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Please cite paper as:
Londono, Juan M. (2016). Bad Bad Contagion
International Finance Discussion Papers 1178.

http://dx.doi.org/10.17016/IFDP.2016.1178

International Finance Discussion Papers
Board of Governors of the Federal Reserve System

Number 1178

September 2016

Board of Governors of the Federal Reserve System

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This Version: August 18, 2016

Abstract

Bad contagion, the downside component of contagion in international stock markets, has negative implications for financial stability. I propose a measure for the occurrence and severity of global contagion that combines the factor-model approach in Bekaert et al. (2005) with the model-free or co-exceedance approach in Bae et al. (2003). Contagion is measured as the proportion of international stock markets that simultaneously experience unexpected returns beyond a certain threshold. I decompose contagion into its downside or bad component (the co-exceedance of low returns) and its upside or good component (the co-exceedance of high returns). I find that episodes of bad contagion are followed by a significant drop in country-level stock index prices and by a deterioration of financial stability indicators, especially for more open economies.

JEL Classification: G15, F36, F65.
Keywords: International stock markets, Bad contagion, Downside contagion, Interconnectedness, International integration, Financial stability, SRISK.

*I would like to thank Nathan Mislang for outstanding research assistance. I would also like to thank the participants at the Federal Reserve Board IF and IFS workshops. The analysis and conclusions set forth are those of the author and do not indicate concurrence by other members of the research staff or the Board of Governors.

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1. Introduction

I provide new empirical evidence that episodes of downside or bad contagion are followed by a drop in international stock prices and by a deterioration of financial stability indicators. Bad contagion is measured as the co-exceedance of unexpectedly low stock returns in international stock markets. In other words, bad contagion occurs when several international stock markets simultaneously experience unusual and unexpected drops in prices. To obtain unexpected returns, I propose a world CAPM model with jumps, wherein the exposure of each country's stock index to the world portfolio is a function of a set of country-specific and global economic fundamentals (Bekaert et al., 2005). This setting allows me to differentiate the transmission of international shocks due to changes in fundamental integration from pure contagion in unexpected returns. Thus, my definition of contagion focuses on cross-country tail correlations beyond what are expected from economic fundamentals. This method is therefore not subject to the correlation bias documented by Forbes and Rigobon (2002). To detect jumps in unexpected returns, I use a percentile threshold for each country's stock index. I first explore whether bad contagion has predictive power for international stock returns using a panel-data regression setting. Using the same setting, I then explore the predictive power of bad contagion for the following measures of stability in the financial sector of each country: bank index stock returns, bank CDS spreads, SRISK (Brownlees and Engle, 2016), and capital-to-assets ratios. I find that episodes of bad contagion are followed by significant and economically meaningful deteriorations of financial stability indicators. I also find that the exposure of countries to contagion is somewhat heterogeneous. In particular, more-open economies are usually more vulnerable to bad contagion.

A common debate in the contagion literature is the proper definition of contagion. Contagion usually has a negative connotation and is frequently used in a broad context to describe the transmission of shocks, especially negative shocks, across international markets. Not surprisingly, the number of papers on contagion increases considerably following a crisis as researchers try to explain the observed coincidence of drops in international asset prices. In this paper, I use a specific definition of contagion based on a world CAPM model with jumps. I allow for the exposure of each country's excess stock returns to the global risk factor, the return of the world portfolio, to be time varying as a function of country-specific and global economic fundamentals. Thus, an increase in the exposure to the global factor is one way to characterize the increased transmission of shocks across international markets. However, I focus on the transmission of shocks that cannot be explained by fundamentals. In particular, I obtain the unexpected component of stock returns—that is, the residuals from the world CAPM model—and propose a simple method to extract the jump component of unexpected returns based on a threshold to determine extreme unexpected returns. I aggregate the information from country-level jumps to calculate a global contagion measure. Specifically, my measure of contagion is the proportion of international stock markets that simultaneously experience extreme unexpected returns. Therefore, the measure of contagion in this paper focuses on tail correlations among international stock returns that are above what is expected from changes in economic fundamentals driving international integration. I decompose contagion into its downside or bad component (the co-exceedance of low returns) and its upside or good component (the co-exceedance of high returns). I calculate contagion using weekly excess returns of headline stock indexes for 33 countries between 2000 and 2014.

To understand the predictive power of contagion for international excess stock returns, I use a panel-data setting. I find that contagion is a useful predictor of stock returns. In particular, episodes of contagion are followed by a significant and economically meaningful drop in stock prices for horizons of up to one year. Decomposing contagion into its bad and good components yields that bad contagion is a more useful predictor for stock returns—the gains in predictive power from adding bad contagion to a regression with good contagion and a set of control variables are higher than the gains from adding good contagion. Interestingly, excess stock returns experience significant drops following episodes of either bad or good contagion. The predictive power of bad contagion for stock returns is additional to that of measures of stock market volatility, risk aversion (Bekaert et al., 2014), and time-varying correlation. Moreover, the predictive power of bad contagion is additional to that of country-level dividend yields and to that of jumps in unexpected returns at the country level. The predictive power of contagion is also robust to considering alternative contagion measures. Finally, contagion remains a useful predictor of stock returns after removing the later part of the sample related to the collapse of Lehman Brothers and the euro-area crisis, although the gains in predictive power for stock returns from adding bad contagion are lower than those for the full sample. I then explore whether the predictive power of bad contagion for stock returns is related to the occurrence of contagion or to its severity. I find that the occurrence of contagion, even if only very few markets are involved, is followed by a significant drop in international stock prices. However, the gains in predictive power from adding contagion are much smaller for low-severity (few markets involved) contagion episodes. In contrast, as long as more than one-fourth of the countries in the sample are involved, contagion becomes a more useful predictor for stock returns—the coefficient associated with contagion is negative and significant at any standard confidence level, and the gains in predictive power converge to those in the benchmark regression setting.

