Modelling Financial Markets Comovements During Crises: A Dynamic Multi-Factor Approach.[*]

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Abstract

We propose a novel dynamic factor model to characterise comovements between returns on securities from different asset classes from different countries. We apply a global-class-country latent factor model and allow time-varying loadings. We are able to separate contagion (asset exposure driven) and excess interdependence (factor volatility driven). Using data from 1999 to 2012, we find evidence of contagion from the US stock market during the 2007-09 financial crisis, and of excess interdependence during the European debt crisis from May-2010 onwards. Neither contagion nor excess interdependence is found when the average measure of model implied comovements is used.

JEL: C3, C5, G1.

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1 Introduction

The study of financial market comovements is of paramount importance for its implications in both theoretical and applied economics and finance. The practical relevance of a thorough understanding of the mechanisms governing market correlations lies in the benefits that this induces in the processes of asset allocation and risk management. In particular, recent crisis episodes have shifted the focus of the literature on the characterization of financial market comovements during periods of financial distress. Most of the crises that have hit the financial markets in the past decades are the result of the propagation of a shock which originally broke out in a specific market. This phenomenon has been extensively explored in the literature and has led to the use of the term "contagion" to denote the situation in which a crisis originated in a specific market infects other interconnected markets. For a review of the contributions at the heart of the literature on contagion see the papers by Karolyi (2003), Dungey et al. (2005) and Billio and Caporin (2010).

A well-documented phenomenon linked to a situation of contagion is an increase of the observed correlations amongst the affected markets. The origins of this empirical evidence trace back to the contributions of King and Wadhwani (1990), Engle et al. (1990), and Bekaert and Hodrick (1992). Longin and Solnik (2001) and, in particular, the influential paper by Forbes and Rigobon (2002), criticize the common practice to identify periods of contagion using testing procedures based on market correlations. Forbes and Rigobon (2002) show that the presence of heteroscedasticity biases this type of testing procedure, leading to over-acceptance of the hypothesis of the presence of contagion. Bae et al. (2003), Pesaran and Pick (2007) and Fry et al. (2010) propose testing procedures robust to the presence of heteroscedasticity.

In this paper, we bring together the literature on contagion with the literature on market integration in that we associate a situation of *contagion* to a prolonged episode of market distress altering the functioning of the financial system. On the contrary, a situation of *excess interdependence* is a short lasting phenomenon. Being able to distinguish between contagion and excess interdependence has a crucial information content as to how a crisis develops and spreads out. We propose a modelling framework which allows to contrast a situation of *contagion,* in the Forbes and Rigobon (2002) sense, as opposed to the case in which *excess interdependence* in financial markets is triggered by spiking market volatility. Contagion is no longer thought as correlation in excess of what is implied by an economic model (as in Bekaert et al. 2005 and Bekaert et al. 2014), it instead corresponds to a specific market situation entailing a persistent change in financial linkages between markets. On the contrary, conditional heteroscedasticy of financial time series does not display trending behaviour (Schwert, 1989 and Brandt et al., 2010); thus a rise in correlations caused by excess volatility has only a temporary effect. This feature is in line with the literature on market integration (Bekaert et al. 2009), which explores the degree of interconnectedness of markets through time, borrowing from Forbes and Rigobon's (2002) analysis the fact that excess interdependence, triggered by volatility, might lead to spurious identification of cases of market integration.

We study comovements amongst financial markets during crises, both in a multi-country and a multi-asset class perspective, contributing to the extant empirical literature on international and intra asset class shock spillovers. We decompose an average correlation measure into components that are in turn attributed to volatility and exposure. We analyse stock, bond and FX comovements in US, Euro Area, UK, Japan and Emerging Countries, providing an extensive coverage of the global financial markets. Most of the contributions to the literature on comovements entail single asset classes, with the vast majority focusing on stock and bond markets (see *inter alia* Driessen et al., 2003, Bekaert et al., 2009 and Baele et al., 2010). There is a strand of literature embracing a genuine multi-country and multi-asset-classes approach in the study of shock spillovers. Dungey and Martin (2007) propose an empirical model to measure spillovers from FX to equity markets to investigate the breakdown in correlations observed during the 1997 Asian financial crisis. Ehrmann et al. (2011) analyse the financial transmission mechanism across different asset classes (FX, equities and bonds) in the US and the Euro Area, using a simultaneous structural model.

The main contribution of this paper is twofold. First, we propose a dynamic factor model which allows to test for the presence of comovements (excess interdependence versus contagion) in a multi-asset and multi-country framework. Since the seminal works of Ross (1976) and Fama and French (1993), multifactor models for asset returns have been the main tool for studying and characterizing comovements. Moreover, our model is specified with dynamic factor loadings, to accommodate time-dependent exposures of the single assets to the different shocks. This allows us to disentangle the different sources of comovements between financial markets, and to analyse their dynamics during financial crisis periods. Second, we report an empirical application using a sample period which encompasses both the 2007-09 crisis as well as the current sovereign debt crisis: this is an interesting laboratory to use the proposed framework to explore financial market comovements during crisis periods.

The empirical analysis suggests interesting findings. The global factor is the most pervasive of the considered factors, while the asset class factor is the most persistent and the country factor is negligible in our multiple asset framework. We find evidence of contagion stemming from the US stock market during the 2007-09 financial crisis and presence of excess interdependence during the spreading of the European debt crisis from mid-2010 onwards. Any contagion or excess interdependence effect disappears at the overall average level, and because of this, some of the considered assets display diverging repricing dynamics during crisis periods.

The remainder of the paper is organized as follows. In Section 2, we present our dynamic multi-factor model. Section 3 introduces the data. Section 4 reports the relevant empirical results regarding the relevance of global-asset-country factors and the indentification of the situation of contagion and the case of excess interdependence in financial assets. Section 5 concludes.

2 A Dynamic Multi-Factor Model

In this section, we present the modelling framework we propose. The main novelty of the paper is the formulation and the estimation of a dynamic multi-factor model which allows to test for the presence of *contagion* in the Forbes and Rigobon (2002) sense versus the presence of volatility triggered episodes of *excess interdependence* on financial markets. Contagion is no longer thought as correlation in excess of what is implied by an economic model (as in Bekaert et al. 2005 and Bekaert et al. 2014). It instead corresponds to a specific market situation, that the framework proposed in this paper is able to capture, entailing a persistent change in financial linkages between markets.

Building on the standard latent factor finance literature (Ross, 1976; Fama and French 1992), let $R_t^{i,j}$ represent the weekly return for the asset belonging to asset class $i = 1, \ldots, I$ and country $j = 1, \ldots, J$ at time t. The general representation of the model is as follows:

$$R_t^{i,j} = \mathbf{E}[R_t^{i,j}] + F_t^{i,j}\beta_t^{i,j} + \epsilon_t^{i,j} \tag{1}$$

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + \psi^{i,j}Z_{t-1} + u_t^{i,j} \tag{2}$$

where $\mathbf{E}[R_t^{i,j}]$ is the expected return for asset class i in country j at time t, $\beta_t^{i,j}$ is a vector of dynamic factor loadings, mapping from the zero-mean factors $F_t^{i,j}$ to the single asset returns. We allow the factors $F_t^{i,j}$ to be heteroscedastic, that is $\mathbf{E}[F_t^{i,j\prime}F_t^{i,j}] = \Sigma_{F^{i,j},t}$, where $\Sigma_{F^{i,j},t}$ is the time-varying covariance matrix of the factors. The error $\epsilon_t^{i,j}$ is assumed to be white noise and independent of $F_t^{i,j}$, the vector $\beta^{i,j}$ is the long-run value of $\beta_t^{i,j}$, while $\phi^{i,j}$ and $\psi^{i,j}$ are 3-dimensional vectors of parameters to be estimated, the errors $\{u_t^{i,j}\}_{t=1,\ldots,T}$ are independent and normally distributed. We assume $u_t^{i,j}$ to be independent of $\epsilon_t^{i,j}$. Note that $diag(\cdot)$ is the diagonal operator, transforming a vector into a diagonal matrix. Finally, Z_t represents a conditional variable controlling for period of market distress.

Following Dungey and Martin (2007), different sources of shocks are considered, at global, asset class and country level, in a latent factor framework. A first factor, denoted as G_t, is designed to capture the shocks which are common to all financial assets modelled, whereas A_t^i is the asset class specific factor for asset class $i = 1, \ldots, I$ and the country factor C_t^j is the country specific factor for county $j = 1, \ldots, J$ at time t. We denote $F_t^{i,j} \equiv [G_t \; A_t^i \; C_t^j]$ and, correspondingly, for the factor loading we specify $\beta_t^{i,j} \equiv [\gamma_t^{i,j} \; \delta_t^{i,j} \; \lambda_t^{i,j}]'$.

The full model is a multi-factor model with dynamic factor loadings and heteroscedastic factors. This model setting allows us to explore and characterize dynamically the comovements among the considered assets. Time-dependent exposures to different shocks let us disentangle dynamically the different sources of comovement between financial markets, namely distinguishing among shocks spreading at a global level, at the asset class or rather at the country level. The presence of time-varying exposures to common factors enables us to test for the presence of contagion, controlling at the same time for excess interdependence induced by heteroscedasticity in the factors. In the following sections, we explore the features of the model and use it to characterize financial market comovements during crisis.

In Section 2.1, we describe the estimation of the factors $F_t^{i,j}$, whereas the estimation of Z_{t-1} is presented in Section 2.2.

2.1 Factor Estimation

The factors $F_t^{i,j}$ are estimated by means of principal component analysis (PCA). The choice of PCA is dictated by model simplicity and interpretability, yet providing consistent estimates of the latent factors[1]. The global factor G is extracted using the entire set of variables considered, whereas the other two factors, asset class (A) and the country specific (C) are extracted from the different asset class and country groups, respectively. In this setting, the number of variables from which the factors are extracted, say K, is fixed and small, whilst the number of observations T is large.

2.1.1 Global factor (G).

Let us first consider the global factor G. In order to estimate it, let $\mathbf{E}[R_t^{i,j}]$ be the conditional mean by asset class and by country, we define the series of the demeaned returns as $\bar{R}_t^{i,j} \equiv R_t^{i,j} - \mathbf{E}[R_t^{i,j}]$ and we stack them into the matrix $\mathbf{r}$. We then consistently estimate the

[1] In the factor model literature, consistency of the factor estimation is a well established result for the case in which the factor loading is stable. In this paper, we make use of the limiting theory developed by Stock and Watson (1998, 2002 and 2009) and Bates et al. (2013) for the case of instability of the factor loading, suggesting that factors are consistently estimated using principal components.

variance-covariance matrix of $\mathbf{r}$, say $\Sigma_{\mathbf{r}}$, via maximum likelihood, as

$$\hat{\Sigma}_{\mathbf{r}} \equiv \frac{1}{(T-1)}\mathbf{r}'\mathbf{r} \tag{3}$$

Let $(l_k, \mathbf{w_k})$ be the eigencouples referring to the covariance matrix $\Sigma_{\mathbf{r}}$, with $k = 1, \ldots, K$, such that $l_1 \geq l_2 \geq \ldots \geq l_K$. We estimate $(l_k, \mathbf{w_k})$ by extracting the eigenvalue-eigenvector couples from the estimated covariance matrix of the returns $\hat{\Sigma}_{\mathbf{r}}$, denoted as $(\hat{l}_k, \hat{\mathbf{w}}_{\mathbf{k}})$.

The estimate $\hat{G}$ of the common factor G is given by the principal component extracted using the matrix $\hat{\Sigma}_{\mathbf{r}}$, that is:

$$\hat{G} = \mathbf{r}\hat{\mathbf{w}}_{\mathbf{1}} \tag{4}$$

$\hat{G}$ is a consistent estimator of the factor G. Indeed, from the standpoint that $\hat{\Sigma}_{\mathbf{r}}$ is a consistent estimator of $\Sigma_{\mathbf{r}}$ as a direct consequence of the invariance property for maximum likelihood estimators, the estimated eigencouples $(\hat{l}_k, \hat{\mathbf{w}}_{\mathbf{k}})$ consistently estimate $(l_k, \mathbf{w_k})$. See Anderson (2003, p. 473). Note that $\hat{\Sigma}_{\mathbf{r}}$ is a consistent estimator of $\Sigma_{\mathbf{r}}$ if the number of series is considered as fixed or increases at a slower rate than time.

2.1.2 Asset class (A) and country specific (C) factors.

Following the same procedure used for the estimation of global factor, in order to estimate the asset class and the country specific factors A^i and C^j (with $i = 1, \ldots, I$ and $j = 1, \ldots, J$) respectively, we define $\mathbf{r^i} \equiv [r_t^{i,j}]_{j=1,\ldots,J}$ and $\mathbf{r^j} \equiv [r_t^{i,j}]_{i=1,\ldots,I}$ as the matrices of returns referred to asset class i and country j, respectively. Denote as $\Sigma_{\mathbf{r^i}}$ and $\Sigma_{\mathbf{r^j}}$ the corresponding covariance matrix and let $\hat{\mathbf{w}}_{\mathbf{1}}^{\mathbf{i}}$ and $\hat{\mathbf{w}}_{\mathbf{1}}^{\mathbf{j}}$ be the eigenvectors corresponding to the largest eigenvalues of the estimates $\hat{\Sigma}_{\mathbf{r^i}}$ and $\hat{\Sigma}_{\mathbf{r^j}}$. The estimates of the asset class and the country specific factors $\hat{A}^i$ and $\hat{C}^j$ are then given by:

$$\hat{A}^i = \mathbf{r^i}\hat{\mathbf{w}}_{\mathbf{1}}^{\mathbf{i}} \tag{5}$$

$$\hat{C}^j = \mathbf{r^j}\hat{\mathbf{w}}_{\mathbf{1}}^{\mathbf{j}} \tag{6}$$

As we use demeaned returns, the extracted factors will have zero mean by construction.

