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Abstract

This paper investigates the nature of shocks across international equity markets and evaluates the shifts in their comovements at a business-cycle frequency. Using an "identification through heteroskedasticity" methodology, we compute the impact coefficients on the common and country-specific shocks to stock returns. We then establish three key results regarding the recent comovement amongst returns. First, across all indices, persistent high-volatility spells always coincide with macroeconomic slowdowns. This confirms that market volatility increases as a result of shifts in the perception of macroeconomic risk. Second, there is a rise in the observed responses of international stock returns to common shocks during turbulent periods; such increase is largely attributable to bigger shocks (heteroskedasticity of fundamentals) rather than to breaks in the transmission mechanism or increased structural interdependence between markets. This holds for the Great Financial Crisis too. Third, since the late 1990s returns have been hit more often by high-volatility common shocks, likely because of larger and more persistent macroeconomic disturbances.

Keywords: International equity markets; Volatility; Regime switching; Structural transmission.
JEL Codes: C32, C51, G15.

1 Introduction

Asset prices and economic fluctuations are linked. A key insight of empirical finance is that the equity market's ability to bear risk varies over time, higher in good times, lower in bad times. As a consequence, market returns tend to be serially correlated and heteroskedastic. More precisely,

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returns experience more or less prolonged spells of high volatility. The market prices of risk vary over time, and as a result of their adjustment to new information, they induce time variation in the volatility of returns. Several studies document that the variability of returns tends to be higher during downside or "bear" markets than during upside or "bull" markets. A closely associated phenomenon regards market correlations: they too seem to vary over time and to rise particularly around episodes of financial distress. This has led some observers to argue that times of distress witness contagion, i.e., propagation of shocks from their epicenter towards other financial markets (see King and Wadhwani, 1990; Lee and Kim, 1993). A particularly relevant case is that of comovements between international equity market indices.

This paper identifies shocks across international stock markets and empirically evaluates the nature of shifts in their comovements at a business-cycle frequency. Figure 1 provides some background to our investigation. It shows the cross-country average correlation of monthly returns between six advanced-economy equity markets (USA, Japan, UK, France, Germany, Canada) and an equally-weighted global index.[1] The correlations are computed between 1970 and early 2016 on a rolling 30-month window. The black marks on the x-axis denote periods during which weighted real GDP growth (computed with respect to the same quarter of the previous year) in the six countries was below 1%, whereas the shaded areas indicate NBER-dated recessions in the US. The GDP data show that there is a remarkable synchronization of downturns between the US and the other countries. However, some further regularities emerge from the chart, particularly relevant given the monthly frequency of our data. First, international equity correlations display a clear tendency to rise and remain high around notable episodes of high volatility and financial turbulence, such as 1987, 1997-1998, 2000-2002 and 2008 to 2010. Second, macroeconomic downturns too tend to accompany the increases in correlations, and US recessions always lead slowdowns in the rest of the countries. In those instances international markets seem to move more closely with the US.[2] Third, correlations climbed from around 0.65 in the late 1990s and now appear to have plateaued at a permanently higher level close to 0.9 after the Great Financial Crisis (see also Morana and Beltratti, 2008). All this seemingly points to some structural change having occurred after 1995, either in the transmission or the origination of shocks. However, focus on correlation coefficients might be misleading. In the context of a risk factor model, it is straightforward to show that correlations increase with betas and factor volatilities and decrease with idiosyncratic volatility, everything else being equal. Past studies claimed (see Schwert, 1989a, b, for instance) that market volatility, while varying over time, shows no long-term trend. Therefore, the dynamics of simple measures of comovement such as correlations could be driven either by changes in the size of shocks, or be the result of structural

[1] A very similar behaviour emerges when using a value-weighted index such as the MSCI World.
[2] See Baele and Inghelbrecht (2009), Bekaert et al. (2014) and Pukthuanthong and Roll (2009).

shifts in the sensitivity of returns to systematic disturbances.[3] This is the main focus of our investigation. We employ a parsimonious approach to identify the regime shifts in the comovement across equity indices at business-cycle frequency. The key question is: Are comovements indeed caused by changes in the transmission of shocks hitting the markets, or rather the outcome of changing market volatility?

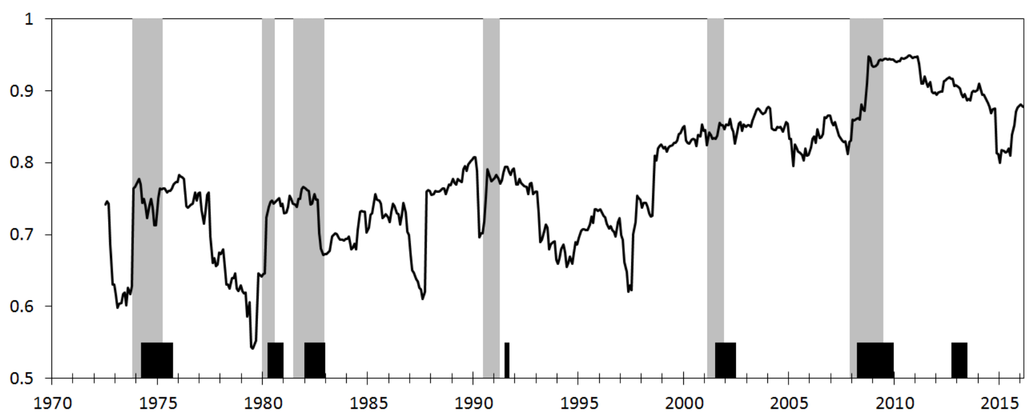

Figure 1. Conditional average correlation across stock market returns

The line represents the cross-market average of the 30-month rolling correlation of each country index with an equally-weighted index of the stock market returns across the US, Japan, UK, France, Germany, Canada. Lower black marks denote periods during which the weighted average of the quarterly GDP growth rate, compared to the same quarter of the previous year and seasonally adjusted, was below 1%; shaded bars indicate NBER-dated recessions of the US economy.

We extend to a stock market context the methodology first employed by Gravelle, Kirchian and Morley (2006) and Flavin et al. (2008, 2009). In contrast to those studies, our specification centers on one-factor models for international stock market indices, where the factor is represented by the return on the global portfolio, a well-diversified basket of international stocks. Also, as we are primarily concerned with developments at a business-cycle frequency, we use monthly data over 1970-2016. Conditional loadings therefore measure the sensitivity of returns to common and country-specific shocks. The parameters governing the transmission of shocks across markets are identified assuming that the volatility of shocks experiences regime shifts. However, we allow for the timing of changes in volatility to be fully endogenous. We posit that a latent variable (the 'state' of the economy) determines both the mean of output growth and the scale of stock return variances and covariances. This latent variable takes on one of an infinite set of values and is presumed to be determined by an unobserved Markov chain. This way, the probability of returns switching from

[3]Trecroci (2014) and Salotti and Trecroci (2014) estimate time-varying parameter models on US portfolios.

a regime of volatility and comovement to another, rather than constant, is made dependent on uncertainty about some underlying macroeconomic fundamental.

