the BEKK-GARCH(1,1) model can be written as:

$$e_t | \mathcal{F}_{t-1} \sim \mathcal{N}(0, H_t) \quad (15)$$

$$H_t = CC' + A'e_{t-1}e_{t-1}'A + G'H_{t-1}G, \quad (16)$$

where $H_t = [h_{ij,t}]$ is the variance-covariance matrix, C, A and G are $N \times N$ parameter matrices and C is upper triangular. Note that the conditional variances ($h_{ii,t}$) and the conditional covariances ($h_{ij,t}$) depend on lagged values of conditional variances ($h_{ii,t-1}$) and the conditional covariances ($h_{ij,t-1}$) as well as on lagged values of squared errors of both series and the cross-products of the errors. This feature distinguishes the BEKK-GARCH model from the univariate GARCH model ([Horvath and Petrovski \(2013\)](#)). Using bivariate BEKK-GARCH we estimate time-varying variances and covariances pairwise between local market returns. Given the resulting estimate of H_t , we compute conditional correlations, which are defined in time t as:

$$\rho_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t}h_{22,t}}}. \quad (17)$$

IV. CONDITIONAL TIME-VARYING BETA

In the following, we model the expected returns on each country portfolio as a function of its conditional covariance with the excess returns on the world market portfolio. The conditional version of ICAPM is

$$E_{t-1}[r_{i,t}] = \frac{Cov_{t-1}(r_{i,t}, r_{m,t})}{Var_{t-1}(r_{m,t})} E_{t-1}[r_{m,t}]. \quad (18)$$

Application of this model requires the specification and estimation of the conditional variances. However, asset-pricing theories do not specify how the conditional second moments should be modeled. Given the vast literature documenting that equities exhibit volatility clustering and leptokurtosis, and the advantages of a multivariate GARCH framework pointed out by [De Santis and Gérard \(1998\)](#) and others, we decide to employ a bivariate version of BEKK-GARCH(1,1) model. The advantage of this popular parametrization is that it guarantees the covariance matrices of the system to be positive definite. We estimate the conditional sensitivities of local stock market index returns to changes in the world portfolio (i.e. the conditional ICAPM betas) for each country separately. The S&P 500 serves as a

proxy for the world market portfolio.¹⁶ Our CAPM-based integration measures – in each group of countries – is then given by the cross-country average beta.

4 Data and summary statistics

Our sample consists of data representing two groups of countries: (i) the G7 (i.e. Canada, France, Germany, Italy, Japan, United Kingdom and United States) and (ii) the non-G7 (i.e. Australia, Belgium, Denmark, Ireland, Sweden, Switzerland and South Africa). Differently from the G7, the second group is composed by economies with a large variety and sizes. As aforementioned, the choice of capturing integration in two different group of countries allows us to account for the sample bias. We use monthly data from April 1985 through December 2014.¹⁷ We stress that the period covered in this study (i) is characterized by a steep increase in the degree of global financial and trade market openness (see Figure 1) and (ii) includes relevant international economic and political events (e.g., Black Monday (October 1987); 1st Gulf War (December 1990) Russian financial crisis (August 1998); China WTO entry (October 2000); 9/11 terrorist attacks (September 2001); Lehman Chapter 11 (September 2008); EU sovereign debt crisis, among others). Monthly data instead of weekly or daily data are used to avoid a set of common high-frequency data issues: (i) presence of zero returns; (ii) noise; (iii) non-synchronicity.

Equity market returns (r) are computed from Share Price Indices (SPI). Formally,

$$r_{i,t} = (SPI_{i,t}/SPI_{i,t-1}) - 1$$

where $SPI_{i,t}$ is the Share Price Index of country i at time t . Share Price Indices have been retrieved from the OECD database (MEI).¹⁸ Monthly summary statistics are reported in

¹⁶In the G7 world, the betas are averaged across six countries as the exposure of the US stock market with respect to the S&P 500 would artificially bias the result upwards.