For the sake of model interpretability, we orthogonalize the factors, so that the three groups of factors are mutually independent. The preliminary correlation analysis presented in Section 3 suggests that the asset class factors are more pervasive than the country ones. So, we first orthogonalize the asset class factors with respect to the global factor, by regressing the global factor on the asset class factors and using the residuals as the orthogonalised asset class factors. Then, we orthogonalize the country factors with respect to the asset class and the global factors, using the residuals in the regression of the country factors on both the asset class and the global factors. This ensures for instance that the US factor is independent of the global factor and of the equity factor. The orthogonalization process, however, is not carried out within the groups of factors, so then the equity factor might have a nonzero correlation with the bond factor, and so the US factor with the EU factor. In the empirical section we report below, we show that our results are robust to the case in which one orthogonalizes the country factors with the global one and then the asset class factors with respect to the others.

2.2 Factor Loading Specification and Estimation

In our specification (2), Z_{t-1} is a control factor extracted from pure exogenous variables and it is supposed to measure market nervousness and accounts for potential increase in the factor loading during market distress periods. In Section 4, we get an estimate $\hat{Z}_{t-1}$ of Z_{t-1} via the principal component extracted from the VIX, which is widely recognized as indicator of market sentiment, the TED spread and the Libor-OIS spread for Europe, which measure the perceived credit risk in the system. Widening spreads corresponds to a lack of confidence in lending money on the interbank market over short-term maturities, together with a flight to security in the form of overnight deposits at the lender of last resort.

Thus, the specification of (2) for the factor loadings $\beta_t^{i,j}$ is now

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + \psi^{i,j}\hat{Z}_{t-1} + u_t^{i,j} \tag{7}$$

The *conditional time-varying factor loading specification*[2] (7) emphasizes that $\beta_t^{i,j}$ tends to its long-run value $\beta^{i,j}$ while following an autoregressive type of process of order one with a purely exogenous variable Z, with Z a zero-mean variable, $\beta^{i,j}$ can indeed be interpreted as the long-run value for $\beta_t^{i,j}$.

Specification (7) nests two special cases. First, a *static specification* of the form:

$$\beta_t^{i,j} \equiv \beta^{i,j}, \quad \forall i = 1, \ldots, I, \quad \forall j = 1, \ldots, J \tag{8}$$

where we assume that the exposure of all modelled variables to the different groups of factors are kept constant through time.

A second nested case is a *time-varying factor loading specification*

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + u_t^{i,j} \tag{9}$$

where it is assumed that no exogenous variables enter in the data generating process of the betas. In Bekaert et al. (2009), the dynamics of the betas is specified using subsamples of fixed length via a rolling window estimation, so that the factor loadings are constant within pools of observations with the factor loadings having the following specification: $\beta_t^{i,j} \equiv \beta^{i,j,s} \quad s = 1, \ldots, S$ where $\beta^{i,j,s}$ is the static factor loading estimate referred to subsample s, while S is the number of subsamples considered. The authors partition the sample in semesters and re-estimate the model every six months. However, the rolling windows estimation is based on changing subsamples of the data and it may not reflect time-variation fairly well especially in small samples as also pointed out, amongst others, by Benerjee, Lumsdaine and Stock (1992). Thus, in our paper we estimate specification (9) using Kalman Filter maximum likelihood estimation to avoid both issues on potential inconsistency of the estimates obtained using sub-samples and any arbitrary choice about

[2]Specification (7) is within the class of the so-called *conditional time-varying factor loading approach* (see Bekaert et al., 2009), where the factor loadings are assumed to follow a structural dynamic equation (see for instance Baele et al., 2010) of the form $\beta_t^{i,j} \equiv \beta(\mathcal{F}_{t-1}, X_t)$where $\{\mathcal{F}_t\}_{t=1,\ldots,T}$ is the information flow and X_t is a set of conditional variables

the inertia, the subsample length, as to which factor loadings evolve through time.

To summarise, our proposed dynamic multi-factor model is:

$$R_t^{i,j} = \mathbf{E}[R_t^{i,j}] + \hat{F}_t^{i,j}\beta_t^{i,j} + \epsilon_t^{i,j} \tag{10}$$

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + \psi^{i,j}\hat{Z}_{t-1} + u_t^{i,j} \tag{11}$$

OLS gives consistent estimates of (10) when using specification (8), corresponding to the static case, which we consider the baseline. When considering the alternative specifications (7) and (9), we allow that the factor loadings show evidence of contagion either in a conditioned way ($\psi^{i,j} \neq \mathbf{0}$) or in an unconditioned way ($\psi^{i,j} = \mathbf{0}$) , according to the specified control variable. In these other two cases, estimates are obtained via maximum likelihood by applying the Kalman filter. The models are nested and thus, the standard likelihood ratio test can be employed for model selection.

2.3 Heteroscedastic Factors

In order to distinguish between spikes in comovements due to increasing exposures to common risk factors from the case in which spikes are triggered by excess volatility in the common factors, we allow for heteroscedastic factors. The extend to which the three groups of factors are mutually independent by construction greatly simplifies the estimation. For the case of the global factor G_t, a univariate GARCH(1,1) with normal innovation is employed to estimate time-varying volatility. For the asset class and the country factors, we apply the Engle's (2002) Dynamic Conditional Correlations (DCC) model of order (1,1) with GARCH(1,1) for the marginal conditional volatility processes with normal innovations separately on $\mathbf{A_t}$ and $\mathbf{C_t}$, defined by stacking the factors into matrices as follows: $\mathbf{A_t} \equiv [A_t^i]_{i=1,\ldots,I}$ and $\mathbf{C_t} \equiv [C_t^j]_{j=1,\ldots,J}$. We obtain estimates of the time-varying covariance matrices of the factors, estimating the DCC model via quasi-maximum likelihood estimation.

2.4 Financial Markets Comovements: Contagion versus Excess Interdependence

From the dynamic factor model introduced above, we can derive the time-varying covariance between pairs of financial assets.

To simplifying the notation, let us introduce the one-to-one mapping $n \equiv \aleph(i,j)$. Given the independence between the factors F_t and the error term ϵ_t, from (1) it follows that the covariance between any pair of assets at time t is given by:

$$cov_t(R^n, R^m) = \mathbf{E}[\beta_t^{n\prime} F_t^{n\prime} F_t^m \beta_t^m] + \mathbf{E}[\epsilon_t^n \epsilon_t^m] \tag{12}$$

for $n = 1, \ldots, N$, $m = 1, \ldots, N$, $n \neq m$. The first term on the right hand side is what is generally referred to as *model implied* covariance, whereas the second is called *residual* covariance. The empirical counterpart of (12) is given by:

$$c\hat{o}v_t(R^n, R^m) = \hat{\beta}_t^{n\prime} \hat{\Sigma}_{F,t}^{n,m} \hat{\beta}_t^m + \hat{\Sigma}_{\epsilon,t}^{n,m} \tag{13}$$

which we rewrite for convenience, as:

$$c\hat{o}v_{n,m,t} = c\hat{o}v_{n,m,t}^F + c\hat{o}v_{n,m,t}^\epsilon \tag{14}$$

Correspondingly, define the quantities $c\hat{o}rr_{n,m,t}^F$ and $c\hat{o}rr_{n,m,t}^\epsilon$ dividing by the appropriate variances. We provide the estimates of $c\hat{o}rr_{n,m,t}^\epsilon$ via the DCC framework. We deliberately do not adjust the residuals of the model by heteroscedasticty and/or serial correlation, which are instead treated as genuine features of the data. We denote the *model implied variance* of the n-th market by $v\hat{a}r_{n,t}$, which is defined as $v\hat{a}r_{n,t} \equiv c\hat{o}v_{n,n,t}$.

During periods of financial distress, soaring empirical covariances are in general observed. Eq. (13) shows that the covariance between R^n and R^m can rise through three different channels: an increase in the factor loadings β_t, an increase in the covariance of the factors

$\Sigma_{F,t}$, and an increase residual covariance $\Sigma_{\epsilon,t}$. Bekaert et al. (2005) and the related literature identify contagion as the comovement between financial markets in excess of what is implied by an economic model. In this view, contagion is associated with spiking residual covariance between markets, which refers to the second term on the right-hand side of both Eq. (13) and Eq. (14). In our modelling set-up, we take a different stand. Consistently with the case brought by Forbes and Rigobon (2002, pp. 2230-1), *contagion* is thought as an episode of financial distress characterized by increasing interlinkages between markets. This event finds its model equivalent in a surge in the factor loadings β_t. On the contrary, spiking volatility in the factor conditional covariances is associated with *excess interdependence*. We formalize this notion in Definition 1 (*contagion*) and Definition 2 (*excess interdependence*) further in the paper.

Following Bekaert et al. (2009), we consider the average measure of model implied comovements:

$$\Gamma_t^F \equiv \frac{1}{N(N-1)/2} \sum_{n=1}^{N} \sum_{m>n}^{N} c\hat{o}rr_{n,m,t}^F \tag{15}$$

and similarly we define Γ_t^ϵ as the residual comovement measure.

In order to characterize financial market comovements, we may assume that the residual covariance $c\hat{o}v_{n,m,t}^\epsilon$ is negligible and focus our attention on the model implied covariance $c\hat{o}v_{n,m,t}^F$. There are two sources through which the covariance between two markets can surge: an increase in the factor loadings β_t, and/or increase in the factor volatilities $\Sigma_{F,t}$. In other words, assuming that our model fully captures the correlations between assets ($\mathbf{E}[\epsilon_t^n \epsilon_t^m] = 0$), the possible sources of a surge in the comovements are either soaring factor volatilities or increasing exposures to the factors. We label the former effect as contagion, whereas we call the latter excess interdependence.

We can get further insights into the covariance decomposition outlined in (12), by recalling that the factors $F_t^{i,j} = [G_t \; A_t^i \; C_t^j]$ are by construction mutually independent. Thus, from (12), denoting $n = \aleph(i_1, j_1)$ and $m = \aleph(i_2, j_2)$, it follows that:

$$cov_t(R^n, R^m) = \mathbf{E}[\gamma_t^{n\prime} G_t{}' G_t \gamma_t^m] + \mathbf{E}[\delta_t^{n\prime} A_t^{i_1\prime} A_t^{i_2} \delta_t^m] + \mathbf{E}[\lambda_t^{n\prime} C_t^{j_1\prime} C_t^{j_2} \lambda_t^m] + \mathbf{E}[\epsilon_t^n \epsilon_t^m] \tag{16}$$

with empirical counterpart of the form:

$$cov_t(R^n, R^m) = \hat{\gamma}_t^{n\prime}\hat{\Sigma}_{G,t}\hat{\gamma}_t^m + \hat{\delta}_t^{n\prime}\hat{\Sigma}_{A,t}^{n,m}\hat{\delta}_t^m + \hat{\lambda}_t^{n\prime}\hat{\Sigma}_{C,t}^{n,m}\hat{\lambda}_t^m + \hat{\Sigma}_{\epsilon,t}^{n,m} \tag{17}$$

which for convenience we write as:

$$c\hat{o}v_{n,m,t} = c\hat{o}v_{n,m,t}^G + c\hat{o}v_{n,m,t}^A + c\hat{o}v_{n,m,t}^C + c\hat{o}v_{n,m,t}^\epsilon \tag{18}$$

Our model framework has the advantage that it allows to discriminate among comovements due to global, asset class or country specific shocks. We define a measure of comovement prompted by the global factor as:

$$\Gamma_t^G \equiv \frac{1}{N(N-1)/2}\sum_{n=1}^{N}\sum_{m>n}^{N} c\hat{o}rr_{n,m,t}^G \tag{19}$$

where:

$$c\hat{o}rr_{n,m,t}^G \equiv \frac{c\hat{o}v_{n,m,t}^G}{\sqrt{v\hat{a}r_{n,t}^F v\hat{a}r_{m,t}^F}} \tag{20}$$

and can be seen as the part of the correlation between markets n and m, due to the common dependence on the global factor. In the same manner, we define Γ_t^A and Γ_t^C as the measures of comovements prompted by asset class and country factors, respectively. By construction we have: $\Gamma_t^F \equiv \Gamma_t^G + \Gamma_t^A + \Gamma_t^C$.

Let $\mathcal{I}_i$ be the set of indices from the sequence $n = 1, \ldots, N$ referred to markets belonging to the asset class i, and $\mathcal{J}_j$ be the indices referred to markets in country j, that is:

$$\mathcal{I}_i = \left\{n \middle| n = \aleph(i,j); j = 1, \ldots, J\right\} \tag{21}$$

$$\mathcal{J}_j = \left\{n \middle| n = \aleph(i,j); i = 1, \ldots, I\right\} \tag{22}$$

The model implied comovement measure for asset class i is given by:

$$\Gamma_t^i \equiv \frac{1}{J\left(J-1\right)/2}\sum_{n\in\mathcal{I}_i}\sum_{\substack{m\in\mathcal{I}_i\\ m>n}} \hat{corr}^F_{n,m,t} \tag{23}$$

and in the same manner for country j, we have:

$$\Gamma_t^j \equiv \frac{1}{I\left(I-1\right)/2}\sum_{n\in\mathcal{J}_j}\sum_{\substack{m\in\mathcal{J}_j\\ m>n}} \hat{corr}^F_{n,m,t} \tag{24}$$

Along with the definition of comovement measures introduced so far, we propose a modification of them, to test for *contagion* versus *excess interdependence*. In the case of Γ_t^F, besides the definition in (15), we consider also:

$$\Gamma_{t,ED}^F \equiv \frac{1}{N(N-1)/2}\sum_{n=1}^{N}\sum_{m>n}^{N} \hat{corr}^F_{n,m,t,ED} \tag{25}$$

$$\Gamma_{t,VD}^F \equiv \frac{1}{N(N-1)/2}\sum_{n=1}^{N}\sum_{m>n}^{N} \hat{corr}^F_{n,m,t,VD} \tag{26}$$

where $\hat{corr}^F_{n,m,t,ED}$ and $\hat{corr}^F_{n,m,t,VD}$ are the correlation coefficients respectively associated with the following covariances:

$$\hat{cov}^F_{n,m,t,ED} \equiv \hat{\beta}_t^{n\prime}\hat{\Sigma}_F^{n,m}\hat{\beta}_t^m \tag{27}$$

$$\hat{cov}^F_{n,m,t,VD} \equiv \hat{\beta}^{n\prime}\hat{\Sigma}_{F,t}^{n,m}\hat{\beta}^m \tag{28}$$

$\Gamma_{t,ED}^F$ differs from Γ_t^F in the sense that the correlations used in its definition are computed assuming constant factor volatilities. In this case, the dynamics of the correlation between two markets is triggered by their time-varying exposures to common factors. We call this correlation measure as *exposure driven* (ED). On the contrary, $\Gamma_{t,VD}^F$ is an average measure of comovements triggered by factor volatility only, while the exposures to the factors are kept constant according to their time series average. We call this type of comovements as *volatility driven* (VD). We consider the same two definitions for Γ_t^G, Γ_t^A and Γ_t^C, as well as for Γ_t^i and Γ_t^j.