We hypothesize that systematic and return-specific disturbances switch between low-volatility and high-volatility states. The intuition that we exploit for the returns on any two indices is as follows. In the baseline scenario, an increase in the comovement between index returns could just reflect larger common shocks, hitting through invariant structural linkages. If this were the case, the coefficients linking the unexpected components of the two returns to the common shocks would both be larger during bad times or financial distress. We evaluate the interdependence between index returns by studying the ratio of the impact coefficients on the common shocks. Hence, in the abovementioned circumstances, they would both increase proportionally to the size of the common shocks, leaving their ratio approximately equal to its normal-times value. By contrast, financial market distress or a shift in underlying economic fundamentals might produce a break in the transmission of systematic shocks to the two returns. This would be a scenario of contagion or increased structural interdependence, and the ratio of impact coefficients would turn out to be higher during bad times than under normal times. We therefore exploit this intuition to test for increased structural interdependence (i.e., contagion) through the analysis of impact coefficients for the systematic shocks and by measuring whether their ratio changes significantly during periods of heightened market volatility.

The main innovations of this paper in relation to existing contributions are in our parsimonious methodology and our focus on equity returns at a business-cycle frequency. We extract the impact coefficients on common and country-specific shocks to international monthly returns in the context of a one-factor model. This reduces the number of hypotheses to be tested. The monthly frequency allows for a reasonable linkage between market volatility and business cycle developments. Moreover, we chose to work with stock market indices since they should display lower comovement than stocks trading on the same market. This also prevents various microstructure issues such as bid/ask bounce, irregular trading, measurement noise and stale pricing from affecting our results.

Despite using no direct information from business-cycle aggregates, our estimates shows that for all index pairs the most persistent high-volatility spells always coincide with recessions. This shows up in the correlations of our estimated probabilities of high volatility with measures of macroeconomic uncertainty and confirms that shifts in the regime of volatility and comovement of equity indices are likely the result of revisions of expectations about underlying macroeconomic conditions. Moreover, the observed increase in the correlation of international stock returns is by and large attributable to larger common shocks creating market turbulence (heteroskedasticity of fundamentals) rather than to increased structural interdependence (contagion) between markets. In the most recent part of the sample, all countries exhibit two major intervals in which systematic shocks show persistently high volatility: 1997-2003 and 2008-2013. These findings adverse to the contagion hypothesis suggest that while variances and covariances across markets do change over time, the spillover effects are essentially a function of the magnitude of common shocks rather than of breaks to the transmission mechanism. In other words, variances, covariances and correlations are both time and state varying. All these results have important implications for portfolio choices.

The remainder of the paper is organised as follows. The next Section provides a brief literature review. Section 3 sets out the methodology. In Section 4 we present estimation results and test for increased interdependence. Section 5 concludes.

2 Related literature

There is ample evidence on the persistence and heteroskedasticity of stock market returns, as well as on their volatility exhibiting switches at business-cycle frequencies (Schwert, 1989a, b; Ramchand and Susmel, 1998). It is straightforward to show that asset covariances and correlations rise as market volatility increases. According to a linear one-factor model, $R_t^i = \alpha^i + \beta_i F_t + \varepsilon_t^i$, the correlation between assets i and j can be simply written as

$$\rho_{ij} = \frac{\beta_i \cdot \beta_j \cdot \sigma_F^2}{\sqrt{\left(\beta_i^2 \cdot \sigma_F^2 + \sigma_{\varepsilon,i}^2\right) \cdot \left(\beta_j^2 \cdot \sigma_F^2 + \sigma_{\varepsilon,j}^2\right)}}, \tag{1}$$

where σ_F^2 is the variance of the structural factor and the σ_ε^2s those of return residuals (also, $\rho_{i,F} = \beta_i \frac{\sigma_F}{\sigma_i}$). The above implies that conventional estimates of the correlation between assets i and j are conditional on the factor variance σ_F. With invariant risk sensitivities, higher systematic risk translates into higher return correlation. This is the key reason why Forbes and Rigobon (2002) and others question the straight study of correlations and correlation tests for the measurement of contagion.

The notion that the shifts in volatility might be associated with revisions of market expectations about business conditions is increasingly accepted, but has not been investigated in depth. What seems to drive the changes in the market's valuation of expected cash flows are revisions in expected values of macroeconomic variables like GDP growth, industrial production, policy interest rates or even fiscal imbalances. These are likely to be the main cause also of observed shifts in market volatility (Hamilton and Lin, 1996; Ang and Bekaert, 2002).[4] Indeed, several contributions point out that during downturns correlations may increase as a result either of shifts in the perception of macroeconomic risk, or of changes in the structural transmission of shocks (Ang and Timmermann, 2012). However, a simple analysis of risk sensitivities (market betas) would not settle the issue,

[4]GARCH models have initially dominated this empirical literature. However, their appeal has subsequently declined as they cannot adequately capture the sudden shifts that are commonly observed in financial market data.

because of the failure of conventional betas to account for the effect of time-variation and various structural changes.[5]

There are several channels through which the business cycle could affect jointly market volatilities and the correlation between stock markets. For instance, at the onset of downturns macroeconomic uncertainty rises sharply, driving up both systematic and idiosyncratic risk. The business cycle of open economies may be driven by fundamental processes whose drift rates are jointly affected by changes in investment growth opportunities (Longin and Solnik, 1995; Ribeiro and Veronesi, 2002; Bekaert et al., 2007; David and Veronesi, 2013). As investors strive to learn the state of the global economy, their uncertainty fluctuates, thereby affecting the cross-covariances and correlations of asset returns. Excess volatility during bad times might be so obtained as a reflection of higher uncertainty.

An additional explanation for the observed changes in the correlation between stock indices relates to economic as well as financial integration. Technological and regulatory changes are often credited with deepening financial interlinkages amongst markets. *Ceteris paribus*, equity markets could be more synchronized, a phenomenon clearly shown in our Figure 1, as a result of greater correlation in their business cycles. This might happen if the fundamentals driving firm profitability and cash flows become more synchronized. However, even when countries become financially more integrated over time, factor exposures or factor volatilities may decrease rather than increase, as long as country-specific residual volatility is not zero (see Pukthuanthong and Roll, 2009 and the references therein). Indeed, increased comovement between asset returns under economic or financial distress may be driven by changes in the structural transmission of shocks across countries, or reflect a change in the size of underlying economic disturbances. The analysis of this scenario has been the subject of an extensive debate, commonly referred to as the contagion or shift-contagion literature (Forbes and Rigobon, 2002; Corsetti et al., 2005; Caporale et al., 2005; Gravelle et al., 2006).

There is a large body of empirical work testing for the existence of contagion. However, different methodologies have led to different results, making it difficult to draw unambiguous conclusions. One of the earliest approaches consists in analyzing the correlations between market indices for crisis and non-crisis periods and then test if there is a significant change in correlations across regimes. However, most of the traditional studies relying on this methodology (King and Wadhwani, 1990; Baig and Goldfajn, 1999) suffer from heteroskedasticity problems. Forbes and Rigobon (2002) employed a test that adjusted for the volatility-induced bias in correlations and found no evidence of contagion in a sample of stock market crises in the 1980s and 1990s. On the other hand, Corsetti et al. (2005) provide theoretical and empirical arguments suggesting that these conclusions tend to be sensitive to restrictions concerning the distribution and the transmission of the shocks. Fazio (2007) uses probit techniques to separate pure contagion from macroeconomic interdependence in the

[5] See Trecroci (2013) for a discussion.

propagation of crises. His results indicate limited evidence for contagion, especially at regional levels. More recently, Baele and Inghelbrecht (2009) and Bekaert et al. (2014)[6] perform comprehensive analyses using global- and local-factor models, finding that most of the variation in correlations is explained by volatility shocks and that there is little evidence of trends in return correlations.[7] Briere et al. (2012) and other studies test for globalization and contagion for different asset classes and across several markets using an ex ante definition of crises. Their results too confirm the instability of correlations but point to contagion on the equity markets as an artifact due to globalization, in line with Forbes and Rigobon (2002). Flavin et al. (2008, 2009) employed the methodology by Gravelle et al (2006) to study the channels of pure and shift contagion between currency and equity markets in East Asian and G-7 economies. They found little evidence of increased market interdependence in turbulent periods. In contrast, Flavin et al. (2010) reverse previous results and detect strong signs of both type of contagion.

