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Financial Contagion: A New Perspective (and a New Test)

This paper analyses the mechanism of financial shocks propagation and how extraordinary jumps in financial market uncertainty alter it substantially.

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Abstract

Contagion has mostly been interpreted and tested as a break from a stable linear correlation of financial markets caused by an extraordinary shock. This paper argues that quantile regression can provide a tool to investigate alterations in other features of financial returns' distribution caused by extraordinary shocks, thus providing additional understanding of the mechanism of financial shock propagation and its instability. Applying the technique to stock market returns, we find evidence that jumps in uncertainty have powerful contagious effects of a form different from an increase in markets' correlation. These effects would not be detectable in standard contagion tests that search for increases in market correlation.

Keywords: Contagion, Correlation Analysis, Quantile Regression
JEL codes: F30, C10, G10, G15

*The views contained here are those of the author and not necessarily those of the EFSF or the ESM.

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1 Introduction

The speed, intensity and pervasiveness of the financial turbulence caused by the 1990s crises led researchers to wonder whether the linkages between financial markets in different countries grew stronger during these turbulent times or had already been this strong beforehand. Forbes and Rigobon (2001) argue that the answer is important because it would shed light on three key aspects of financial and international economics: the effectiveness of international portfolio diversification in reducing risk, the effectiveness of microprudential bank regulation and the empirical relevance of contagion models based on shifts in investor behavior.

While, theoretically, financial markets' integration should reduce consumption volatility via vaster opportunities for risk diversification, the evidence reveals the opposite. Countries undergoing capital account liberalization tend to experience an increase in consumption volatility (Prasad et al. 2003, Kose et al. 2009), over and above increases in output volatility (Kose et al. 2003a). If correlation among asset prices increases during turbulent times the benefits from risk diversification could indeed be small or even nil, explaining this apparent conundrum. The issue also has important policy implications: increased interdependence during crises would justify a stronger coordinated intervention of international financial institutions in such periods.

For these reasons, the instability of the correlation structure between financial markets/assets, often defined "shift contagion", has been studied in depth and a vast array of techniques to detect it has been proposed. A common feature of all leading tests is the definition of contagion as a departure from a stable linear correlation caused by an extraordinary event. In essence, these studies investigate whether the mean return of one market conditional on the return in other markets behaves differently during crises than in tranquil times.[1]

While it is clearly important to identify how contagion affects the conditional mean, external shocks can influence other relevant features of the conditional distribution, for example its 5th quantile (i.e. the worst 5% of the domestic returns conditional distribution). This is the focus of this paper. With the aid of a simple asset price determination model, we develop a framework that complements standard contagion tests by investigating external shocks' effects across the spectrum of the domestic market returns' distribution. We argue that this analysis can shed light on a key aspect of global financial markets' interdependence: whether a weak state of the domestic economy magnifies domestic vulnerability to foreign shocks.

[1] See Dornbusch et al. (2000), Dungey et al. (2005) or Forbes (2012) for reviews on the contagion literature and the various definitions of contagion.

The natural way to perform this analysis is via quantile regression. As Roger Koenker and Kevin Hallock explain in their introduction to the technique: "The recognition that covariates can exert a significant effect on the dispersion of the response variable as well as its location is the first step towards a general acceptance of the expanded flexibility of covariate effects in quantile regression" (Koenker and Hallock 2001). While quantile regression has already been applied to financial contagion (see Baur and Schulze 2005), it was not used to investigate the interaction between domestic macro variables and external shocks in contagion events. To our knowledge no such application has been pursued before.

To minimize the problem of weak instrumentation characterizing contagion studies, we apply the technique to monthly stock returns. While this loses the high frequency dynamics of equity markets, it allows us to exploit the substantial correlation shown by stock markets with own lags and other lagged variables. We show how this choice allows us to find strong instruments and identify endogenous variables without having to find external instruments or pursue innovative identification techniques as in previous contagion tests.

The structure of this paper is as follows: after this introduction, section 2 briefly describes the most common contagion tests in the literature. Section 3 details the quantile regression based test and its relationship with the literature. Section 4 applies the test to a panel of stock market returns, explains how endogeneity is dealt with and discusses the results. Section 5 concludes.

2 Contagion as break in the conditional mean

All leading contagion tests can be described starting from a simple two-factor model of asset market returns. Assume there are two assets whose returns in time *t* are given by $\{x_{1t}, x_{2t}\}$.[2] These can be specific assets, sectoral or national indexes. For concreteness, we assume they are national stock market indices. Their returns are assumed to be determined by the following model:

$$
\begin{aligned}
x_{1t} &= \alpha_1 w_t + \beta_1 x_{2t} + \varepsilon_t \\
x_{2t} &= \alpha_2 w_t + \beta_2 x_{1t} + \eta_t
\end{aligned}
\tag{1}
$$

[2] The model is presented here in a two-asset fashion, but its generalization to *N* assets is straightforward. Both returns are assumed to have zero means.

where w_t represents the common factor affecting all markets with loadings α. This can be thought of as changes in investor risk aversion or changes in world endowment. *w* is assumed to be a latent stochastic process with zero mean and unit variance.[3] ε and η represent the idiosyncratic factor unique to market *1* and *2*, also assumed to be latent stochastic processes with zero mean and unit variance. If $Cov(\varepsilon, \eta) = 0$, correlation among stock returns in country *1* and *2* can arise from two sources only: the common factor and the direct effect of country *1*'s stock market on country *2* (and vice-versa). This second source of correlation, called "market interdependence" is represented by coefficients β. Equation (1) gives an intuitive model of asset returns determined by a common factor, an idiosyncratic factor and the effect of the foreign shocks. This framework has become standard in the contagion literature. Indeed, one can show that all leading contagion tests are equivalent to tests of β's stability in such a framework (see Dungey et al. 2004).

The first studies tackling this issue tested the hypothesis that the betas increase during turbulent times by analyzing whether the linear correlation among markets did so. This stream of literature (often called correlation studies) developed from the seminal contribution of King and Wadhwani (1990), trying to overcome the heteroskedasticity and endogeneity issues that render the estimation of the betas a complicated affair (see Calvo and Reinhardt (1996), Bordo and Mushid (2000) and Bajg and Goldfajn (1999), Forbes and Rigobon (1999), Rigobon (2003)). Unfortunately, as noticed by Corsetti et al. (2005), hardly justifiable assumptions on the form of shocks imposed by a crisis to the system (i.e. on the changes in the variance-covariance matrix of ε and η brought by a crisis) are needed to overcome such econometric issues. Cominetta (2011) shows that these assumptions effectively rule out shifts in investor behavior as a driver of financial contagion. This is at odds with crisis-contingent theoretical contagion models as well as with several empirical studies providing evidence of risk appetite shifts or flight-to-quality phenomena (see Eichengreen and Mody (1998), Kamin and Von Kleist (1999), Ahluwalia (2000), Kumar and Persaud (2001), Basu (2002) among others).