The tools used in the analysis of the resulting time series are based on the Impulse-Indicator Saturation (IIS) technique implemented in Autometrics^{TM}, as part of the software PcGive^{TM} (Hendry and Krolzig, 2005, Doornik, 2009, Castle et al., 2011). Castle et al. (2012) show that Autometrics IIS is able to detect multiple breaks in a time series when the dates of breaks are unknown. Furthermore, the authors demonstrate that the IIS procedure outperforms the standard Bai and Perron (1998) procedure. In particular, IIS is robust in presence of outliers close to the end and the start of the sample[3].

Following Castle et al. (2012), we look for structural breaks in the generic $\Gamma_t^{(\cdot)}$ average comovement measures, by estimating the regression:

$$\Gamma_t^{(\cdot)} = \mu + \eta_t \tag{29}$$

where μ is a constant and η_t is assumed to be white noise. We then saturate the above regression using the IIS procedure, which retains into the model individual impulse-indicators in the form of spike dummy variables, signalling the presence of instabilities in the modelled series. These dummies occur in block between the dates of the breaks. In line with the procedure outlined in Castle et al. (2012), we group the dummy variables "with the same sign and similar magnitudes that occur sequentially" to form *segments* of dummies, whereas the impulse-indicators which can not be grouped will be labelled as *outliers*. A segment consists of at least two significant dummies, and at least two consecutive insignificant dummies need to occur to interrupt the segment. We interpret the segments of spike dummies as a step dummy for a particular regime. We can now state the following:

Definition 1 (*Contagion*). A situation of *contagion* is identified when a segment of dummy variables is detected through the IIS procedure for the average comovement measure $\Gamma_{t,ED}^{(\cdot)}$.

[3] The use of the IIS strategy to identify structural breaks using a number of dummy variables has similarities to the contagion test proposed by Favero and Giavazzi (2002)

Definition 2 (***Excess interdependence***). A situation of *excess interdependence* is identified when a segment of dummy variables is detected through the IIS procedure for the average comovement measure $\Gamma^{(\cdot)}_{t,VD}$.

We set a restrictive significance level of 1%, which leads to a parsimonious specification, as shown in Castle et al. (2012). Section 4.2 gives account of the results of the outlined methodology applied to our data.

3 Data

We analyse comovements of equity indices, foreign exchange rates, money market instruments, corporate and government bonds in US, Euro Area, UK, Japan and Emerging Countries. Following the literature, to minimise the impact of nonsynchronous trading across different markets, we base our study on end of week data, spanning from 1 January 1999 to 14 March 2012, yielding 690 weekly observations. The starting date coincides with the adoption of the Euro, the Euro Area being one of the key geographical areas considered in the analysis. The sample offers the possibility to explore a variety of different market scenarios. The most notable facts are the speculation driven market growth of late 1990s, the financial and economic slowdown of the early 2000s, the burst of the markets during the mid-2000s, the financial turmoil of the period 2007-2009 and the following slow recovery, still pervaded by a high degree of uncertainty, prompted by the sovereign debt crisis in Europe and US between 2010 and 2012. This allows us to pick up from an in-sample analysis what the distinctive features of market comovements during crisis periods are.

Details on the time series used in this paper are reported in Table 1. The data sources are Datastream and Bloomberg. We adopt the MSCI definition of Emerging Markets and we select the 5 most relevant countries in term of size of their economy, according to the ranking based on the real annual GDP provided by the World Bank. Thus we select China, Brazil, Russia, India, and Turkey as Emerging Countries[4]. We exclude from the analysis money

[4]Emerging market weights are the same across different asset classes, are based on GDP and updated annually. The weights for 2012, last year in the sample, are: China 51.3%, Brazil 17.4%, Russia 13.0%, India

and treasury markets for Japan and Emerging Market, as the series were affected by excess noise caused by measurement errors. We consider the US dollar as the numeraire: all the series are US dollar denominated and the US dollar is the base rate for the FX pairs in the dataset. In what follows, we consider simple weekly percentage returns for Equity Indices, Bond Indices and Foreign Exchange Rates, whereas weekly first differences are considered for Money Market and Goverment Rates series. In Table 2, we report some descriptive statistics of the variables.

[Tables 1-2 about here]

The most remarkable facts are the extreme values which were recorded in correspondence of the 2008-2009 crisis period. This is particularly evident for stock markets and for short term rates, whereas along the country spectrum, the most hit were Emerging Markets. All series exhibit the typical characteristic of non normality with high asymmetry and kurtosis. The price series are plotted in Figure 1. The downturn at the end of the year 2008 is immediately apparent and common to all the considered series.

[Figure 1 about here]

We propose a dynamic factor model with multiple sources of shocks, at global, asset class and country level. In order to validate this approach, a first preliminary correlation analysis is undertaken. Table 3 reports the in-sample correlation of the modelled variables. We observe high correlation intra asset class groups. Particularly remarkable are the cases of equity and treasury rates, with correlations in the 70-80% range. We observe substantial correlation even within countries, in particular there is evidence of high interconnection between corporate bonds and FX markets at country level: Euro Area (91.3%), Japan (83.6%) and UK (83.3%). Hence, there is evidence for the presence of both an asset class and a country effect. However, the asset class effect seems to be systematically more pervasive than the country one. Finally, the correlation is high in three clusters (equity indices, corporate bonds and FX, and treasury rate) and treasury rates.

12.9% and Turkey 5.4%.

[Table 3 about here]

4 Empirical Results

In this section, we report the estimates of the dynamic multi-factor model formulated in Section 2. In particular, in Section 4.1 we report the results of the estimation of the factors and the specification of the factor loadings, in Sections 4.2 the empirical analysis of market comovements, both the estimates of measures of market comovements (Section 4.2.1) and the regime of contagion vs excess interdependence we identify in market comovements (Section 4.2.2).

4.1 Factor Estimates and Factor Loading Selection

We start our empirical analysis by extracting the factors according to the methodology outlined in Section 2.1. We extract the first principal component at a global, asset class and country level from the estimate of the covariance matrix of the demeaned return time series. The factors have by construction zero mean.

The extracted factors account in total for 83.28% of the overall variance, thus explaining a substantial amount of the variation of the considered return series. In particular, the global factor extracts as much as 37.27% of the overall variance, whereas the asset class and the country factors account for a quota in the $50-80\%$ range of the variation in the groups they are extracted from.

We then orthogonalize the extracted factors, so that the system $\hat{F}_t^{i,j} \equiv [\hat{G}_t \; \hat{A}_t^i \; \hat{C}_t^j]$ with $i = 1, \ldots, I$ and $j = 1, \ldots, J$ consists of orthogonal factors. We first orthogonalize each of the asset class factors with respect to the global factor and then orthogonalize the country factors with respect to both the global and the asset class factors. In Section 4.2, we show that all our main results do not depend on the particular way the orthogonalization is carried out.

To validate the interpretations we attached to the factors, we map the contributions of the original variables onto the factors via linear correlation analysis. The result of this analysis is reported in Table 4.

[Table 4 about here]

We find that the stock indices are most highly correlated with the global factors, with correlations in the 80%-90% range. This characterizes the global factor as the momentum factor. Such an interpretation seems reasonable in view of the fact that the equity asset class can be thought as the most direct indicator of the financial activity among the asset classes considered here.

More generally, when we sort the different markets by the magnitude of their correlation with the global factor, they tend to group by asset class, rather than by country, with the Treasury and the FX market figure in the 30%-50% range and the money market and the corporate bond market in the 0%-30% range. This again supports the evidence that the asset class effect is more pervasive than the country effect.

To test for excess interdependence prompted by changes in the volatility of the factors, we entertain the possibility that the factor time series might be characterized by volatility clustering. In Table 5, we report the Engle test for residual heteroscedasticity that suggests that at the 1% confidence level this is indeed the case for 7 out of the 11 estimated factors.

[Table 5 about here]

We fit the Engle's DCC model on the series of the estimated factors to get a time-varying estimate of their covariance matrix.

We estimate (10) via OLS when we use the static formulation (8) for the factor loadings, while when the factor loadings are specified as in either the time-varying (9) or the conditional time-varying factor loading (7) model, we estimate (10) via the Kalman filter using maximum likelihood estimation. The models are nested and thus the likelihood ratio test can be employed for model selection. The likelihood ratio statistics are reported in Table 6.

[Table 6 about here]

The test strongly rejects the static alternative in favour of the dynamic ones. The conditional time-varying factor loading approach dominates the time-varying factor loading approach. Thus, there is evidence that the fitting of the model improves when we control for market nervousness by means of the control factor Z.

4.2 Financial Market Comovements Dynamics

4.2.1 Measures of comovements

We turn now to analyse the average measures of comovements introduced in Section 2.4.

We start with the comparison between Γ_t^F and Γ_t^ϵ. The two measures are plotted in Figure 2.

[Figure 2 about here]

As it can be clearly seen, the residual component is negligible throughout the sample period and on average does not convey any information about the dynamics of the comovements of the considered markets. We observed only a small jump in the idiosyncratic component in correspondence to late 2008, which has been considered by many the harshest period of the 2007-09 global financial crisis. The model-implied measure of average comovements Γ_t^F fluctuates around what can be regarded as a constant long-run value of roughly 20%. This erratic behaviour does not allow us to identify any peak in correlation possibly associated to crisis periods. During the period 2007-09 a slightly lower average correlations seem to be observed instead. We give account of this fact in what follows, by disaggregating the model implied covariation measure Γ_t^F.

We start doing this by considering the decomposition of the overall comovement measure Γ_t^F into Γ_t^G, Γ_t^A and Γ_t^C, which is presented in Figure 3. The global factor appears to be the most pervasive of all the three factors considered, shaping the dynamics of the average overall measure. The asset class factor is slightly less pervasive, but it is the most persistent of the three, meaning that its contribution is more resilient to change over time. This expresses the fact that the characteristics which are common to the asset class contribute in a constant proportion to the average overall market correlation. The least important factor is the country one, which is almost negligible. Thus, comovements typically propagate through two channels: a global one, in a time varying manner, and an asset class channel, according to a constant contribution.

[Figure 3 about here]

We consider robustness checks of these conclusions, by pursuing an alternative strategy in orthogonalizing the system of factors considered here. We first orthogonalize the country factor against the global and then the asset class one with respect to the other two. Then we re-estimate the model and construct the comovement measures. Figure 4 shows the results. The dynamics of the comovements are similar. The decomposition changes in favour of the global factor, which is even more pervasive than before. However, the country contribution is almost absent, even when the country factors are extracted and orthogonalized with priority, thus validating our orthogonalization method.

[Figure 4 about here]

4.2.2 Testing for Contagion versus Excess Interdependence

In this section, we propose an empirical analysis of the comovement measures introduced above by testing for the presence of different regimes in the resulting time series by means of Autometrics. Figures 5-7 report the time series analysed. Tables 7-9 show the result of this procedure applied to our data.

[Figures 5–7 about here]

[Tables 7–9 about here]

Let us start with the analysis of the results for Γ_t^F, $\Gamma_{t,ED}^F$ and $\Gamma_{t,VD}^F$ as reported in Table 7. As previously noted for Figure 2, not surprisingly, we do not find any structural clear pattern in the IIS retained by Autometrics when applied to Γ_t^F. We find outliers only, instead. However, when looking at $\Gamma_{t,VD}^F$ we find evidence of excess interdependence, that is excess average correlation prompted by the heteroscedasticity of common factors, in correspondence to the most severe period of the 2007-09 crisis, i.e. the last part of 2008, as well as in August 2011, when the sovereign debt crisis spread from the peripheral countries in Europe to the rest of the continent and ultimately to the US. On the other hand, we detect a significant negative break in the contagion measure $\Gamma^F_{t,ED}$ from late 2007 to the end of 2008, which offsets the peak in $\Gamma^F_{t,VD}$, so that no peaks are detected in Γ^F_t, as shown before. When only factor exposures are concerned, we observe an average de-correlation of more than 6%. We further disaggregate the Γ-measures at the asset class and country level. Along with the detected segments, we observe a few outliers. In the case of $\Gamma^F_{t,ED}$, we find a couple of outliers in proximity of the Dot-Com bubble burst, witnessing de-correlation on the market. All the other IIS identified by Autometrics are in proximity of the start and the end of the sample, a fact observed also in Castle et al. (2012).

We turn our attention to Table 8 which reports the results referred to the single asset classes. For stock indices, we find evidence of contagion from Aug-07 to mid-09, with correlation significantly up by 5% from the average level of 79%. We also find evidence of excess interdependence for three less extended periods, in correspondence to the most dramatic months of 2008 and 2009, as well as in May-2010 and from Aug-2011 on, with a surge of 13-15% in the average correlation. We associate the former event to the first EU intervention in the Greece's bailout programme, which marked the triggering of the sovereign debt crisis in Europe. The second identified period has already been epitomized as the moment in which the sovereign debt crisis spread across and outside Europe. At the aggregate level, the 2007-09 crisis and the debt crisis remain the most relevant episodes in terms of average market correlations.