As the results of existing literature appear far from conclusive, it is hard to adjudicate between these two hypotheses. First, the testing procedures of most existing studies depend heavily on the identification restrictions on which fundamental market linkages are based. The implied null hypothesis is therefore a joint test for no contagion and for the true factor specification. Second, test results depend substantially also on restrictions concerning the time variation in the structural and cyclical component of the factor loadings. Our aim is to revert to the simplest possible factor structure and thus we avoid imposing restrictions on the covariance structure of disturbances. Finally, interdependence and contagion imply an association between markets beyond what one would expect from economic fundamentals. However, most studies focus on returns computed at the daily or weekly frequency, thus making it hard to capture the exact nature of their interplay with the business cycle. This is why we focus on international equity returns and monthly data, which permit to purge returns of short-term noise and best capture the effects on markets of changes in the macroeconomic environment.

3 Econometric framework

In this section we outline our empirical model for the comovements between a country j's stock index and another country i's, or a global index w. A few related studies on interdependence have employed multivariate ARCH/GARCH frameworks or the Markov-switching model developed by Hamilton (1989). The latter permits to identify in an endogenous fashion the turning points in

[6]The former (see also Baele and Inghelbrecht, 2010) develop a volatility spillover model that decomposes total volatilities at the regional, country, and global industry level in a systematic and an idiosyncratic component. They also allow the exposures to global and regional market shocks to vary with both structural changes and temporary fluctuations in the economic environment.

[7]However, Bekaert et al. (2012) study interdependence around the 2007-2009 crisis, finding evidence of contagion, but only from domestic equity markets to individual domestic equity portfolios.

economic activity, thereby circumventing the issue of regime windows being assigned ex post. Our work stems from the approach by Gravelle et al. (2006), further employed by Flavin et al. (2008, 2009, 2010). Unlike previous approaches, the methodology we employ achieves identification of the shocks by exploiting estimates of the variance-covariance matrix to make inferences about each return's sensitivities to idiosyncratic and systematic disturbances. By definition, homoskedastic shocks would imply no change in interdependence between returns over time. On the contrary, with regime switching in the volatility of structural shocks, returns' sensitivities may be recovered using the measured changes in the interdependence between the countries, according to an "identification through heteroskedasticity" methodology (Sentana and Fiorentini, 2001; Rigobon, 2003). However, this paper departs from Gravelle et al. (2006) and Flavin et al. (2008, 2009, 2010) along three important dimensions. First, we study interdependence from a global perspective rather than on a bilateral basis. Most of the literature on contagion has looked at bivariate market linkages for country pairs, whereas we aim at capturing the impact of non-diversifiable risk by looking at comovements between individual countries' indices and well-diversified global portfolios. Second, we look at an extended and more recent sample and only to equity market data. Third, as we are interested in the comovement across equity indices at a business-cycle frequency, we employ monthly data.[8]

Our econometric approach stems from work by Ramchand and Susmel (1998) and Gravelle et al. (2006). Hamilton and Susmel (1994) showed that ARCH models are inadequate when the data are characterized not so much by persistent shocks but by structural breaks leading to switches between variance regimes. Ramchand and Susmel (1998) used a switching ARCH technique that tests for differences in correlations across variance regimes; they found that the correlations between the U.S. and other world markets are on average 2 to 3.5 times higher when the U.S. market is in a high variance state as compared to a low variance regime. Our approach adapts to a stock market context the methodology devised by Gravelle, Kirchian and Morley (2006) for the study of contagion between currency and bond market pairs. The technique can be applied to any pair of returns, but here we extend it to well-diversified international stock portfolios and a global stockmarket index. This represents a parsimonious way to analyze the international transmission of systematic shocks and allows to minimize the effects of idiosyncratic risk. Let R_t^{ej} denote the (log) excess return on stock index j, where $j = i, w$ throughout the paper. Excess returns are the sum of expected and surprise components as follows:

$$R_t^{ej} = \mathbb{E}\left[R_t^{ej}|\psi_{t-1}\right] + u_t^j \tag{2}$$

Here ψ is the information set, $\mathbb{E}\left[R_t^{ej}|\psi_{t-1}\right]$ is the expected return on index j in excess of the risk-free rate, and u_t^j is a forecast error. As the latter mainly reflects unexpected news on the

[8]Flavin et al. (2009) for instance study country pairs on weekly data.

return, forecast errors have zero mean and are uncorrelated over time (i.e., $\mathbb{E}\left[u^j_{t+k}\right] = 0$ for all $k > 0$). However, we assume they are contemporaneously correlated across indices: $\mathbb{E}\left[u^j_t u^{j'}_t\right] \neq 0$ for $j \neq j'$. This assumption in itself implies i) comovement across markets and ii) that the forecast error component of returns responds to common shocks (systematic risk), as well as to purely country-specific disturbances,

$$u^j_t = \beta^c_{jt} z^c_t + \beta_{jt} z^j_t \tag{3}$$

Here z^c_t represents the common shock, z^j_t is a country-specific disturbance, and β^c_{jt} and β_{jt} indicate the respective impact of shocks on returns, measured in terms of standard deviations. The country-specific shocks have zero mean and are uncorrelated both across time and with each other: $\mathbb{E}\left[z^j_{t+k}\right] = 0$ for all $k > 0$ and $\mathbb{E}\left[z_{jt} z_{j't}\right] = 0$.

In our variant of the model we focus on the correlation between the index returns of country i and those on an index w representing the world market portfolio [9]. To evaluate the degree of interdependence amongst stock indices and its relationship with volatility, we study the ratio between the impact coefficients on the systematic shocks. The intuition is as follows. For the return on any index i, an increase in its tendency to vary with the world market portfolio w could just signal larger common shocks z^c_t propagating through invariant market linkages. In this conventional case of interdependence (see Forbes and Rigobon, 2002), both β^c_{it} and β^c_{wt} will be larger during bad times or crises than under normal circumstances. Hence, they will both increase proportionally to the size of systematic shocks, leaving their ratio $\lambda_{i,w} = \beta^c_i / \beta^c_w$ approximately constant across macroeconomic states.

By contrast, let us suppose that, in line with some of the existing evidence (see for instance Corsetti et al., 2005), financial market distress or a shift in underlying economic fundamentals engender a change in the propagation of common shocks to the two indices. This would be the case of increased interdependence, "excessive" correlation, or contagion. This would also imply that the ratio $\lambda_{i,w}$ will be different during bad times than under good times. By measuring factor loadings on the common shocks and analyzing whether their ratio changes significantly during periods of economic and financial distress, we can test for interdependence versus contagion.