To avoid imposing these assumptions, researchers developed a second family of tests (extreme-event-based tests) under a two-step procedure. First, extreme events are identified as outliers in the errors of a vector autoregression of asset returns. Then each outlier is assigned a dummy and is introduced in a simultaneous system such as (1) to see if extreme events have explanatory power over and above the standard interdependence mechanism. Longin and Solnik

[3] ARCH/GARCH dynamics can be introduced in the model without altering the features relevant to our discussion, see Dungey (op. cit.).

(2001), Favero and Giavazzi (2002), Bae et al. (2003), Pesaran and Pick (2003), Boyer at el (2006), Boyson et al (2010) are all variations of such an approach. In practice all these tests investigate the presence of a slope-dummy identifying the increased shift caused by an exceptional foreign shock on the domestic market conditional mean.

3 Beyond the conditional mean: a Quantile Regression-based test

In this brief literature review we showed that contagion has been investigated as an exceptional shift in the mean of the domestic returns conditional on foreign returns $E\left(x_1|x_2\right)$ and $E\left(x_2|x_1\right)$ caused by an exceptional external shock. While this is a key aspect of contagion, it is also a fairly restrictive definition of it. For contagion so defined to take place, a crisis must increase the vulnerability of the domestic market to foreign shocks *irrespective of idiosyncratic factor's realizations*. The latter can be thought of as the set of domestic macroeconomic, financial and political factors determining stock market performance, as well as the interpretation of such factors by investors (i.e. investor behavior). These factors are likely to have a major impact on the way swings in foreign markets' returns and volatility affect the domestic market. For example, it may well be the case that an external crisis does not render a country with strong macro-financial fundamentals more vulnerable to foreign shocks but does do so when the country has weaker domestic fundamentals. This, for instance, is the spirit of multiple equilibria models of contagion, where multiple equilibria can arise only within a range of intermediate macro fundamentals that render a speculative attack against the domestic market potentially successful (Masson 1998). Increased vulnerability to foreign shocks may then arise only when the domestic macro-financial fundamentals are in such a range (i.e. only if associated with particular realizations of the idiosyncratic factor ε). Equally, a major idiosyncratic negative shock such as a sizeable negative revision of its GDP growth, the failure of a domestic bank or a government resignation could render a country more vulnerable to foreign shocks. Both cases represent a shift in $E\left(x_1|x_2\right)$ that takes place only when the idiosyncratic factor ε is within a range of values. Since such values may rarely be reached, a standard test of contagion may fail to detect the shift, averaged out as this is among the preponderant realizations of the "normal" $E\left(x_1|x_2\right)$ associated with "normal" values of the idiosyncratic factor.

In the above examples a break in the interdependence structure of the stock markets would take place. Assuming country *1*'s stock exchange is the one becoming more vulnerable to foreign shocks, we have that when x_1 is large and negative for idiosyncratic reasons (i.e. when ε is large and negative), the effect of x_2 on x_1 increases and the correlation among the markets also increases. Thus, if market interdependence grows after a crisis in country *1*, below-the-conditional-median observations of x_1 should be associated with bigger βs than those associated with median observations. The presence of contagion can then be assessed by estimating $\beta_1(q)$, the interdependence coefficient at a given quantile, and testing the equality of beta at the bottom extreme (say, at the 5th quantile) and the median: $\beta_1(5)=\beta_1(50)$.

A more direct way to investigate the effect of macro-financial fundamentals on the market's vulnerability is simply interacting external shocks with measures of macro-financial fundamentals and investor behaviour. In practice, however, finding proxies for the latter has proven remarkably difficult. Early Warning Systems based on macro and financial variables have a patchy record in predicting financial crises (as shown by, among others, Berg and Pattillo (1999)). The quantile regression test has the advantage of investigating the interaction between external shocks and domestic fundamentals without the need to identify them.

Quantile regression tests investigate a shift in the system coefficients driven by idiosyncratic factors. Standard tests investigate a shift driven by external events. For this reason, we see the quantile regression test as complementary to (and enriching) standard contagion tests.

Quantile regression can also be the starting point for studying the effects of external shocks on higher moments of the returns conditional distribution. These moments describe key features of the asset prices' determination system. For example, if the error variance conditional on common factors $Var(\varepsilon|w)$ decreases in *w*, then a jump in a powerful common factor such as risk aversion will render the idiosyncratic factor less relevant in explaining x_1's volatility. The above finding would thus suggest that the domestic market becomes less idiosyncratic and more predictable when risk aversion jumps. Such a break in the propagation mechanism, as well as the increased interdependence described above, cannot be detected looking at markets' conditional means alone, so they cannot be detected by standard contagion tests. By investigating financial assets' co-movements beyond their conditional means, we can thus have a more complete understanding of the shock propagation mechanism and its eventual instability.

4 Empirical evidence

4.1 The estimated model

To operationalize the framework described in the previous section we estimate an *N>2* country equivalent of (1), expanded with lagged dependent variables, three common shock proxies and country dummies to control for time-invariant country effects:

$$y_{it} = \alpha_0 + \alpha_1 + ... + \alpha_{N-1} + \beta C_{it} + \gamma_0 V_t + \gamma_1 V_t^2 + \gamma_2 IP_t + \rho_0 y_{it-2} + \rho_1 y_{it-3} \quad (2)$$

where: y_{it} is the percentage change in country *i*'s stock market index in month *t*; α_0 is the constant; $\alpha_1 + ... + \alpha_{N-1}$ are a set of *N-1* country dummies; C_{it} is the contagion index for country *i* in month *t* . This is defined as: $C_{it} = \sum_{j \neq i} \frac{EX_{ij}}{TOTEX_i} * y_{jt}$. It is the sum of the returns of all stock markets but *i*, weighted by the relative importance of market *j* for market *i*. The relative importance is measured by the share of country *i*'s total exports directed to country *j*, which is proven by established literature to be a good proxy for trade and financial linkages among countries (see, among others, Goldstein et al. (2000), chapter 6). Note that the weights add up to one for all countries. This allows for a clear interpretation of the interdependence coefficient β as the domestic stock market elasticity to foreign stock market movements.

V_t , a proxy for expected volatility of global equity markets, is the unit change in the monthly average Chicago Board Options Exchange VIX index of implied volatility. The VIX has become the established measure of investor global risk perception/aversion. V_t^2 , the squared monthly change in VIX index, is also included.[4] Notice that V_t^2 is defined so as to maintain the original sign of *V* when squared:

$$V_t^2 = \begin{cases} (\Delta VIX_t)^2 & if\ \Delta VIX > 0 \\ -(\Delta VIX_t)^2 & if\ \Delta VIX < 0 \end{cases} \quad (3)$$

[4]The squared VIX term is introduced as it has proven extremely significant in all preliminary estimations performed to identify the correct model specification. Squared terms and interactions of other covariates have, in contrast, not proven consistently significant.

IP_t is the percentage change of the world industrial production index in month *t*. This variable is intended as a proxy for global growth expectations that affect financial markets simultaneously. It can be thought of as the proxy for the expected average return of global equity markets.