For the other asset classes, the same periods are detected, but most of them are associated with *decreasing* market correlations. This is particularly evident at the aggregate level for Corporate Bonds (with average slumps in correlation as high as 41.34% in the last part of 2008) and Foreign Exchange (-39.93% in roughly the same period). This phenomenon is still present when we look for contagion and excess interdependence. The de-correlation observed in the case of foreign exchange rates is due to the contrasting effects of the crisis on the single pairs. Because of the low costs related to a borrowing position in Yen, since the early 2000s, the Japanese currency has been, together with the US Dollar, the currency used by investors to finance their positions in risky assets. The massive outflow from the markets experienced in the late 2000s, led to the unwinding of these borrowing positions, which fuelled a steady appreciation of the Japanese currency. This results in a massive de-correlation of the Yen against the other currencies. As part of the same phenomenon, the Japanese Corporate Bond market, even though it experienced a sharp capital outflow during the first period of the late 2000s financial crisis, continued to grow rapidly (see Shim, 2012), proving to be a safe haven during this period of generalized financial distress. This again triggered de-correlation of the Japan market with the other countries. See Figure 8 for a graphic comparison of the market dynamics in these periods.

[Figure 8 about here.]

Similarly, the money markets are pervaded by comovements shocks of alternate signs, especially at the aggregate level and when testing for excess interdependence. The series here considered are indicative of the status of the country interbank markets as well as a proxy of the conduct of the monetary policy. The negative breaks in comovements reflect the asymmetries in the shocks on the interbank markets and the differences in the reactions of the monetary policy to the spreading of the crisis. We detect a positive sign at the aggregate level and at the volatility driven level in correspondence to the joint monetary policy intervention in October 2008 by the FED, the ECB, the Bank of England and the Bank of Japan together with three other central banks of industrialized countries (Canada, Switzerland and Sweden). We find no breaks for Treasury rates at the aggregate level.

We now move on to Table 9 and analyse the same average comovement measures at the country level. We find evidence of a peak in the overall comovements in the US during the 2007-09 crisis. In particular there is strong evidence of contagion at the national level characterized by an escalation in the magnitude of the breaks in correspondence to the worsening of the crisis in late 2008. Similarly, in the other countries, we observe peaks during financial crises. In particular, in Europe we observe excess interdependence for most of the period between 2008 and 2012. In the UK we observe positive breaks in the correlations at the aggregate level and at the volatility driven level both for the 2007-09 crisis and for the sovereign debt crisis. For Japan we observe the de-correlation phenomenon described above, with the stock market correlated with the other stock markets, while the national currency was following a steady appreciation path.

The first evidence of contagion during the late 2000's economic and financial crisis was observed for equity markets and the US, as early as August 2007, anticipating the all-time peak of the S&P500 in October, epitomizing the beginning of the 2007-09 global financial crisis. This combined evidence is in line with what has been observed in reality: the crisis originated in the US, spread across the country and then propagated to the global financial markets, affecting first the global stock markets. On the contrary, there is evidence that the sovereign debt crisis that originated in Europe was characterized by excess interdependence, rather than as an example of contagion. Indeed, in this case the most extended episode of excess interdependence was recorded for equity indices and for Europe.

5 Conclusions

This paper studied the determinants of the comovements (contagion vs excess interdependence) between different financial markets, both in a multi-country and a multi-asset class perspective. We proposed a dynamic factor model able to capture multiple sources of shocks, at global, asset class and country level and used it to test for the presence of contagion versus excess interdependence. The model is specified with time-varying factor loadings, to allow for time-dependent exposures of the single assets to the different shocks. We statistically validated the supremacy of this model as compared to a standard static approach and an alternative dynamic approach. The framework is applied to data covering five countries (US, Euro, UK, Japan, Emerging), five asset markets (corporate bond yields, equity returns, currency returns relative to the US, short-term money market yields and long-term Treasury yields) for a total of 20 series. We used weekly data, spanning from 1 January 1999 to 14 March 2012.

The main findings of our empirical analysis can be summarized as follows. First, the global factor is the most pervasive of the considered factors, shaping the dynamics of the comovements of the considered financial markets. On the contrary, the asset class factor is the most persistent through time, suggesting that the structural commonalities of markets belonging to the same asset class systematically contributes in a constant proportion to the average overall comovements. In our multiple asset class framework, the country factor is negligible. In a robustness check, we showed that this result does not depend on the order in which the system of factors is orthogonalized.

Secondly, we find evidence of contagion stemming from the US and the stock market jointly in correspondence to the harshest period of the 2007-09 financial crisis. On the contrary, the currency and sovereign debt crisis, which originated in Europe, is characterized by excess interdependence from mid-2010 onwards. According to the literature on comovements, this lets us characterize the spillover effects during the 2007-09 financial crisis as persistent, altering the strength of the financial linkages worldwide. On the other hand, the shock transmission experienced during the recent debt crisis has *so far* to be understood as temporary, being prompted by excess factor volatilities, which do not display any trend in the long-term.

Finally, at the overall average level, we do not find any evidence of contagion or excess interdependence. We like to interpret this result as follows. During the crises some of the securities considered in the study, the Japanese currency and corporate bond market in particular, displayed diverging dynamics as result of the unwinding of carry positions, built to finance risky investments.

References

[1] Anderson, T. W., 2003. *An Introduction to Multivariate Analysis.* Wiley Series in Probability and Statistics. New Jersey.

[2] Bae, K.-H., Karolyi, G. A., Stulz, R. M., 2003. A new approach to measuring financial contagion. *Review of Financial Studies* 16 (3), 717–763.

[3] Baele, L., Bekaert, G., Inghelbrecht, K., 2010. The determinants of stock and bond return comovements. *Review of Financial Studies* 23 (6), 2374–2428.

[4] Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. *Econometrica* 70 (1), 191–221.

[5] Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. *Econometrica* 66 (1), 47–78.

[6] Benerjee, A., Lumsdaine, R. L., and Stock, J. H., 1992. Recursive and sequential tests of the unit-root and trend-break hypotheses: theory and international evidence. *Journal of Business and Economic Statistics* 10 (3), 271-287.

[7] Bates, B. J., Plagborg-Møller, M., Stock, J., H., Watson, M., W., 2013. Consistent factor estimation in dynamic factor models with structural instability. *Journal of Econometrics* 177 (2), 289-304..

[8] Bekaert, G., Ehrmann, M., Fratzscher, M., Mehl, A., 2014. Global crises and equity market contagion. *Journal of Finance* 59 (6), 2597–2649.

[9] Bekaert, G., Harvey, C. R., Ng, A., 2005. Market integration and contagion. *Journal of Business* 78 (1), 39–69.

[10] Bekaert, G., Hodrick, R., 1992. Characterizing predictable components in excess returns on equity and foreign exchange markets. *Journal of Finance* 47 (2), 467–509.

[11] Bekaert, G., Hodrick, R., Zhang, X., 2009. International stock return comovements. *Journal of Finance* 64 (6), 2591–2626.

[12] Billio, M., Caporin, M., 2010. Market linkages, variance spillovers, and correlation stability: Empirical evidence of financial contagion. *Computational Statistics and Data Analysis* 54 (11), 2443–2458.

[13] Brandt, M. W., Brav, A., Graham, J. R., 2010. The idiosyncratic volatility puzzle: time trend or speculative episodes? *Review of Financial Studies* 23 (2), 863–899.

[14] Castle, J.L., Doornik, J.A. and Hendry, D.F., 2011. Evaluating automatic model selection. *Journal of Time Series Econometrics* 3 (1), Article 8.

[15] Castle, J.L., Doornik, J.A. and Hendry, D.F., 2012. Model selection when there are multiple breaks. *Journal of Econometrics* 169 (2), 239–246.

[16] Doornik, J.A., 2009. Autometrics. In: Castle and Shephard (2009), *The Methodology and Practice of Econometrics*. Oxford University Press. Oxford.

[17] Driessen, J., Melenberg, B., Nijman, T., 2003. Common factors in international bond returns. *Journal of International Money and Finance* 22 (5), 629–656.

[18] Dungey, M., Fry, R. E., González-Hermosillo, B., Martin, V. L., 2005. Empirical modelling of contagion: a review of methodologies. *Quantitative Finance* 5 (1), 9–24

[19] Dungey, M., Martin, V., 2007. Unravelling financial market linkages during crises. *Journal of Applied Econometrics* 22 (1), 89–119.

[20] Ehrmann, M., Fratzscher, M., Rigobon, R., 2011. Stocks, bonds, money markets and exchange rates: measuring international financial transmission. *Journal of Applied Econometrics* 26 (6), 948–974.

[21] Engle, R. F., 2002. Dynamic conditional correlation. *Journal of Business and Economic Statistics* 20 (3), 339–350.

[22] Engle, R. F., Ito, T., Lin, W., 1990. Meteor showers or heat waves? Heteroscedastic intra-daily volatility in the foreign exchange market. *Econometrica* 58 (3), 525–542.

[23] Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1), 3–56.

[24] Favero, C. A., Giavazzi, F., 2002. Is the international propagation of financial shocks non-linear? Evidence from the ERM. *Journal of International Economics,* 57 (1), 231–246.

[25] Forbes, K. J., Rigobon, R., 2002. No contagion, only interdependence: measuring stock market comovements. *Journal of Finance* 57 (5), 2223–2261.

[26] Fry, R., Martin, V. L., Tang, C., 2010. A new class of tests of contagion with applications. *Journal of Business and Economic Statistics* 28 (3), 423–437.

[27] Hendry, D.F., Krolzig, H.–M., 2005. The properties of automatic Gets modelling. *Economic Journal* 115, C32–C61.

[28] Karolyi, G. A., 2003. Does international financial contagion really exist? *International Finance* 6 (2), 179–199.

[29] King, M.A., Wadhwani, S., 1990. Transmission of volatility between stock markets. *Review of Financial Studies* 3 (1), 5–33.

[30] Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. *Journal of Finance* 56 (2), 649–676.

[31] Pesaran, H., Pick, A., 2007. Econometric issues in the analysis of contagion. *Journal of Economic Dynamics & Control* 31 (4), 1245–1277.

[32] Ross, S. M., 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13 (3), 341–360.

[33] Schwert, G. W., 1989. Why does stock market volatility change over time? *Journal of Finance* 44 (5), 1115–1153.

[34] Shim, I., 2012. Development of Asia-Pacific corporate bond and securitisation markets. Working Paper No. 63c. Bank for International Settlements.

[35] Stock, J. H. and Watson, M. W., 1998. Diffusion indexes. Manuscript. Harvard University.

[36] Stock, J. H. and Watson, M. W., 2002. Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association* 97, 1167—1179.

[37] Stock, J. H. and Watson, M. W. (2009), Forecasting in dynamic factor models subject to structural instability, in D. F. Hendry, J. Castle and N. Shephard, *The Methodology and Practice of Econometrics: A Festschrift in Honour of David F. Hendry*, Oxford University Press, pp. 173–205.

ID variable	***Asset class***	***Country***	***Name***	***Source (Ticker)***
CorpBond/US	Corporate Bond	US	BOFA ML US CORP	Datastream (MLCORPM)
CorpBond/EU	"	Euro Area	BOFA ML EMU CORP	Datastream (MLECEXP)
CorpBond/UK	"	UK	BOFA ML UK CORP	Datastream (ML£CAU$)
CorpBond/JP	"	Japan	BOFA ML JAP CORP	Datastream (MLJPCP$)
CorpBond/EM	"	Emerging Countries	BOFA ML EMERG CORP	Datastream (MLEMCB$)
EqInd/US	Equity Indices	US	MSCI USA	Datastream (MSUSAML)
EqInd/EU	"	Euro Area	MSCI EMU U$	Datastream (MSEMUI$)
EqInd/UK	"	UK	MSCI UK U$	Datastream (MSUTDK$)
EqInd/JP	"	Japan	MSCI JAPAN U$	Datastream (MSJPAN$)
EqInd/EM	"	Emerging Countries	MSCI EM U$	Datastream (MSEMKF$)
FX/EU	Foreign Exchange	Euro Area	FX Spot Rate	Bloomberg (EURUSD Curncy)
FX/UK	"	UK	FX Spot Rate	Bloomberg (GBPUSD Curncy)
FX/JP	"	Japan	FX Spot Rate	Bloomberg (JPYUSD Curncy)
FX/EM	"	Emerging Countries	FX Spot Rate	Bloomberg (BRLUSD, CNYUSD, INRUSD, RUBUSD, TRYUSD Curncy)
MoneyMkt/US	Money Market	US	3 month US Libor	Bloomberg (US0003M Index)
MoneyMkt/EU	"	Euro Area	3 month Euribor	Bloomberg (EUR003M Index)
MoneyMkt/UK	"	UK	3 month UK Libor	Bloomberg (BP0003M Index)
Tr/US	Treasury	US	US Govt 10 Year Yield	Bloomberg (USGG10YR Index)
Tr/EU	"	Euro Area	EU Govt 10 Year Yield	Bloomberg (GECU10YR Index)
Tr/UK	"	UK	UK Govt 10 Year Yield	Bloomberg (GUKG10 Index)

Table 1: **List of variables used in the empirical application.** We report the acronyms used to identify each variable (ID variable), the asset class and the country to which they belong, the name of the series, together with the data provider and the ticker for series identification.

	Mean	***St Dev***	***Min***	***Max***	***Skewness***	***Kurtosis***
CorpBond/US	0.119%	0.748%	-5.355%	3.171%	-0.935	8.553
CorpBond/EU	0.103%	1.558%	-5.815%	5.385%	-0.194	3.512
CorpBond/UK	0.100%	1.612%	-13.152%	5.628%	-1.075	10.651
CorpBond/JP	0.092%	1.347%	-5.356%	8.924%	0.572	6.755
CorpBond/EM	0.163%	0.826%	-9.332%	3.724%	-3.717	38.973
EqInd/US	0.014%	2.747%	-20.116%	11.526%	-0.748	8.850
EqInd/EU	-0.011%	3.502%	-26.679%	12.245%	-1.073	9.576
EqInd/UK	-0.009%	3.091%	-27.618%	16.243%	-1.249	14.920
EqInd/JP	0.009%	2.887%	-16.402%	11.016%	-0.258	4.823
EqInd/EM	0.184%	3.380%	-22.564%	18.538%	-0.775	8.889
FX/EU	0.017%	1.468%	-6.048%	4.992%	-0.213	3.831
FX/UK	-0.009%	1.341%	-8.348%	5.195%	-0.588	6.546
FX/JP	0.050%	1.498%	-6.027%	7.445%	0.253	4.304
FX/EM	-0.142%	1.517%	-17.401%	4.786%	-2.961	29.634
MoneyMkt/US	-0.350%	3.814%	-27.877%	21.137%	-1.850	16.873
MoneyMkt/EU	-0.187%	2.087%	-11.989%	15.021%	-0.717	11.723
MoneyMkt/UK	-0.262%	2.091%	-26.170%	8.374%	-4.357	43.968
Tr/US	-0.126%	3.596%	-19.122%	12.110%	-0.045	5.511
Tr/EU	-0.116%	3.056%	-17.838%	14.018%	-0.353	6.476
Tr/UK	-0.105%	2.805%	-16.758%	11.153%	-0.362	5.943

Table 2: **Descriptive statistics for the market returns.** We report summary statistics for the variable used in the empirical application. The number reported refer to the entire sample, which consists of weekly observations from Jan-1999 to Mar-2012.

