Identifying Contagion

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February 2016

Abstract

Identifying contagion effects during periods of financial crisis is known to be complicated by the changing volatility of asset returns during periods of stress. Genuine contagion involves a combination of increased volatility for all assets and an asymmetric effect where the volatility of the recipient increases more than the source. To untangle this we propose a GARCH common features approach, where systemic risk emerges from a common factor source (or indeed multiple factor sources) with contagion evident through possible changes in the factor loadings relating to the common factor(s). Within a portfolio mimicking factor framework this can be identified using moment conditions. We use this framework to identify contagion in three illustrations involving both single and multiple factor specifications; to the Asian currency markets in 1997-98, to US sectoral equity indices in 2007-2009 and to the CDS market during the European sovereign debt crisis of 2010-2013. The results reveal the extent to which contagion effects may be masked by not accounting for the sources of changed volatility apparent in simple measures such as correlation.

JEL Categories: C58, G01

Keywords: contagion, generalized method of moments, factor model, GARCH

Acknowledgements: We are grateful for support from the IdR QUANT-VALLEY/Risk Foundation Development of Quantitative Management Research Initiative.

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1 Introduction

There is widespread agreement that the challenge for identifying contagion is to disentangle it from interdependence. In particular, contagion is not simply revealed by increased correlation of performance indicators during a crisis period – rising correlation coefficients are polluted by the rising volatility conditions which are almost invariably associated with periods of financial stress.[1] Forbes and Rigobon (2002) propose a neat way of correcting the correlation coefficient in order to catch only that part which is not due to rising volatility. However, when contemplating the potential for contagion from a 'source' market to a 'target' market, it is clear that the Forbes and Rigobon correction does not take account of the fact that the volatility of the target market may change both for reasons associated with the source, and for reasons of its own. If this idiosyncratic volatility in the target market is higher (lower) in crisis times than in non-crisis times, we argue that the Forbes and Rigobon correction overestimates (underestimates) the spurious component of the correlation increase.

These observations suggest a factor model structure when considering contagion from multiple sources towards multiple potential targets. It is the simultaneous volatility increase due to the rising volatility of common factors that pertains to interdependence, and should not be dubbed contagion. This framework is compatible with the view of contagion as correlation in excess of that expected via fundamentals, as in Bekaert et al (2005), or later, and more directly related, in Bekaert et al (2014) as "the comovement in excess of that implied by the factor model". While we concur with this definition, our empirical strategy differs.

The originality of our approach is to let the data speak by basing identification of the fundamentals and the link to asset correlation on a statistical testing strategy rather than on an a priori definition of fundamentals based on economic theory; Bekaert et al (2005) acknowledge the problem of identifying both the relevant fundamentals and how they are linked to asset correlation. Following the seminal work of King et al (1994) we note first, that the key to identifying changing

[1] Eichengreen et al (1996) and Pesaran and Pick (2007) for example, both consider contagion between countries as evident when the presence of a crisis in one country increases the probability of a crisis elsewhere, after controlling for the fundamental relationships or non-crisis relationships between them.

conditions for portfolio diversification is to see the time-varying volatility of returns as "induced by changes in the underlying factors", and second, that assuming time-varying conditional variance may ease identification of the factor model.

On one hand, like King et al (1994), we set the focus on factors whose role is to capture the time variations of volatility that are predictable – in contrast with unpredictable structural breaks in crisis times. However, because contagion occurs during crises, basing diversification on tranquil period correlations may not work (King et al 1994), we want to focus on the unpredictable part of correlation as characterized by idiosyncratic terms, and for these to play a role in contagion via structural changes during crisis periods. In other words, in contrast with King et al (1994), our factor model allows idiosyncratic risks to be correlated across assets. For us 'idiosyncratic' means uncorrelated with the factors which drive predictable (GARCH-type for example) components of return volatilities. One of the two channels of contagion we identify will be through structural breaks in so-called 'idiosyncratic betas' (betas of target on source induced only by their idiosyncratic components). Idiosyncratic risks are by definition time invariant, up to structural changes in the crisis period, and we will, roughly speaking, identify factors as capturing all time-varying components of return volatilities. Although we never resort to any specific GARCH or stochastic volatility dynamics, our multivariate volatility model with latent factors can be seen as inspired either by GARCH-factor models or common factor stochastic volatility models studied in a maximum likelihood framework by Diebold and Nerlove (1989) and Engle et al (1990) for GARCH factors as well as Fiorentini et al (2004) for stochastic volatility factors. Note that all of these models are more restrictive than ours as they are both fully parametric (in a likelihood setting) and preclude correlation between idiosyncratic risks. Our model is semi-parametric in nature and implemented with a GMM approach.

On the other hand, like Bekaert et al (2014), we want to characterize contagion as comovements which are not explained by the factor model. Although our statistical strategies are different from Bekaert et al (2014), our definitions of contagion are essentially identical. With weekly data, Bekaert et al (2014) run regressions of returns on lagged values and contemporaneous factors (three value-weighted market indices) with time-varying beta coefficients. Contagion is identified by a non-zero coefficient for a crisis dummy either in time-varying betas or in the intercept. In our framework betas are constant by definition (since time-varying volatilities are fully captured by factors), except for structural breaks at times of crisis. Moreover, since we work with daily data, we cannot set the focus of structural changes on conditional means, but rather on conditional variances. For this reason we consider structural changes in idiosyncratic betas rather than intercept shifts. However, our two preferred characterizations of contagion as structural changes in either conditional factor loadings or in idiosyncratic betas match the spirit of the two dummy coefficients on conditional factor loadings and intercepts in Bekaert et al (2014). Moreover, we are able to understand structural breaks in unconditional betas of the target asset on the source as a weighted average of structural changes in conditional and/or idiosyncratic betas respectively.

Our semi-parametric framework for contagion identification fits within the "GARCH common features" framework as put forward by Engle and Kozicki (1993) and revisited for statistical inference by Doz and Renault (2006) and Dovonon and Renault (2013). The key idea is that heteroskedasticity goes through only a few latent common factors while many linear combinations of primitive returns (called common features and interpreted as returns on portfolios) are actually homoskedastic, a feature implicitly incorporated in the contagion model of Dungey and Martin (2007). To keep this introductory discussion simple, let us assume that out of n primitive asset returns, there is only one common factor of heteroskedasticity while the space of common features is of dimension $(n-1)$.

Then, we will see the common factor as the source of potential contagion (the systematic risk), while defining contagion as change in the factor loading of each of the n primitive asset returns (the n potential targets) on the systematic risk. Interestingly enough, we are very close in spirit, albeit in a completely different framework, to some work developed simultaneously and independently by Darolles et al (2015) who attempt to disentangle frailty (the latent factor explaining correlation in default occurrences) from contagion; see also Duffie et al (2009).

Our framework cannot avoid the reflection problem of Manski (1993): we need some prior information to specify the reference asset. In other words, we must pick an asset that is not in our target set and consider it as the "mimicking portfolio"; that is the portfolio whose return conveys the information about the underlying systematic risk. Contagion will then be characterized by changes in factor loadings of the n assets on the latent common factor. In other examples, Cohen-Cole et al (2012) specify a specific, unchanging network of trading linkages as their informative benchmark to assess systematic risk, but do not go on to assess contagion whilst Bekaert et al (2014) pre-specify three specific factors representing global, US and domestic sources.

To protect ourselves from the spurious identification of contagion, highlighted in Billio and Pelizzon (2003), we ensure that the increase in volatility is due at least as much to the idiosyncratic component as to the potential source of contagion through systematic risk. We recognize that the share of the observed portfolio variance that is borne by the common factor is somewhat arbitrary (above some lower bound in order to capture the genuine time-varying part), although robustness tests suggest there is little sensitivity to this choice.

Whilst contagion is of considerable importance to policy makers and investors alike, there is significant disagreement in the existing literature on how to detect its presence, as the following examples illustrate. Identification via heteroskedasticity forms the basis of tests in Bekaert et al (2014), Dungey et al (2010), Dungey and Martin (2007), and Corsetti et al (2005), with alternative means of controlling for evolution in conditional correlation in Caporale et al (2005) and Kasch and Caporin (2013) who incorporate DCC models, and in Markov switching frameworks such as Ajay et al (2013). Relationships between tail events are differentiated from those in 'normal' times in papers using co-exceedance measures such as Bae et al (2003), Boyson et al (2010), quantiles in Baur and Schulze (2005), Caporin et al (2014) and copulas in Busetti and Harvey (2011) and Rodriguez (2007). The impact of extreme events such as outliers or jumps represents contagion effects in Favero and Giavazzi (2002) and Aït-Sahalia et al (2014), while papers such as Longstaff (2010) rely on changes in transmission mechanisms across periods without specifically accounting for changes in underlying volatility. However, the common feature of all of these models is a concern with the change in the loading on the transmission of the source to the target asset during a crisis period.

We estimate contagion effects as a change in the loading on the source factor for three examples covering different asset markets in different geographical regions and different crisis periods – currencies during the 1997-1998 Asian crisis, sectors of the US equity market in 2007-2009 and European sovereign CDS spreads for 2008-2013. This diverse set of examples allows us to draw out the features of the modelling framework, and develop an analytical narrative that is more revealing about the identification approach than would be obtained by a deeper analysis of an individual crisis event. We conclude a number of important common outcomes from the examples. First, we find evidence of contagion in almost every case investigated here. Contagion effects are sometimes the result of increased loadings on the source factor, but equivalently sometimes reveal decreased loadings as assets disconnect from the crisis source.

Second, these effects are not necessarily revealed in analyses that concentrate on changes in correlation or (unconditional) regression coefficients, as the increased residual volatility for the asset may be sufficient to mask the change in the underlying factor loadings. Third, while a single source factor model is statistically acceptable to all examples through a standard over-identification test, and reduces the amount of ARCH in the residuals from that found in the original data during the crisis period, there are circumstances where a two factor extension is both warranted and useful in capturing behavior during the crisis.

The paper proceeds as follows. Section 2 sets up the problem of identifying contagion as separate from interdependence through carefully differentiating explained and unexplained volatility and predicted and unpredicted volatility for the target asset in order to develop our modelling framework. Section 3 explains the econometric method and testing strategies adopted in Section 4, where three empirical examples are given. Section 5 concludes.

2 Interdependence versus contagion

In this section we analyze the different reasons why comparing the correlation between the returns of two assets during a crisis period and the corresponding correlation during a non-crisis period is not an accurate way to identify contagion.

2.1 Source versus target

We are mainly interested in the impact of a given source of contagion, namely some reference asset return r_0, on a family of possible targets, namely asset returns

$r_i, i = 1, ..., n$. It is then natural to think about the relationship between source and target in a linear regression framework:

$$\begin{aligned} r_i &= \alpha_i + \beta_i r_0 + u_i \\ E[u_i] &= 0, Cov[r_0, u_i] = 0 \end{aligned}$$

The contagion effect will then be identified as a structural break in the joint distribution of asset returns. Since financial crises correspond in general to a pervasive increase of volatility among all asset returns, we will actually consider two sets of regression equations, one for the crisis period (defined by an index H for High volatility) and one for the non-crisis period (designated by an index L for Low volatility):[2]

$$\begin{aligned} r_{iH} &= \alpha_{iH} + \beta_{iH} r_{0H} + u_{iH} \\ E_H[u_{iH}] &= 0, Cov_H[r_{0H}, u_{iH}] = 0 \end{aligned} \tag{1}$$

and:

$$\begin{aligned} r_{iL} &= \alpha_{iL} + \beta_{iL} r_{0L} + u_{iL} \\ E_L[u_{iL}] &= 0, Cov_L[r_{0L}, u_{iL}] = 0 \end{aligned} \tag{2}$$

With obvious notations:

$$\beta_{iL} = \rho_{iL} \frac{\sigma_{iL}}{\sigma_{0L}}, \beta_{iH} = \rho_{iH} \frac{\sigma_{iH}}{\sigma_{0H}} \tag{3}$$

As it is now well known, formula (3) clearly shows why comparing correlations ρ_{iH} and ρ_{iL} to identify contagion is biased towards finding contagion if the rate of increase of volatility $(\sigma_{0H}/\sigma_{0L})$ for the source country exceeds the rate of increase $(\sigma_{iH}/\sigma_{iL})$ for the target country. More precisely, when $\beta_{iH} = \beta_{iL}$, we have:

$$\rho_{iH} > \rho_{iL} \Leftrightarrow \frac{\sigma_{iH}}{\sigma_{iL}} < \frac{\sigma_{0H}}{\sigma_{0L}}$$

[2] In this way we deviate importantly from Bekaert et al (2014), Forbes and Rigobon (2002) and the regression model approach of Dungey et al (2005) who each impose a single homoskedastic error structure across both the non-crisis and crisis periods.

This remark has led Forbes and Rigobon (2002) to propose a corrected correlation measure for the purpose of contagion identification, that is based on the rates of increase of volatility in both markets. We will now show that such a correction is not sufficient in general.

2.2 Unexplained versus explained volatility

By standard decomposition of variance formulas, we define unexplained volatility in both crisis and non-crisis periods as follows:

$$\begin{aligned} \omega_{iH} &= Var_H(u_{iH}) = (1-\rho_{iH}^2)\sigma_{iH}^2 \\ \omega_{iL} &= Var_L(u_{iL}) = (1-\rho_{iL}^2)\sigma_{iL}^2 \end{aligned}$$

We can then prove the following identity:

Proposition 2.1.:

$$\beta_{iH} = \beta_{iL} \Rightarrow \rho_{iH} = \rho_{iL}\left[\frac{1+\delta}{1+\delta\rho_{iL}^2 + \frac{\omega_{iH}-\omega_{iL}}{\sigma_{iL}^2}}\right]^{1/2}$$

where:

$$1+\delta = \frac{\sigma_{0H}^2}{\sigma_{0L}^2}$$

Proof:

$$\begin{aligned} \beta_{iH} &= \beta_{iL} \Leftrightarrow \rho_{iH}\frac{\sigma_{iH}}{\sigma_{0H}} = \rho_{iL}\frac{\sigma_{iL}}{\sigma_{0L}} \\ &\Leftrightarrow \rho_{iH} = \rho_{iL}[1+\delta]^{1/2}\frac{\sigma_{iL}}{\sigma_{iH}} \end{aligned}$$

But with $\beta = \beta_{iH} = \beta_{iL}$:

$$\frac{\sigma_{iH}^2}{\sigma_{iL}^2} = \sigma_{iH}^2\frac{\rho_{iL}^2}{\beta^2\sigma_{0L}^2} = \rho_{iL}^2\frac{\beta^2\sigma_{0H}^2+\omega_{iH}}{\beta^2\sigma_{0L}^2} = \rho_{iL}^2\left[1+\delta+\frac{\omega_{iH}}{\beta^2\sigma_{0L}^2}\right]$$

Therefore we will get the announced result if we show that:

$$\rho_{iL}^2 + \rho_{iL}^2\frac{\omega_{iH}}{\beta^2\sigma_{0L}^2} = 1 + \frac{\omega_{iH}-\omega_{iL}}{\sigma_{iL}^2}$$

that is:

$$\rho_{iL}^2\sigma_{iL}^2 + \omega_{iH} = \sigma_{iL}^2 + \omega_{iH} - \omega_{iL}$$

which is true since $\omega_{iL} = (1 - \rho_{iL}^2)\sigma_{iL}^2$.