To explore the extent to which bad contagion has long-lasting effects on the stability of the financial sector, I propose a panel-data setting for the predictive power of contagion for alternative financial stability indicators. I find that episodes of bad contagion are followed by a significant deterioration of country-level bank index stock returns. In fact, the drop in bank stock prices is much larger than the drop in headline stock index prices following episodes of contagion. Episodes of bad contagion are also followed by a significant increase in country-level average bank CDS spreads. I also explore the predictive power of contagion for SRISK, the measure in Brownlees and Engle (2016). SRISK quantifies the amount of capital that banks would need if markets experienced large drops and has been largely used in the literature to quantify systemic risk. I find that bad contagion is a useful predictor of SRISK—episodes of bad contagion are followed by a significant increase in SRISK. Finally, I use measures of financial stability that do not depend on market prices and that characterize banks' resilience. In particular, I investigate the predictive power of bad contagion for capital-to-assets ratios and for regulatory-capital-to-risk-weighted-assets ratios. As for the market-based financial stability measures, I find that episodes of bad contagion are followed by a deterioration in these ratios. The financial stability implications of contagion are robust to an extended set of control variables, to alternative contagion measures, and to a subsample excluding the collapse of Lehman Brothers and the euro-area crisis.

I investigate whether the effect of bad contagion on financial stability indicators varies across countries and whether the economic fundamentals driving international integration explain these heterogeneous patterns. Although I find that financial stability indicators in more open economies are more sensitive to contagion, overall, the results suggest that very few of the variables driving international integration actually explain the heterogeneous predictability patterns of contagion for financial stability indicators. I interpret this result as preliminary evidence that the effect of contagion is mostly uniform across countries.

Related literature

The transmission of shocks across international stock markets has received much attention in the literature. It has been extensively documented that stock markets are interconnected and that the degree of interconnectedness is time varying (King and Wadhwani, 1990; Bekaert and Harvey, 1995; Longin and Solnik, 2001; and Karolyi and Stulz, 1996, among others). In particular, stock markets tend to simultaneously experience large price drops around episodes of financial crisis, high macroeconomic uncertainty, or even seemingly idiosyncratic shocks stemming from a particular market. Thus, international markets appear to co-move more around crises than they do in "normal" times. However, there is little agreement in the literature on how to measure co-movement and, especially, on how to determine whether the co-movement experienced around crisis episodes is unusual. For instance, Forbes and Rigobon (2002) and Bae et al. (2003) show that traditional correlation measures are biased measures of co-movement, as they increase mechanically with volatility and give equal weights to small and large changes in stock prices. To address this criticism to traditional correlation measures, the literature has proposed an important number of contagion measures. A survey of contagion measures can be found in Dungey et al. (2005) and Karolyi (2003). The empirical evidence on contagion is not consistent across papers, however, and depends heavily on the alternative definition of contagion considered, particularly, on whether the methodology used can disentangle international integration from contagion. More importantly, the literature falls short in exploring the informational content of contagion and whether and why economic agents should be really worried about contagion. In this paper, I do a rigourous analysis of the market price of contagion across international stock markets and its financial stability implications. I show that contagion has predictive power for stock returns and economically meaningful negative implications for financial stability, even if the global financial crisis (GFC) of 2008 is removed from the sample, and even if only a portion of international stock markets experience large price drops simultaneously.

The methodology in this paper borrows from the factor model approach in Bekaert et al. (2005) to model time-varying integration driven by economic fundamentals, and from the co-exceedance measure proposed by Bae et al. (2003) to determine the simultaneous occurrence of jumps in several stock markets. Bekaert et al. (2005) formalize the global integration models in Bekaert and Harvey (1995) and Ng (2000). In this framework, contagion can be due to an unusual increase in international integration around a particular episode (see, for instance, Bekaert et al., 2014, for an exploration of this type of contagion around the 2008 GFC) or to the transmission of unexpected shocks across markets. Bae et al. (2003) focus on model-free measures of contagion that take into account nonlinearities in the distribution of stock returns. They compare the observed occurrence of simultaneous large drops (co-exceedance) in stock prices with that implied by several distributions to determine whether observed co-exceedances are "unusual." Thus, as the measure in Bae et al. (2003), my measure of contagion quantifies cross-country average tail correlations above what is expected from economic fundamentals driving integration in international stock markets in "normal" times.