¹⁷Our sample starts when all equity market data are available from the OECD database.

¹⁸Notice that our results are robust to using different equity indices (e.g. Morgan Stanley Capital International (MSCI) Price Indices, Datastream Global Equity Indices).

Figure 1: FINANCIAL AND TRADE MARKET OPENNESS. *Notes:* This figure reports the evolution of the total trade (sum of import and exports as a % of GDP), foreign direct investment (FDI, net inflows, as % of GDP) and stocks traded (market value, as % of GDP) in the following “Regions”: High Income Countries (*HI*, solid black line) and Low & Middle Income Countries (*LMI*, dotted line) . Data are annual and run from 1985 to 2012. Source: World Development Indicators (World Bank).

Table 2.

Table 2: EQUITY MARKET RETURNS: MONTHLY STATISTICS.							
PANEL A: G7							
	CAN	FRA	DEU	ITA	JPN	GBR	USA
Mean	0.570	0.650	0.570	0.560	0.230	0.530	0.710
StDev	0.417	0.518	0.495	0.582	0.490	0.385	0.362
Skew	-0.959	-0.534	-0.987	-0.550	-0.179	-1.670	-1.211
Kurt	5.930	5.353	5.645	4.299	3.776	7.660	8.741
PANEL A1: Correlation Matrix							
	CAN	FRA	DEU	ITA	JPN	GBR	USA
CAN	1.000						
FRA	0.486	1.000					
DEU	0.485	0.737	1.000				
ITA	0.427	0.624	0.716	1.000			
JPN	0.389	0.495	0.485	0.423	1.000		
GBR	0.563	0.672	0.678	0.615	0.519	1.000	
USA	0.627	0.697	0.797	0.597	0.557	0.795	1.000
PANEL B: non-G7							
	AUS	BEL	DNK	IRL	SWE	CHE	RSA
Mean	0.680	0.650	0.810	0.810	0.990	0.670	0.150
StDev	0.664	0.442	0.458	0.556	0.534	0.439	0.479
Skew	0.153	-0.672	-0.662	-1.950	-0.599	-0.915	-1.146
Kurt	7.110	6.367	5.550	8.790	5.245	6.812	6.864
PANEL B1: Correlation Matrix							
	AUS	BEL	DNK	IRL	SWE	CHE	RSA
AUS	1.000						
BEL	0.480	1.000					
DNK	0.541	0.575	1.000				
IRL	0.547	0.683	0.570	1.000			
SWE	0.493	0.620	0.576	0.664	1.000		
CHE	0.495	0.692	0.638	0.663	0.681	1.000	
RSA	0.481	0.458	0.452	0.513	0.542	0.483	1.000

Notes: This table reports the mean, standard deviation, skewness and kurtosis values of the equity market returns for the G7 and non-G7 countries. PANELS A1 and B1 reports the correlation matrix for the G7 and non-G7, respectively. Monthly equity returns are computed from OECD Share Price Indexes. Sample: April 1985-December 2014.

5 A comparison of financial integration indicators

Figure 2 reports the equity market integration patterns generated by the unconditional correlation, 1st PC and R-square for the G7 (left panel) and Non-G7 (right panel). Our results suggest that the basic unconditional correlation and the two recently introduced PCA-based measures give rise to almost identical integration dynamics. Two differences are noteworthy: (i) the R-square is always above the other two indicators and (ii) the R-square tends to be more stable over time.¹⁹ Notice also that all the indicators generate a stable degree of integration when the dispersion among the correlation coefficients is low (i.e., post-

¹⁹We stress that the result is mainly driven by the fact that (in each window) the selected PCs explain a large part of returns' variation (i.e. around 90%).

Lehman period). By accounting for stochastic interdependence, in the spirit of [Ball and Torous \(2006\)](#), similar conclusions can be drawn (see [Figure 3](#)).