	CorpBond/US	*CorpBond/EU*	*CorpBond/UK*	*CorpBond/JP*	*CorpBond/EM*	*EqInd/US*	*EqInd/EU*	*EqInd/UK*	*EqInd/JP*	*EqInd/EM*	*FX/EU*	*FX/UK*	*FX/JP*	*FX/EM*	*MoneyMkt/US*	*MoneyMkt/EU*	*MoneyMkt/UK*	*Tr/US*	*Tr/EU*
CorpBond/EU	0.393																		
CorpBond/UK	0.462	0.694																	
CorpBond/JP	0.264	0.312	0.171																
CorpBond/EM	0.578	0.539	0.516	0.046															
EqInd/US	-0.041	0.087	0.080	-0.260	0.207														
EqInd/EU	0.004	0.411	0.288	-0.161	0.351	0.785													
EqInd/UK	0.028	0.326	0.403	-0.229	0.329	0.764	0.884												
EqInd/JP	0.145	0.238	0.208	0.129	0.272	0.405	0.480	0.444											
EqInd/EM	0.044	0.286	0.272	-0.211	0.448	0.693	0.785	0.755	0.545										
FX/EU	0.178	0.913	0.566	0.232	0.402	0.126	0.435	0.333	0.217	0.291									
FX/UK	0.162	0.616	0.833	0.060	0.358	0.156	0.373	0.502	0.251	0.336	0.642								
FX/JP	0.181	0.295	0.138	0.836	0.054	-0.226	-0.112	-0.177	0.269	-0.140	0.262	0.101							
FX/EM	0.079	0.349	0.296	-0.151	0.356	0.434	0.548	0.522	0.244	0.593	0.338	0.328	-0.094						
MoneyMkt/US	-0.342	-0.233	-0.174	-0.133	-0.247	-0.020	-0.094	-0.091	-0.076	-0.088	-0.144	-0.081	-0.102	-0.077					
MoneyMkt/EU	-0.177	-0.056	0.001	-0.009	-0.141	0.030	0.053	0.034	0.029	-0.005	0.015	0.036	-0.007	-0.018	0.385				
MoneyMkt/UK	-0.227	-0.104	-0.002	-0.077	-0.245	0.061	-0.002	0.033	-0.017	-0.037	-0.023	0.119	-0.083	-0.003	0.536	0.525			
Tr/US	-0.733	-0.246	-0.292	-0.388	-0.230	0.329	0.294	0.262	0.061	0.275	-0.104	-0.037	-0.295	0.152	0.141	0.112	0.090		
Tr/EU	-0.548	-0.171	-0.280	-0.310	-0.152	0.297	0.337	0.276	0.114	0.277	0.045	0.040	-0.219	0.167	0.105	0.152	0.118	0.731	
Tr/UK	-0.531	-0.205	-0.330	-0.313	-0.176	0.266	0.268	0.267	0.121	0.247	-0.031	0.083	-0.208	0.133	0.084	0.105	0.159	0.715	0.798

Table 3: **Sample correlations among the market returns.**

	Global	***Corp Bond***	***EqInd***	***FX***	***Money Mkt***	***Tr***	***US***	***EU***	***UK***	***JP***	***EM***
CorpBond/US	-0.188	0.595	0.684	0.325	-0.337	-0.714	-0.234	0.017	0.032	0.098	0.059
CorpBond/EU	0.237	0.884	0.350	0.822	-0.211	-0.472	0.028	0.150	-0.120	-0.039	-0.044
CorpBond/UK	0.185	0.882	0.425	0.700	-0.131	-0.550	0.038	-0.163	0.145	0.052	-0.022
CorpBond/JP	-0.300	0.450	0.279	0.402	-0.128	-0.245	-0.106	0.107	-0.027	-0.129	0.015
CorpBond/EM	0.281	0.587	0.413	0.377	-0.248	-0.475	-0.007	-0.078	-0.153	0.061	0.278
EqInd/US	0.816	-0.072	0.248	-0.146	0.004	-0.214	0.138	-0.029	-0.035	-0.136	-0.167
EqInd/EU	0.907	0.193	0.275	0.127	-0.066	-0.284	-0.008	0.263	-0.024	-0.129	-0.156
EqInd/UK	0.875	0.206	0.290	0.119	-0.057	-0.307	-0.016	-0.011	0.312	-0.118	-0.188
EqInd/JP	0.541	0.177	0.350	0.096	-0.063	-0.288	-0.143	-0.181	-0.101	0.624	0.036
EqInd/EM	0.854	0.143	0.289	0.078	-0.072	-0.290	0.009	-0.177	-0.167	0.016	0.422
FX/EU	0.313	0.730	0.167	0.830	-0.117	-0.293	-0.012	0.226	-0.114	-0.078	-0.099
FX/UK	0.373	0.683	0.133	0.720	-0.032	-0.260	-0.061	-0.185	0.328	0.027	-0.092
FX/JP	-0.205	0.379	0.226	0.441	-0.104	-0.186	-0.089	0.044	-0.024	-0.026	0.022
FX/EM	0.557	0.225	0.122	0.421	-0.061	-0.222	0.119	-0.131	-0.169	0.088	0.212
MoneyMkt/US	-0.021	-0.241	-0.175	-0.139	0.973	0.187	0.133	-0.019	-0.034	-0.059	0.040
MoneyMkt/EU	0.092	-0.061	-0.138	-0.030	0.551	0.108	-0.360	0.152	-0.021	0.193	-0.096
MoneyMkt/UK	0.065	-0.104	-0.150	-0.010	0.697	0.118	-0.332	-0.031	0.176	0.120	-0.109
Tr/US	0.559	-0.474	-0.716	-0.350	0.153	0.738	0.309	-0.142	-0.123	-0.025	0.028
Tr/EU	0.577	-0.403	-0.700	-0.224	0.130	0.708	-0.229	0.248	-0.045	0.016	-0.025
Tr/UK	0.536	-0.439	-0.695	-0.239	0.118	0.712	-0.250	-0.059	0.266	0.023	-0.017

Table 4: **Correlations between the market returns and the extracted factors.** We report the correlation between the factors and the market returns from which the factors are extracted. There are 20 series displayed in the rows and 11 factors (one global, 5 asset class and 5 country factors), which are displayed in the columns. The numbers reported are in-sample linear correlations.

FACTOR	***STAT***	
Global	51.982	***
CorpBond	7.577	***
EqInd	0.458	
FX	3.254	*
MoneyMkt	59.335	***
Tr	0.318	
US	31.535	***
EU	21.421	***
UK	26.668	***
JP	3.386	*
EM	25.878	***

Table 5: **Engle test for residual heteroscedasticity for the estimated factors.** We report the results of the test for residual heteroscedasticity for the 11 extracted factors (one global, 5 asset class and 5 country factors). The first columns reports the name of the factor, the second reports the test statistics in the Engle test for residual heteroscedasticity. In the third column, ***, ** and * indicate rejection of the null of no ARCH effect at the 1%, 5% and 10% significance level, respectively.

	Alternative model	
Null model	***Time-varing factor loading***	***Conditional time-varying factor loading***
Static factor loading	260142.36***	261869.86***
Time-varing factor loading		1727.50***

Table 6: **Likelihood ratio test for the alternative models.** We report the test statistics for the likelihood ratio test comparing the proposed alternative models. The test is employed to evaluate the null hypothesis that the *Null model* provides a better fit than the *Alternative model*. The models refer to the following alternative formulation for the factor loadings: the static factor loading in Eq. (8), the time-varying factor loading in Eq. (9) and the conditional time-varying factor loading in Eq. (7). *** indicates rejection of the null model at the 1% significance level.

Γ_t^F		
Outliers		
26/02/1999	-0.0583	**
...		
16/12/2011	-0.0584	**
Constant	0.2230	***

$\Gamma_{t,ED}^F$		
Segments		
17/08/2007 - 21/11/2008	-0.0670	***
Outliers		
07/04/2000	-0.0608	**
30/06/2000	-0.0607	**
09/03/2001	-0.0746	***
25/11/2011	-0.0646	***
02/12/2011	-0.0583	**
Constant	0.2282	***

$\Gamma_{t,VD}^F$		
Segments		
31/10/2008 - 05/12/2008	0.0564	***
12/08/2011 - 26/08/2011	0.0594	***
Outliers		
23/04/1999	-0.0507	***
Constant	0.2320	***

Table 7: **IIS results for the overall average comovement measures.** Γ_t^F is the average comovement measure at the overall level, defined as the mean of the model implied correlations between all the couples of asset considered. $\Gamma_{t,ED}^F$ ($\Gamma_{t,VD}^F$) considers the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time). We report the results of the saturation of model in Eq. (29) by means of Autometrics. We report the dates detected via the IIS technique, together with the estimated coefficients. *Segment* refers to group of sequential dummies with the same size and similar magnitude. *Outliers* are dummies which can not be grouped. *Constant* refers to the constant term μ in Eq. 29 (***, ** and * indicate significance of the coefficient at the 1%, 5% and 10% significance level, respectively).

$\Gamma_t^{CorpBond}$			Γ_t^{EqInd}			Γ_t^{FX}			$\Gamma_t^{MoneyMkt}$			Γ_t^{Tr}		
Segments			*Segments*			*Segments*			*Segments*			*Outliers*		
24/08/2007 - 26/09/2008	-0.1614	***	10/10/2008 - 27/03/2009	0.1664	***	26/05/2006 - 04/08/2006	-0.1623	***	29/01/1999 - 20/04/2001	-0.0748	***	15/01/1999	-0.4502	***
03/10/2008 - 23/01/2009	-0.4134	***	12/08/2011 - 03/02/2012	0.1447	***	16/03/2007 - 25/07/2008	-0.1681	***	14/03/2008 - 28/03/2008	-0.9199	***	...		
06/02/2009 - 04/06/2010	-0.1867	***	*Outliers*			19/09/2008 - 15/05/2009	-0.3993	***	11/04/2008 - 19/09/2008	-0.0650	***	16/12/2011	-0.7062	***
12/08/2011 - 03/02/2012	-0.3610	***	01/01/1999	0.1596	***	12/08/2011 - 27/01/2012	-0.2528	***	26/09/2008 - 14/11/2008	0.0521	**	*Constant*	0.8238	***
Outliers			18/02/2000	-0.1695	***	*Outliers*			06/02/2009 - 22/01/2010	-0.1794	***			
22/01/1999	-0.1643	***	24/03/2000	-0.1718	***	22/01/1999	-0.1107	**	07/05/2010 - 28/05/2010	0.0525	**			
21/04/2000	-0.1535	***	*Constant*	0.7408	***	07/04/2000	-0.1149	***	15/04/2011 - 29/07/2011	-0.1010	***			
28/09/2001	-0.1812	***				09/03/2001	-0.1756	***	12/08/2011 - 19/08/2011	-1.2057	***			
05/10/2001	-0.1859	***				28/09/2001	-0.1433	***	11/11/2011 - 27/01/2012	-0.1060	***			
12/10/2001	-0.1343	***				21/05/2004	-0.1340	***	*Outliers*					
Constant	0.8557	***				24/07/2009	-0.1781	***	28/09/2001	0.0570	**			
						21/05/2010	-0.1111	**	16/11/2001	0.0550	**			
						Constant	0.7481	***	22/11/2002	-0.1174	***			
									21/02/2003	-0.0593	**			
									28/03/2003	-0.1570	***			
									04/04/2003	-0.0613	**			
									27/06/2003	-1.2632	***			
									01/02/2008	0.0524	**			
									29/02/2008	-0.0606	**			
									05/12/2008	-0.3098	***			
									26/12/2008	0.0502	**			
									02/07/2010	-0.0835	***			
									03/09/2010	0.0522	**			
									26/11/2010	-0.0771	***			
									14/01/2011	-0.0900	***			
									Constant	0.9421	***			