I decompose contagion into its downside (bad) and upside (good) components and center most of the attention on bad contagion, which relates to the literature of contagion around market downturns. Overall, this literature finds that deviations from popular distributions used to model stock returns are more severe in the left (downside) tail of the distribution; that is, around market downturns. In particular, Butler and Joaquin (2002) find that correlations around market downturns are "unusual" with respect to several distributions used to model stock returns. Longin and Solnik (2001) model returns as a multivariate normal and show that deviations from this distribution are only significant for the left tail. Pownall and Koedijk (1999) document that deviations from the mean-variance framework are more severe around market downturns. I find that bad contagion is a more useful predictor of stock returns than the good component of contagion, and that episodes of bad contagion are followed by a significant deterioration of financial stability indicators.

The rest of the paper is organized as follows. Section 2 proposes a framework to measure contagion in international stock markets. Section 3 summarizes the main empirical findings for the predictive power of contagion for stock returns. Section 4 explores the financial stability implications of bad contagion and the heterogeneous exposure to contagion across countries. Section 5 concludes.

2. Contagion: Definitions and measures

In this section, I set the framework to measure contagion and its bad and good components. I first introduce a world CAPM model with jumps and define contagion as the coincidence of extreme unexpected returns in international stock markets. I then discuss alternative contagion measures based on the method used to extract unusual returns and to detect extreme unexpected returns.

2.1. An international CAPM framework for contagion

I depart from an international CAPM model with jumps to disentangle interconnectedness across international stock markets driven by economic fundamentals from contagion among unexpected returns. Based on the model, I propose a definition for the occurrence and severity of contagion. Finally, I decompose contagion into its bad and good components.

I assume that the excess return of country j's stock market—that is, the return of a headline stock index minus the global risk-free interest rate—follows a world CAPM model:

$$r_{j,t} = \alpha_{j,t} + \beta_{j,t} r_{m,t} + \mu_{j,t}, \tag{1}$$

where $r_{m,t}$ is the excess return of the world market portfolio, which is calculated as a value-weighted average of all countries' excess returns, as follows:

$$r_{m,t} = \sum_{j=1}^{N} \omega_j r_{j,t},$$

where N is the number of countries in the world portfolio and ω_j is the weight of each country, which is calculated as the ratio of the country's market capitalization to the world market capitalization (fixed, for simplicity, at this point). $\beta_{j,t}$ is the conditional beta or systematic relevance of country j, which measures the interconnectedness of market j with the world portfolio, and $\mu_{j,t}$ is the unexpected component of returns.

I assume that unexpected stock returns, $\mu_{j,t}$ in equation 1, can be decomposed as follows:

$$\mu_{j,t} = \epsilon_{j,t} + q_{j,t},$$

where $\epsilon_{j,t}$ are normally distributed i.i.d shocks with zero mean and idiosyncratic volatility

$\sigma_{j,t}$, which are uncorrelated across countries and uncorrelated with $q_{j,t}$. $q_{j,t}$ is the unusual component of unexpected returns, which follows a Poisson jump process with jump size $J_{j,t}$. Unlike $\epsilon_{j,t}$, I assume that jumps might be correlated across countries, which is precisely the assumption that yields the definition of contagion used in this paper.

I define the occurrence of contagion as the coincidence of unusual unexpected returns.[1] Specifically, contagion in international stock markets occurs when a jump is detected in several markets' unexpected returns at day t. That is,

$$I_t^C = 1 \text{ if } \sum_{j=1}^{N} I_{j,t} \geq 2, \tag{2}$$

where $I_{j,t}$ is a dummy that takes a value of 1 if a jump is detected in market j at time t. I measure the severity of global contagion as the proportion of stock markets that experience extreme unexpected returns simultaneously,

$$C_t = \frac{\sum_{j=1}^{N} I_{j,t}}{N} \text{ if } \sum_{j=1}^{N} I_{j,t} \geq 2. \tag{3}$$

The contagion measure in equation 3 can be decomposed into its upside and downside components. I refer to the coincidence of unusually low returns as downside or bad contagion and to the coincidence of unusually high returns as upside or good contagion. Thus, the severity of bad and good contagion are formally defined as follows:

$$C_t^{bad} = \frac{\sum_{j=1}^{N} I_j(\mu_{j,t} < \kappa_j^-)}{N} \text{ if } \sum_{j=1}^{N} I_j(\mu_{j,t} < \kappa_j^-) \geq 2, \tag{4}$$

and

$$C_t^{good} = \frac{\sum_{j=1}^{N} I_j(\mu_{j,t} > \kappa_j^+)}{N} \text{ if } \sum_{j=1}^{N} I_j(\mu_{j,t} > \kappa_j^+) \geq 2, \tag{5}$$

where κ^- and κ^+ are the low and high thresholds, respectively, for unexpected returns to be considered as unusual—that is, when either a bad or a good jump occurs.[2]

2.2. Contagion measures

There are two key methodological choices to calculate the contagion index and its bad and good components (equations 3 to 5). The first choice is how to estimate the coefficients $\alpha_{j,t}$ and $\beta_{j,t}$ in the international CAPM model in equation 1. The second choice is the method used to detect jumps in unexpected returns (the residuals from the model). I discuss several alternative contagion measures based on different combinations of these two methodological choices.

[1] My measure is similar to that in Bae et al. (2003), although their measure calculates the coincidence in unusual returns rather than in unusual unexpected returns. In other words, my measure converges to that in Bae et al. (2003) if $\alpha_{j,t} = \beta_{j,t} = 0$.