QED

Forbes and Rigobon (2002) set the focus on the increasing function (for positive ρ):

$$\phi(\rho) = \rho\left[\frac{1+\delta}{1+\delta\rho^2}\right]^{1/2}$$

They propose to correct ρ_{iH} as follows:

$$\tilde{\rho}_{iH} = \phi^{-1}(\rho_{iH}) \qquad (4)$$

before assessing contagion through correlation increase. They argue that the relevant test for contagion is indeed the test of the inequality $\tilde{\rho}_{iH} > \rho_{iL}$. Their rationale is as follows:

If the contagion were spurious (in the sense that indeed $\beta_{iH} = \beta_{iL}$), we would have $\rho_{iH} = \phi(\rho_{iL})$ and thus $\tilde{\rho}_{iH} = \rho_{iL}$. Thus, computing the corrected correlation is an edge against the upper-bias of ρ_{iH} that may spuriously lead to the conclusion that there was a contagion effect, while it was only an artefact of soaring volatility ($\delta > 0$). Our general proposition above shows that their argument is fully correct only in the particular case $\omega_{iH} = \omega_{iL}$, while by contrast (still assuming $\beta_{iH} = \beta_{iL}$):

$$\omega_{iH} > \omega_{iL} \Rightarrow \rho_{iH} < \phi(\rho_{iL}) \Rightarrow \tilde{\rho}_{iH} < \rho_{iL}$$

In this case, as pointed out by Billio and Pelizzon (2003), Forbes and Rigobon (2002) overestimate the spurious component of correlation increase (and thus overcorrect for it) because "a significant part of the increase in volatility is due to the idiosyncratic component". However, we must acknowledge that there is no such thing as a generalization of Forbes and Rigobon (2002) bias correction strategy for the general case where idiosyncratic risk may change. There is no alternative to the function $\phi(.)$ above since the correction term $\frac{\omega_{iH}-\omega_{iL}}{\sigma_{iL}^2}$ in Proposition 2.1. is not a function of ρ_{iL} alone.

The bottomline is that only variation of beta coefficients between non-crisis and crisis periods (corresponding respectively to equations (2) and (1)) provide some reliable measures of contagion.

2.3 Predictable versus unpredictable volatility

Obviously, in a time of crisis, all the parameters of the economy may change. However, when trying to identify contagion, we are more interested in knowing whether change is about the structural linkages in the economy. In particular, since it is known that asset return volatility is stochastically time-varying and highly persistent, an important aspect of contagion would be a change in regime in this respect. Is there such thing as a structural component of volatility, that is always time-varying, but would have an even more pervasive impact on all financial markets in crisis periods? While a precise multivariate stochastic volatility model with latent factors as structural components will be studied in the next sections, we can already give an informal sketch of the modelling approach. With respect to the approach of Forbes and Rigobon (2002) described in previous sections, we will introduce two additional features:

First, we set the focus on volatility dynamics rather than on some otherwise constant volatility parameters that suffer from structural breaks in the crisis period.

Second, the source of contagion is no longer a given asset return but rather one (or possibly several) latent factor(s) that are responsible for time variations of volatility.

However, for econometric identification purposes, the dynamic of these latent factors will be studied through the observed dynamics of some mimicking portfolios.

For the sake of expositional simplicity, let us first imagine that only one factor, f, is responsible for volatility dynamics while the so-called source return, r_0, is actually the return of some mimicking portfolio. This leads us to revise the model of the previous subsections as described below. In all subsequent equations, we refer to a given increasing filtration $(I_t), t = 1, 2..., T$, such that the first two conditional moments of returns observed a time $(t + 1)$ are computed given the information I_t available at time t, and then accordingly denoted by $E_t(.), Var_t(.)$ and $Cov_t(.)$. Note that conditioning information I_t may include not only observed values of past and present returns but also unobserved values of some latent variables, in order to accommodate latent volatility factors.

2.3.1 Model for the source return

The source return is seen as a noisy observation of the latent volatility factor:

$$r_{0,t+1} = f_{t+1} + u_{0,t+1}$$

where $u_{0,t+1}$ is an homoskedastic error term:

$$E_t\left(u_{0,t+1}\right) = 0, Var_t(u_{0,t+1}) = \omega_{00}.$$

In contrast, the factor is conditionally heteroskedastic:

$$E_t\left(f_{t+1}\right) = 0, Var_t(f_{t+1}) = \sigma_t^2$$

Note that, for expositional simplicity, we assume that all returns and factors have a zero-conditional expectation given past information. Assuming a zero conditional covariance between factor and noise, we have the following variance decomposition:

$$Var_t(r_{0,t+1}) = \sigma_{0,t}^2 = \sigma_t^2 + \omega_{00}.$$

In other words, the role of the factor is to decompose the variance of the source between a time-varying part and a constant part. Of course, such a decomposition is not unique. The time-varying part can always be artificially inflated by incorporating a constant component. That is, it takes an identification assumption to decide the share of the variance of the source carried by the factor:

Identification assumption $A(\alpha)$

For some $\alpha \in]0,1[$ given:

$$Var(f_t) = \alpha Var(r_{0,t+1})$$

Note that the parameter α can be interpreted as the (unconditional) squared correlation coefficient between the volatility factor f and its mimicking portfolio return r_0. In other words, by picking a particular value of α, we identify a factor that is all the more correlated to the source when α is large. However, the smaller the α, the smaller the part of time invariant volatility carried by the factor, since for the source, the residual volatility is:

$$\omega_{00} = (1-\alpha)Var(r_{0,t+1})$$

In other words, the choice of α is constrained by the fact that the volatility of the factor must be sufficiently high to allow the factor to capture at least the time-varying part of the variance of the source or equivalently, the residual variance is upper bounded as follows:

$$\omega_{00} \leq \min_{1 \leq t \leq T} \sigma_{0,t}^2$$

Then, the variance of the factor would be kept at its minimum possible value if one chooses $\alpha = \bar{\alpha}$ defined as follows

$$\bar{\alpha} = 1 - \frac{\min_{1 \leq t \leq T} \sigma_{0,t}^2}{Var(r_{0,t+1})} \tag{5}$$

The choice of the identifying parameter α in the interval $[\bar{\alpha}, 1]$ will be discussed below, in relation to identification of contagion.

2.3.2 Model for the target return

The key idea is that the volatility factor is able to capture all time-varying volatility. This statement entails two restrictions:

First, target returns $r_{i,t+1}, i = 1, ..., n$ have a time invariant conditional regression coefficient b_i on the volatility factor,

Second, the vectors of residuals of this $n-$dimensional regression is homoskedastic.

Formally, for $i, j = 0, 1, ..., n$:

$$\begin{aligned} r_{i,t+1} &= b_i f_{t+1} + u_{i,t+1} \\ E_t\left(u_{i,t+1}\right) &= 0, Cov_t[f_{t+1}, u_{i,t+1}] = 0 \\ Cov_t[u_{i,t+1}, u_{j,t+1}] &= \omega_{ij} \end{aligned} \tag{6}$$

Of course, as explained in the next sections, the empirical validity of this one factor model should be properly tested. Multi-factor extensions might be worth considering when the one factor model does not pass specification tests (we lay out a two factor model in Appendix 2). Let us just emphasize at this stage that the one factor model allows us to be more precise in the identification of contagion, as discussed in previous sections. So far, we have concluded that the best tool to identify contagion is akin to comparing the values of the (unconditional) regression coefficient β_i (regression of the target return r_i on the source return r_0) during a crisis period and a non-crisis period respectively.

It turns out that the one factor model (6), jointly with the specification of the share α for factor volatility in (5), provides an interesting decomposition for this regression coefficient. Since by definition:

$$Cov_t[r_{i,t+1}, r_{0,t+1}] = b_i\sigma_t^2 + \omega_{i0}$$

by taking unconditional expectations:

$$Cov[r_{i,t+1}, r_{0,t+1}] = b_i Var(f_{t+1}) + \omega_{i0}$$

and dividing on both sides by $Var(r_{0,t+1}) = \frac{Var(f_t)}{\alpha} = \frac{\omega_{00}}{1-\alpha}$:

$$\beta_i = \alpha b_i + (1-\alpha)\gamma_i$$

where $\gamma_i = \omega_{i0}/\omega_{00}$ is the regression coefficient (both a conditional and an unconditional one) of u_i on u_0. As rigorously explained in the next section, under the maintained assumption (6), the two beta coefficients β_i and b_i are identified from the observation of the time series $(r_{i,t})_{1\leq t\leq T}$, $i = 0, 1...., n$ of asset returns. The intuition is quite clear: while β_i can be consistently estimated by ordinary least squares, b_i is characterized as the only slope coefficient such that $[r_{i,t+1} - b_i r_{0,t+1}]$ is homoskedastic. It is only for the true unknown value of b_i that the time-varying volatility due to the volatility factor will be erased in the difference.

By contrast, identification of γ_i takes a choice of the value α of the share of the variance of the factor in the total variance of the source return; only the knowledge of this share allows identification of the variance of the homoskedastic part of the return.

2.3.3 Identifying contagion

Our identification strategy will then be germane to the "identification from change in variance" approach promoted by Rigobon (2003). We will pick a particular value of α and keep it invariant from the non-crisis period to the crisis period. Note that as far as comparison of crisis and non-crisis periods is concerned, this is quite a natural normalization condition; we assume that from one period to the other, the mimicking portfolio keeps the same correlation with the latent volatility factor.

Then, we end up with well identified parameter values for the two periods respectively, namely $(\beta_{iL}, b_{iL}, \gamma_{iL})$ and $(\beta_{iH}, b_{iH}, \gamma_{iH})$ that are conformable to the following decompositions:

$$\begin{aligned} \beta_{iL} &= \alpha b_{iL} + (1-\alpha)\gamma_{iL} \\ \beta_{iH} &= \alpha b_{iH} + (1-\alpha)\gamma_{iH} \end{aligned} \tag{7}$$

Our claim is that decompositions (7) allow us to go deeper in the identification of contagion. We will be able not only to measure the structural change of the unconditional regression coefficient β_i (of the target on the source), but also to disentangle the two components of this structural change:

First, structural change in the impact of the volatility factor on the different markets.

And second, structural changes in the time invariant residual correlations between the various markets.

Since by definition, the volatility factor is highly predictable, the first kind of contagion is obviously much more a phenomenon of interest, as far as economic policy is concerned. In other words, we rather see the (structural changes in) unconditional beta coefficients β_i as imprecise signals of contagion since the phenomenon of interest (structural changes in factor loadings b_i) may be blurred by idiosyncratic issues.

3 Econometric Inference on Contagion in a one factor model

3.1 Estimation of factor loadings

The one factor model described in section 2 is one of the examples of common features put forward by Engle and Kozicki (1993), for which they propose a GMM inference technique. Since the source is supposed to capture all time variations in return volatility, we are able to write down the following conditional moment restrictions for each target asset $i = 1, ..., n$:

$$E_t \left[\left(r_{i,t+1} - b_i r_{0,t+1} \right)^2 \right] = d_i \tag{8}$$

for some time-invariant unknown parameters $d_i, i = 1, ..n$. Unfortunately, for any choice of a vector of instruments (beyond the constant one), these moment restrictions lead to a singular Jacobian matrix, since, when differentiating with respect to factor loading b_i, one obtains:

$$E \left[z_t r_{0,t+1} \left(r_{i,t+1} - b_i r_{0,t+1} \right) \right] = E(z_t) E \left[r_{0,t+1} \left(r_{i,t+1} - b_i r_{0,t+1} \right) \right]$$

since:

$$E_t \left[r_{0,t+1} \left(r_{i,t+1} - b_i r_{0,t+1} \right) \right] = E_t \left[r_{0,t+1} \left(u_{i,t+1} - b_i u_{0,t+1} \right) \right] = \omega_{i0} - b_i \omega_{00}$$

is a constant. Hence, GMM inference based on these conditional moment restrictions must be non-standard as extensively discussed by Dovonon and Renault (2013). Fortunately, as shown by Doz and Renault (2006), standard and efficient GMM inference can be performed thanks to the complete set of conditional moment restrictions implied by our one factor model:

$$E_t \left[r_{j,t+1} \left(r_{i,t+1} - b_i r_{0,t+1} \right) \right] = c_{i,j}, \forall i = 1, ..., n, \forall j = 0, 1, ..., n \tag{9}$$

since the volatility factor is by definition erased in the difference $(r_{i,t+1} - b_i r_{0,t+1})$. Note that the common features model (8) of Engle and Kozicki (1993) is obviously nested in the one factor model characterized by (9) with:

$$d_i = c_{i,i} - b_i c_{i,0}$$

For a given vector z_t of G instruments, we end up with the following unconditional moment restrictions for each $i = 1, ..., n$:

$$E \left[z_t r_{j,t+1} \left(r_{i,t+1} - b_i r_{0,t+1} \right) \right] = c_{i,j} E(z_t), \forall j = 0, 1, ..., n. \tag{10}$$

In other words, for each target asset $i = 1, ..., n$, we have a linear regression model with unknown slope parameters $b_i, (c_{i,j})_{0 \leq j \leq n}$ that can be written as follows:

$$(r_{t+1} \otimes z_t)\, r_{i,t+1} = (r_{t+1} \otimes z_t)\, r_{0,t+1} b_i + [Id_{n+1} \otimes z_t] c_{i\bullet} + \varepsilon_{i,t+1} \tag{11}$$

where $r_{t+1} = (r_{j,t+1})_{0 \leq j \leq n}, \varepsilon_{i,t+1}$ is a $(n+1)G-$dimensional martingale difference sequence, $c_{i\bullet} = (c_{i,j})_{0 \leq j \leq n}$ and Id_{n+1} stands for the identity matrix of dimension $(n+1)$.