Figure 2: EQUITY MARKET INTEGRATION PATTERNS *Notes:* This figure reports the equity market integration dynamics generated by the unconditional correlation coefficient (black line), R-Square (blue line) and 1st PC (orange line) for the G7 (left panel) and non-G7 (right panel). The unconditional correlation, R-Square and 1st PC are computed using a rolling window of 60 months. The gray shaded area depicts the dispersion of bilateral unconditional correlation coefficients within each rolling window. Sample: April 1985-December 2014.

Figure 4 plots the equity market integration dynamics generated by the employed volatility- and heteroskedasticity-adjusted measures (i.e. Forbes-Rigobon correlation, DCC-GARCH, BEKK, Conditional Beta). Even if adjusted for volatility, the underlying trend of all these indicators seems to be similar to those reproduced in [Figures 2 and 3](#) (see [Figure 4, Panel A](#)). This is clear also from [Figure 4 \(Panel B\)](#) which plots the trend – extracted via a standard Hodrick-Prescott filter – for all these indicators. The filtered indicators exhibit a S-shaped trend, although with some differences among groups (see [Figure 4, Panel B](#)). Overall, we observe an increase in the trend from the mid-1990s, and a drop in the post-Lehman period. This result supports the stylized facts reported in [Figure 1](#) showing that in the aftermath of the subprime crisis a drop in international trade among countries occurred.

Results reported in [Figure 4](#) suggest the following. First, the use of both set of measures does not generate relevant long-run differences in the equity market integration process.

ASI-ADJUSTED MEASURES

Figure 3: EQUITY MARKET INTEGRATION PATTERNS *Notes:* This figure reports the equity market integration dynamics generated by the unconditional correlation coefficient (black line), R-Square (blue line) and 1st PC (orange line) for the G7 (left panel) and non-G7 (right panel). All measures account for stochastic interdependence using the model proposed by Ball and Torous (2006) and are computed using a rolling window of 60 months. Sample: April 1985-December 2014.

Second, although the trend is similar, by accounting for volatility a higher degree of heterogeneity among indicators emerges. All these volatility-adjusted measures are much more volatile than the measures plotted in Figures 2 and 3. This because they capture periods of higher uncertainty, which of course are characterized by higher volatility.²⁰

Generally, our findings allows us to understand if a common equity market integration trend exists. As aforementioned, all the proposed measures suggest that after slowing down during crisis-period at the end of the 90's and beginning of 00's the equity market integration picked up again in the period 2004-2008 and flattened (or slightly decreased) in the aftermath of the subprime crisis.

However, the detected common trend may be not sufficient. For instance, for an agent interested in investing in international markets or for a policymaker involved in fixing specific policy targets. It is thus crucial to have insights on the cyclicity of the pattern, especially if

²⁰Our results are robust to: (i) the use of a different number of PCs; (ii) different window-lengths (e.g. 48 or 72 months); (iii) the inclusion of additional countries in each group; (iv) using the covariance matrix in performing the PCA; (v) different time periods; (vi) using asymmetric specifications in the GARCH. Some of these robustness checks are reported in Appendix B. For brevity's sake we only report the results for the G7 group.

PANEL A: VOLATILITY- AND HETEROSK.-ADJUSTED MEASURES
G7 NON-G7

PANEL B: VOLATILITY- AND HETEROSK.-ADJUSTED MEASURES (HP-FILTERED)
G7 NON-G7

Figure 4: EQUITY MARKET INTEGRATION PATTERNS *Notes:* This figure depicts the equity market integration pattern – generated by volatility- and heteroskedasticity adjusted measures – for the G7 (left panel) and non-G7 (right panel) along with the one generated by the standard unconditional correlation (black line). The Forbes-Rigobon correlation (brown line) is computed using a rolling window of 60 months (i.e. 5 years). DCC-GARCH (green line) and BEKK-GARCH (violet line) are the average bilateral correlation coefficients obtained from applying an ARMA(1,1)-DCC-GARCH and ARMA(1,1)-BEKK-GARCH model, respectively. Conditional Beta (turquoise line) is the average regression coefficient between the country index returns and the S&P 500 from a bivariate ARMA(1,1)-BEKK-GARCH model. Panel B report the trend component – obtained via a standard Hodrick-Prescott filter (with $\lambda = 14,400$) – of the equity market integration patterns Sample: April 1985-December 2014.

they look at the short- and medium-run. For this purpose an evaluation is needed to compare financial integration indicators' effectiveness. We address this issue in the next section by

relying on most recent IBC studies showing that the presence of moderate risk-sharing (i.e., non-segmented markets) is coupled with a sizable RER volatility.