[2] The condition for multiple markets involved in each episode, $\sum_{j=1}^{N} I_{j,t} \geq 2$ in equation 3, implies that $C_t \geq C_t^{bad} + C_t^{good}$.

My benchmark measure for $\alpha_{j,t}$ and $\beta_{j,t}$ follows closely the CAPM version of the global integration model in Bekaert and Harvey (1995) and Bekaert et al. (2005).[3] According to this model,

$$\alpha_{j,t} = \gamma_{\mathbf{0}} \mathbf{X_{j,t-1}}, \tag{6}$$

where $\mathbf{X_{j,t}}$ contains each country's dividend yield, and

$$\beta_{j,t} = \gamma_{\mathbf{1}} \mathbf{Y_{j,t-1}} + \gamma_{\mathbf{2}} \mathbf{Z_{t-1}}, \tag{7}$$

where $\mathbf{Y_{j,t}}$ is a set of country-specific variables that drive the integration of the country with the rest of the world and $\mathbf{Z_t}$ is a set of market-wide variables. The fundamental determinants of international integration in vectors $\mathbf{Y_{j,t}}$ and $\mathbf{Z_{j,t}}$ are lagged to control for endogeneity.[4] As discussed by Bekaert et al. (2005), an initial test for global integration at the country level would involve testing whether markets are entirely driven by the idiosyncratic component of expected returns—$\alpha_{j,t} \neq 0$ and $\beta_{j,t} = 0$. If markets are integrated with the rest of the world, and, therefore, $\beta_{j,t} \neq 0$, one could test whether the transmission of shocks across countries stems from economic fundamentals—changes in $\beta_{j,t}$ around a particular market event—or is beyond what is expected from these fundamentals—changes in the correlation among residuals ($\mu_{j,t}$ in equation 1). In this paper, I focus on the transmission of shocks among unexpected returns. On the one hand, this focus allows me to investigate the average effect of contagion on stock returns and financial stability indicators rather than to examine a specific event. On the other hand, my measure of contagion is an aggregate measure, while changes in $\beta_{j,t}$s collect country-level information.[5] Thus, my measure of contagion is a global measure of tail correlation among international stock markets above what is expected from economic fundamentals driving market integration. The set of country-specific and global variables are described in detail in appendix A. The coefficients in equations 6 and 7 are calculated using pooled least squares, as I explain in more detail in section 3.1. I also consider an alternative measure of $\alpha_{j,t}$ and $\beta_{j,t}$ as the unconditional estimate of these coefficients ($\alpha_{j,t} = \alpha_j$ and $\beta_{j,t} = \beta_j$), which can be calculated using ordinary least squares (OLS) for the relation between each country's excess returns and the world portfolio's excess returns.

Because my benchmark model for the expected component of returns includes fundamental economic determinants, I face a tradeoff between using low-frequency returns, which are traditionally used to understand the expected component of returns, or high-frequency (intraday) returns, which are traditionally used in the literature to detect jumps (see, for instance, Barndorff-Nielsen and Shephard, 2004, and, for the coincidence of jumps in several markets, Bollerslev et al., 2008). In the remainder of the paper, I focus on returns sampled at the weekly frequency. As shown in section 3.1, most fundamental economic determinants

[3] Bekaert et al. (2005) propose a model with two factors: a global factor and a regional factor. In addition, their model allows for time-varying volatility. The restricted CAPM version of the model assumes only a global factor, the return of the world portfolio, and constant volatility.

[4] The minimum lag is one week, although the lag used for each variable depends on the informational set available at time $t-1$. Specifically, for variables available at a frequency lower than one week, I assume a step function to interpolate between two data points, which implies that the lag is essentially longer than one week. In unreported results, I have tried additional minimum lags (one, three, and six months), and the main empirical results remain virtually unchanged.

[5] One could perfectly aggregate the information from time-varying betas using, for instance, measures of dispersion. I leave the exploration of the effects of global fundamental interconnectedness for further research.

play a role in explaining international integration at this frequency. Moreover, the weekly frequency allows me to deal with the asynchronicity of trading hours across international stock markets.

To detect jumps, I use a simple percentile threshold for unexpected returns. Specifically, I set a percentile of the distribution of each country's residuals ranging from 2 to 10 percent for bad contagion and from 90 and 98 percent for good contagion. For the benchmark contagion measure, unusual returns are those below the 5^{th} and above the 95^{th} percentile. These are the benchmark threshold levels traditionally used in the literature (see, for instance, Bae et al., 2003, and Baur and Schulze, 2005). The contagion measures obtained from the alternative model and threshold specifications are discussed in detail in section 3.1.

3. Predictive power of contagion for stock returns

In the previous section, I define contagion as a global measure of tail correlation in international unexpected stock returns. In this section, I provide empirical evidence for the predictive power of contagion for stock returns. In the first part of the section, I describe the data and provide a set of summary statistics for the alternative contagion measures based on the model described in section 2. In the second part, I provide empirical evidence for the predictive power of contagion for international stock returns for the benchmark panel-data setting. In the third part, I provide a set of robustness tests. In the final part of the section, I investigate the impact of the severity of contagion on its predictive power for stock returns.