Therefore, for each asset $i = 1, ..., n$, efficient GMM on moment restrictions (10) is akin to solving some linear equations about sample averages over observations $t = 1, 2, ..T$ of equations (11). Of course, there is a non-zero correlation between equations for two different assets, and thus some efficiency gains would be possible by performing joint GMM on the set of all assets together. Zellner's theorem does not apply since, for each equation, OLS is not efficient. However, we will overlook the possible efficiency gain of grouping and estimate regression equations (11) asset by asset. Finally, it is worth keeping in mind that our analysis remains multivariate because the vector z_t of instruments will include squared values of all returns $r_{jt}, j = 0, 1, ...n$. In all our applications, z_t is the $(n+2)$-dimensional vector containing the constant and these squared values. Thus we will take $G = n + 2$ throughout.

3.2 Decomposition of variance

As explained above, we identify the decomposition of variance between factor and residual term by the choice of some $\alpha \in [\bar{\alpha}, 1]$ such that :

$$Var(f_{t+1}) = \alpha Var(r_{0,t+1})$$

and then:

$$Cov(r_{i,t+1}, r_{0,t+1}) = \alpha b_i Var(r_{0,t+1}) + \omega_{i0}.$$

It is then convenient to consider for each asset $i = 1, ...n$ an augmented set of moment restrictions as follows:

$$\begin{aligned} E\left[z_t r_{j,t+1}\left(r_{i,t+1} - b_i r_{0,t+1}\right)\right] &= c_{i,j} E(z_t), \forall j = 0, 1, ..., n \qquad (12) \\ E\left[r_{0,t+1}\left(r_{i,t+1} - \alpha b_i r_{0,t+1}\right)\right] &= \omega_{i,0}. \end{aligned}$$

Note that while (12) entails one more moment restriction than (10), it does not modify the asymptotic variance of an efficient GMM estimator of factor loading b_i (or of residual parameters $c_{i,j}$) because the additional moment restriction just identifies the additional parameter $\omega_{i,0}$. By contrast, the GMM estimator of $\omega_{i,0}$ should be more efficient than its naive sample counterpart obtained by plugging in the GMM estimator of b_i deduced from (10), because (10) actually overidentifies its unknown parameters $(b_i, c_{i\bullet})$ and thus provides "implied probabilities" to improve the estimation of additional moments $\omega_{i,0}$ (see e.g. Back and Brown (1993)). This is the reason why all inference throughout will be performed from moment restrictions (12). However, it is worth keeping in mind that the efficient GMM estimator of $(b_i, c_{i\bullet})$ deduced from (12) is asymptotically equivalent to that deduced from (10) and in particular its asymptotic distribution does not depend on the chosen value of α.

In terms of regression equations, the augmented set of moment conditions (12) can be rewritten:

$$\begin{bmatrix} (r_{t+1} \otimes z_t)\, r_{i,t+1} \\ r_{0,t+1}.r_{i,t+1} \end{bmatrix} = \begin{bmatrix} (r_{t+1} \otimes z_t)\, r_{0,t+1} & Id_{n+1} \otimes z_t & 0 \\ \alpha r_{0,t+1}^2 & 0 & 1 \end{bmatrix} \begin{bmatrix} b_i \\ c_{i\bullet} \\ \omega_{i,0} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t+1} \\ \eta_{i,t+1} \end{bmatrix} \tag{13}$$

Note that while $\varepsilon_{i,t+1}$ is a martingale difference sequence, $\eta_{i,t+1}$ will in general display some serial correlation such that a Newey-West correction will be required for efficient GMM. To summarize, our efficient GMM estimator of $\theta^{(i)} = [b_i, c_{i0}, c_{i1}, ..., c_{in}, \omega_{i0}]'$ will be:

$$\hat{\theta}_T^{(i)} = \left[\bar{X}_T'(\hat{\Sigma}_T^{(i)})^{-1}\bar{X}_T\right]^{-1} \bar{X}_T'(\hat{\Sigma}_T^{(i)})^{-1}\bar{Y}_T^{(i)}$$

with:

$$\begin{aligned} \bar{Y}_T^{(i)} &= \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} (r_{t+1} \otimes z_t)\, r_{i,t+1} \\ r_{0,t+1}.r_{i,t+1} \end{bmatrix} \\ \bar{X}_T &= \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} (r_{t+1} \otimes z_t)\, r_{0,t+1} & Id_{n+1} \otimes z_t & 0 \\ \alpha r_{0,t+1}^2 & 0 & 1 \end{bmatrix} \end{aligned} \tag{14}$$

while $\hat{\Sigma}_T^{(i)}$ is the estimated long-run variance matrix of $[\varepsilon_{i,t+1}, \eta_{i,t+1}]'$ (with no lag for $\varepsilon_{i,t+1}$ and a MA representation for $\eta_{i,t+1}$) deduced from a first-step GMM estimator:

$$\tilde{\theta}_T^{(i)} = \left[\bar{X}_T' \bar{X}_T\right]^{-1} \bar{X}_T' \bar{Y}_T^{(i)}$$

3.3 Identifying contagion

As already mentioned, contagion will be identified by comparing the model parameter values between a crisis period and a non-crisis period. We will always assume that the possible break point date is known, such that we have:

First a non-crisis period for observations at dates $t = 1, ..., T_L$,

Second a crisis period for observations at dates $t = (T_L + 1), ..., (T_L + T_H)$.

We assume that each sample size goes to infinity such that valid asymptotic theory can be used for inference within each sample.

3.3.1 Estimating the parameters

We have three kinds of parameters to estimate:

(i) Model free parameters:

We estimate within each sample the correlation (including the Rigobon's corrected correlation (4)) and regression coefficients between each asset return and the source by the sample counterparts. We end up with consistent asymptotically normal estimators of:

$$\begin{aligned} (\rho_{iL}, \rho_{iH}, \tilde{\rho}_{iH}), i &= 1, ..., n \\ (\beta_{iL}, \beta_{iH}), i &= 1, ..., n \end{aligned}$$

(ii) One factor model-based parameters:

We maintain the assumption that the one factor model, or at least its characterization through the moment conditions (10), is well-specified, for each of the two periods. Using by GMM we can then estimate, for each period, the asset i parameters $(b_i, c_{i\bullet}), i = 1, ..., n$, denoted respectively as:

$$\begin{aligned} (b_{i,L}, c_{i\bullet,L}), i &= 1, ..., n \\ (b_{i,H}, c_{i\bullet,H}), i &= 1, ..., n \end{aligned}$$

(iii) Decomposition of variance parameters:

As explained above, we maintain the same identification assumption $A(\alpha)$ for the two periods (see the empirical section for an empirical strategy to pick a specific value of α). This assumption identifies in particular the residual covariance parameters $\omega_{i0}, i = 1, ..., n$. Then, using moment conditions (12), we can estimate jointly by GMM for each period the asset i parameters $\theta_i = (b_i, c_{i\bullet}, \omega_{i0}), i = 1, ..., n$ denoted respectively as:

$$\begin{aligned} \theta_L^{(i)} &= (b_{i,L}, c_{i\bullet,L,}\omega_{i0,L}), i = 1, ..., n \\ \theta_H^{(i)} &= (b_{i,H}, c_{i\bullet,H,}\omega_{i0,H}), i = 1, ..., n \end{aligned}$$

It is worth recalling that the parameters $(b_i, c_{i\bullet}), i = 1, ..., n$ are actually the same whether they are identified by just the one factor-based moment conditions (10) or by the augmented set of moment conditions (12) that incorporates the decomposition of variance. For the sake of convenience, we set the focus on (12) for statistical inference. Once all parameters are estimated for the two periods, it is easy to run some Wald tests to test for structural change between non-crisis and crisis periods. However, as far as model-based parameters are concerned, GMM inference paves the way for several interesting tests about structural stability that we review below (see Hall (2005) section 5.4 for a comprehensive survey).

3.3.2 Testing hypotheses about structural stability

Since our focus of interest is the characterization of the differences between crisis and non-crisis periods, we never try to estimate or to test for the specification of a model pretending that there is no such thing as a structural change between the two periods. Thus, right after having computed GMM estimators $\hat{\theta}_{T_L,L}^{(i)}, i = 1, ..., n$ of parameters of the first (non-crisis) period it is safe to perform two sets of specification tests:

First, the standard Hansen's J-specification test based for asset $i = 1, 2, ...n$ on the test statistics:

$$J_{i,L} = T_L \left(\bar{Y}_{T_L,L}^{(i)} - \bar{X}_{T_L,L} \hat{\theta}_{T_L,L}^{(i)} \right)' (\hat{\Sigma}_{T_L,L}^{(i)})^{-1} \left(\bar{Y}_{T_L,L}^{(i)} - \bar{X}_{T_L,L} \hat{\theta}_{T_L,L}^{(i)} \right)$$

where we use a straightforward extension of the notation in (14) to denote sample means over the first period.

Second the Ghysels and Hall's predictive test, which for asset $i = 1, 2, ...n$, is based on the test statistics:

$$GH_i(H/L) = T_H \left(\bar{Y}^{(i)}_{T_H,H} - \bar{X}_{T_H,H}\hat{\theta}^{(i)}_{T_L,L}\right)' (\hat{\Omega}^{(i)}(H/L))^{-1} \left(\bar{Y}^{(i)}_{T_H,H} - \bar{X}_{T_H,H}\hat{\theta}^{(i)}_{T_L,L}\right)$$

where:

$$\hat{\Omega}^{(i)}(H/L) = \hat{\Sigma}^{(i)}_{T_H,H} + \frac{T_H}{T_L}\bar{X}_{T_H,H}\left(\bar{X}_{T_L,L}(\hat{\Sigma}^{(i)}_{T_L,L})^{-1}\bar{X}'_{T_L,L}\right)^{-1}\bar{X}'_{T_H,H}$$

The first test statistic tests for the null hypothesis, $H_{0,L}$, of the validity of the one factor model (12) during the first (non-crisis) period. Note that the validity of (12) is actually equivalent to the validity of (10). Under the null, the test statistic $J_{i,L}$ is asymptotically distributed (when T_L goes to infinity) as a chi-square $\chi^2[(n+1)^2]$. The second test statistic examines the validity of the orthogonality conditions in the second period, given that the conditions hold in the first period at some specific value $\theta^{(i)}_L$ of the parameters. Let us denote by $H_0(H/L)$ this null hypothesis. Under the null, the test statistic is asymptotically distributed as a chi-square $\chi^2[(n+1)^2 + n + 2]$.

Two remarks are in order: First Ghysels and Hall (1990) prove this result by assuming that T_L goes to infinity and $T_H = \lambda T_L$ for some $\lambda > 0$. The result is clearly valid more generally when both T_L and T_H go to infinity and the ratio (T_H/T_L) has a finite limit. Second, even though it is not discussed by Ghysels and Hall (1990), one can perform sequentially the two tests of $H_{0,L}$ and $H_0(H/L)$ by taking advantage of the fact that the latter hypothesis is nested in the former.

Our preferred approach will however be different. In each of our examples, we study a crisis period with a non-negligible duration. In other words, we have an intrinsic interest in characterizing this new period that goes beyond just checking by Ghysels and Hall's (1990) predictive test whether there are some structural changes. In particular, we want to know whether a one factor model is still valid in this new period, albeit with different parameter values. The amount and direction of changes in structural parameters of the one factor model are informative about the economic underpinnings of the observed phenomena. Thus, our testing strategy is twofold.

First, we run the overidentification test of the one factor model for the crisis period. It is of course different from the Ghysels and Hall's (1990) predictive test above because the goodness of fit of the data during the crisis period is now assessed through the lenses of a second period GMM estimator. For asset $i = 1, 2, ...n$ the test statistic is:

$$J_{i,H} = T_H \left(\bar{Y}^{(i)}_{T_H,H} - \bar{X}^{(i)}_{T_H,H} \hat{\theta}^{(i)}_{T_H,H} \right)' (\hat{\Sigma}^{(i)}_{T_H,H})^{-1} \left(\bar{Y}^{(i)}_{T_H,H} - \bar{X}^{(i)}_{T_H,H} \hat{\theta}^{(i)}_{T_H,H} \right)$$

This test statistic tests for the null hypothesis, $H_{0,H}$, of validity of the one factor model (12). Under the null, the test statistic $J_{i,H}$ is asymptotically distributed (when T_H goes to infinity) as a chi-square $\chi^2[(n+1)^2 - 1]$.

Second, when the validity of a one factor model has not been rejected for each of the two periods, it makes sense to compare the two models by comparing the values of their parameters. Hall (2005) states the convenient result that under the null hypothesis of no change, the two J-test statistics on the one hand, and the Wald test statistics comparing parameter values on the other, are asymptotically independent. We will set the focus on the Wald test of no change in the factor loadings. In other words, for each asset $i = 1, 2, ...n$, the Wald test statistic will be:

$$\xi_i^W = (T_L + T_H) \frac{\left(\hat{b}_{i,H} - \hat{b}_{i,L} \right)^2}{\hat{V}_{i,b}(H/L)}$$

where:

$$\hat{V}_{i,b}(H/L) = \left[\frac{T_L}{T_L + T_H} \right]^{-1} \hat{\sigma}^2(\hat{b}_{i,L}) + \left[\frac{T_H}{T_L + T_H} \right]^{-1} \hat{\sigma}^2(\hat{b}_{i,H})$$

and $\hat{\sigma}^2(\hat{b}_{i,L})$ (resp. $\hat{\sigma}^2(\hat{b}_{i,H})$) stands for the estimated asymptotic variance of the GMM estimator$\sqrt{T_L}\hat{b}_{i,L}$ (resp. $\sqrt{T_H}\hat{b}_{i,H}$).

4 Empirical Implementation:

A challenge to testing for contagion is the variety of assets, markets and time periods in which these problems apply. Here we provide three different examples to illustrate the outcomes for evidence of contagion when the tests are applied to the change to the underlying factor loadings rather than the correlation coefficients.