The covariance matrix of the forecast errors u^j_t can be written in terms of the β coefficients:

$$\Sigma_t = \begin{bmatrix} (\beta^c_{it})^2 + \beta^2_{it} & \beta^c_{it}\beta^c_{wt} \\ \beta^c_{it}\beta^c_{wt} & (\beta^c_{wt})^2 + \beta^2_{wt} \end{bmatrix} \tag{4}$$

One can therefore employ estimates of the covariance matrix to make inferences about β^c_{it} and β^c_{wt} and to test for shifts (increases) in the international interdependence of country i. The variances

[9] Of course, the same specification applies to any pair of country indices.

and covariances of the forecast errors have a correspondence with the vector of structural shocks:

$$var\left(u_t^i\right) = \left(\beta_i^c\right)^2 + \beta_i^2 \tag{5}$$
$$var\left(u_t^w\right) = \left(\beta_w^c\right)^2 + \beta_w^2 \tag{6}$$
$$cov\left(u_t^i, u_t^w\right) = \beta_i^c \beta_w^c \tag{7}$$

By definition, homoskedastic disturbances would imply no shifts in interdependence over time. By contrast, with regime switches in the volatility of structural shocks, the factor sensitivities may be identified based on the observed changes in the interdependence between the countries. Let us assume that common and country-specific shocks switch between low-volatility (L) and high-volatility (H) states. The two types of structural shock sensitivities can then be represented as follows:

$$\beta_{jt}^c = \beta_j^{cL}\left(1 - S_t^c\right) + \beta_j^{cH} S_t^c \tag{8}$$
$$\beta_{jt} = \beta_j^L\left(1 - S_t^j\right) + \beta_j^H S_t^j \tag{9}$$

where $S_t^j = \{0, 1\}$ are the latent regime variables governing the volatility state.

This scheme of "identification through heteroskedasticity" (Sentana and Fiorentini, 2001; Rigobon, 2003) becomes clear by writing the moments related to the H regime for each structural shock affecting the returns on i and w:

$$var\left(u_t^i | S_t^c = 1\right) = \left(\beta_i^{cH}\right)^2 + \left(\beta_i^L\right)^2 \tag{10}$$
$$var\left(u_t^w | S_t^c = 1\right) = \left(\beta_w^{cH}\right)^2 + \left(\beta_w^L\right)^2 \tag{11}$$
$$cov\left(u_t^i, u_t^w | S_t^c = 1\right) = \beta_i^{cH} \beta_w^{cH} \tag{12}$$
$$var\left(u_t^i | S_t^i = 1\right) = \left(\beta_i^{cL}\right)^2 + \left(\beta_i^H\right)^2 \tag{13}$$
$$var\left(u_t^w | S_t^w = 1\right) = \left(\beta_w^{cL}\right)^2 + \left(\beta_w^H\right)^2 \tag{14}$$

Combined with the three moments in (5)–(7) corresponding to low-variability regimes, these relationships identify the eight structural parameters in (8)–(9).

The model is closed by defining the probabilities of regime switching between low and high volatility,

$$\Pr\left[S_t^j = 0 | S_{t-1}^j = 0\right] = q^j \tag{15}$$
$$\Pr\left[S_t^j = 1 | S_{t-1}^j = 1\right] = p^j \tag{16}$$

Again in contrast with some of the existing literature, in which regime shifts are identified ex-post via ad hoc thresholds or anecdotal evidence, our methodology allows to endogenize the timing of changes in volatility. This is alternative to the traditional factor-model approach employed by Corsetti et al. (2005) in the context of higher-frequency returns: their tests measure the relative variability of common against country-specific factors. In such a framework, however, if the ratio of factor loadings during crises is not significantly different from its value during tranquil periods, there would be no contagion, regardless of the variance of country-specific disturbances. In any case, the impact of the latter on equilibrium returns is muted, thanks to diversification across countries. As a further consequence, our results do not suffer either from the biases described by Forbes and Rigobon (2002) and Corsetti et al. (2005), or from the errors-in-variables bias typical of standard factor model approaches.

Finally, we assume that there is a further, important channel through which the returns' forecast error can exhibit serially correlated dynamics. In line with evidence, for instance by Ferson and Harvey (1993) and Kim et al. (2004), we posit that this short-horizon predictability is the result of a risk premium that varies with the level of volatility in the stock market. Specifically, we assume that expected returns change over time and depend on the volatility regime of the common shock:

$$\mathbb{E}\left[R_t^{ej}|\psi_{t-1}\right] = \mu^{jL}\left(1 - S_t^c\right) + \mu^{jH} S_t^c \tag{17}$$

As in standard asset pricing theory, idiosyncratic shocks do not affect expected returns. Under the assumption of normality for the underlying structural shocks, we estimate the parameters via maximum likelihood using the Markov-switching approach pioneered by Hamilton (1989).[10]

4 Data and estimates

As we look at the interdependence between stock returns and business cycle developments, data at the monthly frequency over an extended time span represents the logical choice. The dataset consists of US-dollar denominated, total return indices over the period January 1970 - February 2016, provided by Morgan Stanley Capital International (MSCI) for 6 markets: USA, Japan, United Kingdom, France, Germany and Canada.[11] The US 1-Month Treasury Bill rate is used to compute excess returns. All indices are value-weighted and are obtained via Thomson Reuters Datastream. The global market portfolio is either the MSCI WORLD total return index, or an equally-weighted average of all countries in our sample.

Table 1 reports results from diagnostic tests on our return data. As is common with equity returns, there is strong evidence of nonnormality. The autocorrelation coefficients and, to a lesser extent, the Ljung-Box Q statistics, indicate the presence of significant autocorrelations in many

[10] We thank James Morley for making the Gauss code available to us.

[11] We have also estimated the model using local currency excess returns with qualitatively similar results.

instances, pointing to some short-term predictability of returns even at the monthly frequency. The two ARCH rows reveal significant autoregressive conditional heteroskedasticity for all the series, thus motivating the adoption of methods that account for the change in volatility. In the last row, we present standardised Likelihood Ratio statistics for the presence of Markov-switching behaviour in the returns (Hansen, 1992, 1996). The statistics tests the hypothesis of linear variance against the alternative of Markov switching. The results strongly and everywhere reject the null. We therefore proceed and maintain the assumption of heteroskedastic, regime-switching volatility, in keeping with most of the literature (see also Hamilton and Susmel, 1994).