6 Financial integration, international risk-sharing and real exchange rate volatility

The issue on whether all these indicators – introduced in Section 3 and plotted in Section 5 – really capture the cross-country equity market integration pattern is still open. We address this point by examining the relationship between the RER volatility and each of the employed integration measures. Precisely, we measure the average correlation between the indicators plotted in Figures 2-4 and the volatility of the RER. In this respect, we rely on the recent macro-finance literature suggesting that the presence of a certain amount of risk-sharing (i.e. full financial integration) is necessary to reproduce the RER volatility observed in the data over the last two decades (Kollmann (2009); Kollmann (2015); Colacito and Croce (2010); Colacito and Croce (2013); Donadelli and Paradiso (2014a); Caporale, Donadelli, and Varani (2015)). For example, Kollmann (2015) (see Table 1) shows that a long-run risk model with recursive preferences and efficient risk sharing is able to reproduce high RER volatility, whereas the same model with financial frictions exhibits lower RER volatility. Loosely speaking, according to this IBC literature, if the proposed indicator is meant to measure the level of integration, then it should be increasing during period of increasing RER volatility. We stress that this simple approach allows us also to evaluate the performance of the proposed financial integration measures.

Table 3 reports the average correlation between the RER volatility and all the financial indicators. Correlations are computed over two different periods: (i) full period; (ii) crisis period. To avoid any possible non-stationarity issues and meet the needs of investors or policymakers, both series are Hodrick-Prescott filtered in order to isolate the cyclical component.

The results are straightforward: (i) regardless of the analyzed period, the standard unconditional correlation performs well and gives, in the worst case, the same correlation value of more sophisticated integration measures; (ii) the volatility-adjusted measures perform poorly – if compared to the others – suggesting that by accounting for changes in volatility we may add noise, which in turn affects the performance (see also Longin and Solnik (2001) and Forbes and Rigobon (2002)). The results hold across both group of countries (i.e., G7 and Non-G7).

Table 3: AVERAGE CORRELATIONS: RER VOLATILITY VS. MEASURED INTEGRATION

	Full Period		Crisis Period	
	G7	Non-G7	G7	Non-G7
Uncond. Correlation	0.166	0.173	0.578	0.538
R-square	0.174	0.110	0.479	0.470
1st PC	0.175	0.177	0.582	0.541
Correlation (ASI)	0.193	0.145	0.590	0.521
R-square (ASI)	0.136	0.149	0.474	0.466
1st PC (ASI)	0.199	0.147	0.591	0.523
Forbes-Rigobon Corr	0.056	0.086	0.203	0.251
DCC-GARCH	0.037	0.166	0.127	0.371
BEKK-GARCH	0.018	0.150	0.140	0.315
Conditional Beta	-0.043	0.173	0.080	0.278

Notes: This Table reports the average correlation between the RER volatility and the proposed integration measures. Correlation coefficients are estimated using a rolling sample of 60 months. In order to detect the cyclical component, both RER volatility series and integration indexes are Hodrick-Prescott filtered (with smoothing parameter $\lambda = 14.400$). Average correlation is computed over two different periods: (i) Full period (1995-2014); (ii) Crisis Period (2007-2014). For the G7 group, the USD is used as benchmark currency. For the non-G7 group the Swiss Franc is used as benchmark.