$\Gamma_{t,ED}^{CorpBond}$			$\Gamma_{t,ED}^{EqInd}$			$\Gamma_{t,ED}^{FX}$			$\Gamma_{t,ED}^{MoneyMkt}$			$\Gamma_{t,ED}^{Tr}$		
Segments			*Segments*			*Segments*			*Segments*			*Outliers*		
24/08/2007 - 05/09/2008	-0.0805	***	24/08/2007 - 15/05/2009	0.0448	***	19/03/1999 - 09/07/1999	-0.1037	***	08/11/2002 - 29/11/2002	-0.0623	***	08/01/1999	-0.1247	**
19/09/2008 - 03/04/2009	-0.1858	***	*Outliers*			20/05/2005 - 19/09/2008	-0.1385	***	14/02/2003 - 20/06/2003	-0.0190	***	...		
10/04/2009 - 18/09/2009	-0.0686	***	01/01/1999	0.1132	***	26/09/2008 - 02/01/2009	-0.2525	***	17/08/2007 - 01/02/2008	-0.0207	***	16/12/2011	-0.7230	***
12/08/2011 - 23/12/2011	-0.0628	***	26/03/1999	0.0267	***	09/01/2009 - 15/05/2009	-0.1326	***	14/03/2008 - 21/03/2008	-1.3015	***	*Constant*	0.8304	***
Outliers			18/06/1999	0.0387	***	12/08/2011 - 25/11/2011	-0.1176	***	04/04/2008 - 24/04/2009	-0.0313	***			
22/01/1999	-0.0803	***	02/03/2001	-0.0931	***	*Outliers*			05/06/2009 - 27/11/2009	-0.0204	***			
22/10/1999	-0.0574	***	28/09/2001	-0.0413	***	22/01/1999	-0.0871	**	14/05/2010 - 29/07/2011	-0.0311	***			
21/04/2000	-0.0419	***	05/10/2001	-0.0386	***	14/01/2000	-0.1109	***	12/08/2011 - 19/08/2011	-1.2619	***			
15/09/2000	0.0415	***	15/03/2002	0.0367	***	07/04/2000	-0.1090	***	26/08/2011 - 16/12/2011	-0.0321	***			
10/11/2000	0.0403	***	09/03/2007	-0.0312	***	09/03/2001	-0.2604	***	*Outliers*					
08/12/2000	0.0493	***	17/07/2009	-0.0435	***	16/03/2001	0.1068	***	18/06/1999	-0.0142	***			
05/01/2001	0.0440	***	14/08/2009	-0.0267	***	*Constant*	0.7349	***	30/07/1999	-0.0134	***			
02/08/2002	-0.0440	***	12/03/2010	-0.0257	***				17/09/1999	0.0157	***			
01/08/2003	0.0403	***	14/05/2010	-0.0460	***				08/10/1999	-0.0175	***			
Constant	0.8276	***	21/05/2010	-0.0336	***				12/01/2001	-0.0233	***			
			20/08/2010	0.0271	***				10/08/2001	-0.0259	***			
			08/04/2011	-0.0345	***				28/12/2001	-0.0165	***			
			15/04/2011	-0.0522	***				08/02/2002	-0.0148	***			
			26/08/2011	0.0293	***				27/06/2003	-1.2770	***			
			23/09/2011	0.0290	***				28/03/2008	-0.2650	***			
			11/11/2011	0.0305	***				01/05/2009	-1.0106	***			
			Constant	0.7860	***				29/05/2009	-0.2165	***			
									Constant	0.9720	***			

$\Gamma_{t,VD}^{CorpBond}$			$\Gamma_{t,VD}^{EqInd}$			$\Gamma_{t,VD}^{FX}$			$\Gamma_{t,VD}^{MoneyMkt}$			$\Gamma_{t,VD}^{Tr}$		
Segments			*Segments*			*Segments*			*Segments*			*Segments*		
28/09/2001 - 26/10/2001	-0.1392	***	18/02/2000 - 14/04/2000	-0.1367	***	28/09/2001 - 02/11/2001	-0.1156	***	29/01/1999 - 30/04/1999	-0.0511	**	01/10/1999 - 05/05/2000	-0.0650	***
23/12/2005 - 27/01/2006	0.0485	*	12/09/2008 - 13/03/2009	0.1491	***	01/04/2005 - 15/04/2005	0.0495	*	17/12/1999 - 10/03/2000	-0.0891	***	06/12/2002 - 21/03/2003	-0.0536	***
24/08/2007 - 28/09/2007	-0.1147	***	14/05/2010 - 28/05/2010	0.1366	***	19/09/2008 - 04/12/2009	-0.1399	***	26/09/2008 - 16/01/2009	0.0540	**	31/10/2008 - 07/11/2008	0.0571	***
17/10/2008 - 31/07/2009	-0.1823	***	12/08/2011 - 10/02/2012	0.1347	***	14/05/2010 - 16/07/2010	-0.0955	***	06/02/2009 - 20/03/2009	-0.1680	***	17/04/2009 - 11/09/2009	-0.0502	***
14/05/2010 - 11/06/2010	-0.1108	***	*Constant*	0.7437	***	15/07/2011 - 17/02/2012	-0.1452	***	22/05/2009 - 29/05/2009	0.0534	**	*Outliers*		
08/07/2011 - 24/02/2012	-0.1627	***				*Outliers*			17/07/2009 - 11/09/2009	0.0525	**	29/01/1999	-0.0454	**
Outliers						14/05/1999	-0.0794	***	16/10/2009 - 20/11/2009	-0.0697	***	12/08/2011	0.0545	***
21/04/2000	-0.0857	***				18/10/2002	-0.1335	***	07/05/2010 - 03/09/2010	0.0541	**	*Constant*	0.8791	***
04/07/2003	0.0503	*				25/10/2002	-0.0899	***	*Outliers*					
12/12/2003	0.0499	*				30/07/2004	0.0523	*	15/10/1999	0.0491	**			
30/09/2005	0.0513	*				*Constant*	0.7604	***	19/09/2008	-0.0521	**			
15/02/2008	-0.0854	***							19/06/2009	-0.0690	***			
Constant	0.8623	***							08/01/2010	-0.0504	**			
									26/11/2010	-0.0522	**			
									11/11/2011	-0.0583	**			
									06/01/2012	-0.0865	***			
									13/01/2012	-0.1019	***			
									Constant	0.9401	***			

Table 8: **IIS results for the average comovements measures at the asset class level.** $\Gamma_t^{CorpBond}$ is the average comovement measure within the corporate bond market, defined as the mean of the model implied correlations between all the couples of securities in the corporate bond asset class. Γ_t^{EqInd}, Γ_t^{FX}, $\Gamma_t^{MoneyMkt}$ and Γ_t^{Tr} are analogously defined for the other asset classes. Exposure-driven (mid-panel) and volatility-driven (bottom panel) comovement measures consider the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time). Refer to the caption of Tab. 7 for a legend of the results of the estimation.

Γ_t^{US}			Γ_t^{EU}			Γ_t^{UK}			Γ_t^{JP}			Γ_t^{EM}		
Segments			*Outliers*			*Segments*			*Segments*			*Ouliers*		
22/10/1999 - 29/10/1999	0.0576	***	27/06/2008	-0.2400	**	11/02/2000 - 21/04/2000	0.1197	***	08/10/1999 - 12/05/2000	-0.2752	***	22/01/1999	0.1323	***
04/02/2000 - 18/02/2000	0.0643	***	05/12/2008	0.2282	**	04/07/2003 - 08/08/2003	-0.1149	***	17/08/2007 - 24/07/2009	-0.3622	***	...		
24/11/2000 - 22/12/2000	0.0516	***	19/12/2008	0.2436	**	10/10/2008 - 13/03/2009	0.1552	***	21/05/2010 - 25/06/2010	-0.2484	***	09/12/2011	0.0618	**
28/09/2001 - 02/11/2001	-0.0532	***	10/07/2009	-0.2203	**	12/08/2011 - 18/11/2011	0.1079	***	12/08/2011- 27/01/2012	-0.3288	***	*Constant*	0.6248	***
19/07/2002 - 27/09/2002	0.0568	***	07/05/2010	-0.2203	**	*Outliers*			*Outliers*					
24/08/2007 - 26/09/2008	0.0566	***	07/01/2011	-0.2155	**	06/11/2009	0.1012	***	30/05/2003	0.1582	*			
03/10/2008 - 19/12/2008	0.1524	***	29/07/2011	0.2320	**	16/07/2010	0.1076	***	16/06/2006	-0.2002	**			
02/01/2009 - 16/07/2010	0.0545	***	12/08/2011	0.2404	**	03/12/2010	-0.0992	***	*Constant*	0.3496	***			
Outliers			26/08/2011	0.2648	**	*Constant*	0.1988	***						
08/08/2003	-0.0515	***	21/10/2011	0.2253	**									
Constant	-0.1399	***	18/11/2011	0.2779	***									
			23/12/2011	0.2197	**									
			06/01/2012	0.2225	**									
			Constant	0.1667	***									

$\Gamma_{t,ED}^{US}$			$\Gamma_{t,ED}^{EU}$			$\Gamma_{t,ED}^{UK}$			$\Gamma_{t,ED}^{JP}$			$\Gamma_{t,ED}^{EM}$		
Segments			*Ouliers*			*Outliers*			*Segments*			*Outliers*		
06/08/1999 - 08/12/2000	0.0331	***	13/08/1999	-0.2253	**	01/01/1999	0.0567	***	27/08/1999 - 02/06/2000	-0.2321	***	22/01/1999	0.1545	***
19/07/2002 - 11/10/2002	0.0291	***	04/02/2000	-0.2319	**	...			17/08/2007 - 10/07/2009	-0.3365	***	...		
23/07/2004 - 14/04/2006	-0.0147	*	03/03/2000	-0.2266	**	01/10/2010	-0.0249	***	12/08/2011 - 20/01/2012	-0.2486	***	21/10/2011	0.1071	***
17/08/2007 - 05/09/2008	0.0436	***	14/04/2000	-0.2216	**	*Constant*	0.1989	***	*Outliers*			*Constant*	0.6273	***
12/09/2008 - 30/01/2009	0.0766	***	23/06/2000	-0.2245	**				12/03/2004	0.2703	***			
06/02/2009 - 17/07/2009	0.0447	***	23/02/2001	-0.2252	**				04/02/2005	0.1355	*			
12/08/2011 - 09/03/2012	0.0331	***	07/06/2002	-0.2163	**				27/05/2005	0.1404	*			
Outliers			11/10/2002	-0.2222	**				08/07/2005	0.1449	*			
11/06/2010	0.0252	**	07/03/2003	-0.2263	**				*Constant*	0.3521	***			
03/12/2010	0.0275	***	23/07/2004	-0.2145	**									
Constant	-0.1457	***	20/08/2004	-0.2269	**									
			08/04/2005	-0.2288	**									
			Constant	0.1805	***									

$\Gamma_{t,VD}^{US}$			$\Gamma_{t,VD}^{EU}$			$\Gamma_{t,VD}^{UK}$			$\Gamma_{t,VD}^{JP}$			$\Gamma_{t,VD}^{EM}$		
Segments			*Segments*			*Segments*			*Segments*			*Segments*		
28/09/2001 - 19/10/2001	-0.0484	***	27/06/2003 - 08/08/2003	-0.0716	**	04/07/2003 - 08/08/2003	-0.1111	***	20/06/2003 - 27/02/2004	0.1288	***	23/04/1999 - 04/06/1999	0.0683	***
26/07/2002 - 20/09/2002	0.0451	***	23/01/2004 - 01/10/2004	-0.0565	*	17/10/2008 - 20/03/2009	0.1308	***	17/10/2008 - 19/12/2008	-0.1532	***	30/07/1999 - 20/08/1999	-0.0542	***
20/06/2008 - 25/09/2009	-0.0365	***	17/10/2008 - 26/12/2008	0.1748	***	06/11/2009 - 13/11/2009	0.0826	**	19/11/2010 - 14/01/2011	0.1434	***	26/01/2001 - 02/11/2001	0.0680	***
19/11/2010 - 17/12/2010	-0.0336	**	02/01/2009 - 23/07/2010	0.1044	***	02/07/2010 - 16/07/2010	0.0863	**	12/08/2011 - 18/11/2011	-0.1162	***	05/07/2002 - 01/11/2002	0.0660	***
19/08/2011 - 09/03/2012	-0.0377	***	08/07/2011 - 27/01/2012	0.1300	***	12/08/2011 - 11/11/2011	0.1050	***	*Constant*	0.2815	***	07/05/2004 - 21/05/2004	0.0519	***
Constant	-0.1346	***	*Outliers*			*Outliers*						24/08/2007 - 14/09/2007	0.0688	***
			31/08/2007	0.0796	**	20/06/2008	-0.0976	***				18/04/2008 - 31/10/2008	0.0479	***
			Constant	0.2112	***	03/12/2010	-0.0978	***				12/08/2011 - 11/11/2011	0.0505	***
						Constant	0.1994	***				*Outliers*		
												29/09/2000	0.0593	***
												Constant	0.6394	***

Table 9: **IIS results for the average comovements measures at the country level.** Γ_t^{US} is the average comovement measure within the US market, defined as the mean of the model implied correlations between all the couples of securities in the US group. Γ_t^{EU}, Γ_t^{UK}, Γ_t^{JP} and Γ_t^{EM} are analogously defined for the other countries. Exposure-driven (mid-panel) and volatility-driven (bottom panel) comovement measures consider the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time). Refer to the caption of Tab. 7 for a legend of the results of the estimation.

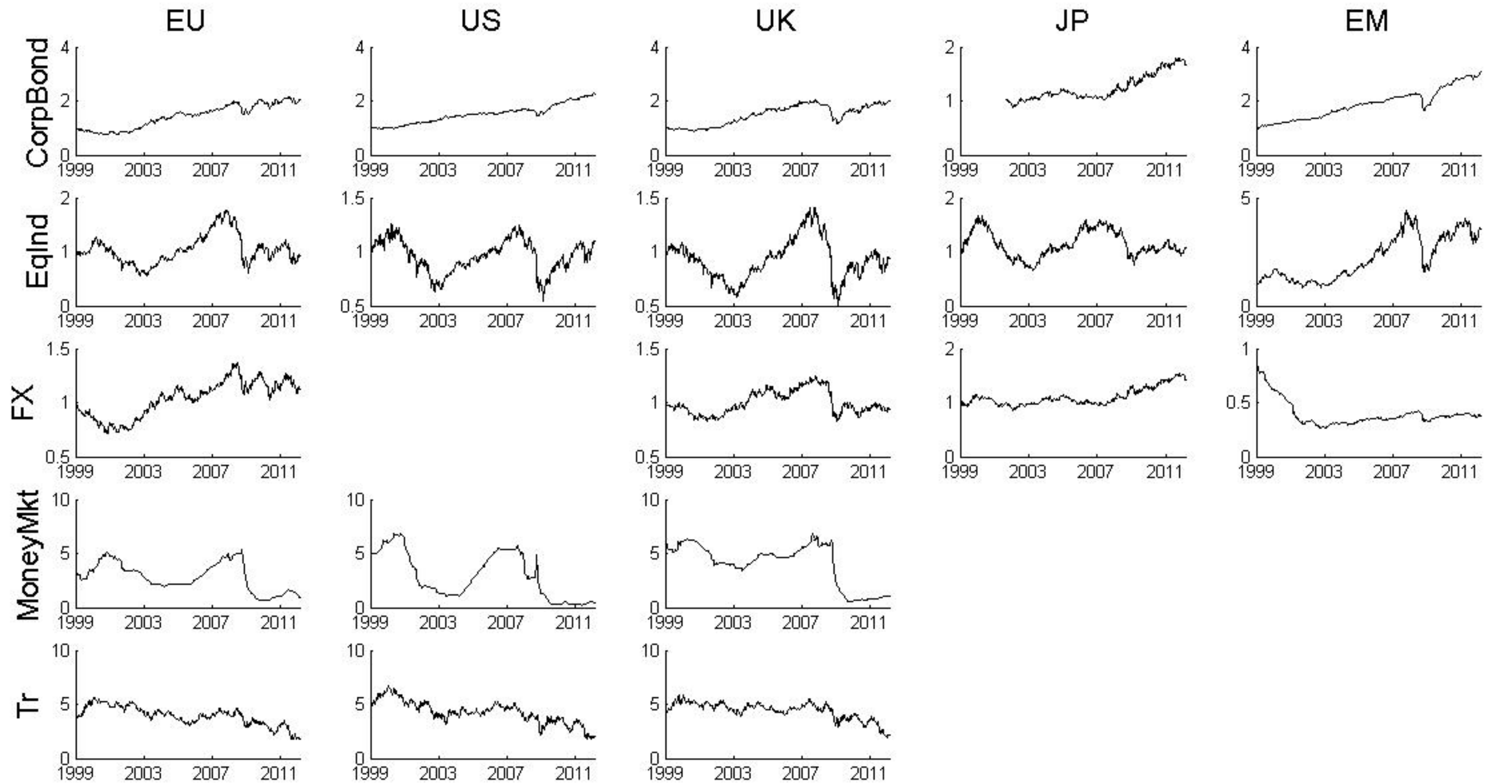

Figure 1: **Price data used in the empirical application.** Asset classes are displayed in the rows, whereas countries are in the columns. We plot the weekly price series for the considered markets. Corporate bond, equity indices and foreign exchange rates (top three rows) are rebased using the first available observation. US foreign exchange is excluded from the analysis because is used as the numeraire. The other missing series are not considered due to lack of data.