3.1. Data and summary statistics

To calculate the contagion index defined in equation 3 and its bad and good components in equations 4 and 5, respectively, I use weekly excess log returns for a sample spanning from January 2000 to December 2014 for the following countries: Australia, Belgium, Brazil, Canada, China, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Indonesia, Ireland, Italy, Japan, Malaysia, Mexico, the Netherlands, New Zealand, Norway, the Philippines, Poland, Portugal, Russia, South Africa, Spain, Sweden, Switzerland, Thailand, the United Kingdom, and the United States. The return series are obtained from Bloomberg. As is standard in the literature, I use weekly frequency returns to avoid asynchronicity problems due to the wide differences in trading hours for the markets considered. To obtain excess returns, I use the one-month zero-coupon U.S. Treasury bond yields, which are obtained from the Federal Reserve Board.

Table 1 shows a set of summary statistics for one-week excess returns for all countries in the sample as well as for the world portfolio. Average weekly excess returns range from negative 0.25 percent (Greece) to 0.42 percent (Philippines). The average return for the world portfolio is close to 0 percent and its median return is 0.23 percent. Stock returns display considerable volatility in most countries. Volatility is particularly high for Russia (4.63), Brazil (3.77), Finland (3.86), and Greece (4.05). The volatility of the world portfolio is 2.20 percent. Stock returns also deviate from the normal distribution, with negative skewness for all countries but South Africa, and excess kurtosis ranging from 0.77 (Belgium) to 11.04 (Canada). The world portfolio's skewness is negative 1 and its excess kurtosis is 9.86.

Table 2 shows the parameter estimates for the alternative specifications of the CAPM model in equations 1, 6, and 7. The fundamental determinants of integration are described in appendix A. For the benchmark specification, the following variables drive integration among international markets: current account deficit (negative and significant at the 5 percent level), foreign currency reserves (negative and significant at the 10 percent confidence level), market capitalization (positive and significant at the 1 percent level), total exports and imports (not significant at any standard confidence level), proportion of bank international claims (not significant at any standard confidence level), proportion of assets held by foreigners (positive and significant at the 10 percent level), and Chinn-Ito financial openness index (positive and significant at the 1 percent level). Overall, these results are in line with those in the related literature in that more-open economies, proxied either by the Chinn-Ito index or the ratio of stock market capitalization, are more exposed to the world portfolio and, therefore, more integrated. Also, countries with higher current account deficits seem to be less integrated. The results also suggest that an increase in the exposure to international markets via asset holdings by foreigners increases the exposure to the world portfolio. However, international bank claims do not seem to have additional informational content to explain international integration across international stock markets.

I also consider alternative model specifications. In the second specification (vulnerability), I include variables that characterize each country's vulnerability: portfolio liabilities, sovereign yields, and SRISK. However, none of these variables turn out to be significant, although some of them are significant in a univariate setting. In the third specification (uncertainty), I consider U.S. variables that characterize global risk aversion and macroeconomic uncertainty. For this specification, both the U.S. variance risk premium (VP) and the U.S. macroeconomic uncertainty index are positive and significant—an increase in risk aversion or in macroeconomic uncertainty increases integration across markets. In the fourth specification (size), I consider measures of absolute size, which are useful to determine the increased relevance of large economies with traditionally small or relatively closed financial markets, such as China. I find that, in line with the intuition, an increase in GDP share comes hand in hand with an increase in integration. Interestingly, after controlling for GDP share, the stock market share is inversely related to integration. However, in a multivariate version of the model without GDP share, the coefficient associated with each country's stock market capital share is positive and significant, as expected.

In table 3, I compare alternative bad contagion measures based on the different model specifications (columns 1 to 5) and on the threshold levels used to determine unusual unexpected returns (columns 6 and 7). I also compare the benchmark specifications for the bad and good components of contagion (column 8).[6] The number of episodes of contagion identified depends mostly on the threshold used to identify jumps in unusual returns—a higher threshold leads to more episodes of contagion. Moreover, for a fixed threshold, the identification of contagion episodes overlaps almost exactly across measures, and the severity of contagion is of a similar average magnitude—the average severity of contagion ranges narrowly between 11.39 for the unconditional beta to 12.79 for the uncertainty model. Interestingly, even for alternative threshold levels, the unconditional correlation with the benchmark contagion measure is quite large—0.82 (for the 10 percent threshold) and 0.83 (for the 2 percent threshold). However, as lower-threshold contagion measures identify fewer contagion episodes, the overlap in the number of episodes identified with the benchmark measure decreases with the threshold—35 percent for the 2 percent threshold. Irrespective of the measure considered, contagion is highly persistent, with autoregressive coefficients

[6] All other results for the contagion and good contagion indexes are left unreported to save space and are available, upon request, from the author.

ranging between 0.31 and 0.42, all significant at the 1 percent confidence level. Finally, an interesting finding that results from comparing the benchmark bad and good contagion measures (columns 1 and 8, respectively) is that it is difficult to fully disentangle good from bad episodes of contagion. In particular, in almost half of the episodes of contagion, bad and good contagion occur at the same time, which provides preliminary evidence in favor of international stock market diversification. In unreported results, I also show that episodes of bad contagion are often followed by episodes of good contagion, which suggests that stock markets tend to, at least partially, recover following large unexpected drops.

In the following section, I discuss the results for the predictive power of the benchmark contagion measure for headline country stock indexes, and, in section 3.3, I investigate the robustness of these results to the alternative contagion measures introduced in this section.