	USA	Japan	UK	France	Germany	Canada	*MSCIW*	*EWW*
Mean	0.52	0.58	0.42	0.48	0.51	0.46	0.49	0.50
SD	4.44	6.03	6.14	6.53	6.40	5.75	4.31	4.63
SK	-0.65	-0.01	0.31	-0.45	-0.63	-0.85	-0.75	-0.76
K	2.45	0.70 could	5.49	1.45	1.77	3.40	2.14	2.50
JB	178.91***	11.30***	705.89***	67.01***	108.38***	334.82***	158.04***	198.03***
DH	56.70***	11.27***	258.19***	31.85***	39.29***	75.04***	48.03***	54.95***
ρ_1	0.05	0.11	0.08	0.08	0.03	0.07	0.11	0.11
Q(1)	1.51	6.77***	3.62*	3.49*	0.68	2.46	6.45	6.41
Q(2)	3.69	13.83***	9.44 *	11.86**	6.57	4.22	10.84**	12.81**
ARCH(1)	17.39***	10.31***	16.63***	10.84***	17.17***	8.50***	17.30***	14.75***
ARCH(2)	25.01***	17.19***	33.56***	26.74***	26.77***	12.44**	27.79***	21.99***
LR-M	4.83***	4.07***	5.25***	5.34***	5.63***	5.13***	5.22***	5.22***

Table 1 - Diagnostic tests for stock returns

$Mean$ is the sample average, SD the standard deviation, SK the skewness coefficient, K the kurtosis coefficient; JB and DH refer to the tests of normality by Jarque and Bera (1987) and Doornik and Hansen (1994), respectively; ρ_1 is the first-order autocorrelation coefficient; $Q(k)$ is the Ljung and Box (1978) statistic for no residual autocorrelation up to lag k; $ARCH(k)$ is the test for ARCH effects at k-order lags (Engle, 1982); $LR-M$ is the standardized likelihood ratio statistics for the Markov-switching parameter based on Hansen (1992, 1996). *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 2 reports estimates of some model parameters for common structural shocks (measured in standard deviations). For each country, we report the coefficients that quantify the impact of shocks common to a world portfolio (either the value-weighted $MSCIW$ or the equally-weighted index EWW) and to the country index at hand. In the bottom panel of the table we also report estimates from bilateral models for the three most important markets. Estimated parameters refer to the low-volatility state (β_i^{cL}, β_w^{cL}) and to the high-volatility regime (β_i^{cH}, β_w^{cH}).

We observe several interesting patterns. First, as expected, in each country the responses of returns to high-volatility common shocks are markedly larger than those to low-volatility disturbances. The estimated values of high-volatility impact coefficients also tend to vary more widely across markets. Of course, only the statistical analysis of their ratio can tell whether and how impact coefficients vary across volatility regimes. In the simple case of interdependence (only the size of shocks increases), the ratio would not change significantly across regimes, whereas with a strengthened transmission of shocks across countries, i.e., contagion, the ratio would go up. Second, the estimates of impact coefficients for individual countries are very similar no matter whether one employs the MSCIW or the EWW basket as the reference portfolio. This means that our identification scheme captures the systematic components of shocks to volatility in a fashion that is remarkably consistent across portfolios and markets.

Third, the impact of shocks to returns on the US and UK indices, the deepest markets, tend to be smaller during normal times than those on most other countries. Index returns for Germany, Canada and France markets are at the opposite end of the shock distribution. Under high-volatility regimes those differences disappear. Fourth, when bilateral models are estimated, the size of impact coefficients is on average significantly lower, particularly during normal times. This occurs likely because the returns on world market portfolios have a larger exposure to systematic risks.

	β_i^{cL}	β_w^{cL}	β_i^{cH}	β_w^{cH}	λ
Index Returns (MSCIW Portfolio)					
USA	2.65 (0.21)	2.78 (0.26)	5.39 (0.35)	5.71 (0.33)	1.01
Japan	3.63 (0.35)	3.14 (0.14)	4.27 (0.37)	5.89 (0.40)	1.59
UK	2.80 (0.22)	2.87 (0.25)	5.73 (0.43)	5.83 (0.44)	1.01
France	3.71 (0.24)	2.61 (0.17)	7.29 (0.48)	5.83 (0.40)	1.14
Germany	3.66 (0.18)	2.37 (0.15)	7.64 (0.01)	5.75 (0.01)	1.16
Canada	4.1 (0.01)	2.26 (0.21)	9.07 (0.30)	4.98 (0.58)	1.00
Index Returns (EWW Portfolio)					
USA	2.49 (0.17)	2.53 (0.26)	5.57 (0.41)	5.92 (0.44)	1.05
Japan	3.40 (0.27)	3.30 (0.18)	4.25 (0.437)	6.32 (0.40)	1.53
UK	4.10 (0.16)	3.51 (0.17)	12.13 (1.79)	8.00 (1.15)	1.30
France	3.72 (0.27)	3.08 (0.19)	7.46 (0.47)	6.31 (0.49)	1.02
Germany	3.86 (0.16)	2.81 (0.15)	8.42 (0.70)	6.26 (0.54)	1.02
Canada	3.83 (0.22)	2.50 (0.23)	8.73 (0.70)	5.69 (0.44)	1.00
Index Returns (Bilateral)					
USA/Japan	1.72 (1.10)	1.61 (1.38)	4.66 (0.58)	4.20 (0.61)	1.04
USA/UK	2.20 (0.32)	2.50 (0.42)	5.61 (0.572)	6.40 (0.76)	1.00
Japan/UK	1.83 (0.28)	2.66 (0.04)	3.94 (0.230)	5.78 (0.44)	1.01

Table 2 - Estimates of impact coefficients for common shocks

Estimates of model parameters (expressed in terms of standard deviations) for common structural shocks. For each country, we report the estimated impact of shocks common to a world portfolio (either the value-weighted $MSCIW$ or the equally-weighted index EWW) and to the country index at hand. The bottom panel of the table reports estimates from bilateral models. Parameters refer to the low-volatility state (β_i^{cL}, β_w^{cL}) and to the high-volatility regime (β_i^{cH}, β_w^{cH}). Standard errors are reported in parentheses.

To determine whether impact coefficients remain proportional across volatility regimes, let us define by $\lambda = \left|\frac{\beta_i^{cH}\beta_w^{cL}}{\beta_i^{cL}\beta_w^{cH}}\right|$ the absolute value of the ratio of the impact coefficients in the high volatility regime to the ratio of the impact coefficients in the low volatility regime. The last column of Table 2 reports its values as implied by our estimates: in most cases the ratio is very close to one, pointing to the changing size of common shocks as the main reason for closer comovements. However, there are a few cases in which λ rises further above one. To check whether the ratios of estimated impact coefficients are significantly above one, we follow Gravelle et al. (2006) and construct a simple likelihood ratio test as follows:

$$\mathbf{H}_0 : \frac{\beta_1^{cH}}{\beta_2^{cH}} = \frac{\beta_1^{cL}}{\beta_2^{cL}} \text{ against } \mathbf{H}_1 : \frac{\beta_1^{cH}}{\beta_2^{cH}} \neq \frac{\beta_1^{cL}}{\beta_2^{cL}}$$

The implied null hypothesis is that there is no change in the ratio during periods of heightened market volatility, i.e., there is no contagion. The test statistic has a $\chi^2(1)$ distribution under the null hypothesis. Table 3 contains the test's results. The statistic is very small in all cases, rising somewhat in the specifications including Japan. However, the associated p-value confirms that we cannot reject the null hypothesis of no contagion for all the indices pairs. This strong result is in line with the strand of evidence started by Forbes and Rigobon (2002). This evidence supports the notion that the closer comovement we observe in correspondence of the most recent financial crises is essentially the result of more sizeable common shocks hitting the markets, rather than the effect of increased structural interdependence.