A world business cycle as documented by Kose et al. (2003b) would affect the risk-return profile of more markets simultaneously, thereby biasing the interdependence coefficients upwards. The same is true for investors' risk perception/aversion shifts. *IP* and *V* are thus included in the estimated model in order to avoid this possibility. Industrial production and changes in risk premia have indeed long been identified as key drivers of equity markets (see, for example, Chen et al. (1986)). Furthermore, their inclusion in the quantile regression analysis makes it possible to investigate their effect on the conditional distribution of *y*.

The model is completed with the second and third lag of the dependent variable. These are included in order to identify relevant autoregressive dynamics.[5] The country dummies included ensure no autocorrelation is built into the error by the time-invariant country effects, and they also allow us to take full advantage of the panel nature of the dataset. The estimated model is equivalent to a fixed-effects estimator.

The model is estimated at the median and two extreme quantiles, the 5th and the 95th .[6] The contagion tests examine the null hypothesis of stability in the interdependence and risk aversion coefficients: $\beta_q = \beta_M$, $\gamma_{0q} = \gamma_{0M}$ and $\gamma_{1q} = \gamma_{1M}$ for *q=5, 95*; where $\beta_M, \gamma_{0M}, \gamma_{1M}$ are the coefficients in the median equation while $\beta_q, \gamma_{0q}, \gamma_{1q}$ are the ones in the extreme quantile *q* equation. A rejection of the null is interpreted as the detection of contagion.

To perform the test it is necessary to estimate a system of *3* equations (one per quantile) and obtain the systemic variance-covariance matrix. Following the method suggested by Koenker and Bassett (1982), this procedure is implemented estimating all the equations in the system simultaneously and then obtaining the inter-quantile variance-covariance matrix of the estimators by bootstrapping. The estimated system is thus described by:

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[5] Preliminary estimations identified the second and third lagged dependent variable as strongly significant and errors of a model including them have shown no signs of autocorrelation. We thus include those two lagged dependent variables.

[6] Choosing quantiles requires trading off granularity of the conditional distribution mapping and reliability of the estimates. As pointed out by Chernozhukov (2000), to achieve consistency, one needs to have enough observations on both sides of the estimated quantile regression. We try different definitions of extreme quantiles in the sensitivity section.

$$y_{it}^{95} = \alpha_0^{95} + \alpha_1^{95} + ... + \alpha_{N-1}^{95} + \beta^{95} C_{it} + \gamma_0^{95} V_t + \gamma_1^{95} V_t^2 + \gamma_2^{95} IP_t + \rho_0^{95} y_{it-2} + \rho_1^{95} y_{it-3}$$

$$y_{it}^{M} = \alpha_0^{M} + \alpha_1^{M} + ... + \alpha_{N-1}^{M} + \beta^{M} C_{it} + \gamma_0^{M} V_t + \gamma_1^{M} V_t^2 + \gamma_2^{M} IP_t + \rho_0^{M} y_{it-2} + \rho_1^{M} y_{it-3} \qquad (4)$$

$$y_{it}^{5} = \alpha_0^{5} + \alpha_1^{5} + ... + \alpha_{N-1}^{5} + \beta^{5} C_{it} + \gamma_0^{5} V_t + \gamma_1^{5} V_t^2 + \gamma_2^{5} IP_t + \rho_0^{5} y_{it-2} + \rho_1^{5} y_{it-3}$$

Where y_t, y_{t-2}, y_{t-3} are *NT*x*1* vectors with *T* observations for each of the *N* countries in the sample, *C* is the *NT*x*1* vector containing the contagion index *C* while *V*, V^2 and *IP* are *Tx1* vectors stacked *N* times.

4.2 Endogeneity and instrumentation

If stock returns are interdependent (i.e. if the true β's are positive), *C* is endogenous and simple *QR* regressions will then give biased and inconsistent estimators. Similar issues of endogeneity may affect the lagged dependent variables and the VIX, insofar as idiosyncratic country shocks can alter global risk aversion/perception and thus affect the level of *V*.

Amemiya (1982) proposed a class of two-stage estimators for *QR* models with endogenous variables and called it "two-stage least absolute deviation" estimators (*2SLAD*). This is the equivalent of a two-stage least squares procedure where the second stage is a quantile regression. Powell (1986) derived the large-sample properties of such estimators, which have since become well established in the literature. The underlying idea is simple enough. The regressors suspected to be endogenous are regressed on the whole set of exogenous variables. The fitted values of these first-stage regressions are then introduced in the second-stage (quantile) regression. The variance-covariance matrix of the coefficients is then obtained via bootstrapping. There is a long literature on bootstrap methods for quantile regression estimators, so that a bootstrap with a valid resampling scheme is a well-established way of obtaining a consistent estimator for the variance of the estimator (see Buchinsky (1995) and Koenker (2005) and references therein). The valid resampling scheme is implemented by bootstrapping *both* stages of the procedure. In other words, each bootstrap replication generates a subset of observations on which the first- and second-stage equations are estimated. The estimate for the coefficient is the one estimated on the full sample, while the variance-covariance matrix of coefficients is obtained by calculating the variance of each second-stage coefficient around the coefficient estimated on the full sample. We estimate (4) with this procedure, instrumenting *C, V*, V^2 and y_{t-2}.

The key issue in estimating this model is the choice of instruments. The problem of weak instrumentation has long accompanied contagion studies. Since financial markets tend to show little (if any) autocorrelation at high frequencies, own lags of endogenous variables were found to be weak instruments. For this reason, previous contagion tests required the use of external instruments or the search for innovative identification techniques. In contrast, we focus on monthly data, where we find substantial autocorrelation.[7] We thus exploit this autocorrelation and use own lags as instruments. On the downside, this implies that we are investigating contagion at a frequency that may miss some of the faster dynamics driving stock markets.

We dedicate this section to showing how our instruments comfortably pass all standard tests for weak instrumentation and orthogonality. This underpins our identification strategy, which makes it possible to overcome the endogeneity issue and identify the parameters of interest.[8]

To choose what lags to use as excluded instruments, we tried all combinations of lags from the second to the eighth, of both level and first-differenced covariates (we left out the 1st lag as this is endogenous by construction with regressors in monthly percentage change). The combination chosen (4th lags of level and first-differenced C, V and V^2) is the one that provided the strongest correlation with instrumented variables and the lowest probability of endogeneity.

Results for all standard weak instrumentation tests (Staiger-Stock, Stock-Yogo, Angrist-Pischke, Kleinberger-Paap) and first-stage regressions are provided in Appendix 1. These results provide grounds to dispel the weak instrumentation hypothesis with confidence.

A look at the instruments' coefficients in the first stage regressions already shows the very strong significance of most instruments, own lags included (table A.1). Tellingly, the VIX indexes (denoted V and Vsq in the table) appear to be very strong instruments. Going beyond stock markets' own lags as instruments seems thus to help considerably in identifying the estimated model. As a consequence, in all first-stage regressions the F-test of excluded instruments is comfortably above 10, which is Staiger and Stock's proposed rule of thumb for IV strength and widely used in empirical research. Angrist-Pischke multivariate F-tests are also passed comfortably.