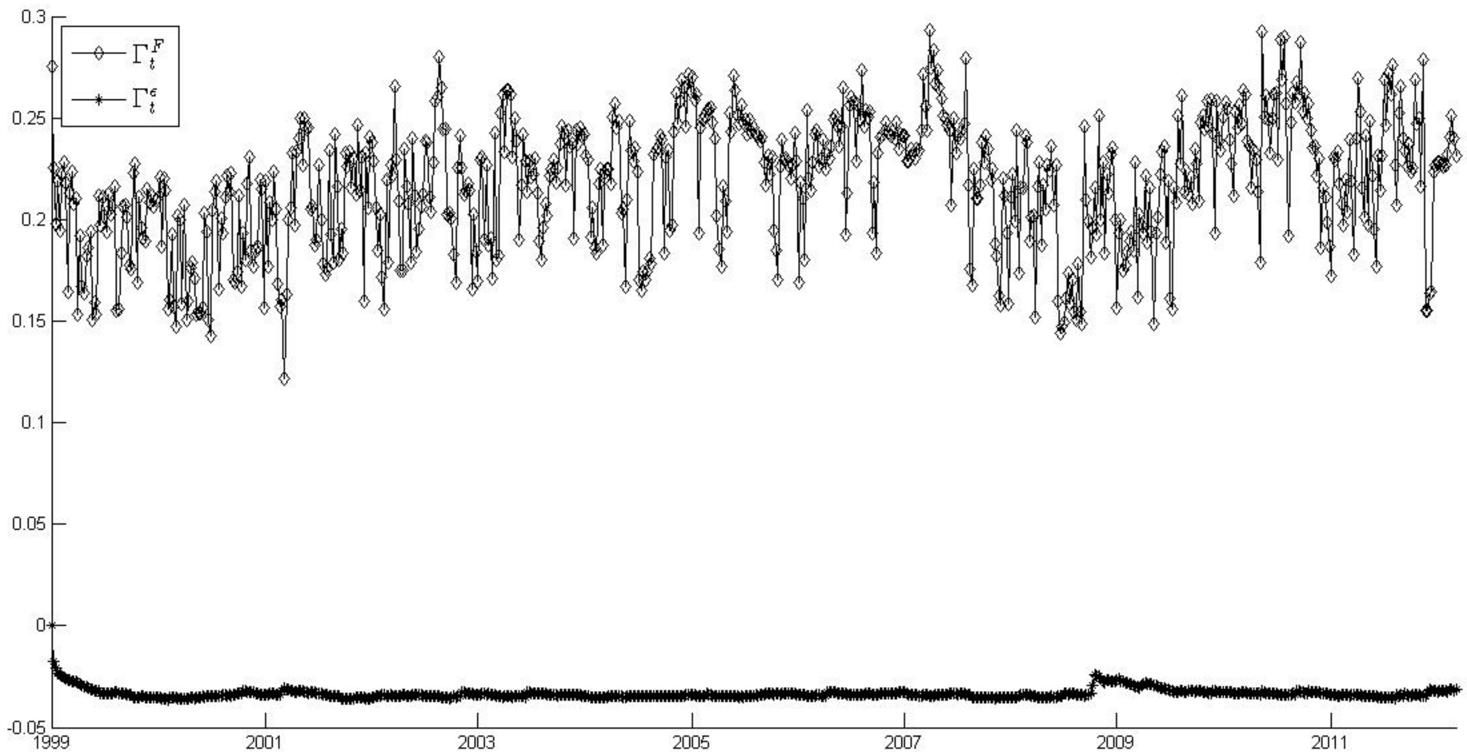

Figure 2: **Model implied versus residual average correlation measures.** Γ_t^F is the average comovement measure at the overall level, defined as the mean of the model implied correlations between all the couples of asset considered. Γ_t^ϵ is the average residual comovement measure, defined as the mean of the correlations between the error term in the model for all the couples of asset considered.

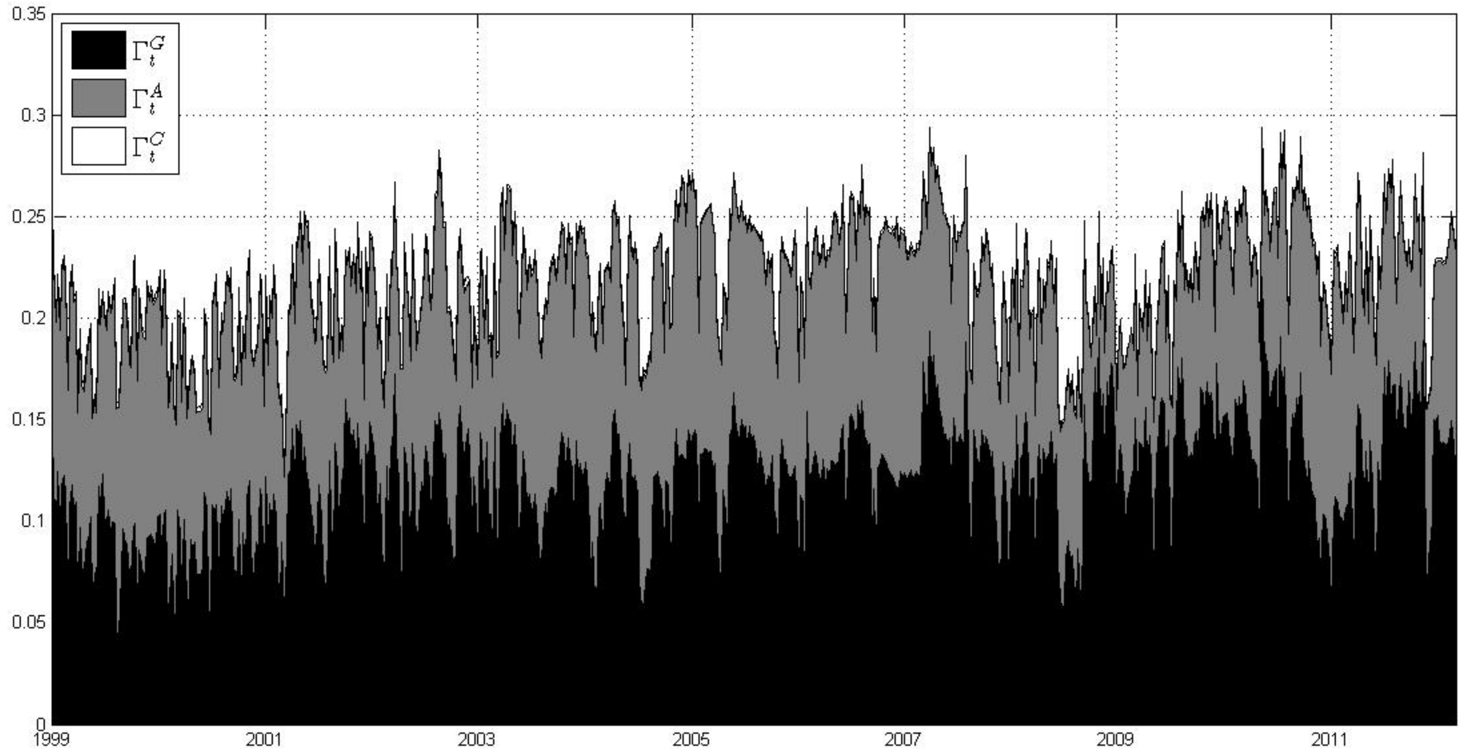

Figure 3: **Decompositions of the overall average comovements by source of the shock.** Γ_t^G, Γ_t^A Γ_t^C are the average measures of comovement prompted by the global, the asset class and the country factor, respectively.

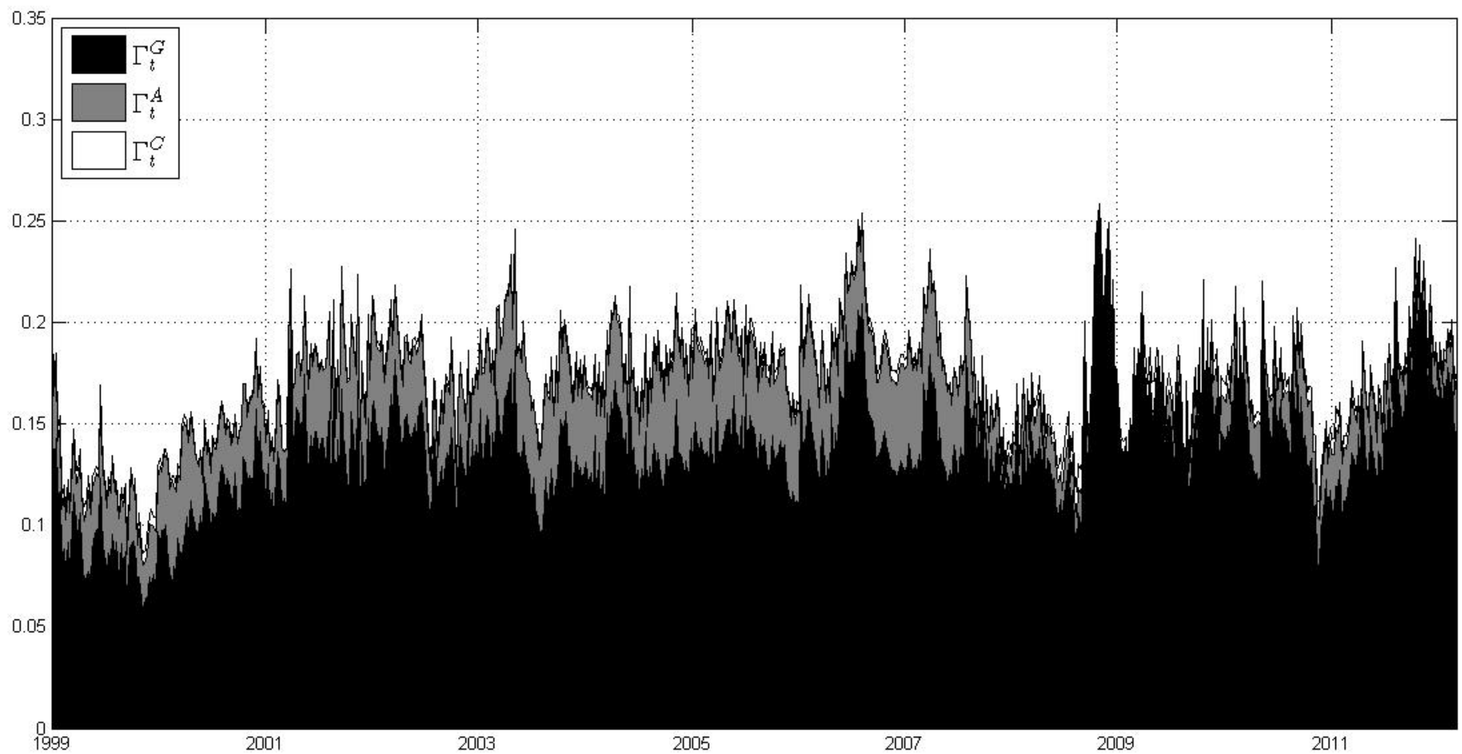

Figure 4: **Robustness check of the decomposition by source.** Fig. 3 reports the decompositions of the overall average comovements by source of the shock, for the case in which the asset class factors are first orthogonalized with respect to the global factor and then the country factors are orthogonalized with respect to the asset class and the global factors. Here we report the same decomposition for the case in which the country factors are orthogonalized with respect to the global factor and then the asset class factors are orthogonalized with respect to the others.