	Stat	$p - value$
Index Returns (MSCIW Portfolio)		
USA	0.008	0.926
Japan	0.405	0.524
UK	0.006	0.936
France	0.111	0.739
Germany	0.131	0.718
Canada	0.003	0.953
Index Returns (EW Portfolio)		
USA	0.039	0.843
Japan	0.370	0.543
UK	0.226	0.634
France	0.018	0.892
Germany	0.018	0.892
Canada	0.001	0.971
Index Returns (Bilateral)		
USA/Japan	0.033	0.856
USA/UK	0.003	0.953
Japan/UK	0.008	0.929

Table 3 - LR test

The implied null hypothesis is that there is no change in the ratio during periods of heightened market volatility, i.e., there is no contagion. The test statistic has a $\chi^2(1)$ distribution under the null hypothesis (p-values are reported in parentheses).

To gain further insight, in Figures 2-4 we plot the filtered probabilities of high-volatility regimes for common shocks. As before, small black marks on the x-axis denote periods of below-1% GDP growth in the G7 countries, while the shaded areas indicate NBER-dated recessions in the US. The model for the US shows the highest occurrence of high-volatility periods, with Canada the lowest one, but overall similarities in the patterns displayed are striking. Post mid-1990s, all countries exhibit two major intervals of persistent high volatility of systematic shocks: 1997-2003 and 2008-2013. These periods seem the culmination of financial cycles (Schularick and Taylor, 2012; Juselius et al., 2016). Both the average filtered probability as well as the duration of the high-volatility regime (not shown but available on request) are significantly higher after 1996. The charts also show that for all index pairs the timing of persistent high-volatility spells coincides with that of GDP slowdowns. In particular, the start of US recessions always coincide with a switch to a persistent high-volatility regime. US recessions always precede downturns elsewhere. These findings are in line, inter alia, with those in Corradi et al. (2013) and Kim and Nelson (2014) and are particularly valuable, as we model the interdependence amongst returns by drawing no information from business-cycle variables. Our estimates of common shocks confirm that the probability of switching from low to high volatility and thus comovement is dependent on underlying business-cycle conditions, with the latter nicely summarized by NBER-dated peaks and troughs. Therefore, shifts in volatility regimes are likely to occur because of widespread revisions to expectations about underlying macroeconomic fundamentals. This straightforward evidence points to the presence of cyclical variation in the co-movement across equity indices.

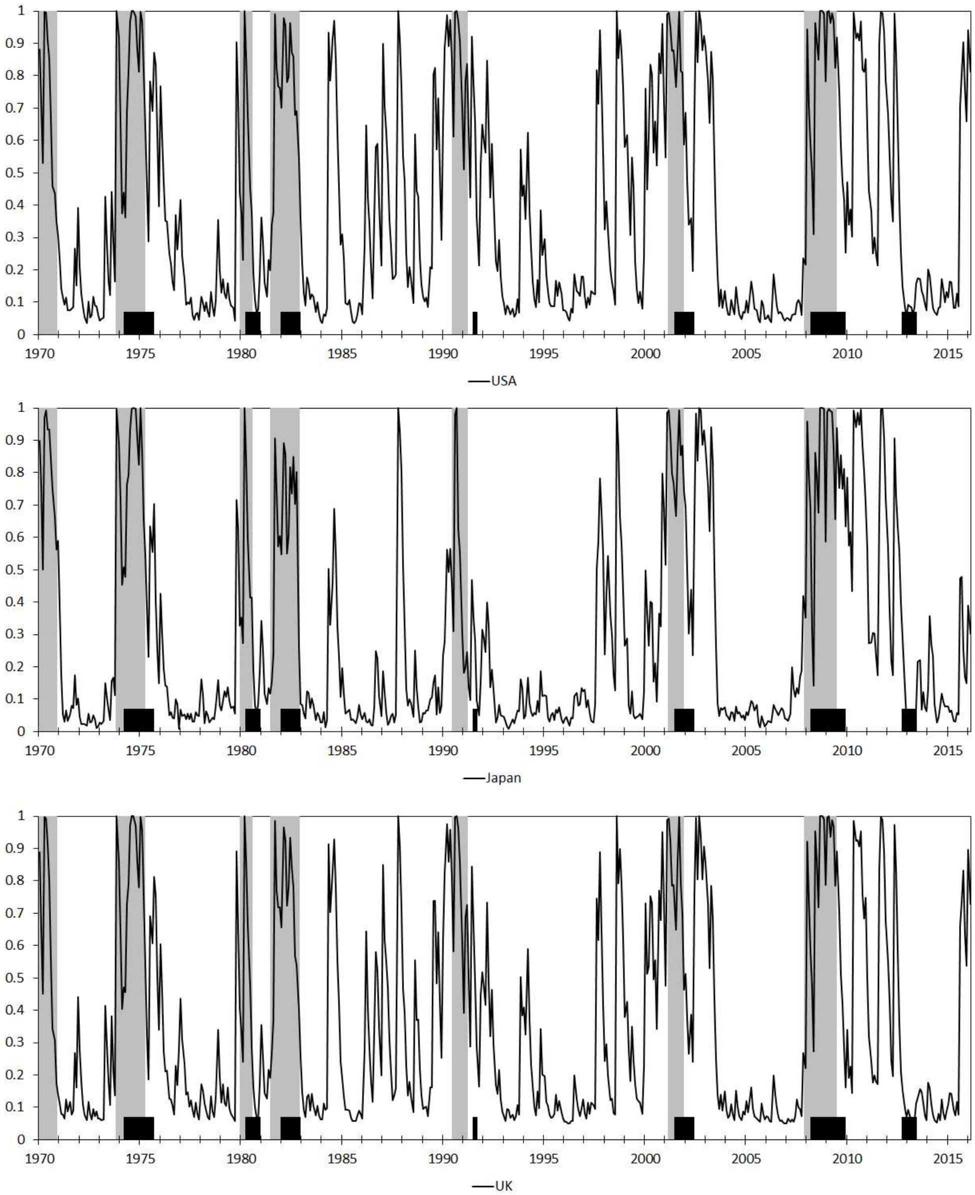

Figure 2. Timing of high volatility regimes for common shocks to country index returns against the MSCI World Index

The charts show the filtered probabilities of high volatility regimes for common shocks for the USA, Japan and the UK. For each country, we report the probability associated with shocks common to the world portfolio and to the country index at hand. Lower black marks denote periods during which quarterly GDP growth rate, compared with the same quarter of the previous year and seasonally adjusted, was below 1%; shaded bars indicate NBER-dated recessions of the US economy.