The illustrations cover different markets, assets and sample periods. We consider currency markets during the Asian financial crisis of 1997-1998, industry sectoral equity market indices for the US during the period of disruption to the financial sector in 2007-2009 and the CDS market for European sovereigns over the period of 2008-2013. In each case our selection of precise demarcation between the non-crisis and crisis period draws on the commonly accepted dates in the existing literature.[3]

The first example concerns the behavior of currency markets during the East Asian crisis of 1997-1998. This crisis is commonly dated from the float of the Thai baht on July 2, 1997. We include as a non-crisis period from January 2,1995 to July 1, 1997 ($T_L = 650$) and the crisis period from July 2, 1997 to August 31,1998 ($T_H = 305$). The data are drawn from Dungey and Martin (2007) and consist of daily US dollar exchange rate returns for the Thai baht, Indonesian rupiah, Malaysian ringgit and Australian dollar. There is a significant literature on the detection of contagion from Thailand during this crisis; see for example, the review in Dungey et al (2006).

The second example considers contagion from the financial sector in the US to other sectors of the economy using daily returns in the S&P500 sector indices for the banking, insurance, industrials, health, utilities, food and information technology sectors from August 1, 2004 to June 30, 2009. In the first instance we consider the US banking sector as the source asset; see for example Bekaert et al (2014), King (2012). To illustrate the reflection problem of Manski (1993), we also consider the case where the source sector is the insurance industry; contributing to the debate on the role of insurance in crises.[4] The results shed light on the role of the reflection problem in identifying contagion between markets. The demarcation between non-crisis and crisis period is the date on which the ECB first became active in extending its support to markets following the revelations of stress, splitting the sample at August 9, 2007, so that $T_L = 788$ and $T_H = 498$. The start of our non-crisis sample is consistent with the previous monetary policy cycle in the US, and the end point for the crisis is consistent with Bekaert et al

[3]Exogenous dating choices for crisis periods are common in the literature, and usually relate to observed events. For a few recent attempts to endogenously choose both crisis dates and explore contagion effects see Dungey et al (2015) and Contessi et al (2014).

[4]There is an active debate on whether prudential regulation is appropriate for the insurance sector focussed on its role as a potential propagator or instigator of systemically important shocks. See for example evidence that insurers may be important in Acharaya and Richardson (2014) and Dungey et al (2014) and contrasting evidence that insurers are better characterized as recipients of banking sectors shocks in Chen et al (2014).

(2014) with recent support for dates around that time in Contessi et al (2014). A detailed description of the events of the crisis may be found in sequential issues of the IMF Global Financial Stability Reports for 2008 and 2009.

The final example examines the daily changes in 5-year CDS spreads for the sovereign debt of Ireland, Italy, Portugal and Spain and Germany during the Greek debt crisis and subsequent difficulties in European sovereign debt markets. The 5-year spread has been investigated as a benchmark in understanding crisis conditions in Wang and Bhar (2014) and Merton et al (2013).[5] As the source factor for Greece we construct a proxy measure of the risk premium it faces as the differential between the Greek and US 10 year bonds – daily CDS data for Greece are not available on the Markit database for the sample period.[6] The European sovereign debt markets remained relatively calm for the period September 9, 2008 to March 31, 2010 compared with the turmoil in equity and money markets. Although there were earlier indications of Greek stress from mid-2009, crisis conditions emerged near the end of the first quarter of 2010, culminating in the announcement of the first IMF package for Greece; see also Arghyrou and Kontonikas (2012) who point to a distinctive change in behavior for European sovereign debt markets after March 2010. Our sample ends November 21, 2013 so that $T_L = 403$ and $T_H = 951$.

The descriptive statistics of daily returns in each of the currency and equity markets, and the daily changes in 5-year CDS spreads, for the non-crisis and crisis periods of each example are given in Table 1. Data sources are provided in Appendix 1. Each example shows the typical increase in unconditional variance of the asset returns (changes in CDS spreads) and the associated increase in range of returns in the form of both more extreme maxima and minima during the crisis period than the non-crisis period.

Given that the model incorporates unconditional moments it is reasonable to assume that associated estimates may require some degree of serial correlation correction, such as is often provided via a Newey-West correction. However, such a correction is not necessary for the conditional moments which make up the majority of the conditions in the model. In order to apply an appropriate correction,

[5] CDS spreads at firm level are used to study contagion in Jorion and Zhang (2009).

[6] Arghyrou and Kontonikas (2012) demonstrate the strong relationship between Greek bond and CDS spreads using monthly data during this period.

without unnecessarily applying them to the majority of the estimates, we adopt a moving average representation of the data in the unconditional moment conditions. We adopt a 5 day backwards looking moving average, with the length chosen to represent the approximate half-life of the typically supported GARCH(1,1) representation of daily financial returns data. The values of α are calibrated from univariate GARCH(1,1) estimates of the minimum conditional variance for the source asset over the non-crisis period.[7]

The estimated results for each of the three applications provide evidence that the single factor framework passes the overidentification tests in both the non-crisis and crisis periods of the sample.[8] However, the Ghysels-Hall break tests suggest that in the vast majority of cases the estimated parameters from the non-crisis period do not provide a good representation of the second period loadings, implying that something has changed over the sample. Tests of structural changes reject the hypothesis that the underlying parameters remain the same. The structural break tests are provided in Panels C and D of Table 2 to 8 which report the results relevant for each application.

To some extent the changes are captured by the Forbes and Rigobon tests; however, we show that our model-based comparison is more informative. For each of the applications Tables 2 to 8 report the unconditional correlations between the demeaned returns (or changes in daily spreads in the case of CDS data) in Panel A of the tables for each of the non-crisis and crisis samples along with the correlation coefficient adjusted for increasing heteroskedasticity as suggested by Forbes and Rigobon (2002) – see equation (4) – and tests of the significance between them.[9] Panel B reports the β_i coefficient from regressing r_i on r_0 in each of the non-crisis and crisis samples. These β_i are statistically significant for each asset in each application, and in each case they also show a statistically significant

[7] However, the empirical results are not sensitive to alternative choices which conform to the restriction in (5).

[8] Note here the difference between our approach and the results for European CDS data in Broto and Pérez-Quirós (2015) whose detection of contagion relies on the emergence of a second principal component during the course of the sample to determine the existence of crisis conditions.

[9] The t-test statistic for the difference between the non-crisis period correlation and the Forbes and Rigobon adjusted crisis period correlation is properly formulated with a Fisher correction as shown in Dungey et al (2005):

change between the non-crisis and crisis periods at standard significance levels (to conserve space Panel B of each table reports the individual β_i and associated standard error but we suppress reporting the formal test of change between the sub-samples).

The necessity of using our model based approach to examine changes in b_i as opposed to β_i is evident across all the examples. In each application the estimated values of $\omega_{i,0}$ in the non-crisis period are statistically significant for every asset, and increase in value in the crisis periods. Typically the changes in b_i are not identified by changes in β_i, due to the role of $\omega_{i,0}$, pointing to the importance of this decomposition in correctly detecting contagion effects. Not only do the applications detect the existence of contagion effects which are distinct from those which might be detected with analysis of β_i, ARCH-LM tests also provide supporting evidence that the model accommodates the conditional volatility of the data.[10]

The three examples serve to show how the framework applies in different contexts, and for different asset classes. Extensions to increased numbers of sources of potentially contagious shocks in any individual application are easily countenanced in our approach (the relevant theory may be found in Appendix 2). To illustrate we provide an extension of the European CDS market application to a two factor model.

4.1 Contagion between Currencies: 1997-1998 East Asian crisis

Our modelling framework provides clear evidence of contagion from the Thai baht to the Indonesian rupiah, Malaysian ringgit and Australian dollar exchange rates in the form of a statistically significant increase in the factor loadings b_i between

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$$FR = \frac{0.5\ln\left(\frac{1+\widetilde{\rho}_H}{1-\widetilde{\rho}_H}\right) - 0.5\ln\left(\frac{1+\rho_L}{1-\rho_L}\right)}{\sqrt{\frac{1}{T_L-3}+\frac{1}{T_H-3}}}.$$

The test statistic reported in the original paper contains an error.

[10] In each example we also fitted the estimated factor loadings for the crisis period to the non-crisis data and conducted ARCH-LM tests on the resulting residuals. In each case the results were uniformly inferior in capturing the non-crisis period conditional volatility structure than the estimated non-crisis factor model. These figures are not reported in the paper but are included in the output of the accompanying code or available from the authors on request.

the non-crisis and crisis periods; see Panel D of Table 2, estimated with $\alpha = 0.3$. This evidence is completely consistent with the vast majority of the empirical studies on this crisis; see the summary in Dungey et al (2006). While the loadings on the Thai baht exchange rate as the mimicking factor change from significantly negative during the non-crisis period, $b_{i,L}$, to significantly positive in the crisis period, $b_{i,H}$, for Indonesia and Malaysia, they do not change sign in the Australian case. Instead, the Australian loading becomes absolutely smaller during the crisis period, but remains negative. This is a good illustration of the information content of the factor loadings b_i for identifying contagion.

First, correlation coefficients between each currency return and the Thai baht are hardly informative. While unadjusted correlation coefficients increase statistically significantly between the non-crisis and crisis period, the rise in correlation becomes statistically insignificant after the heteroskedasticity adjustment, supporting the conclusion of no contagion.

Second, all unconditional beta coefficients β_i significantly increase, giving an indication that there was indeed a contagion phenomenon that has been hidden by over-correction of the regression coefficient. This reflects the fact that a significant part of the increase in the volatility component is due to the idiosyncratic component.

This dual evidence suggests that controlling for the role of the idiosyncratic component is especially important. It is typically the reason why the factor loadings b_i shed more light on the contagion mechanism than the unconditional beta coefficients β_i. This fact is obvious when looking at the pattern of signs: while all beta coefficients are non-negative over the two periods (the slightly negative beta for Australia in the non-crisis period is not statistically different from zero), we have, as described above, much more interesting patterns of sign changes in the factor loadings b_i.

During the crisis period, Indonesia and Malaysia were both affected as near-neighbors with potentially similar economic structural problems to Thailand, subjecting them to contagion channels through both regional proximity and the wake-up call of contagion, see Goldstein (1998). This is reflected in the change in the loadings; in the crisis period the loading $b_{i,H}$ for Indonesia is not only positive, but over 40 times greater than the pre-crisis loading in absolute value. For Malaysia, it is correspondingly over 20 times larger. Indonesia and Malaysia both suffered significantly during this crisis period, in terms of both GDP loss and capital outflow, as well documented elsewhere. Moreover, it is worth keeping in mind that only the absolute values of the loadings b_i matter for characterization of the transmission of the GARCH effect. The multiplicative factors 40 and 20 are even more impressive in this respect.

This striking evidence of contagion from Thailand to Indonesia and Malaysia is somewhat less compelling when looking at unconditional beta coefficients. While they do increase between non-crisis and crisis periods, it is by a smaller extent (factors of 2 and 10 respectively instead of 40 and 20) and is always positive. This is due to strongly positive regression coefficients between idiosyncratic components, even in the non-crisis periods, that are able to mask the actual behavior of factor loadings b_i. In other words, while not surprisingly, these Asian currencies are all unconditionally positively correlated, the strength of their link with the common volatility factor has been magnified by the crisis.

The fact that the impact of the crisis is better identified through the common factor model is even more striking for Australia. It is first worth keeping in mind the spread of orders of magnitude in terms of worldwide importance of currencies. While the Australian dollar amounts to a significant proportion of global turnover, at 3 percent in 1998 according to the BIS(2013) triennal FX turnover survey, the Thai baht turnover was only 0.1 percent of global turnover while Indonesian and Malaysian FX markets were likewise small. As a result, the pre-crisis unconditional beta coefficient of Australian dollar on Thai baht was not significantly different from zero. By contrast, it became significantly positive in the crisis period. But even more strikingly, its factor loading stayed negative and the common volatility factor captures most of the ARCH effect for Australian dollar in the crisis period (see ARCH-LM test in table 2), which was not achieved in the non-crisis period. Note that the constantly negative sign of the factor loadings confirms the idea that, in spite of the crisis, the Australian dollar continued to play the role of a safe-haven asset, albeit to a smaller extent in the crisis period (smaller absolute value of the factor loading); see also Debelle and Ellis (2005). Again, the strongly positive correlation between idiosyncratic components implies that the negative patterns of factor loadings cannot be seen in unconditional beta coefficients.

Further support for the model specification can be found in the ARCH-LM tests reported in Panel F of Table 2. The model aims to reduce the extent of heteroskedasticity observed in the returns data, focussing on the crisis period. The last two rows of the table report that for the Malaysian and Australian exchange rates the model is sufficient to effectively eliminate the ARCH effects present in the data, and in the Indonesian case to substantially reduce it. This test attests to the effectiveness of the choice of mimicking factor.

4.2 Contagion between Industries in the US: 2007-2009 crisis

Recent studies have concluded that contagion within industrial sectors may work in different directions depending on the degree of industry concentration. While the bankruptcy of other firms tends to spread negative effects to others via bank lending and economic linkages, more concentrated industries seem to have offsetting competitive advantages from the misfortunes of their rivals; Jorion and Zhang (2009), Hertzel and Officer (2012). Contagion between industry sectors has not been extensively examined using the frameworks applied to either country-wide indices or other markets, although there is an earlier literature regarding the transmission of shocks related to bankruptcy announcements (which may be considered as contagious) as in Lang and Stulz (1992). There is now considerable interest in the issue of systemically risky sectors, and in particular the financial or banking sectors; for example Diebold and Yilmaz (2014), Merton et al (2013), Brownlees and Engle (2011).

The general consensus of the literature on the crisis of 2007-2008 is that the problems originated in the US financial sector, and particularly the banking sector driven by regulatory structures which encouraged innovations in credit risk transfer through markets such as mortgage securitization and the use of off-balance sheet transactions; see Bekaert et al (2014) for example. Insurance firms were often large purchasers of the credit risk products banks produced from their securitization processes, although they to a lesser extent participated in origination as well. When the market for securitized mortgages collapsed, banks were at the forefront of events, taking massive losses on to their balance sheet and absorbing the costs of having let their loan origination process get ahead of the securitization process (warehousing); see Ashcraft and Schuermann (2008).

Our model results report significant contagion from the banking sector as the source market to all other sectors of the economy, with $\alpha = 0.7$; see Panel E of Table 4. For each asset the non-crisis period loading on the banking factor, $b_{i,L}$, is positive and significant, consistent with the role that the banking sector plays in facilitating real economic activity by credit creation; see Acemoglu et al (2015) for a formal treatment of the relationship between banking networks and real economy firms. The loading in each of insurance, industrials, health and utilities are all around 0.8, while those in food and IT are each over unity.