7 Concluding remarks

The understanding of the financial integration process is a key aspect for policymakers, investors and consumers, being their decisions (i.e. fixing policy targets, asset allocation, consumption smoothing) affected by the degree of global integration. In this respect, financial integration has received an enormous amount of attention in the international finance literature and its evolution is still at the center of the academic and policy debate. As there are many possible measures of financial integration, it is natural to ask if they all provide similar information. To this end, this paper compares and evaluates the financial integration pattern produced by a battery of different indicators proposed in the literature over the last decades. In particular, we rely on: (i) the standard unconditional correlation; (ii) two PCA-based measures and (iii) a bunch of well-known volatility-and heteroskedasticity-adjusted measures. Three new indicators are also introduced: (i) a volatility-adjusted measure relying on main international financial crises episodes and (ii) two PCA-based measures with stochastic interdependence. Moreover, to be sure that our results are robust with respect to the chosen sample, integration is investigated on two different groups of countries: G7 (i.e. a group formed by homogeneous countries) and non-G7 (i.e. a group of economies with a large variety of sizes and degrees of openness). Results, for both groups of countries, suggest that: (i) the unconditional correlation and the two measures based on the PCA give rise to very similar equity market integration patterns; (ii) volatility-and heteroskedasticity-adjusted measures, including the newly introduced indicators, produce high volatile patterns; (iii) all measures exhibit a very similar trend.

To evaluate the performance of the proposed indicators, we relate them with the RER volatility. Our simple empirical strategy is based on recent International Business Cycle studies showing that to an increase in risk-sharing (i.e. financial integration) corresponds an increase in the RER volatility. As a first attempt, we compute the average correlation between the RER volatility and the set of equity market integration patterns. Our numbers suggest that the standard unconditional correlation performs as well as more sophisticated

measures. Therefore, the dynamic unconditional correlation seems to capture equity market integration patterns rather well. This represents an important and unexpected result, since a branch of the empirical financial literature is trying to build more and more sophisticated measures without a clear understanding on what they are really capturing. We acknowledge that the proposed evaluation approach relies on a very simple and intuitive economic idea, but it constitutes a first attempt in this direction and gives interesting and encouraging results.

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A Data

SAMPLE:

G7: Canada, France, Germany, Italy, Japan, United Kingdom and United States

Non-G7: Australia, Belgium, Denmark, Ireland, Sweden, Switzerland, and South Africa

OECD DATA:

Monthly Monetary and Financial Statistics (MEI): Share prices

Share Price Indices are usually calculated by the stock exchange, although occasionally agencies such as central banks will compile them. Monthly data are averages of daily quotations, quarterly and annual data are averages of monthly figures. The Main Economic Indicator share indices are targeted to be national, all-share or broad, price indices and use the closing daily values for the monthly data, normally expressed as simple arithmetic averages of the daily data.

Real Exchange Rate

The real exchange rate, ϵ , is defined as $\epsilon = E \cdot \frac{P}{P^*}$, where $E = F/1D$ is the nominal exchange rate and indicates how much foreign currency (F) can be obtained with one unit of the domestic currency ($1D$). P = level price of domestic country; P^* = level price of foreign currency. In the G7 group the US\$ is assumed to be the benchmark currency (domestic country), whereas for the Non-G7 the benchmark currency is the *Swiss Franc*. All data for E and CPI for various countries are taken from Federal Reserve Economic Data (FRED).

B ROBUSTNESS

Figure B.1: ROBUSTNESS CHECKS ON EQUITY MARKET INTEGRATION PATTERNS (G7) *Notes:* The top left (right) panel depicts the unconditional correlation coefficient, R-Square and 1st PC when using rolling windows of length 36 (96) months. The mid left panel depicts the variation explained by the 1st and 2nd principal component while the remaining two measures are not modified. The mid right panel depicts R-Square and 1st PC if the PCA is applied using the covariance matrix of index returns instead of the correlation matrix. In the bottom left panel the measures DCC-GARCH, BEKK-GARCH and Conditional Beta were calculated using the BIC criterion to determine the optimal p and q in AMRA(p,q) and the Forbes-Rigobon Correlation was estimated using a one-year variance correction δ . The bottom right panel depicts ADCC-GARCH, ABEKK-GARCH and Conditional Beta assuming an asymmetric volatility model.