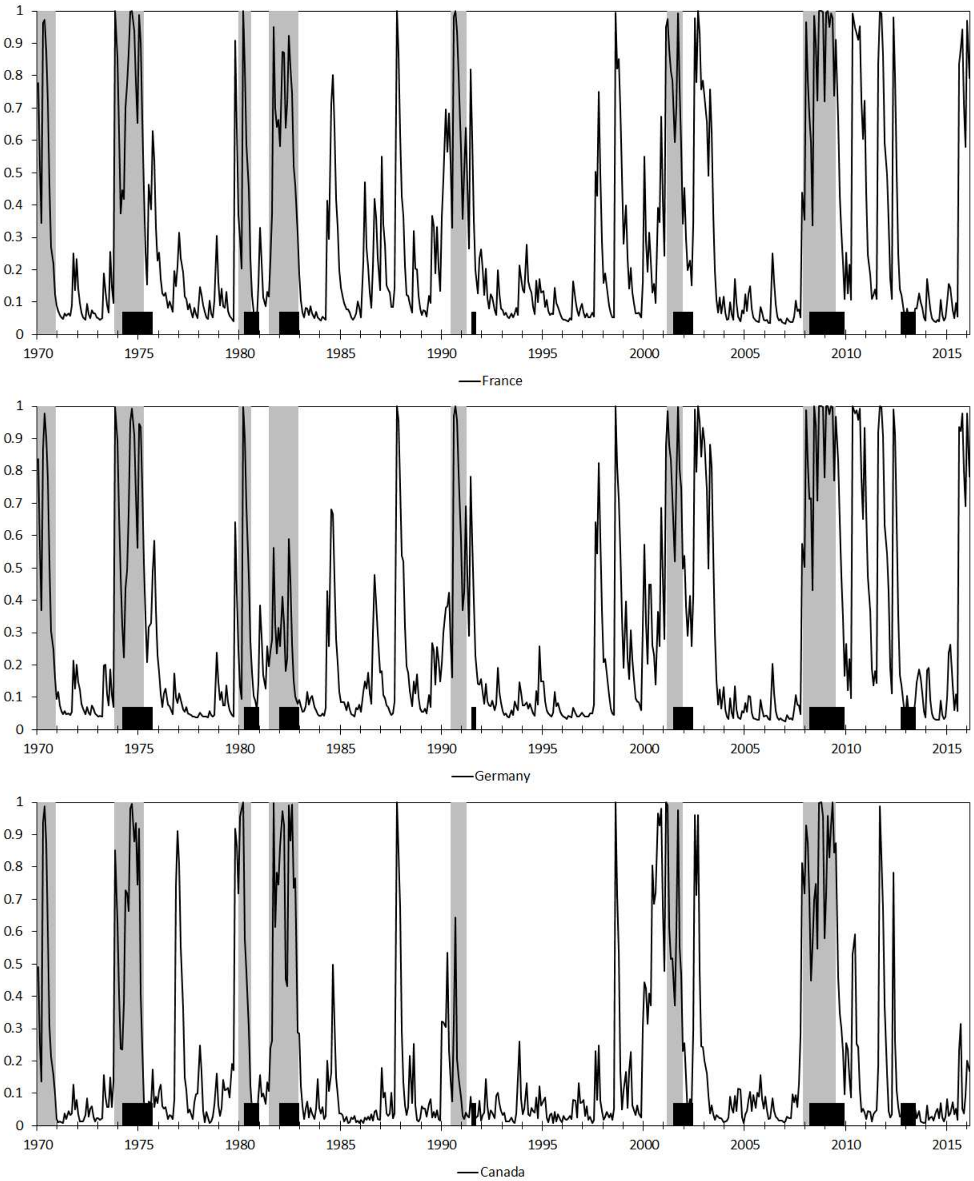

Figure 3. Timing of high volatility regimes for common shocks to country index returns against the MSCI World Index

The charts show the filtered probabilities of high volatility regimes for common shocks for France, Germany and Canada. For each country, we report the probability associated with shocks common to the world portfolio and to the country index at hand. Lower black marks denote periods during which quarterly GDP growth rate, compared with the same quarter of the previous year and seasonally adjusted, was below 1%; shaded bars indicate NBER-dated recessions of the US economy.

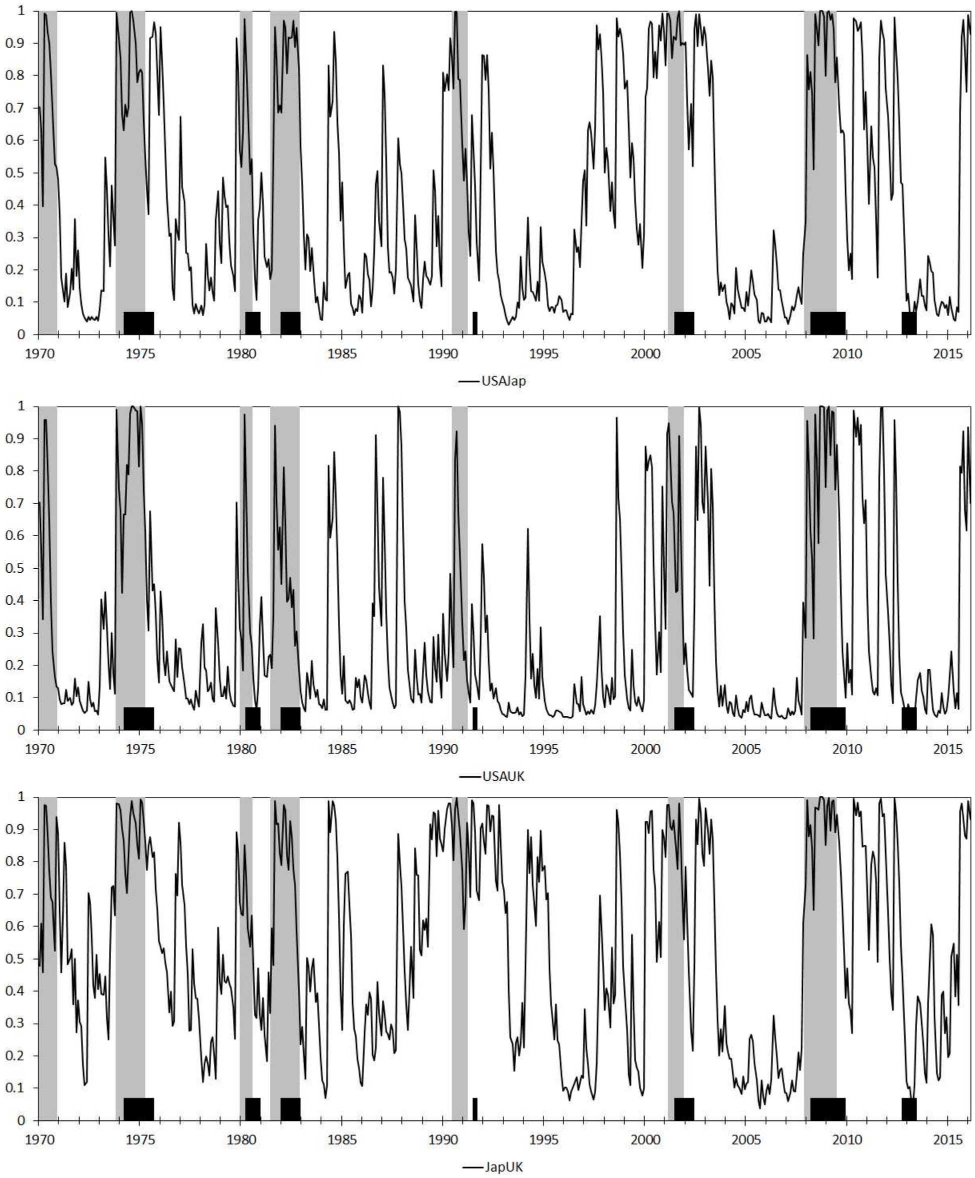

Figure 4. Timing of high volatility regimes for common shocks to country-pair index returns
The charts show the filtered probabilities of high volatility regimes for common shocks for USA/Japan, Usa/UK, Japan/UK models. Lower black marks denote periods during which quarterly GDP growth rate, compared with the same quarter of the previous year and seasonally adjusted, was below 1%; shaded bars indicate NBER-dated recessions of the US economy.