During the crisis period the loadings, $b_{i,H}$, change dramatically and become negative, although insignificant in each sector. The loadings on the banking factor become absolutely less in each of health, food and IT (in the latter two the absolute size of the crisis loading is around half that of the non-crisis loading). The most dramatic changes in the loading point estimates occur for those industries most closely aligned with banking, and those where other instances of rescue packages were implemented; insurance and industrials.[11] However, in the crisis period the banking sector is no longer an individually significant factor in determining the volatility of the other assets. This dramatic change reflects contagion in the form of removed linkages between the banking sector and the other sectors – in the network finance modelling framework of Gai and Kapadia (2010), the removal of linkages is consistent with contagion effects (although they do not consider real economy linkages). Bekaert et al (2014) and Dungey et al (2014) also find evidence that government policy interventions during the crisis period disconnected the banking sector from the real economy; see King (2012) on the role of regulatory interventions.

The regression analysis parameters, $\beta_{i,L}$ and $\beta_{i,H}$, reported in Panel B of Table 3 are consistent with the separation of the financial sector from the real economy in the crisis period. Only in the insurance sector is $\beta_{i,H} > \beta_{i,L}$. The Forbes and Rigobon results reported in Panel A, also show that although the unadjusted correlation coefficient rises in each sector, their adjusted correlation coefficients fall.

[11] Exemplars of rescued or assisted firms include the insurance giant AIG and TARP support to conglomerates such as GE, and ‘cash for clunkers’ style programs.

In the original Forbes and Rigobon analysis this would be interpreted as consistent with no-contagion, as they conduct only a one-sided test for an increase in correlation. However, it is apparent from the model analysis that there has been a dramatic change in the structure of the underlying loadings on the factor and the unexplained variation. In particular, the $\omega_{i,0}$ parameters increase substantially between the two periods, moving from significantly negative to insignificantly positive (and while the standard deviation of banking returns increases almost four-fold – see Table 1 – the $\omega_{i,0}$ increase by a multiple of between 9 and 150 times their non-crisis values such that $\gamma_{i,H} > \gamma_{i,L}$ in each case). This example illustrates how the contribution of the unexplained variation may lead to incorrect conclusions by comparing either $\beta_{i,H}$ with $\beta_{i,L}$ or examining correlation coefficients when true interest is located in changes in the loading $b_{i,L}$ to $b_{i,H.}$

The ARCH-LM tests reported in Panel F of Table 4 show that during the crisis period evidence of ARCH is reduced by the factor model in the crisis period for the majority of the assets, although this effect is not dramatic – unlike the Asian currency example we do not eliminate this problem for any individual sector. However, it shows that the factor loadings in the crisis period, although hardly significant, play a role in capturing the time-varying volatility. The results suggest that perhaps our choice of mimicking portfolio could be improved.

One possibility is that the insurance sector may provide a better mimicking factor. Diebold and Yilmaz (2014) find that shocks transmitted by the insurance giant AIG to the banking sector exceed those transmitted by the banking sector to AIG. Although the consensus in the literature is that the source shock originated in banking, there is some dissent about the potential importance of insurance; Chen et al (2014) argue that it is a 'victim' of banking shocks, Acharya and Richards (2014) and Dungey et al (2014) provide evidence of its systemic importance and Harrington (2009) documents that the majority of the bailout support for AIG was ultimately transferred to the banks.

We re-estimate the model using insurance as the mimicking factor asset using $\alpha = 0.8$. The results are reported in Tables 5 and 6. The ARCH-LM results in Panel F of Table 6 shows that this strategy has not improved the model performance, this specification does not remove volatility from the returns, implying that the insurance sector does not perform well as a source for potential contagion to these sectors. This result is reflected in the estimates of the b_i parameters. The factor loadings in the non-crisis period, $b_{i,L}$, are all insignificant at the 10 percent level, and even more so during the crisis period, $b_{i,H}$. Furthermore, although the estimates of $\omega_{i,0,L}$ are statistically significant and positive, those of $\omega_{i,0,H}$ are positive but insignificant and have at least doubled. In consequence the increase in the volatility of the source shock for insurance results in $\gamma_{i,H} < \gamma_{i,L}$ for a number of sectors. We conclude that the insurance sector does not provide a good mimicking factor for this analysis, and thus was not a source of contagion effects to other sectors in general (although there is some evidence of feedback to banking). The results presented here are a good example of the reflection problem of Manski (1993).[12]

4.3 Contagion in the CDS market: European sovereigns 2008-2013

The CDS market data comprise spreads paid on 5-year CDS contracts for sovereign debt by each of five European nations: Ireland, Italy, Portugal, Spain and Germany. An increase in the premia represents a perceived increase in sovereign default risk. The extreme problems in Greece during this period mean that comparable CDS contracts for Greek sovereign debt were not liquid during the sample period. As a source factor we construct the interest differential between the Greek and US 10 year indicative bond rates as a measure of the changing credit risk differential between Greece and the dominant benchmark global sovereign debt market. Figure 1 shows the constructed Greek-US spread and the other European CDS spreads over the sample period, where the vertical line represents the change between non-crisis and crisis sub-samples. The major increase in Greek spreads from the first quarter of 2010 onwards is clearly apparent, as are the less substantive rises for the other GIIPS countries. German CDS spreads rose only marginally in comparison - from an average of 35 basis points to 53 basis points between the non-crisis and crisis sample (see Table 1). The other clearly notable feature of the Greek spread

[12] We also implemented a 2 factor representation for this sector with both banking and insurance as mimicking portfolios. The deterioration in the performance of the model was marked with increased evidence of ARCH after applying the factor model to the data. We do not report the results but they are available from the authors on request.

data is the abrupt drop in the spread on March 12, 2012 associated with IMF approval of the Extended Fund Facility of 28 billion Euros on that date - this incident appears to have been largely idiosyncratic and related to fears of Greek exit from the Eurozone and is not represented in the behavior of the markets for sovereign debt of other European countries.

Using Greek spreads as the source factor we find evidence of contagion in the form of statistically significant changes between the factor loadings $b_{i,L}$ and $b_{i,H}$ for each of the other European sovereigns considered with $\alpha = 0.6$; see Panel E of Table 8. However, unlike the previous two cases here $b_{i,L} > b_{i,H}$. This recognizes that an increase in the CDS spread (as opposed to an increase in returns in the value of the domestic currency or the equity return) is associated with poor news for financial markets. In the pre-crisis period the $b_{i,L}$ are all positive indicating a positive association between the European CDS spreads and the Greek factor; increases in Greek spreads were generally associated with declining European conditions and the parameter loadings on the factor for the GIIPS countries were all near unity (although significantly different from it). In contrast, the loading $b_{i,L}$ for Germany is considerably lower, about one-tenth of that of the GIIPS assets. It is worth noting that although Table 1 clearly indicates that the standard deviation of Greek spreads was higher than most countries, it was not the highest.[13]

During the second part of the sample, when the Greek crisis became severe, the negative $b_{i,H}$, represent the changes in the relationship between Greece and Europe, where there were doubts concerning its ability to remain in the Euro system, and great concern over its fiscal and debt stance. Not only have the loadings for each asset, $b_{i,H}$, become negative, but they have also reduced in absolute size. The factor loadings on Greece for each of Ireland, Italy and Spain are no more than 25 percent of the pre-crisis loading; and the factor loading on Greece is only 20 percent of the already small pre-crisis loading. This represents a decoupling of these markets, something also noted in Caporin et al (2014), which they denote as Euro-disintegration. The factor loading for Portugal also decreases in the crisis period, from highest of the estimated loadings on the Greek factor in the non-crisis

[13] The first signs that Greece may have impending problems emerged in the latter part of 2009, but as is clearly evident in Figure 1 this was not a clear indication of the emergence of crisis conditions.

period (1.3110) to the largest in absolute terms of the negative linkages during the crisis period (-0.0562). The Portuguese case is also shown to be separable from Greece in Caporin et al (2014). The decoupling of a previously grouped market in this example is reminiscent of the behavior of Mexican bonds which ceased following Latin American bond market factors after being upgraded to investment grade in 2000, and instead joined the North American group; see Rigobon (2002).

The results in panels A and B of Table 7 show a decline in both the correlation coefficients and the estimated regression β_i; the lower correlation during crisis for this market is also reported in Broto and Pérez-Quirós (2015). The Forbes and Rigobon adjusted correlation coefficients show an even greater decline, sufficient to support a statistically significant decline in correlation (which, as before, Forbes and Rigobon would not recognize as contagion due to the one-sided nature of their test). The resolution to the apparent contradiction between these results and those from our model lies in the role of $\omega_{i,0.}$ The estimates of $\omega_{i,0,L}$ are absolutely less than those for $\omega_{i,0,H}$, and in this example the $\omega_{i,0}$ are statistically significant in both sub-periods. The source factor volatility, $\omega_{0,0}$, also increases from the non-crisis to crisis period (see Table 1), and in this case the relative changes in volatility for each asset are such that $\gamma_{i,H} > \gamma_{i,L}$. Thus the apparent drop in the β_i and correlation coefficients is a consequence of significantly negative $\omega_{i,0,L}$ effects and significantly positive $\omega_{i,0,H}$ effects. The underlying parameter of interest in assessing contagion effects has changed significantly during the period, but in this instance it has acted to reduce the links with the source factor. It is worth noting that the reduction is not only in terms of levels of spreads ($b_{iH} < b_{iL}$) but also in terms of volatility transmission ($|b_{iH}| < |b_{iL}|$). As a result, the factor captures only a part of the ARCH effect, even in the crisis period.

The one factor framework acts to reduce the ARCH present in the data, as shown in Panel F of table 8, but it is not particularly satisfactory as there remains a significant effect even after the application of the model. The results of Broto and Pérez-Quirós (2015) support not only Greece as a source of contagion but also other European sovereign markets. We explore whether statistical improvement can be obtained from a two factor specification, with Germany forming the source asset for the second factor. There are firm economic grounds to consider that our sample contains elements of reaction to both the unfolding uncertainty around

Greece and the relatively safety of Germany. The political leadership of German Chancellor Angela Merkel in the crisis, the anchor that Germany provides to the Euro system, and its role in providing safe-haven assets, are motivating economic factors; see Arghyrou and Kontonikas (2012),

We posit that the markets may receive source shocks from both Greece, as the crisis country, and from Germany as the relevant safe-haven. Figure 1 supports the quite different evolution of the German CDS spreads – the descriptive statistics provided in Table 1 show that the variance of the changes in German CDS spreads barely changes between the non-crisis and crisis periods. We implement the model with $\alpha = 0.8$, representing the maximum of the potential values for α estimated using univariate GARCH for the two source factors; the value using Germany of 0.8 exceeds that for Greece of 0.6 used in the one factor model.

The two factor model provides a dramatic improvement in the ARCH-LM diagnostic provided in Panel F of Table 9. The ARCH effects present in the crisis data are eliminated in the crisis period (this is not true of the non-crisis period but our objective is here focused on the crisis period). The two factor specification is also sufficient in this case to lead to acceptance of the Ghysels-Hall test for structural stability. Panel B reports the β_i obtained for each of the mimicking factors from regression analysis, with significant loadings on both for all the remaining CDS spreads.

The loadings on each of the two factors, $b_{GRE,i}$ and $b_{GER,i}$, shown in Panel E display a now familiar pattern. During the non-crisis period the loadings on both factors are significant and positive for all markets and in the crisis period the loadings on both factors are significant and negative. The non-crisis period loadings on the Greek factor, $b_{GRE,i,L}$ are qualitatively similar to those estimated in the one factor model, displaying stronger loadings for the Portuguese and Spanish CDS than for the Irish and Italian, but all four of these loadings are positive and statistically significant. The loadings on the German factor in the non-crisis period, $b_{GER,i,L}$, are also positive and significant, largest for the Irish and Italian CDS and closer to unity for the Portuguese and Spanish. During the crisis period these loadings switch signs, and for Ireland, Italy and Spain are up to 50 percent higher than in the non-crisis period, reflecting their stronger connection to the German factor during this period (consistent with the reduced attention to Greece). This outcome is even more pronounced for Portugal, where the ratio of the loading in the crisis period, $b_{GER,i,H}$ to that in the non-crisis period, $b_{GRE,i,L}$, exceeds nine.

The interpretation of these results is aided by considering the relative changes in volatility in the returns between the non-crisis and crisis periods. For each of the remaining European CDS markets, (Ireland, Italy, Portugal and Spain) the rise in volatility between the non-crisis period and crisis period was both less than that experienced in Greek spreads, and greater than that experienced in German spreads. Interpreting the changes in b_i in that light shows that the weights on the Greek factor, $b_{GRE,i}$, fall in absolute value because the markets disconnect from Greece. Greece's problems are seen as highly idiosyncratic. However, they do not escape completely as evidenced by the fact that this is a significant change in $b_{GRE,i}$, triggered by the Greek shock and thus consistent with contagion. In the case of the loadings on the German factor, $b_{GER,i}$, the increase in volatility for the other markets distances them somewhat from Germany, which as a safe-haven does not suffer from the same market reassessment of potential default risk. Thus, Greece and Germany represent extremes – Greece becomes a relatively more risky proposition and Germany a safe haven – and consequently the factor loadings on both assets become negative, representing the different ways in which they have separated from the remaining CDS markets in the sample.

5 Conclusion

This paper has proposed a method to identify contagion. We detect the change in the loadings on the underlying source factor driving the financial measure of interest (be it returns or changes in spreads), obtaining identification by taking advantage of heteroskedasticity via the conditional volatility which characterizes most financial data at other than very low frequency. In this way we extend the insights of Bekaert et al (2014) who use conditional means on low frequency data to identify changes in factor loadings in detecting contagion. But we also take advantage of financial econometric developments in a GARCH common features framework and associated statistical inference techniques. In this way we are able to both detect contagion in higher frequency data, more akin to the typically 'fast and furious' nature of financial crises (Kaminsky and Reinhart, 2003), and to directly test for significant changes in the loadings on the chosen source asset. Our framework provides further information on whether we have made the correct choice of source for the mimicking factor to represent potential contagion effects in the crisis period in the form of ARCH-LM tests; when the model is well-specified ARCH effects will be reduced by the factor model during the crisis period. The model has an important advantage in dimensionality. Most contagion tests are difficult to estimate for large selections of assets. This framework can handle a substantial number of assets, and what is more, multiple sources of contagion simultaneously. Future extensions are intended to consider the interactions of multiple asset classes, and to address the issue of whether pre-crisis conditions are ever re-established following crisis events.[14]

[14] Contessi et al (2014) and Dungey et al (2010) provide evidence of permanent changes in the transmission loadings between US bond yields after the crisis of 2007-2009 and Asian equity returns after the 1997-1998 Asian crisis respectively.