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[7] While substantial autocorrelation is found, series appear strongly stationary: augmented Dickey-Fuller tests consistently reject the unit-root null for each stock market. This is unsurprising, since stock markets enter the equation as a monthly percentage change. It is unlikely that stock indexes grow or decline at an ever faster *rate*.

[8] We also show (in the following sections) that the instrumented variables perform well in the second stage, providing extremely significant and correctly signed coefficients and that these results are robust to a vast array of different lags used as instruments. This is hardly achievable with weakly instrumented variables.

We also test for underidentification performing the robust Kleinbergen-Paap test (table A.2). The null of non-full-rank of the reduced form coefficients' matrix is rejected with a P-value of 0.0002. Finally, the Anderson-Rubin weak-instrument-robust test of significance of instrumented variables in the second-stage regression rejects the null of non-significance with P-value of 0. This strong result is consistent with the significance we detect in all instrumented variables' coefficients in the second-stage regressions, a result hardly obtainable with weak instruments. Notice also that using different lags as instruments is shown not to affect the significance of coefficients in the second stage (see *Sensitivity analysis* section below). Thus, all common tests for weak instrumentation provide a consistent answer: instruments appear very strongly correlated with the instrumented variables.

The instruments appear to be valid as well, passing exogeneity tests comfortably (table A.3). To show this, we start testing whether the error of the second-stage regression presents signs of autocorrelation. Absence of autocorrelation is indeed a pre-requisite for own lags to be exogenous instruments. We run a 2SLS model and subject its error to the Cumby-Huizinga test for autocorrelation, which generalizes the standard Arellano-Bond AR test to investigate the presence of autocorrelation up to the 8^{th} order. The test fails to reject the null of no autocorrelation on all orders, with comfortable P-values. These positive results are confirmed by the Hansen-Sargan test of overidentifying restrictions. The null of instruments exogeneity is not rejected with an 80% P-value. These results thus build trust in the exogeneity of instruments. It appears that the substantial autocorrelation detected in the stock market indexes is captured by the regressors appearing in the second stage. The model appears dynamically complete, thus allowing the use of own lags as instruments.

Altogether, the vast array of standard tests provides strong evidence of the validity and relevance of our chosen instruments.

Other econometric issues

While the *QR* analysis finds its main justification in the investigation of the effects of external shocks on features of stock markets' conditional distribution other than the mean, the *QR* test also leaves the variance-covariance matrix of the idiosyncratic factors and its change during crisis unrestricted. This makes it a more robust test than those in correlation studies and, in particular, one that is robust to shifts in investor behavior. Since these have been widely recognized as an important source of contagion during major crises, this seems a relevant advantage.

The *QR* setting also avoids filtering the data to identify extreme events, therefore extracting more information than extreme-event-based tests from the data. The consequences of filtering on the power of extreme-event-based tests are shown to be serious by Dungey et al. (2004) with a Monte Carlo experiment. They show that, in general, both correlation studies and extreme-event tests exhibit very low power. Favero and Giavazzi (2002) also show how full information estimation techniques devise more powerful tests. Avoiding filtering should thus make the *QR* a more powerful test of instability in the shock propagation mechanism.

We now proceed to detail the data used in the estimation before moving on to present and discuss its main results. Data on stock market indices, implied volatility indexes, world industrial production, commercial paper and Libor-OIS spreads are taken from Bloomberg. Data on exports are taken from the IMF Directorate of Trade Statistics' (*DOTS*) database. Data on commercial paper spreads as well as US interest rates are taken from the *FRED* dataset of the Federal Reserve.

The sample covers 49 countries[9] from January 1998 to March 2014, giving 195 monthly observations for each country, for a total of 9,555 observations. The sample covers two crises originating in emerging markets (Brazil-Russia 1998 and Argentina 2002), two originating in financial centers (the dot-com crash of 2001-2002 and the global crisis starting in 2008) and the "great moderation" period. It should thus provide plenty of variety and different regimes in which to investigate the international shock propagation mechanism. Summary statistics are given in table 1.

[9] These are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Hong Kong, China, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, South Korea, Kuwait, Lebanon, Malaysia, Mauritius, Mexico, Netherlands, Nigeria, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Russian Federation, Saudi Arabia, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Turkey, United Kingdom, Ukraine, United States and Venezuela.

Table 1
Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Obs.
y	overall	0,919	7,607	-44,154	79,794	N = 9506
	between		0,700	0,035	3,665	n = 49
	within		7,575	-45,560	78,316	T = 194
C	overall	0,592	4,851	-28,120	22,630	N = 9506
	between		0,148	0,349	1,327	n = 49
	within		4,849	-28,855	21,895	T = 194
V	overall	21,771	8,466	10,820	62,640	N = 9555
	between		0,000	21,771	21,771	n = 49
	within		8,466	10,820	62,640	T = 195
cps	overall	41,030	45,341	1,220	355,220	N = 9555
	between		0,000	41,030	41,030	n = 49
	within		45,341	1,220	355,220	T = 195
lois	overall	27,163	36,008	6,390	293,970	N = 7252
	between		0,000	27,163	27,163	n = 49
	within		36,008	6,390	293,970	T = 148
IP	overall	0,002	0,006	-0,032	0,014	N = 9506
	between		0,000	0,002	0,002	n = 49
	within		0,006	-0,032	0,014	T = 194

4.3 Results

4.3.1 Preliminary estimations

As a starting point we look briefly at the results from a *2SLS* estimation of the model. This will give us the average relationship between domestic stock market fluctuations and external shocks, the benchmark against which to compare the relationship at different quantiles. The results are presented in table 2 (country dummies are excluded for brevity). A first look finds all key coefficients correctly signed, sizeable and significant.

Looking more in detail, the interdependence coefficient (*C* in the table) is found correctly signed and extremely significant. The average elasticity of domestic stock markets to foreign shocks is estimated at 0.76. Thus, a 1% increase in all foreign markets in the sample causes a 0.76% increase in the domestic stock index value, on average and ceteris paribus.