3.2. Predictive power for stock returns

The empirical regression setting for the predictive power of contagion for stock returns is the following:

$$r_{j,t+h} = b_j(h) + b_C(h)C_t + \mathbf{B(h)W_t} + u_{j,t+h}, \tag{8}$$

where $r_{j,t}$ is the log excess return of the headline index of country j, C_t is the contagion index, and $\mathbf{W_t}$ is a vector of global control variables. The set of control variables includes a decomposition of the VIX (the S&P 500 option-implied volatility index) into its uncertainty and risk aversion components (see Bekaert et al., 2013). Market uncertainty is characterized by the realized volatility of the U.S. stock index, which is calculated as the squared root of the sum of daily squared returns over a 22-day window (roughly one month). Risk aversion is characterized by the U.S. VP, which is measured as the difference between the squared of the VIX and the squared of the U.S. index realized volatility (Bollerslev et al., 2009). I also include a measure of correlation among all stock markets, which is calculated as the equal-weighted average of all pairwise correlations. For each pair of countries, the correlation coefficient is calculated using a 22-day moving window. In section 3.3, I expand the set of control variables to assess the robustness of my empirical results and to determine the additional predictive power of contagion. The coefficients in equation (8) are estimated using pooled OLS in which all coefficients but $b_j(h)$ are restricted to be homogeneous across countries.[7]

Table 4 reports the estimates for $b_C(h)$ and $\mathbf{B(h)}$. Panel A shows the results when the contagion index takes into account both tails of the distribution (equation 3). The results suggest that episodes of contagion are followed by a significant decrease in stock returns for all within-one-year horizons considered. The economic magnitude of this effect is considerable: If all countries were to experience extreme unexpected returns at the same time; that is, if contagion goes from 0 to 100 percent, one-week-ahead stock returns would decrease by 2 percent, which is slightly below the standard deviation of the world portfolio. The effect of contagion remains significant after one year, although the magnitude of the estimated coefficient decreases (becomes closer to zero) rapidly after one week. The gains in predictive power after adding contagion to the set of control variables peak at the one-year horizon at 0.65 percent.

Decomposing contagion into its bad and good components yields interesting results (panels B and C of table 4). In particular, while the one-week-ahead effect on stock returns is

[7] As pointed out by Bansal and Dahlquist (2000), a panel-data setting reduces imprecision in the estimation of country-specific parameters.

similar in magnitude for contagion and its components, the effect of bad contagion is much larger for all other horizons than the effect of contagion and that of good contagion. Moreover, the gains in predictive power from adding bad contagion are much larger for horizons longer than one week than those from adding good contagion. In any case, stock returns experience significant drops following episodes of either bad or good contagion. The result for good contagion is rather intuitive: Stocks are relatively expensive in episodes of good contagion and should experience a subsequent price drop. However, the result for bad contagion is, at first, puzzling, as episodes of bad contagion, which are characterized by relatively low stock prices, should be followed by a subsequent increase in stock prices. Although the evidence for the predictive power of bad contagion for stock returns could be affected by the difficulty to fully disentangle good from bad contagion, as discussed in section 3.1, it could also suggest that contagion has long-lasting negative effects on stock returns due to either an initial market underreaction, the transmission of negative shocks across stock markets, or negative spillovers to the financial system, as we discuss in detail in section 4, or to the real economy.

To explore further which component of contagion is more useful to predict stock returns, figure 1 shows the results for a multivariate regression setting that includes the control variables and both components of contagion. The gains in predictive power are, in this case, those from adding each component to all other variables. The results suggest that bad contagion (panel A) has predictive power for future stock returns that is additional to that of good contagion. On the one hand, the coefficient associated with bad contagion remains significant at every standard confidence level, and its estimate is similar to that reported for the regression in which I do not control for good contagion (table 4). The coefficients associated with good contagion, although of a similar magnitude as those in table 4, become borderline significant for several horizons shorter than six months. On the other hand, the gains in predictive power are considerably larger for bad contagion and, in fact, almost null for good contagion at horizons under six months.

3.3. Robustness tests

In this section, I explore the robustness of the predictive power of contagion for stock returns. I focus on the predictive power of bad contagion, as the evidence in section 3.2 suggests that this is the most useful component of contagion to predict future stock returns. I first explore the robustness to alternative control variables. I then analyze the predictive power of the alternative contagion measures in table 3. Finally, I investigate the predictive power of contagion for a sample before mid-2008 (pre-GFC), right before the collapse of Lehman Brothers.

Table 5 summarizes the results for alternative sets of control variables, $\mathbf{W_t}$ in equation 8, for the two-month horizon. The results suggest that bad contagion remains a useful predictor of stock returns after controlling for country-specific dividend yields (column 2).[8] Moreover, bad contagion has additional predictive power after controlling for country-specific extreme events, which are characterized by a dummy for the occurrence of jumps at the country level (column 3). The main empirical results also remain robust when I add a measure of macroeconomic uncertainty in the United States (column 4). Finally, contagion also remains

[8]The empirical evidence in the related literature consistently finds that the dividend-yield ratio is a useful predictor of stock returns at longer-than-one-year horizons (see, for instance, Fama and French, 1988). In this paper, however, I focus on short- to medium-term predictive power.

a useful predictor after controlling for an alternative correlation measure calculated using the DCC model in Engle (2002) (see appendix B).