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6 Appendix 1: Data Sources

- **Asian currencies example:** Data are daily exchange rates against the US dollar for the sample period July 2, 1995 to August 31, 1998. The original data are sourced from Thomson Financial Datastream with codes as shown in the Table below. These data were also used in Dungey and Martin (2007).
- **US equity sectors example:** Data are daily equity indices for sectors of the US economy from the S&P500 for sample period August 2, 2004 to June 30, 2009. The original data are sourced from Thomson Financial Datastream with codes as shown in the Table below.
- **European CDS example:** Data are sourced from Markit for European sovereign USD issued CDS for the period September 15, 2008 to November 21, 2013. These data are available for purchase direct from the vendor. The bond yields used in the application are sourced from Thomson Financial Datastream with codes as given in the Table.

Asian currencies		US equities	
currency	Datastream code	sector	Datastream code
Australia	AUSTRUS	banking	SP5SIBB
Indonesia	USINDON	food	SP5SFRT
Malaysia	MYUSDSP	health	SP5EHCR
Thailand	USTHAIB	industry	SP5SEIND
		insurance	SP5GINS
		IT	SP5EINT
		utilities	SP5GUTL

European CDS	
Sovereign	Markit code
Ireland	IRELND_Rep Irlnd_4A88DE
Italy	ITALY_Rep Italy_4AB951
Germany	DBR_Fed Rep Germany_3AB549
Portugal	PORTUG_Rep Portugal_7AA999
Spain	SPAIN_Kdom Spain_8CA965
10 year bonds	Datastream code
Greek yield	GRBRYLD
US yield	USBRYLD

7 Appendix 2 : Contagion with two sources

For convenience this appendix follows the same (although abbreviated) structure as the description of the one factor model in the main text.

7.1 Model for the source returns

Consider now two source returns as noisy observations of two latent volatility factors:

$$\begin{bmatrix} r_{01,t+1} \\ r_{02,t+1} \end{bmatrix} = \begin{bmatrix} f_{1,t+1} \\ f_{2,t+1} \end{bmatrix} + \begin{bmatrix} u_{01,t+1} \\ u_{02,t+1} \end{bmatrix} = F_{t+1} + U_{0,t+1}$$

where $U_{0,t+1} = [u_{01,t+1}, u_{02,t+1}]'$ is an homoskedastic error term, and the factors are conditionally heteroskedastic:

$$E_t\left(U_{0,t+1}\right) = 0, Var_t(U_{0,t+1}) = \Omega_{00}$$

$$E_t\left(f_{t+1}\right) = 0, Var_t(F_{t+1}) = \begin{bmatrix} \sigma^2_{11,t} & \sigma_{12,t} \\ \sigma_{12,t} & \sigma^2_{22,t} \end{bmatrix}$$

As before all returns and factors have a zero-conditional expectation given past information and we assume zero conditional covariance between factors and noise, so that the variance of the source is decomposed into time-varying and constant components.

$$Var_t\left(\begin{bmatrix} r_{01,t+1} \\ r_{02,t+1} \end{bmatrix}\right) = \Sigma_{0,t} = Var_t(F_{t+1}) + \Omega_{00}$$

Since the conditional covariances of the two source returns may be time-varying, it may not be possible to normalize the two latent factors to make then conditionally uncorrelated. By contrast, we can assume without loss of generality that they are unconditionally uncorrelated, that is:

$$E\left[Var_t(F_{t+1})\right] = \begin{bmatrix} \sigma^2(f_1) & 0 \\ 0 & \sigma^2(f_2) \end{bmatrix}$$

Note that the unconditional variance of factors is not identified. The time-varying part of return variance can always be artificially inflated by incorporating a constant component. In other words, it takes an identification assumption to decide the share of the variance of the sources carried by the factors:

Identification assumption $A(\alpha)$

For some $\alpha \in]0,1[$ given:

$$\frac{\sigma^2(f_1)}{Var(r_{01,t+1})} = \frac{\sigma^2(f_2)}{Var(r_{02,t+1})} = \alpha$$

Note that for $i = 1,2$ the parameter α can be interpreted as the (unconditional) squared correlation coefficient between the volatility factor $f_{i,t+1}$ and its mimicking portfolio return $r_{0i,t+1}$. By choice of α, we identify two factors that are more correlated with the source when α is large. The smaller the α, the smaller the part of time-invariant volatility carried by the factor, since for the source, the residual variance is:

$$\Omega_{00} = \begin{bmatrix} \omega_{00,11} & \omega_{00,12} \\ \omega_{00,12} & \omega_{00,22} \end{bmatrix} = \begin{bmatrix} (1-\alpha)Var(r_{01,t+1}) & \omega_{00,12} \\ \omega_{00,12} & (1-\alpha)Var(r_{02,t+1}) \end{bmatrix}$$

The choice of α is constrained analogously to the one factor model as follows:

$$\begin{aligned} \omega_{00,11} &\leq \min_{1\leq t\leq T} \left[Var_t\left(r_{01,t+1}\right)\right] \\ \omega_{00,22} &\leq \min_{1\leq t\leq T} \left[Var_t\left(r_{02,t+1}\right)\right] \end{aligned}$$

Then, the variance of the factor would be kept at its minimum possible value if one chooses $\alpha = \bar{\alpha}$ defined as follows:

$$\bar{\alpha} = 1 - \min\left\{\frac{\min_{1\leq t\leq T}\left[Var_t\left(r_{01,t+1}\right)\right]}{Var(r_{01,t+1})}, \frac{\min_{1\leq t\leq T}\left[Var_t\left(r_{02,t+1}\right)\right]}{Var(r_{02,t+1})}\right\}$$

7.2 Model for the target return

To capture the time-varying volatility the model entails two restrictions:

First, target returns $r_{i,t+1}, i = 1,...,n-1$, have a time invariant conditional regression coefficient b_i on the volatility factor. Second, the vectors of residuals of this $(n-1)-$dimensional regression are homoskedastic.

For the sake of conforming with the notation in the main body of the paper, we consider now only $(n-1)$ target returns, admitting that one of the initial n target returns is now seen as a source.

Formally, for $i, j = 1, ..., n-1$:

$$\begin{aligned} r_{i,t+1} &= b_{i1} f_{1,t+1} + b_{i2} f_{2,t+1} + u_{i,t+1} \\ E_t\left(u_{i,t+1}\right) &= 0, Cov_t[u_{i,t+1}, u_{j,t+1}] = \omega_{ij} \\ Cov_t[f_{1,t+1}, u_{i,t+1}] &= Cov_t[f_{2,t+1}, u_{i,t+1}] = 0 \end{aligned} \quad (15)$$

and for $i = 1, ..., n-1$:

$$Cov_t[u_{i,t+1}, u_{0j,t+1}] = \omega_{i,0j}, j = 1, 2$$

Then the two factor model (15), jointly with the specification of the share α for factor volatility, provides a decomposition of unconditional beta coefficients of asset $i = 1, ..., n-1$ defined as:

$$\beta_{ij} = \frac{Cov[r_{i,t+1}, r_{0j,t+1}]}{Var(r_{0j,t+1})}, j = 1, 2$$

Since by definition:

$$\begin{aligned} Cov_t[r_{i,t+1}, r_{01,t+1}] &= b_{i1}\sigma^2_{11,t} + b_{i2}\sigma^2_{12,t} + \omega_{i,01} \\ Cov_t[r_{i,t+1}, r_{02,t+1}] &= b_{i1}\sigma^2_{12,t} + b_{i2}\sigma^2_{22,t} + \omega_{i,02} \end{aligned}$$

by taking unconditional expectations:

$$\begin{aligned} Cov[r_{i,t+1}, r_{01,t+1}] &= b_{i1}\sigma^2(f_1) + \omega_{i,01} \\ Cov[r_{i,t+1}, r_{02,t+1}] &= b_{i2}\sigma^2(f_2) + \omega_{i,02} \end{aligned}$$

and dividing on both sides respectively by $Var(r_{01,t+1}) = \frac{\sigma^2(f_1)}{\alpha} = \frac{\omega_{00,11}}{1-\alpha}$ and by $Var(r_{02,t+1}) = \frac{\sigma^2(f_2)}{\alpha} = \frac{\omega_{00,22}}{1-\alpha}$ we get:

$$\begin{aligned} \beta_{i1} &= \alpha b_{i1} + (1-\alpha)\gamma_{i1} \\ \beta_{i2} &= \alpha b_{i2} + (1-\alpha)\gamma_{i2} \end{aligned}$$

where $\gamma_{ij} = \omega_{i,0j}/\omega_{00,jj}, j = 1, 2$ is the regression coefficient (both a conditional and an unconditional one) of u_i on u_{0j}. As rigorously explained in the next section, under the maintained assumption (15), the four beta coefficients β_{ij} and $b_{ij}, j = 1, 2$, are identified from the observation of the time series $(r_{i,t})_{1 \leq t \leq T}$, $i = 0, 1...., n$ of asset returns. By contrast, identification of $\gamma_{ij}, j = 1, 2$, takes a choice of the value α of the share of the variance of the factors in the total variance of the source returns.

7.3 Estimation of factor loadings

Following Doz and Renault (2006), standard and efficient GMM inference can be performed thanks to the complete set of conditional moment restrictions implied by our two factor model:

$$E_t \left[r_{j,t+1} \left(r_{i,t+1} - b_{i1} r_{01,t+1} - b_{i2} r_{02,t+1} \right) \right] = c_{i,j}, \forall i = 1, ..., n-1, \forall j = 0, 1, ..., n$$

where for notational simplicity we use the dual notation:

$$\begin{aligned} r_{0,t+1} &= r_{01,t+1} \\ r_{n,t+1} &= r_{02,t+1} \end{aligned}$$

For a given vector z_t of G instruments, we end up with the following unconditional moment restrictions for each $i = 1, ..., n-1$:

$$E \left[z_t r_{j,t+1} \left(r_{i,t+1} - b_{i1} r_{01,t+1} - b_{i2} r_{02,t+1} \right) \right] = c_{i,j} E(z_t), \forall j = 0, 1, ..., n \tag{16}$$

In other words, for each target asset $i = 1, ..., n-1$, we have a linear regression model with unknown slope parameters $b_{i1}, b_{i2}, (c_{i,j})_{0 \leq j \leq n}$ that can be written as follows:

$$\begin{aligned} & \left(r_{t+1} \otimes z_t \right) r_{i,t+1} && (17) \\ = & \left(r_{t+1} \otimes z_t \right) r_{01,t+1} b_{i1} + \left(r_{t+1} \otimes z_t \right) r_{02,t+1} b_{i2} + [Id_{n+1} \otimes z_t] c_{i\bullet} + \varepsilon_{i,t+1} && (18) \end{aligned}$$

where, as in Section 3.1, $r_{t+1} = (r_{j,t+1})_{0 \leq j \leq n}, \varepsilon_{i,t+1}$ is a $(n+1)G-$dimensional martingale difference sequence, $c_{i\bullet} = (c_{i,j})_{0 \leq j \leq n}$ and Id_{n+1} stands for the identity matrix of dimension $(n+1)$ and estimation proceeds analogously.

7.4 Decomposition of variance

We identify the decomposition of variance between factor and residual term by the choice of some $\alpha \in [\bar{\alpha}, 1]$ such that :

$$Var(f_{j,t+1}) = \alpha Var(r_{0j,t+1}), j = 1, 2$$

and

$$Cov(r_{i,t+1}, r_{0j,t+1}) = \alpha b_{ij} Var(r_{0j,t+1}) + \omega_{i0}, j = 1, 2$$

Consider for each asset $i = 1, ...n-1$ an augmented set of moment restrictions as follows:

$$\begin{aligned} E\left[z_t r_{j,t+1}\left(r_{i,t+1} - b_{i1} r_{01,t+1} - b_{i2} r_{02,t+1}\right)\right] &= c_{i,j} E(z_t), \forall j = 0, 1, ..., n \quad (19) \\ E\left[r_{01,t+1}\left(r_{i,t+1} - \alpha b_{i1} r_{01,t+1}\right)\right] &= \omega_{i,01} \\ E\left[r_{02,t+1}\left(r_{i,t+1} - \alpha b_{i2} r_{02,t+1}\right)\right] &= \omega_{i,02} \end{aligned}$$

As in the one factor model while (19) entails two more moment restrictions than (16), it does not modify the asymptotic variance of an efficient GMM estimator of factor loadings (b_{i1}, b_{i2}) (and of residual parameters $c_{i,j}$ as well) because the additional moment restrictions just identify the additional parameters $(\omega_{i,01}, \omega_{i,02})$, but the GMM estimates of the latter parameters will be more efficient. (Refer to Section 3.2 for more details.)