Table 2
2SLS estimation results

Variable	Coefficient	Std. Err.	t	P > |t|	95% conf. Interval	
C	0,756	0,145	5,22	0,000	0,464	1,047
V	-0,506	0,235	-2,15	0,037	-0,980	-0,033
Vsq	0,021	0,009	2,23	0,030	0,002	0,040
IP	1,387	0,791	1,75	0,086	-0,203	2,976
L2.y	-0,216	0,172	-1,26	0,215	-0,562	0,130
L3.y	0,036	0,020	1,83	0,073	-0,004	0,076

Observations: 9,261

R-squared: 0.3059

The monthly change in VIX index is found to have a non-linear effect on stock returns. The coefficient associated with *V* is negative, sizeable and significant. The estimated negative effect on the domestic stock market is however somewhat mitigated by the positive effect identified by the coefficient of V^2 (denoted *Vsq* in table 2). Putting the two together, a unit increase in the *V* (i.e. *V*=1) is estimated to cause a 0.48% decrease in stock market indexes. A 10-unit jump is estimated to cause a proportionally smaller 2.9% decrease in stock markets, while a 30-unit jump is estimated to increase stock markets performance by 3.8%, on average and ceteris paribus. The VIX effect on markets is estimated to be negative for changes in the -23.7/+23.7 range and positive outside that range. To put this in context, all *V* observations in the sample except October 2008, the month after the Lehman Brothers collapse, are within the -/+23.7 range. Thus, the estimated model suggests that in all cases but that one increases in the VIX index had a negative effect on the stock markets. Nonetheless, the negative effect becomes smaller as the size of the VIX shock increases. We will discuss this counter-intuitive result more in depth in the next section, for now suffice it to say that we suspect that official intervention explains it. As long as the VIX jump does not represent a threat to global financial stability, markets are left free to react and increases in risk aversion/perception identified by VIX jumps exert their full negative force. When the shock hitting the markets is of a magnitude endangering global financial stability (and the VIX jump is accordingly extraordinary) central banks and governments intervene with market-supporting measures. As a consequence the negative effect of the VIX is dimmed, and even totally offset for shocks (and official reaction) of a magnitude of the Lehman collapse episode.

4.3.2 The QR test

We now proceed to investigate whether or not the coefficients of the mean regression just presented average out very different coefficients associated with extreme quantiles. Figure 1 provides a complete mapping of key covariates' coefficients across quantiles, giving an immediate feel for the coefficients' stability (country dummies are not presented for brevity). Table 3 below provides the results for the full 3-equations model estimation.

Focusing on the interdependence coefficients *C* (top left panel) we can see that they show some instability: the coefficients at the bottom of the distribution tend to be bigger than at the median, and lie outside the mean estimate's confidence interval (the dotted lines). We thus find some evidence that markets' interdependence seems to be higher when the domestic market is underperforming for idiosyncratic reasons. Top tail coefficients zigzag instead around the mean estimate (dashed line) and never break out of its confidence interval. A clear pattern is not discernible here.

Figure 1
Coefficients quantile mapping

The intuitions the graphs provide are formally confirmed by the regression results (Table 3): betas are estimated to increase in bottom quantiles but the difference between the extreme coefficient *C5* and the median one (*C50*) is not statistically significant, and this notwithstanding coefficients themselves being significant at all quantiles. The *QR* test therefore finds only some weak evidence of unstable market linear interdependence. Stock markets' linear correlation appears to be mildly affected by the idiosyncratic factor's realizations; it seems similarly strong at the median as at the extremes of the conditional distribution. Thus, while standard contagion tests find that extraordinary *external* shocks trigger a break in the shock propagation mechanism, the *QR* test cannot find solid evidence that extraordinary *domestic/idiosyncratic* shocks do.

Table 3
Quantile regression results

Variable	Coefficient	Std. Err.	t	P > |t|	95% conf. Interval	
C5	1,290	0,599	2,150	0,031	0,116	2,464
C50	1,075	0,219	4,910	0,000	0,646	1,504
C95	0,981	0,494	1,990	0,047	0,013	1,949
C5 - C50	0,215	0,611	0,350	0,725	-0,982	1,411
C95 - C50	-0,094	0,564	-0,170	0,868	-1,199	1,012
V5	3,364	1,068	3,150	0,002	1,270	5,457
V50	0,394	0,365	1,080	0,281	-0,322	1,110
V95	-1,917	0,797	-2,400	0,016	-3,480	-0,354
V5 - V50	2,970	1,103	2,690	0,007	0,807	5,133
V95 - V50	-2,310	0,954	-2,420	0,015	-4,181	-0,440
Vsq5	-0,139	0,043	-3,270	0,001	-0,223	-0,056
Vsq50	0,005	0,013	0,390	0,698	-0,021	0,031
Vsq95	0,072	0,032	2,260	0,024	0,009	0,134
Vsq5 - Vsq50	-0,145	0,043	-3,370	0,001	-0,229	-0,061
Vsq95 - Vsq50	0,067	0,037	1,810	0,071	-0,006	0,139

Observations: 9,261

Countries: 49

The picture is very different when looking at the risk aversion/perception coefficients, which are found to be extremely unstable across quantiles. A look at Figure 1 immediately shows this: the coefficient on *V* (central top panel in the figure) shows a steep continuous decline from levels around 3 to -2 as one moves toward top quantiles. An equally steep but opposite dynamic is detected for the coefficient of V^2 (top right panel). Extreme coefficients are very far from the median coefficient of both variables. The mean estimate (and its confidence interval) clearly do not seem very informative here, averaging out (and dwarfed by) the very different coefficients at extreme quantiles.

Regression results formally confirm these intuitions: first, the difference between extremes and median coefficients associated with both V and V^2 are very significant.[10] Furthermore, while V and V^2 coefficients at the median (*V50* and *Vsq50* respectively) are not significant, they are extremely so at the extremes. The estimation thus provides a clear message: jumps in risk aversion/perception do not impact at the median of the conditional distribution, but instead have powerful effects when domestic returns stand out (positively or negatively) for idiosyncratic reasons. Something substantial seems to be happening at the tails of the distribution. A graph helps illustrate these non-linear effects driving the action at the tails.