For the US and Japan, our estimates identify several instances in which very synchronous switches to high-volatility regimes took place. For instance: around 1970, 1975, the sharp recessions around early 1980s, 1987, around 1990, the run-up to the exuberance and subsequent fall of the stock market around 2000, as well as the Great Financial Crisis started in 2007. For all countries our estimates also signal August 2015 as a switch to high volatility. Strikingly similar too across all index pairs are the intervals of persistent low volatility: indeed, early-to-mid 1990s, 2003-2007 and 2013-2014 stand out as periods of compressed market variability. Other interesting features emerge from individual countries' filtered probabilities. For instance, volatility states for French and German returns (see Figure 3) look remarkably synchronous, whereas the UK market follows patterns closer to those experienced by the US. Finally, bilateral models in Figure 4, despite being based on more indirect information than (world) market models are, portrait regime switches that are consistent with all other cases. The Japan-UK model in particular points to a relative prevalence of high-volatility states.

The occurrence of shifts in the volatility regime is likely to be tied to the volatility and uncertainty of macroeconomic conditions. The association between the probability of high-volatility states and fluctuations in the expectations of the business cycle, as well as their conditional volatility, will be the object of further specific investigation. Here we simply show for the US monthly correlations of filtered probabilities with a battery of state variables that capture the evolution of expected macroeconomic conditions: the log of the ISM manufacturing PMI (PMI), the 4-week Treasury bill rate (TBILL), the yield spread between ten-year and one-year Treasury bonds (TERM), the yield spread between Moody's seasoned Baa and Aaa corporate bonds (DEF), the log change in the cyclically-adjusted price/earnings yield by R. Shiller (CAPE) and, in turn, one of three common measures of uncertainty. The latter are: the VXO stock market volatility index constructed by the Chicago Board of Options Exchange from the prices of options contracts written on the S&P 100 Index (VXO, monthly average of daily data since 1986), the Financial Uncertainty index (FUNC) and the Macroeconomic Uncertainty index (MUNC), both introduced by Jurado et al (2015). Table 4 shows contemporaneous as well as 3-month lagged and forward correlations. We find that our estimated filtered probabilities are more highly correlated with the indicator of financial uncertainty FUNC and that of stock market volatility VXO. In particular, the correlation with FUNC, a composite measure of financial uncertainty constructed using 147 financial time series[12], is positive and almost always the highest, with values ranging from 0.53 to 0.66. Stock market volatility clearly accounts for much of this correlation, as the numbers for VXO show. However, both the PMI, which is a leading indicator for the level of economic activity in the manufacturing sector, and MUNC, a composite aggregator of 132 macroeconomic time series[13], display quite high (and very significant) correlations

[12]They include valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads, yields on corporate bonds of different ratings grades, yields on Treasuries and yield spreads, and a broad cross-section of industry, size, book-market, and momentum portfolio equity returns (see Jurado et al. 2015).

[13]It includes broad categories of macroeconomic time series: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, bond and stock market

with our probabilities. In contrast, the short interest rate and the long-short spread, commonly used as simple predictors for economic downturns, have much looser associations, whereas the DEF spread appears to be informationally more relevant, perhaps because of its proven ability to track relative financial distress. We therefore infer that the shifts in the volatility regime, as estimated through our parsimonious approach using only stock return data, are clearly associated, besides with market volatility, to changes in the macroeconomic and more general financial conditions.

Variable/Lag	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$
PMI	-0.340	-0.383	**-0.420**	**-0.456**	**-0.477**	**-0.493**	**-0.490**
TBILL	0.091	0.074	0.062	0.040	-0.053	-0.023	0.010
TERM	-0.085	-0.065	-0.037	0.004	0.170	0.129	0.068
DEF	0.254	0.290	0.329	0.369	**0.402**	**0.406**	**0.400**
CAPE	-0.196	-0.208	-0.220	-0.220	0.048	0.077	-0.052
VXO	**0.521**	**0.574**	**0.627**	**0.678**	**0.466**	**0.519**	**0.612**
FUNC	**0.612**	**0.643**	**0.658**	**0.642**	**0.494**	**0.535**	**0.583**
MUNC	0.390	**0.404**	**0.412**	**0.409**	0.364	0.378	0.393

Table 4 - USA, correlations between filtered probabilities of high-volatility regime and selected macroeconomic variables

Contemporaneous, lagged and forward correlations with estimated filtered probabilities of high-volatility state. The variables are: the log of the ISM manufacturing PMI (PMI), the 4-week Treasury bill rate (TBILL), the yield spread between ten-year and one-year Treasury bonds (TERM), the yield spread between Moody's seasoned Baa and Aaa corporate bonds (DEF), the log change in the cyclically-adjusted price/earnings yield by R. Shiller (CAPE) and, in turn, one of three common measures of: the VXO stock market volatility index constructed by the Chicago Board of Options Exchange from the prices of options contracts written on the S&P 100 Index (VXO, monthly average of daily data since 1986), the Financial Uncertainty index (FUNC) and the Macroeconomic Uncertainty index (MUNC) by Jurado et al (2015). Values above 0.40 in bold.

5 Concluding remarks

Equity returns are correlated with business cycles: at the bottom of downturns, expected returns and risk premia are high (equity prices are low), whereas close to the peaks of booms they are low (prices are high). The market prices of risk vary over time, and as a result they induce time variation in the volatility of returns. When market volatility is high, increased risk will be compounded by

indexes, and foreign exchange measures.

a decline in diversification potential. Interdependence and contagion are not necessarily mutually exclusive phenomena, but for investors, the difference surely matters in terms of portfolio choices.

We establish the following stylized facts regarding return comovements. First, across all indices, persistent high-volatility spells always coincide with macroeconomic slowdowns. This is highlighted by the correlations of our estimated probabilities of high volatility with measures of macroeconomic uncertainty and confirms that shifts in the regime of volatility and comovement of equity indices are likely the result of revisions of expectations about underlying macroeconomic conditions. This confirms that market volatility may increase as a result of worldwide shifts in the perception of macroeconomic risk. Second, impact coefficients of common shocks are significantly larger during times of high volatility. Third, this increase in the observed responses of international stock returns to common shocks is largely attributable to the occurrence of bigger shocks (heteroskedasticity of fundamentals) rather than to breaks in the transmission mechanism or increased structural interdependence between markets. Fourth, since the late 1990s correlations between international stock indices appear to have stepped up. Our estimates confirm that returns have since then entered more often a regime of high-volatility common shocks, likely because of more sizeable and persistent macroeconomic disturbances. Of course, the question of the origins and nature of those larger perturbations remains to be answered, as well as that of the role of uncertainty (Bansal et al., 2014; Baker et al., 2016).

These results suggest that while variances and covariances across markets do shift over time, the spillover effects are essentially a function of the magnitude of cross-country shocks rather than of breaks to the transmission mechanism. In other words, variances, covariances and correlations are both time and state varying and mainly reflect the size of systematic shocks. The relevance of our results is immediately apparent. First, the optimal asset weights in internationally diversified portfolios are a function of cyclical changes in expected returns, volatilities, and correlations of the assets. The resulting portfolio rebalancing may consequently affect the dynamics of returns on all assets, particularly across international financial markets that are increasingly integrated at a global level. In addition, as the market linkages across markets appear overall stable, international diversification is still effective in mitigating risk during episodes of market turbulence. One interesting extension would be to investigate the degree of interdependence amongst returns on bond, stock and currency markets, particularly given the events surrounding the Great Financial Crisis.

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