The augmented set of moment conditions (19) can be rewritten for the two factor model as:

$$\begin{bmatrix} (r_{t+1} \otimes z_t)\, r_{i,t+1} \\ r_{01,t+1} r_{i,t+1} \\ r_{021,t+1} r_{i,t+1} \end{bmatrix} = \begin{bmatrix} (r_{t+1} \otimes z_t)\, r_{01,t+1} & (r_{t+1} \otimes z_t)\, r_{02,t+1} & [Id_{n+1} \otimes z_t] & 0 & 0 \\ \alpha r^2_{01,t+1} & 0 & 0 & 1 & 0 \\ 0 & \alpha r^2_{02,t+1} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} b_{i1} \\ b_{i2} \\ c_{i\bullet} \\ \omega_{i,01} \\ \omega_{i,02} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t+1} \\ \eta_{i1,t+1} \\ \eta_{i2,t+1} \end{bmatrix} \quad (20)$$

and, as before the series $\eta_{ij,t+1}, j = 1, 2$, will generally require correction for serial correlation. Our efficient GMM estimator of $\theta^{(i)} = [b_{i1}, b_{i2}, c_{i0}, c_{i1}, ..., c_{in}, \omega_{i,01}, \omega_{i,02}]'$ will be:

$$\hat{\theta}_T^{(i)} = \left[\bar{X}_T'(\hat{\Sigma}_T^{(i)})^{-1}\bar{X}_T\right]^{-1} \bar{X}_T'(\hat{\Sigma}_T^{(i)})^{-1}\bar{Y}_T^{(i)}$$

with:

$$\bar{Y}_T^{(i)} = \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} (r_{t+1} \otimes z_t)\, r_{i,t+1} \\ r_{01,t+1} r_{i,t+1} \\ r_{02,t+1} r_{i,t+1} \end{bmatrix} \tag{21}$$

$$\bar{X}_T = \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} (r_{t+1} \otimes z_t)\, r_{01,t+1} & (r_{t+1} \otimes z_t)\, r_{02,t+1} & [Id_{n+1} \otimes z_t] & 0 & 0 \\ \alpha r_{01,t+1}^2 & 0 & 0 & 1 & 0 \\ 0 & \alpha r_{02,t+1}^2 & 0 & 0 & 1 \end{bmatrix} \tag{22}$$

while $\hat{\Sigma}_T^{(i)}$ is the estimated long-run variance matrix of $[\varepsilon_{i,t+1}, \eta_{i,t+1}]'$ (with no lag for $\varepsilon_{i,t+1}$ and a MA representation for $\eta_{i,t+1}$) deduced from a first-step GMM estimator:

$$\tilde{\theta}_T^{(i)} = \left[\bar{X}_T'\bar{X}_T\right]^{-1} \bar{X}_T'\bar{Y}_T^{(i)}$$

We maintain the same identification assumption $A(\alpha)$ for the two periods (see empirical section for discussion of the way to pick a specific value of α). This assumption identifies in particular the residual covariance parameters $\omega_{i,01}, \omega_{i,02}, i = 1, ..., n-1$. Then, using moment conditions (19), we can estimate jointly by GMM for each period the asset i parameters $\theta_i = (b_i, c_{i\bullet}, \omega_{i0}), i = 1, ..., n-1$ denoted respectively as:

$$\begin{aligned} \theta_L^{(i)} &= (b_{i,L}, c_{i\bullet,L}, \omega_{i0,L}), i = 1, ..., n-1 \\ \theta_H^{(i)} &= (b_{i,H}, c_{i\bullet,H}, \omega_{i0,H}), i = 1, ..., n-1 \end{aligned}$$

7.5 Testing hypotheses about structural stability

The structural stability tests described in Section 3.3.2 also apply here, with the degrees of freedom for the J-test applied to the validity of the two factor model in the non-crisis period of $\chi^2\left[(n+1)^2 - 2\right]$, for the test of the validity of orthogonality conditions in the second period of $\chi^2\left[(n+1)^2 + n + 3\right]$ and for the test of over-identification for the crisis period of $\chi^2\left[(n+1)^2 - 2\right]$.

When the validity of a two factor model has not been rejected for each of the two periods, it makes sense to compare the two models by comparing the values of their parameters. Hall (2005) states the convenient result that under the null hypothesis of no change, the two J-test statistics on the one hand and the Wald test statistics comparing parameter values on the other hand are asymptotically independent. We will set the focus on the Wald test of no change in the factor loadings. In other words, for each asset $i = 1, 2, ...n - 1$ and each factor $j = 1, 2$ the Wald test statistic will be:

$$\xi_{ij}^{W} = (T_L + T_H)\frac{\left(\hat{b}_{ij,H} - \hat{b}_{ij,L}\right)^2}{\hat{V}_{ij,b}(H/L)}$$

where:

$$\hat{V}_{i,b}(H/L) = \left[\frac{T_L}{T_L + T_H}\right]^{-1} \hat{\sigma}^2(\hat{b}_{ij,L}) + \left[\frac{T_H}{T_L + T_H}\right]^{-1} \hat{\sigma}^2(\hat{b}_{ij,H})$$

and $\hat{\sigma}^2(\hat{b}_{ij,L})$ (resp. $\hat{\sigma}^2(\hat{b}_{ij,H})$) stands for the estimated asymptotic variance of the GMM estimator$\sqrt{T_L}\hat{b}_{ij,L}$ (resp. $\sqrt{T_H}\hat{b}_{ij,H}$).

Figure 1: European Spreads:
5 year CDS premia for Ireland, Italy, Portugal,
Spain and Germany:
10 year bond spread for Greece over the US

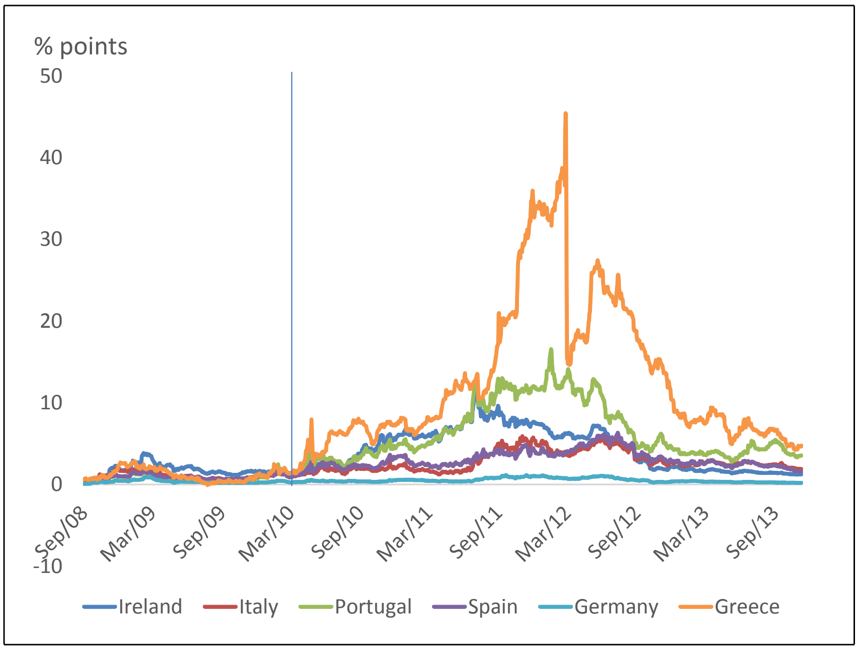

Table 1: Descriptive statistics for returns in non-crisis and crisis periods

	Example 1: Daily currency returns				*Example 2: Daily US equity sector returns*						
	AUD	IND	MYR	THB	Banking	Food	Health	Industry	I.T.	Insur	Utilities
non-crisis:		Jan 2, 1995 - July 1, 1997					Aug 2, 2004 - Aug 8, 2007				
mean	0.0045	0.0155	-0.0019	-0.0040	0.0724	0.0315	0.02387	0.0425	0.0362	0.0242	0.0655
max	2.5004	1.3649	0.7049	6.1875	4.9202	5.3536	2.9703	2.3912	3.1952	5.1788	3.6599
min	-1.6616	-0.7800	-1.1559	-4.5425	-5.6792	-5.3675	-2.7464	-2.9858	-4.0188	-7.1311	-3.9865
s.d.	0.4449	0.1562	0.1810	0.4914	1.2376	1.1089	0.6983	0.7402	0.9150	0.8678	0.8644
crisis:		July 2, 1997 - Aug 31, 1998					Aug 9, 2007 - June 30, 2009				
mean	0.0903	0.5024	0.1670	0.1772	-0.1784	-0.0932	-0.0564	-0.1300	-0.0653	-0.2180	-0.0743
max	3.045	31.5853	7.1165	17.0666	23.7262	7.8388	11.7131	9.5164	11.4610	16.3780	12.6840
min	-2.7257	-23.6063	-6.7593	-6.1702	-21.2461	-9.7258	-7.4152	-9.2150	-9.6701	-14.2109	-8.5299
s.d.	0.7590	5.8578	1.6658	1.9443	4.8275	2.1385	1.6838	2.3146	2.2612	3.8225	1.9640

	Example 3: Daily changes in sovereign CDS spreads					
	Ireland	Italy	Germ	Greece	Portugal	Spain
			Sept 15, 2008 - Mar 31, 2010			
mean	0.0027	0.0018	0.0006	0.0026	0.0025	0.0019
max	0.6018	0.2099	0.1110	0.4459	0.3350	0.1921
min	-0.2740	-0.1549	-0.1013	-0.4878	-0.2876	-0.1734
s.d.	0.0802	0.0475	0.0199	0.1124	0.0554	0.0476
			Apr 1, 2010 - Nov, 21, 2013			
mean	-0.0001	0.0008	-0.0001	0.0033	0.0023	0.0005
max	1.1379	0.7180	0.1175	6.9930	1.77066	0.5921
min	-1.5245	-0.7404	-0.1336	-27.4580	-1.6724	-0.6960
s.d.	0.1670	0.1277	0.0216	1.0223	0.2526	0.1279

Table 2: Asian currencies against the US dollar: contagion from Thai baht. Non-crisis period January 2, 1995 - July 1, 1997. Crisis period July 2, 1997 - December 31, 1998.

		Indonesia	Malaysia	Australia
A: Correlation Coefficients				
non-crisis period	ρ_L	0.0297	0.0973	-0.0186
crisis period: not adjusted	ρ_H	0.3194	0.4903	0.2994
crisis period: FR adjusted	$\widetilde{\rho}_H$	0.0847	0.1406	0.0789
t-test of change	$\rho_H - \rho_L$	4.3219	6.2977	4.6985
	p-value	(0.0114)	(0.0040)	(0.0091)
t-test of change	$\widetilde{\rho}_H - \rho_L$	0.7920	0.6304	1.4019
	p-value	(0.2431)	(0.2866)	(0.1278)
B: Regression coefficients				
non-crisis period	$\beta_{i,L}$	0.4515	0.0478	-0.0105
	s.e.	(0.0174)	(0.0149)	(0.0354)
crisis period	$\beta_{i,H}$	0.9685	0.4219	0.1182
	s.e.	(0.1635)	(0.0428)	(0.0214)
C: J-test for one factor model				
non-crisis period	test statistic	0.0558	0.1514	0.0095
	p-value	(1.0000)	(1.0000)	(1.0000)
crisis period	test statistic	0.2883	0.2217	0.1991
	p-value	(1.0000)	(1.0000)	(1.0000)
D: Tests for structural stability				
Break in number of factors	$\chi^2(15)$	0.2883	0.2217	0.1991
	p-value	(1.0000)	(1.0000)	(1.0000)
Ghysels-Hall test	$\chi^2(21)$	40.9617	66.1898	52.5505
	p-value	(0.0006)	(0.0000)	(0.0002)
Break in factor loadings	$\chi^2(5)$	54.3679	79.9407	52.4656
	p-value	(0.0000)	(0.0000)	(0.0000)
E: parameter estimates				
non-crisis period	$b_{i,L}$	-0.0388	-0.0286	-0.4891
	s.e.	(0.0004)	(0.0000)	(0.0013)
	$\omega_{i,0,L}$	0.0107	0.0043	0.0039
	s.e.	(0.0000)	(0.0000)	(0.0000)
crisis period	$b_{i,H}$	1.6250	0.5288	-0.1109
	s.e.	(0.1676)	(0.0154)	(0.0015)
	$\omega_{i,0,H}$	0.2064	0.2428	0.0512
	s.e.	(13.5861)	(0.8193)	(0.1144)
	$b_{i,H} - b_{i,L}$	173.0834	632.0749	3702.6824
	p-value	(0.0000)	(0.0000)	(0.0000)
F: ARCHLM tests				
non-crisis returns	$\chi^2(1)$	2.4614	1.6421	0.0457
	p-value	(0.1167)	(0.2000)	(0.8307)
factor model	$\chi^2(1)$	2.5735	1.0035	4.0516
	p-value	(0.1087)	(0.3165)	(0.0441)
crisis returns	$\chi^2(1)$	10.5641	1.9581	7.2559
	p-value	(0.0012)	(0.1617)	(0.0071)
factor model	$\chi^2(1)$	4.6731	0.3210	1.3472
	p-value	(0.0306)	(0.5710)	(0.2458)

Table 3: Sectors of the US economy: contagion from banking.
Non-crisis period August 2, 2004 - August 8, 2007. Crisis period August 9, 2007 - June 30, 2009.

		Insurance	Industrials	Health	Utilities	Food	Info Tech
A: Correlation Coefficients							
non-crisis period	ρ_L	0.6448	0.7262	0.5866	0.5028	0.4107	0.6781
crisis period: not adjusted	ρ_H	0.8408	0.7682	0.6948	0.6009	0.5835	0.7633
crisis period: FR adjusted	$\widetilde{\rho}_H$	0.3699	0.2940	0.2404	0.1892	0.1811	0.2897
t-test of change	$\rho_H - \rho_L$	7.9510	1.6576	3.2105	2.4587	4.0198	3.1013
	p-value	(0.0021)	(0.0980)	(0.0245)	(0.0455)	(0.0138)	(0.0266)
t-test of change	$\widetilde{\rho}_H - \rho_L$	-3.5708	-10.7349	-7.4264	-6.2838	-4.4015	-9.1620
	p-value	(0.0036)	(0.0009)	(0.0025)	(0.0041)	(0.0109)	(0.0014)
B: Regression Coefficients							
non-crisis period	$\beta_{i,L}$	0.4552	0.4359	0.3309	0.3525	0.3687	0.5008
	s.e.	(0.0191)	(0.0146)	(0.0162)	(0.0215)	(0.0290)	(0.0193)
crisis period	$\beta_{i,H}$	0.6661	0.3687	0.2424	0.2448	0.2587	0.3576
	s.e.	(0.0193)	(0.0138)	(0.0113)	(0.0146)	(0.0162)	(0.0136)
C: J-test for one factor model							
non-crisis period	test statistic	0.3514	0.1410	0.1960	0.2390	0.2322	0.1514
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
crisis period	test statistic	0.3838	0.3771	0.6054	0.5592	0.6199	0.4401
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
D: Tests for structural stability							
Break in number of factors	$\chi^2(48)$	0.3838	0.3771	0.6054	0.5592	0.6199	0.4401
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Ghysels-Hall test	$\chi^2(57)$	104.7720	95.0621	59.4962	65.6339	68.7445	89.6968
	p-value	(0.0001)	(0.0012)	(0.3849)	(0.2025)	(0.1370)	(0.0037)
Break in factor loadings	$\chi^2(7)$	63.1646	92.6913	44.2733	57.9599	89.4685	68.1595
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 4: Sectors of the US economy: contagion from banking.
Non-crisis period August 2, 2004 - August 8, 2007. Crisis period August 9, 2007 - June 30, 2009.