Figure 2
VIX effects

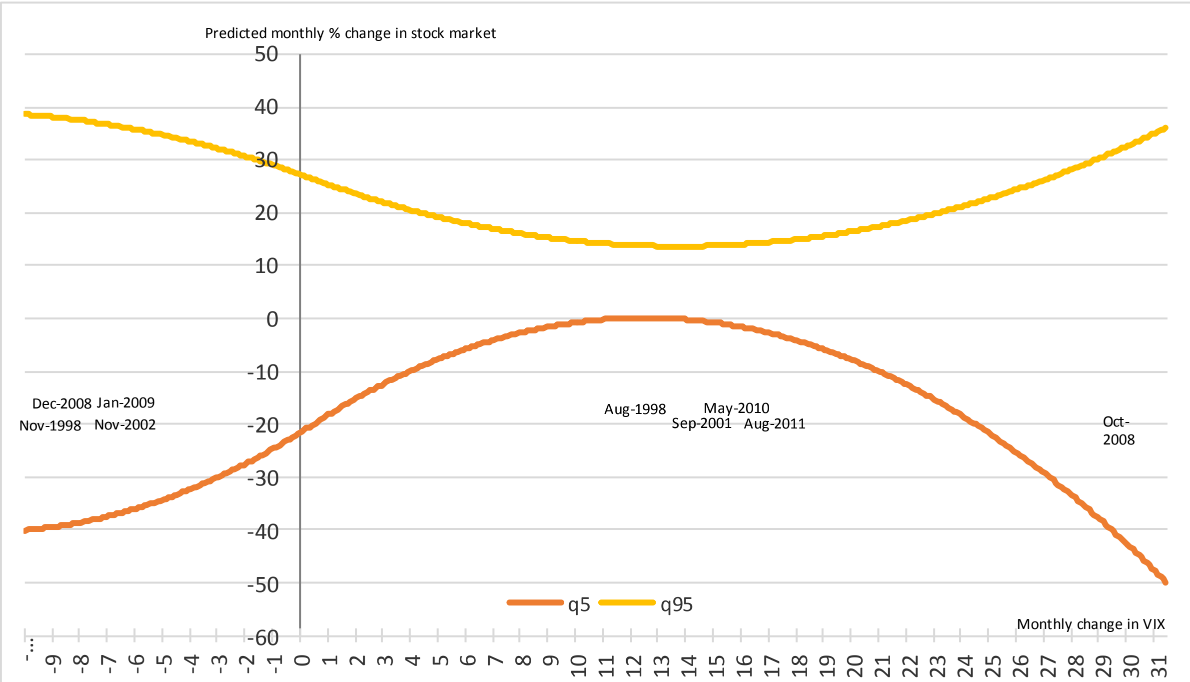

Figure 2 plots the monthly percentage stock market return predicted by the QR model for different levels of V (i.e. for different changes in the VIX index), for the extreme quantiles[11] and holding other covariates constant at their sample average[12]. The horizontal axis covers the support of V on the sample, ranging from -10.4 (November 1998) to 30.9 (October 2008). The

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[10] These are, respectively: V5 – V50, V95 – V50, Vsq5 – Vsq50 and Vsq95 – Vsq50.
[11] We do not plot the median because VIX coefficients are non-significant in the median equation
[12] The *y*-intercepts are, respectively, the top performer's intercept at the 95th quantile and the worst performer's intercept at the 5th quantile. Note that intercepts used in this graph are illustrative: because of the presence of country dummies we cannot know the average country intercept at a given quantile. To compute this we would need the country intercepts at given quantile (which we have) and the relative weight of each country in the quantile (i.e. the proximity of each observation to the quantile regression line, which we do not have).

dates on the graph mark the widest VIX swings. These are instructive as they readily identify the most severe crises in the last 20 years: October 2008, when the full effect of the Lehman Brothers' bankruptcy was transmitted to global stock markets; August 2011 (contagion to Italian and Spanish sovereign bond markets); May 2010 (first Greek bailout), 9-11 and the Russian default in August 1998. Interestingly, the biggest drops in VIX are all associated with the containment of the above crises, except November 2002, which identifies the end of the correction after the dot-com crash.

When at the top quantile (yellow line), stock markets are affected badly by an increase in risk aversion/perception, unless this is close to that seen in October 2008. A unit increase in the VIX index is estimated to decrease their returns by 1.8p.p, on average and ceteris paribus. This negative effect becomes proportionally smaller as the size of the VIX jump increases: a 10-unit jump is estimated to cause only a 12p.p. decline. For VIX jumps above 26.7 the effect turns positive. A Lehman-type jump (30 units) will boost returns by 7.1p.p.

A specular effect is visible at the bottom quantile (orange line). Here stock markets see their negative performance somewhat improved by an increase in risk. Here too this effect is inverted for Lehman-type shocks, turning negative. A unit increase in the VIX is estimated to cause a 3.2p.p. increase in returns, on average and ceteris paribus. This positive effect becomes proportionally smaller as the size of the VIX jump increases: a 10-unit jump is estimated to cause only a 19.7p.p. improvement. For VIX jumps above 24.2 the effect turns negative. A Lehman-type jump (30 units) will push returns down by 24.3p.p.

Averaging out opposite VIX effects at the tails of the distribution, it is unsurprising that the median coefficient is found to be non-significant. Focusing on the median (and mean) is scarcely informative. Here is where the *QR* analysis shows its usefulness, suggesting that external shocks can affect the response variable's conditional distribution in ways that would be lost in a mean regression.

Figure 2 suggests a possible interpretation of these results. When perceived uncertainty in global equity markets is unchanged in the month (i.e. when V is close to 0), investors understand the idiosyncratic macro-financial drivers at play in different markets and therefore differentiate among them: there is a wide gap between top and bottom performers. The idiosyncratic factor's variance is relatively more important than the common factor's variance in explaining overall variance. Decreases in perceived risk (negative values of V) reinforce investor beliefs, allowing for even greater differentiation: the gap between best and worst performers widens. On the other hand, when perceived uncertainty increases in the month (i.e. V rises), the idiosyncratic drivers and their effect on future returns become less clear. Investors cannot differentiate as easily: the best performers suffer while the worst are relatively better off: "cards are reshuffled". The idiosyncratic factor's variance loses importance relative to the common factor one in explaining overall variance. For shocks big enough to test investors' understanding but not to trigger coordinated official intervention (i.e. for *V* around 12), idiosyncratic factors become the least relevant, and most markets are compressed in the tightest range of relative performance (the smallest simulated 5-95 interquantile range is reached at *V*=12.5).

Shocks that endanger global financial stability and trigger substantial official reactions shatter the "reshuffling cards" regime. Here flight-to-quality behavior prevails and market differentiation remerges. With shocks of the Lehman-size, top performers are virtually unaffected by the VIX explosion (if anything they're better off) while bottom performers are hard hit. It is telling that all top 10% of outliers in October 2008 except one[13] are either safe havens (Switzerland, Finland, UK) or macroeconomically sound commodity exporters (Chile, Australia). At the bottom 10% we instead have particularly volatile Emerging Markets (Argentina, Peru, Ukraine, Romania, Indonesia). Our model identifies four shocks in the flight-to-quality range: 9-11, the first Greek bailout, the European sovereign bond contagion in summer 2011 and Lehman Brothers' collapse. All featured substantial official policy responses.

Notice that the simulations discussed in this section are all based on ceteris paribus assumptions, while all covariates tend to turn sharply negative in global meltdowns such as those identified by huge VIX jumps. The model is therefore not forecasting an unaffected stock market performance in presence of VIX shocks such as the ones just described.