C THE R-SQUARE VS. THE 1ST PC: ADDITIONAL INSIGHTS

I. THE EMPIRICAL EVIDENCE

G7

x	(%) var explained by	Mean	Mean	R-square from regression on						
	first x PCs	Adj. R-square	R-square	x global factors						
PANEL (A): G7				CAN	FRA	DEU	ITA	JPN	GBR	USA
1	65.0%	64.9%	65.0%	48.3%	71.2%	74.7%	61.7%	44.5%	74.9%	79.5%
2	74.4%	74.3%	74.4%	73.6%	74.7%	82.6%	78.2%	55.8%	75.0%	81.1%
3	83.3%	83.1%	83.3%	91.8%	74.8%	82.6%	78.2%	98.3%	75.9%	81.5%
PANEL (B): Non-G7				AUS	BEL	DNK	IRL	SWE	CHE	RSA
1	62.7%	62.6%	62.7%	50.6%	67.2%	60.8%	71.2%	69.2%	72.0%	48.2%
2	72.1%	72.0%	72.1%	68.4%	75.5%	62.4%	72.1%	69.7%	78.2%	78.5%
3	79.8%	79.6%	79.8%	96.0%	75.6%	66.5%	72.1%	74.1%	78.4%	96.1%

Table C.1: ADDITIONAL EVIDENCE: THE R-SQUARE VS. THE 1ST PC. *Notes:* Volosovych's 1st PC and the *R-square* yield exactly the same results (see columns 2 and 4). The calculations are based on the whole sample period using the correlation matrix of G7 market index returns.

II. ON THE RELATION BETWEEN THE R-SQUARE AND THE 1ST PC

The following example illustrates that **R-square** and **1st PC** give rise to almost identical results.²¹ The following calculations are based on the procedure presented in Section 3.2. For simplicity, assume $N = 2$ and $K = 1$. That is, we have two countries with one global factor driving the individual returns r_i , $i = 1, 2$. $r_i = (r_{i1}, \dots, r_{iT})'$ being a vector of past T returns for country i . The correlation matrix between the countries is given by

$$P = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \quad (C.1)$$

with eigenvalues $\lambda_1 = 1 + \rho$, $\lambda_2 = 1 - \rho$, and corresponding eigenvectors $v_1 = (1, 1)'$, $v_2 = (1, -1)'$. Assume that $\rho < 0$. Then, the proportion of variance explained by the first principal component is given by

$$\text{prop. of var. explained by 1st PC} = \frac{\lambda_1}{\lambda_1 + \lambda_2} = \frac{1}{2}(1 + \rho), \quad (C.2)$$

where $\rho = r_1' r_2 / \sqrt{(r_1' r_1)(r_2' r_2)}$. Following Eq. (1), the corresponding global factor is defined as $f_1 = r_1 + r_2$. Regressing returns r_i on f_1 according to eq. (2) yields

$$R_i^2 = \frac{r_i' f_1 (f_1' f_1)^{-1} f_1' r_i}{r_i' r_i}. \quad (C.3)$$

Substituting f_1 and rearranging the above equation gives $R_i^2 = \frac{1}{2} \left(1 + \frac{r_1' r_2}{\sqrt{(r_1' r_1)(r_2' r_2)}} \right)$. This simple illustration confirms that the cross-country average R-square measures exactly the same information as the proportion of variance explained by 1st PC in Eq. (C.2). Please note that in general, for $N > 2$, $R_i^2 \neq R_j^2$. However, its cross-country average still corresponds to the proportion of variance explained as shown in Jong and Kotz (1999) and illustrated in Table C.1.

²¹Since the adjusted R-square is simply a modified version of R-square that has been adjusted for the number of predictors in the regression model it will also provide almost identical results.