		Insurance	Industrials	Health	Utilities	Food	Info Tech
E: Parameter estimates							
non-crisis period	$b_{i,L}$	0.8056	0.7681	0.8784	0.8055	1.2020	1.0392
	s.e.	(0.2076)	(0.0813)	(0.1406)	(0.1834)	(0.2189)	(0.0945)
	$\omega_{i,0,L}$	-0.0237	-0.0212	-0.0626	-0.0351	-0.0908	-0.0518
	s.e.	(0.0354)	(0.0127)	(0.0223)	(0.0290)	(0.0340)	(0.0148)
crisis period	$b_{i,H}$	-1.5959	-1.0218	-0.2502	-0.7598	-0.6607	-0.4221
	s.e.	(19.4449)	(5.0796)	(5.7446)	(6.5101)	(3.3987)	(6.6373)
	$\omega_{i,0,H}$	3.5239	2.0204	0.5875	1.0971	1.2798	1.1990
	s.e.	(41.1238)	(11.2498)	(10.8324)	(13.3088)	(7.5592)	(12.9693)
t-test	$b_{i,H} - b_{i,L}$	-2.7422	-7.8233	-4.3612	-5.3312	-12.1537	-4.8880
	p-value	(0.0356)	(0.0022)	(0.0111)	(0.0064)	(0.0060)	(0.0082)
F: ARCHLM tests							
non-crisis							
returns	$\chi^2(1)$	21.1283	5.7105	4.2011	36.8332	6.2800	0.6466
	p-value	(0.0000)	(0.0169)	(0.0404)	(0.0000)	(0.0122)	(0.4213)
factor model	$\chi^2(1)$	46.6887	14.0296	4.0236	13.7342	4.1850	5.9994
	p-value	(0.0000)	(0.0002)	(0.0449)	(0.0002)	(0.0408)	(0.0143)
crisis							
returns	$\chi^2(1)$	31.2394	4.0340	22.3828	18.4958	5.0645	4.7180
	p-value	(0.0000)	(0.0446)	(0.0000)	(0.0000)	(0.0244)	(0.0298)
factor model	$\chi^2(1)$	11.3412	5.0065	13.8777	10.9839	10.2388	3.7902
	p-value	(0.0008)	(0.0253)	(0.0002)	(0.0009)	(0.0014)	(0.0516)

Table 5: Sectors of the US economy: contagion from insurance. Non-crisis period August 2, 2004 - August 8, 2007. Crisis period August 9, 2007 - June 30, 2009.

		Banking	Industrials	Health	Utilities	Food	Info Tech
A: Correlation Coefficients							
non-crisis period	ρ_L	0.6448	0.6664	0.6049	0.4994	0.4127	0.5794
crisis period: not adjusted	ρ_H	0.8408	0.8216	0.7564	0.6536	0.5822	0.7731
crisis period: FR adjusted	$\widetilde{\rho}_H$	0.3325	0.3110	0.2539	0.1924	0.1605	0.2667
t-test of change	$\rho_H - \rho_L$	7.9510	6.2144	4.9850	4.0500	3.9447	6.3686
	p-value	(0.0021)	(0.0042)	(0.0078)	(0.0136)	(0.0145)	(0.0039)
t-test of change	$\widetilde{\rho}_H - \rho_L$	-7.3124	-8.3871	-7.6694	-6.1466	-4.8145	-6.7849
	p-value	(0.0026)	(0.0018)	(0.0023)	(0.0043)	(0.0085)	(0.0033)
B: Regression Coefficients							
non-crisis period	$\beta_{i,L}$	0.9210	0.5701	0.4850	0.4984	0.5273	0.6088
	s.e.	(0.0308)	(0.01554)	(0.0130)	(0.0306)	(0.0412)	(0.0305)
crisis period	$\beta_{i,H}$	1.0618	0.4978	0.3332	0.3362	0.3260	0.4573
	s.e.	(0.0308)	(0.01554)	(0.0130)	(0.0175)	(0.0205)	(0.0169)
C: J-test for one factor model							
non-crisis period	test statistic	0.2345	0.1413	0.2460	0.2362	0.2322	0.1925
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
crisis period	test statistic	0.5803	0.6322	0.6898	0.6840	0.5598	0.5658
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
D: Tests for structural stability							
Break in number of factors	$\chi^2(48)$	0.5803	0.6322	0.6898	0.6840	0.5598	0.5658
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Ghysels-Hall test	$\chi^2(57)$	121.8264	116.3280	88.9501	93.7993	108.8607	117.0698
	p-value	(0.0000)	(0.0000)	(0.0040)	(0.0015)	(0.0000)	(0.0000)
Break in factor loadings	$\chi^2(7)$	108.7764	160.5182	93.7757	67.5299	89.9499	122.4142
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 6: Sectors of the US economy: contagion from insurance.
Non-crisis period August 2, 2004 - August 8, 2007. Crisis period August 9, 2007 - June 30, 2009.

		Banking	Industrials	Health	Utilities	Food	Info Tech
E: Parameter estimates							
non-crisis period	$b_{i,L}$	-0.1103	-0.1104	0.1199	-0.1200	0.0629	0.2664
	s.e.	(0.2646)	(0.0666)	(0.1416)	(0.1340)	(0.1732)	(0.0841)
	$\omega_{i,0,L}$	0.0967	0.0639	0.0308	0.0500	0.0336	0.0248
	s.e.	(0.0280)	(0.0070)	(0.0068)	(0.0148)	(0.0190)	(0.0089)
crisis period	$b_{i,H}$	0.4697	0.9548	0.7278	0.9180	0.4994	1.1065
	s.e.	(12.2243)	(3.3088)	(3.5081)	(3.6916)	(3.6822)	(4.9786)
crisis period	$\omega_{i,0,H}$	1.2762	0.1850	0.0856	-0.0587	0.1088	-0.0878
	s.e.	(15.0534)	(3.7782)	(3.9898)	(4.3927)	(4.1686)	(4.9786)
t-test	$b_{i,H} - b_{i,L}$	1.0533	7.1466	3.8469	6.2404	2.6300	4.2117
	p-value	(0.1848)	(0.0028)	(0.0155)	(0.0041)	(0.0392)	(0.0122)
F: ARCHLM tests							
non-crisis							
returns	$\chi^2(1)$	7.5253	5.7105	4.2010	6.2800	0.6466	36.8332
	p-value	(0.0061)	(0.0169)	(0.0404)	(0.0122)	(0.4213)	(0.0000)
factor model	$\chi^2(1)$	8.2645	5.7403	2.6956	5.8946	1.2274	40.6671
	p-value	(0.0040)	(0.0166)	(0.1006)	(0.0152)	(0.2679)	(0.0000)
crisis							
returns	$\chi^2(1)$	6.1260	5.6679	14.9774	6.8721	6.8720	15.3856
	p-value	(0.0133)	(0.0173)	(0.0001)	(0.0088)	(0.0003)	(0.0000)
factor model	$\chi^2(1)$	5.4743	38.3640	12.3630	29.2393	9.3644	47.0779
	p-value	(0.0193)	(0.0000)	(0.0000)	(0.0000)	(0.0022)	(0.0000)

Table 7: The European sovereign CDS: contagion from Greece.
Non-crisis period September 15, 2008 - March 31, 2010. Crisis period April 1, 2010 - November 21, 2013.

		Ireland	Italy	Germany	Portugal	Spain
A: Correlation Coefficients						
non-crisis period	ρ_L	0.2660	0.3738	0.2429	0.4277	0.4406
crisis period: not adjusted	ρ_H	0.1216	0.1330	0.1219	0.1112	0.1267
crisis period: FR adjusted	$\widetilde{\rho}_H$	0.0135	0.0147	0.0140	0.0135	0.0123
t-test of change	$\rho_H - \rho_L$	-2.5208	-4.3458	-2.1013	-5.7939	-5.7963
	p-value	(0.0431)	(0.0112)	(0.0051)	(0.0051)	(0.0632)
t-test of change	$\widetilde{\rho}_H - \rho_L$	-4.3454	-6.3419	-3.9305	-7.4609	-7.6978
	p-value	(0.0113)	(0.0040)	(0.0147)	(0.0025)	(0.0023)
B: Regression Coefficients						
non-crisis period	$\beta_{i,L}$	0.1897	0.1580	0.0429	0.2107	0.1864
	s.e.	(0.0343)	(0.0196)	(0.0086)	(0.0222)	(0.0189)
crisis period	$\beta_{i,H}$	0.0200	0.0161	0.0026	0.0275	0.3260
	s.e.	(0.0053)	(0.0040)	(0.0007)	(0.0080)	(0.0040)
C: J-test for one factor model						
non-crisis period	test statistic	0.2612	0.2099	0.2370	0.2360	0.1859
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
crisis period	test statistic	0.0767	0.0651	0.0745	0.0705	0.0605
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
D: Tests for structural stability						
Break in number of factors	$\chi^2(35)$	0.0768	0.0651	0.0745	0.0705	0.0605
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Ghysels-Hall test	$\chi^2(43)$	85.6107	97.5238	121.8878	76.3008	100.3313
	p-value	(0.0001)	(0.0000)	(0.0000)	(0.0013)	(0.0000)
Break in factor loadings	$\chi^2(6)$	172.5274	232.9313	98.0784	212.0940	246.6114
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 8: The European sovereign CDS: contagion from Greece.
Non-crisis period September 15, 2008 - March 31, 2010. Crisis period April 1, 2010 - November 21, 2013.

		Ireland	Italy	Germany	Portugal	Spain
E: Parameter estimates						
non-crisis period	$b_{i,L}$	0.9433	1.0178	0.1230	1.3110	1.1041
	s.e.	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	$\omega_{i,0,L}$	-0.0009	-0.0005	-0.0000	-0.0007	-0.0006
	s.e.	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
crisis period	$b_{i,H}$	-0.0132	-0.0256	-0.0023	-0.0562	-0.0324
	s.e.	(0.0001)	(0.0001)	(0.0000)	(0.0004)	(0.0000)
	$\omega_{i,0,H}$	0.0062	0.0059	0.0009	0.0106	0.0050
	s.e.	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
t-test	$b_{i,H} - b_{i,L}$	-211087	-221822	-96014	-402433	-1400787
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
F: ARCHLM tests						
non-crisis						
change in spread	$\chi^2(1)$	0.3480	12.5183	11.0347	102.3182	27.7450
	p-value	(0.5553)	(0.0000)	(0.0009)	(0.0000)	(0.0000)
factor model	$\chi^2(1)$	6.8773	16.5379	9.0352	19.1074	11.8641
	p-value	(0.0087)	(0.0000)	(0.0026)	(0.0000)	(0.0006)
crisis						
change in spread	$\chi^2(1)$	42.0411	35.7617	95.6644	7.1181	39.6071
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0076)	(0.0000)
factor model	$\chi^2(1)$	40.7659	25.0687	91.4056	6.6447	27.9763
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0099)	(0.0000)

Table 9: Two factor model The European sovereign CDS: sources from Greece and Germany.
Non-crisis period September 15, 2008 - March 31, 2010. Crisis period April 1, 2010 - November 21, 2013.

		Ireland	Italy	Portugal	Spain
C: J-test for two factor model					
non-crisis period	test statistic	0.2058	0.1877	0.1914	0.1640
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)
crisis period	test statistic	0.0468	0.0624	0.0537	0.0600
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)
D: Tests for structural stability					
Break in number of factors	$\chi^2(35)$	0.0468	0.0625	0.0536	0.0600
	p-value	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Ghysels-Hall test	$\chi^2(44)$	28.7194	32.9920	30.4601	30.3790
	p-value	(0.9637)	(0.8880)	(0.9397)	(0.9411)
Break in factor loadings	$\chi^2(7)$	71.0385	185.4015	133.6123	246.8636
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B: Regression Coefficients					
non-crisis period	$\beta_{GRE,i,L}$	0.1017	0.0977	0.1532	0.1282
	s.e.	(0.0306)	(0.0160)	(0.0198)	(0.0155)
	$\beta_{GER,i,L}$	2.0325	1.4007	1.3316	1.3520
	s.e.	(0.1730)	(0.0904)	(0.1116)	(0.0878)
crisis period	$\beta_{GRE,i,H}$	0.0094	0.0060	0.0123	0.0059
	s.e.	(0.0045)	(0.0029)	(0.0069)	(0.0031)
	$\beta_{GER,i,H}$	4.0652	4.1053	5.8908	3.8589
	s.e.	(0.2139)	(0.1380)	(0.1460)	(0.1460)
E: Parameter estimates					
non-crisis period	$b_{GRE,i,L}$	0.8717	0.6376	1.1725	1.2094
	s.e.	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	$b_{GER,i,L}$	5.0838	2.8542	1.1287	1.3801
	s.e.	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	$\omega_{GRE,i,0,L}$	-0.0009	-0.0003	-0.0011	-0.0013
	s.e.	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	$\omega_{GER,i,0,L}$	-0.0001	-0.0000	0.0001	0.0009
	s.e.	(0.0000)	(0.0000)	(0.0000)	(0.0000)
crisis period	$b_{GRE,i,H}$	-0.0207	-0.0303	-0.0635	-0.0338
	s.e.	(0.0002)	(0.0002)	(0.0004)	(0.0001)
	$b_{GER,i,H}$	-7.9511	2.9525	-9.0794	-1.6482
	s.e.	(0.0351)	(0.0102)	(0.0479)	(0.0089)
	$\omega_{GRE,i,0,H}$	0.0076	0.0076	0.0119	0.0062
	s.e.	(0.0000)	(0.0000)	(0.0001)	(0.0000)
	$\omega_{GER,i,0,H}$	0.0007	-0.0000	0.0007	0.0002
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
F: ARCHLM tests					
non-crisis					
change in spreads	$\chi^2(1)$	0.3480	12.5183	102.3182	27.7450
	p-value	(0.5553)	(0.0000)	(0.0000)	(0.0000)
factor model	$\chi^2(1)$	35.6363	34.2822	14.0564	17.7144
	p-value	(0.0000)	(0.0000)	(0.0002)	(0.0000)
crisis					
change in spreads	$\chi^2(1)$	42.0411	35.7617	7.1181	39.6071
	p-value	(0.0000)	(0.0000)	(0.0076)	(0.0000)
factor model	$\chi^2(1)$	0.4089	0.4199	0.4171	0.4110
	p-value	(0.5225)	(0.5170)	(0.5184)	(0.5214)