Our interpretation of the findings suggests that, as global instability increases (VIX rises), the importance of the common factor relative to the idiosyncratic increases. This is analogous to Diebold and Yilmaz (2009), who find that market returns' volatility becomes more correlated across countries during crises. In other words, they find that less of the market volatility is explained by idiosyncratic volatility during crises. This is consistent with our interpretation of our results, in particular noticing that their sample ends in 2007, thus containing only shocks associated with VIX jumps in the "reshuffling cards" range. Their findings together with ours seem to suggest that market returns' volatility does become less idiosyncratic as risk aversion/perception jumps, except for extreme (Lehman-type) jumps. To test this insight

[13] Pakistan, whose macro vulnerabilities had already developed into a full-blown balance of payment crisis and whose stock market had already dropped 39% before August. By mid-October Pakistan had already appealed (and was believed to have secured) an IMF loan.

formally, one should model stock markets' volatility together with their mean as a function of risk aversion/perception measures (in a stochastic volatility fashion) or introduce such measures in Diebold and Yilmaz' variance decomposition framework. This is beyond the scope of this paper but is another natural extension to it.[14]

An alternative interpretation of our results is that it is the divergence between different times rather than different countries that diminishes with VIX increases below 12.5. Under this interpretation, the results would suggest that the cross-country divergence of stock markets is unaffected by VIX while it is the range within which the common factor moves all countries' stock markets that becomes tighter as VIX increases (by less than 12.5). Since we estimate the model on a pooled sample, it is not possible to distinguish extreme country performances from extreme times. It is, however, hard to imagine an unobserved common factor that is associated with VIX movements and that moves all markets up or all down simultaneously in different times. Furthermore, if such a common factor were behind our results, then the same results should appear in a country-by-country estimation of the model. This is instead not the case: different VIX effects at extreme quantiles, extremely strong in the panel estimation, vanish in the country-by-country ones.[15] That said, distinguishing between extreme country performances and extreme times is important to support our interpretation of the results and it is therefore a relevant extension to this work.

4.3.3 Sensitivity analysis

Looking at the stock market returns' distribution (both unconditional and conditional on the regressors) one finds that emerging markets (*EMs*) are far more represented at the extreme quantiles, while financial centers (*FC*s) are more represented at the median. For example, looking at the errors from the 2SLS estimation, *EMs* represent 92.7% of observations in the top 5 percentiles of the distribution and 91.8% of those in the bottom 5 percentiles. By contrast, they represent only 46% of observations in the median (49^{th} to 51^{st}) percentiles. It could thus be that

[14] Our interpretation of the results also provide an explanation of the apparent conundrum of finding small/nil effects of VIX jumps on the average/median stock performance while the importance of surprise effects on the contagiousness of a shock has been firstly identified by Kaminsky et al (2003) and subsequently by many others. The conundrum can be explained by the fact that on top of the negative effects of surprises on *average* performance (identified by the VIX coefficients in the 2SLS estimation), there are substantial and offsetting effects on the *relative* performance that attenuate the estimated 2SLS coefficients. These are identified by the quantile regression analysis.

[15] Results available upon request.

the cross-quantile differences in coefficients are simply driven by the fact that VIX shocks have different effects on *EMs* than *FC*s. To test this hypothesis we re-run the *QR* test on the two country-homogenous samples, one with *EMs* only and another with *FCs* only. If the skeptics are right and the differences in coefficients are only caused by the higher sensitivity of *EMs,* we should see no cross-quantile differences in the coefficients of the *FCs* sample. This and other robustness tests are presented in the following. We examine whether the "reshuffling cards/flight-to-quality" effects identified by the baseline model are robust to the following alterations:

a) Different lags as instruments. First stage diagnostics provide strong evidence of the chosen instruments' (endogenous variables' 4th lags) relevance and validity. Nonetheless, as a further test we re-run the analysis using 2nd to 8th lags as instruments.

b) Homogenous country composition sample. As just discussed, to test the country-composition hypothesis, the *QR* test is run on *EMs* and *FCs* samples.

c) Different extreme quantiles. Figure 1 shows how V and V^2 coefficients' instability is pervasive across the quantile spectrum. We test this conjecture formally re-running the analysis with less extreme quantiles: *0.1* and *0.9*.

d) Different time spans. The global financial crisis that started in 2008 has been outstanding in the depth and breadth of implications on GDP, financial markets and fiscal dynamics. To discern whether our findings are specific to such an extraordinary event or were instead present before, we re-run the analysis for a pre- and post-2007 sample, as well as excluding the biggest VIX outlier in the sample (October 2008).

e) We use different measures of risk aversion/perception, less related than the VIX index to stock markets. We re-run the analysis with the US T Bill-commercial paper and Libor-OIS spreads instead of the VIX.

Tables A.4 and A.5 in Appendix 2 provide the results for all sensitivity tests. From these we can see that the VIX effects on stock markets' conditional distribution are robust, appearing strongly in all different specifications.

Different lag specifications for the instruments provide further evidence to dispel the weak instrumentation hypothesis. Using lags from the 2nd to the 8th provides coefficients associated to V and V^2 and their interquantile differences that are remarkably similar to the baseline estimation: their sign and relative size is stable across all specifications and their significance remains high in all but one specification (6^{th} lags). Considering that we are using lags up to 8 months old, the phenomenon identified appears extremely strong.

The disaggregation of the sample into *EMs* and *FCs* shows that country composition is not the driving force behind the results. The "reshuffling cards" and "flight-to-quality" phenomena do not appear to be exclusive to *EMs*. On the contrary, and somewhat surprisingly, these appear even more strongly in the *FCs*-only sample.

Consistent with the conjecture suggested by Figure 1, similar VIX effects are found when extreme quantiles closer to the median are tested (10% and 90%). Thus, shifting the definition of extreme quantile does not alter the results.

The 2008 global crisis affected substantially the relationship between stock markets and risk aversion/perception swings. While the flight-to-quality effects triggered by the biggest VIX jumps do not appear significant in the pre-2007 sample (i.e. the V^2 coefficient is not significant), they are extremely so in the post-2007 one. Also, excluding October 2008 from the sample points toward the same direction: the reshuffling cards phenomenon identified by coefficients on V remains sizeable and significant, while the coefficient on V^2 becomes insignificant. It is, however, hard to extrapolate whether the global crisis constituted a structural break in the relationship between VIX and stock returns or instead provided the only shock of a size necessary to trigger dynamics that were dormant before, but never triggered. Finally, the pre-/post-2007 split, or using commercial paper-Treasury bill or Libor-OIS spreads, do not alter the main results.

5 *Concluding remarks*

Contagion has mostly been interpreted and tested as a break from a stable linear correlation among financial markets returns caused by an extraordinary shock. This paper argues that quantile regression can provide a tool to investigate alterations in other features of financial returns' distribution caused by extraordinary shocks, thus providing additional understanding of the mechanism of financial shock propagation and its instability.

Applying a quantile regression approach to stock market returns, we find that jumps in risk aversion tend to drive financial markets closer together, narrowing the gap between best and worst performers and best and worst times. We suggest an interpretation according to which investors' understanding of macro-financial idiosyncrasies driving markets apart becomes disturbed by increasing uncertainty, leading to less differentiation. Extraordinary jumps, such as those associated with shocks endangering global financial stability, trigger, however, the opposite effect: the divergence between best and worst performers (and times) widens hugely. We suggest interpreting this as a flight-to-quality phenomenon. Macro-financial idiosyncrasies are overrun by tail-risks materializing. In such a situation all but the markets considered safest suffer badly.

We thus find evidence that jumps in uncertainty have powerful contagious effects of a form different from an increase in markets' correlation. These effects would not be detectable in standard contagion tests that search for increases in market correlation.