Apart from the robustness of the predictive power of bad contagion for stock returns, another interesting result from table 5 is that the predictive power of correlation is highly sensitive to the set of control variables. In particular, the predictive power of correlation for stock returns becomes insignificant at any standard confidence level when I add the country-specific dividend yield or the U.S. macroeconomic uncertainty index.

Figure 2 shows the estimated coefficients associated with the predictive power of selected alternative contagion measures (see table 3). For the alternative integration model including country-level vulnerabilities, global uncertainty variables, and absolute size, the estimated coefficient is very similar to that for the benchmark setting and is significant at any standard confidence level. In fact, in unreported results, I show that using alternative specifications of the integration model (table 2) leaves the benchmark results for the predictive power of bad contagion for stock returns virtually unchanged. The coefficient associated with bad contagion is smaller when each country's systematic relevance is calculated as the unconditional beta of the international CAPM model. However, for most horizons, bad contagion remains a useful predictor of international stock returns. Similarly, when the threshold to detect jumps is increased to 10 percent, the estimated coefficient is smaller than that for the benchmark contagion measure and insignificant for very short horizons but clearly significant for all other horizons considered. Finally, when the threshold is increased to 2 percent, bad contagion is still a useful predictor of stock returns for horizons shorter than nine months.

Figure 3 shows the predictability of bad contagion for stock returns for the pre-GFC sample. Bad contagion remains a useful predictor for stock returns for medium one- to six-month horizons, although the coefficient associated with bad contagion is borderline significant for some horizons. Also, the gains in predictive power are considerably lower compared with those for the full sample. These results are not surprising given that the estimation of the contagion measure depends critically on the threshold used to determine unusual returns, and this threshold is fixed for the full sample. The GFC is, by far, the largest contagion episode when the full sample is considered, and stock prices deteriorated considerably after this episode. However, it is comforting to see that recalibrating the threshold for a shorter sample that removes important episodes of contagion, including the collapse of Lehman Brothers and several episodes of the euro-area crisis, maintains the significance of the predictability of bad contagion, although it reduces the gains in predictive power.

3.4. The severity of contagion

In section 3.2, I show that contagion has predictive power for international stock returns and that the gains in predictive power are higher for the downside component of contagion. In section 3.3, I show that these results are robust to an extended set of control variables, alternative contagion measures, and, to a lesser extent, considering a pre-GFC sample. A natural question at this point is the extent to which the severity of contagion matters for its predictive power for stock returns.

To explore the effect of the severity of contagion, I propose the following alternative regression setting:

$$r_{j,t+h} = b_j(h) + b_D(h)D_t + \mathbf{B(h)W_t} + u_{j,t+h}, \tag{9}$$

where D_t is a dummy that takes a value of 1 when the severity of contagion is lower than a certain threshold and zero otherwise.[9]

Figure 4 shows the estimated coefficients associated with the dummy for alternative contagion thresholds and the gains in predictive power in each case. Episodes of contagion where 10 percent or less of the countries in the sample experienced unusually low unexpected returns are followed by a significant decrease in stock prices. However, the gains in predictive power after adding the contagion dummy to the benchmark set of control variables are very small and practically zero for most of the horizons considered. In contrast, for episodes involving at least one-fourth of the markets in the sample, the patterns for the predictive power of contagion and the gains in predictive power resemble those in the benchmark setting (table 4).[10] Thus, contagion seems to be a useful predictor of stock returns, as long as a good portion (at least one-fourth) of the markets are involved in the contagion episodes.

In sum, in this section, I show that contagion is a useful predictor of stock returns, with the bad component of contagion being a more useful predictor than its good component. I also show that this result is robust to alternative control variables, alternative control measures, and the subsample before the 2008 GFC. Moreover, I show that the severity of contagion matters for its predictive power of stock returns: Episodes of contagion involving very few markets (10 percent or less of the markets in the sample) do not have significant predictive power for future stock returns. In the following section, I show that episodes of bad contagion are also followed by a significant deterioration of indicators for the health and stability of the financial sector.

4. Financial stability implications of contagion

In this section, I explore the financial stability implications of bad contagion. In the first part of the section, I introduce several indicators for the health and stability of the financial sector in each country. In the second part, I present the main empirical findings for the predictive power of bad contagion for financial stability indicators. In the final part of the section, I explore the determinants of heterogeneous exposures to bad contagion across countries.

4.1. Indicators of financial stability

For each country in the sample, I consider the following three indicators of financial stability based on market prices: the excess return of a representative bank stock index, the country-average bank CDS spreads, and the country-aggregate SRISK. I also consider financial stability indicators based on banks' balance sheets. In particular, I consider two proxies for the capital-to-assets ratio: a country-level average of capital-to-assets ratios and an average of regulatory-capital-to-risk-weighted-assets ratios. Details of the financial stability indicators, including the data source, are presented in appendix A.

Table 6 reports summary statistics for the alternative financial stability indicators considered. To save space, I only show the summary statistics for a reduced sample of countries. The column labeled "World" reports the average of each statistic across all countries with

[9]The threshold for the severity of contagion should not be confused with the threshold used to detect jumps. The former should be interpreted as the proportion of markets that experience unusual unexpected returns simultaneously.