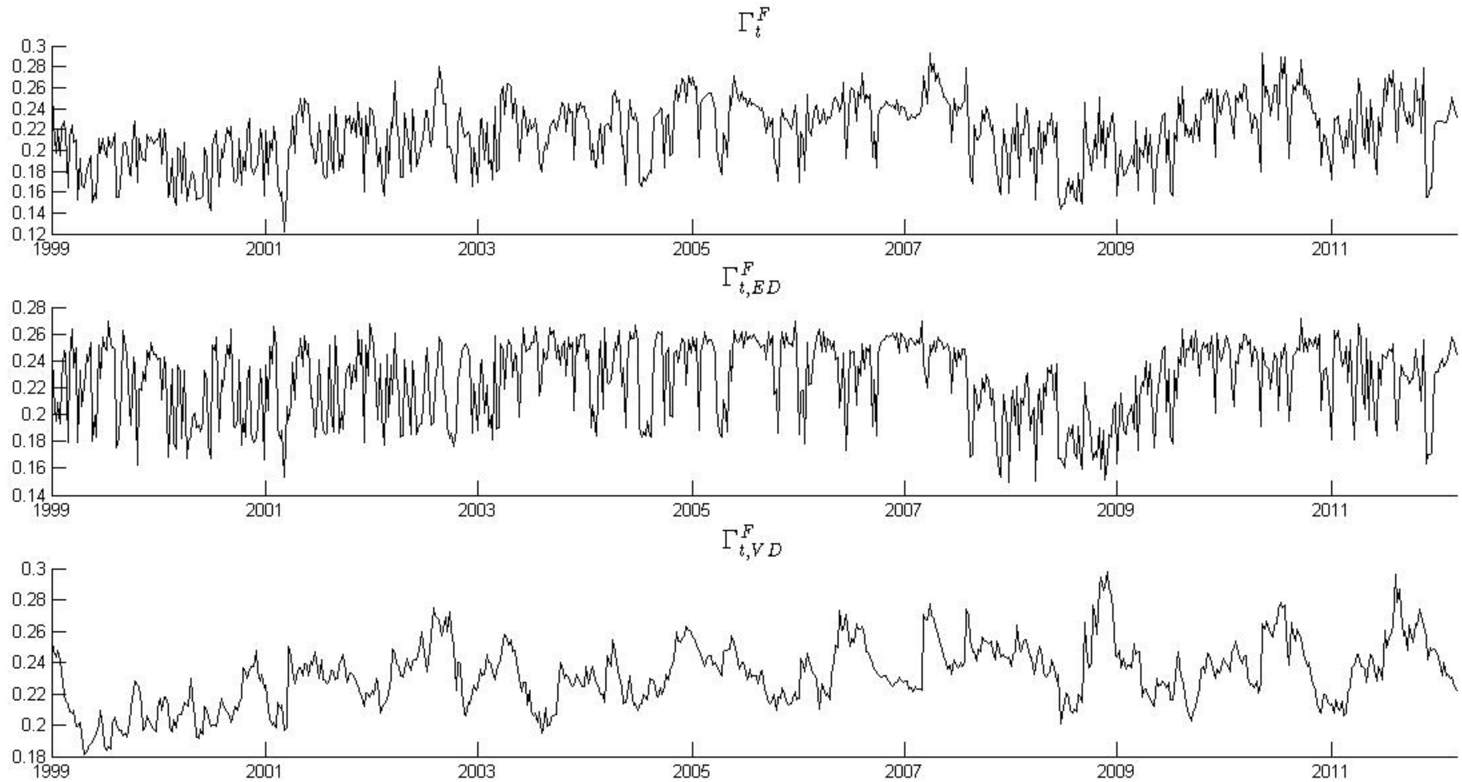

Figure 5: **Average correlation measures.** Γ_t^F (top panel) is the average comovement measure at the overall level, defined as the mean of the model implied correlations between all the couples of asset considered. $\Gamma_{t,ED}^F$ -mid panel- ($\Gamma_{t,VD}^F$ -bottom panel-) considers the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time).

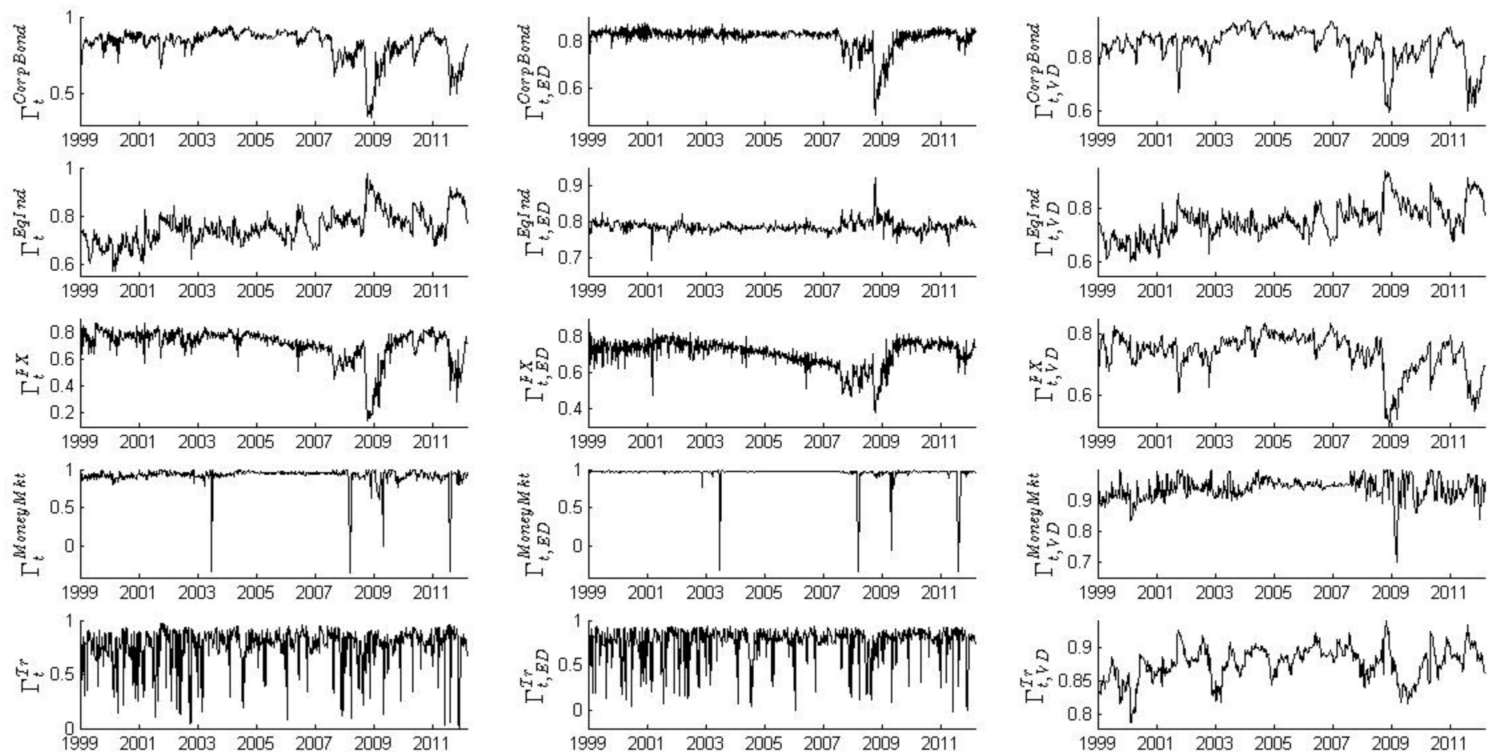

Figure 6: **Average correlation measures at the asset class level**. $\Gamma_t^{CorpBond}$ is the average comovement measure within the corporate bond market, defined as the mean of the model implied correlations between all the couples of securities in the corporate bond asset class. Γ_t^{EqInd}, Γ_t^{FX}, $\Gamma_t^{MoneyMkt}$ and Γ_t^{Tr} are analogously defined for the other asset classes. Exposure-driven (second column) and volatility-driven (third column) comovement measures consider the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time).

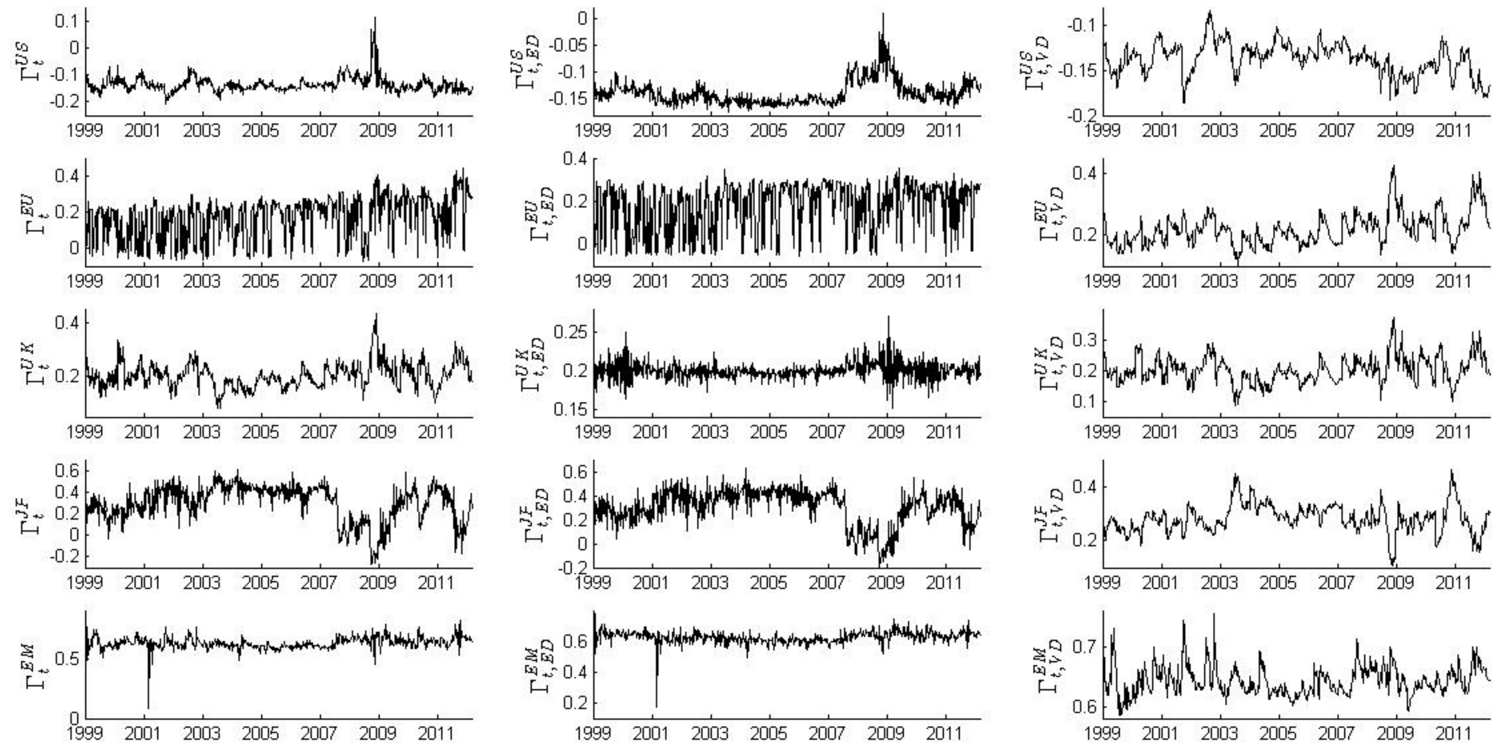

Figure 7: **Average correlation measures at the country level.** Γ_t^{US} is the average comovement measure within the US market, defined as the mean of the model implied correlations between all the couples of securities in the US group. Γ_t^{EU}, Γ_t^{UK}, Γ_t^{JP} and Γ_t^{EM} are analogously defined for the other countries. Exposure-driven (second column) and volatility-driven (third column) comovement measures consider the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time).

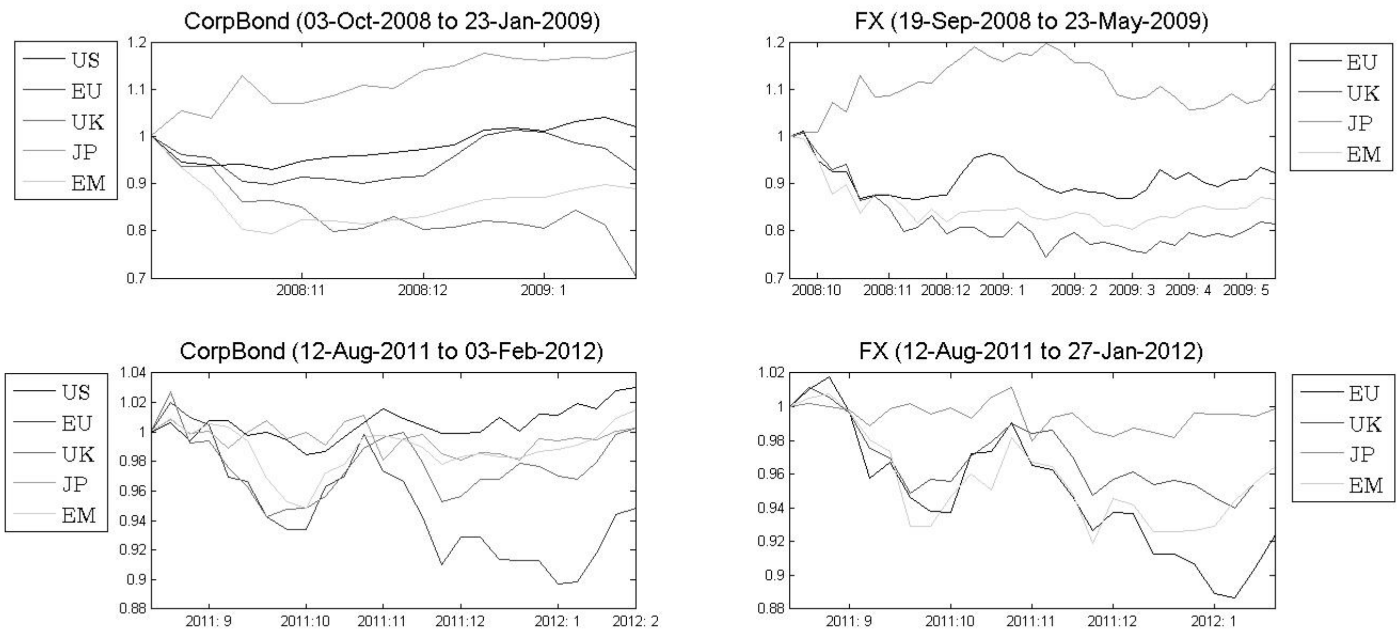

Figure 8: **Comparison among selected securities during the detected regimes.** We report corporate bond and foreign exchange price levels for periods in which decorrelation was detected. The price are rebased using the first observation in each subperiod.