Appendix 1: First stage diagnostics

Table A.1
First stage regressions - coefficients

	Instrumented variable			
Instrument	L2.y	C	V	Vsq
L4.C	-0,051	0,009	-0,033**	-1,961***
L4.V	0,046***	0,051***	-0,102***	-0,717***
L4.Vsq	-0,01***	-0,01***	0,01***	0,017***
L4D.C	0,024	0,032***	-0,042**	-0,868***
L4D.V	0,138***	0,097***	-0,119***	-1,317**
L4D.Vsq	0,007***	-0,002***	-0,004***	-0,026***
IP	3,445***	1,482***	-0,188***	-9,07***
L3.y	0,063***	0,007	0,045***	0,329***

Observations: 9,269

Table A.2
Weak and underidentification tests

Variable	F(6, 48)	P-value	AP Chi-sq(3)	P-value
L2.y	12,94	0,000	33,09	0,000
C	730,88	0,000	861,35	0,000
V	5654,68	0,000	1908,87	0,000
Vsq	3992,07	0,000	2005,88	0,000

Underidentification test
Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified)
Ha: matrix has rank=K1 (identified)
Kleibergen-Paap rk LM statistic Chi-sq(3)=20.12 P-val=0.0002

Weak-instrument-robust inference
Tests of joint significance of endogenous regressors B1 in main equation
Ho: B1=0 and orthogonality conditions are valid
Anderson-Rubin Wald test Chi-sq(6)= 128.05 P-val=0.0000

Table A.3
Instruments orthogonality tests

Cumby-Huizinga test for autocorrelation (Arellano-Bond)
H0: variable is MA process up to order q
HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) HA: s.c. present at range specified				H0: q=specified lag-1 HA: s.c. present at lag specified			
Lags	Chi-sq	df	P-value	Lags	Chi-sq	df	P-value
1-1	0,524	1	0,469	1	0,524	1	0,469
1-2	1.098	2	0,577	2	0,006	1	0,940
1-3	2.079	3	0,556	3	0	1	0,993
1-4	2.651	4	0,618	4	0,2	1	0,655
1-5	2.651	5	0,754	5	0,09	1	0,765
1-6	4.318	6	0,634	6	0,047	1	0,829
1-7	4.416	7	0,731	7	0,035	1	0,852
1-8	5.765	8	0,674	8	0,117	1	0,732

Test allows predetermined regressors/instruments
Test robust to heteroskedasticity and within-cluster autocorrelation

Hansen J statistic (overidentification test of all instruments): 0.453
Chi-sq(2) P-val = 0.7974

Appendix 2: Sensitivity analysis

Table A.4
Sensitivity analysis – different lags as instruments

Variable	2nd Lag	3rd Lag	5th Lag	6th Lag	7th Lag	8th Lag
C5	-1,351**	0,149	2,332***	0,527	1,34***	-0,323
C50	0,616***	0,577***	0,944***	0,747	1,214***	0,864***
C95	1,761***	1,356***	0,022	1,937	0,459	0,101
C5 - C50	-1,968***	-0,429*	1,388***	-0,220	0,126	-1,187
C95 - C50	1,144***	0,779***	-0,922**	1,190	-0,755	-0,763
V5	1,472**	0,897**	3,243***	1,010	1,94***	1,425**
V50	-0,001	-0,35**	0,174	-0,186	0,17	-0,528**
V95	-1,947***	-1,333***	-2,895***	-1,021	-3,498***	-1,805***
V5 - V50	1,473**	1,247***	3,068***	1,195	1,77***	1,953***
V95 - V50	-1,946***	-0,983***	-3,069***	-0,836	-3,667***	-1,277**
Vsq5	-0,199***	-0,075***	-0,176***	-0,061	-0,241***	-0,1***
Vsq50	0,001	0,029**	0,009	0,018	-0,016	0,013
Vsq95	0,153***	0,066***	0,145***	0,046	0,139***	0,088***
Vsq5 - Vsq50	-0,2***	-0,104***	-0,185***	-0,079	-0,225***	-0,113***
Vsq95 - Vsq50	0,152***	0,037*	0,136***	0,028	0,155***	0,075***
Observations	9359	9310	9212	9163	9114	9065
Countries	49	49	49	49	49	49
Replications	200	200	200	200	200	200

Table A.5
Sensitivity analysis – other models

Variable	*EM* only	*FC* only	10/90 quant	pre-2007	post-2007	no Oct-08	cps	lois
C5	1,715	1,658**		3,106***	1,533***	2,331***	0,856*	0,991
C50	0,879**	1,024***		1,472***	1,079***	1,194***	1,027***	1,143***
C95	1,003	0,523		-2,501***	0,573	0,844**	0,998***	0,847
C5 - C50	0,837	0,634		1,634*	0,455	1,137*	-0,172	-0,152
C95 - C50	0,124	-0,501		-3,973***	-0,506	-0,349	-0,03	-0,297
V5	3,916*	3,904***		0,723	2,226*	4,747***		
V50	-0,134	0,479		0,198	0,313	0,409		
V95	-2,253	-2,17***		-0,428	-1,518***	-2***		
V5 - V50	4,05	3,425***		0,525	1,913*	4,337***		
V95 - V50	-2,119	-2,649***		-0,626	-1,831**	-2,409***		
Vsq5	-0,111*	-0,228***		0,185	-0,119***	-0,139		
Vsq50	0,029	-0,001		0,055	0,004	0,021		
Vsq95	0,091*	0,08**		-0,444**	0,07**	0,058		
Vsq5 - Vsq50	-0,139**	-0,227***		0,13	-0,122***	-0,16*		
Vsq95 - Vsq50	0,062	0,081*		-0,5*	0,067**	0,037		
C10			1,219**					
C50			1,075***					
C90			0,451					
C10 - C50			0,144					
C90 - C50			-0,624					
V10			2,145**					
V50			0,394					
V90			-2,256***					
V10 - V50			1,752*					
V90 - V50			-2,65***					
Vsq10			-0,07**					
Vsq50			0,005					
Vsq90			0,088***					
Vsq10 - Vsq50			-0,075**					
Vsq90 - Vsq50			0,083***					
CPS5							1,21***	
CPS50							0,044	
CPS95							-0,484***	
CPS5 - CPS50							1,165***	
CPS95 - CPS50							-0,528***	
CPSsq5							-0,01***	
CPSsq50							0	
CPSsq95							0,005***	
CPSsq5 - CPSsq50							-0,01***	
CPSsq95 - CPSsq50							0,005***	
LOIS5								1,075***
LOIS50								0,041
LOIS95								-0,298**
LOIS5 - LOIS50								1,034***
LOIS95 - LOIS50								-0,339***
LOISsq5								-0,006*
LOISsq50								0
LOISsq95								0,003*
LOISsq5 - LOISsq50								-0,006
LOISsq95 - LOISsq50								0,003*
Observations	5670	3591	9261	5341	3871	9212	9261	6958
Countries	30	19	49	49	49	49	49	49
Replications	200	200	200	200	200	200	200	200

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