[10]The magnitude of the coefficients in figure 4 and table 4 are not comparable, as the setting in equation 8 quantifies the severity of contagion while the setting in equation 9 uses a dummy to identify episodes of contagion.

available information. Country bank index returns, in panel A, display similar dynamics to headline stock indexes (table 1). Specifically, weekly average returns are relatively low and vary widely across countries, while standard deviations are considerably high (as high as 9.16 percent for Ireland). Bank stock returns also deviate from the normal distribution, with skewness ranging from negative 0.79 for the Netherlands to 0.51 for Canada, and kurtosis ranging from 4.29 for Japan to 17.54 for the United States. Bank CDS spreads, in panel B, also vary widely across countries and are particularly high for the so-called peripheral euro-area countries: Ireland (344 basis points), Portugal (250), and Spain (132), and for some emerging market economies, such as Brazil (202) and Thailand (124). The cross-country average of bank CDS spreads is 129.75 basis points. The volatility of CDS spreads for countries with high average CDS spreads is also relatively higher—Brazil (116 basis points), Ireland (469), Portugal (367), Spain (138), and Thailand (97).

The average SRISK-to-GDP ratio ranges from 0.82 percent for Malaysia to 8.55 percent for the Netherlands, and the cross-country average ratio is 3.52 percent (panel C). SRISK ratios display moderate volatility, most of which is explained by the overall increase in ratios around the 2008 GFC. Volatility ranges from 0.60 percent for Malaysia to 5.47 percent for the Netherlands. The average volatility across countries is 3.61 percent. As with volatility, most of the skewness and kurtosis of the ratios is explained by the 2008 GFC. The cross-country average skewness is 1.46, and the average kurtosis is 6.32.

Banks' capital-to-assets ratios vary widely across countries, with average ratios ranging from 4.06 for the Netherlands to 11.36 for the United States (panel D). Similarly, regulatory capital-to-assets ratios, in panel E, range from 11.26 (Portugal) to 16.94 (Brazil). These ratios are somewhat stable throughout the sample and, therefore, their volatility is relatively small. The cross-country average of the volatility is 0.95 and 1.71 for capital-to-assets and regulatory-capital-to-assets, respectively.

4.2. Predictive power of contagion for financial stability measures

The regression setting to test the financial stability implications of contagion is similar to that in equation 8:

$$\Delta FS_{j,t,t+h} = b_j(h) + b_C(h)C_t + \mathbf{B(h)W_t} + u_{j,t+h}, \tag{10}$$

where the dependent variable, $\Delta FS_{j,t,t+h}$, is the change in each one of the financial stability indicators introduced in section 4.1 between times t and $t+h$.[11] Table 7 shows the predictive power of bad contagion for the market-based financial stability indicators that are available at a weekly frequency, and table 8 shows the results for the predictive power of bad contagion for capital-to-assets ratios, which are only available at a quarterly frequency.

The results in table 7 show that bad contagion is a useful predictor of bank index stock returns for all horizons considered (panel A). Moreover, the economic magnitude of the effect of bad contagion is much larger than that for headline indexes. In other words, the results suggest that bank stock prices deteriorate more after episodes of contagion than stock prices for other industries—one-week-ahead bank stock prices drop by as much as 6.47 percent at the one-week horizon, and, at the one-year horizon, bank prices drop by 0.52 percent.[12] The

[11] Bank stock returns are treated as in equation 8; that is, for bank stocks, $\Delta FS_{j,t,t+h}$ is the return of the bank stock index over the period.

[12] Because, for most countries, banks represent an important component of the headline index, differentiating the effect of bad contagion on bank indexes from that on headline indexes is not simple. In unreported

gains in predictive power after adding bad contagion are also higher than those for headline stock indexes and are maximized at the one-week horizon at 0.96 percent.

The results in panel B suggest that episodes of contagion are also followed by a significant increase in bank CDS spreads. Specifically, if all markets were to experience jumps in unexpected returns at the same time (contagion goes from 0 to 100 percent), CDS spreads will increase by a maximum of 97 basis points at the two-month horizon. This magnitude is quite considerable when compared with the cross-country average CDS spread of 130 basis points. The gains in predictive power for CDS spreads from adding contagion to the set of control variables are maximized at the two-month horizon at 0.78 percent and practically disappear at the one-year horizon.

The SRISK-to-GDP ratio also increases significantly after episodes of contagion (panel C). SRISK ratios increase by as much as 1.45 percentage points following episodes of contagion that involve all countries in the sample. The economic magnitude of this effect is also economically meaningfully—for the two-month horizon, the effect is almost half the cross-country average of SRISK ratios. As for bank CDS spreads, the gains in predictive power are maximized at the two-month horizon (0.53 percent) and decrease considerably at the one-year horizon (0.13 percent).

The financial stability indicators considered so far are market-based measures and can, therefore, be affected by changes in investors' attitudes toward risk, especially around episodes of high uncertainty or even episodes of contagion. Table 8 shows the results for financial stability measures based on balance sheet data, which are more stable and might be less prone to endogenously determine contagion. However, these measures are only available at the quarterly frequency and for a much smaller sample, starting in 2005. Therefore, I only report the results for the one-quarter-ahead horizon. The results suggest that episodes of bad contagion are followed by a deterioration in capital-to-assets ratios. The magnitude of the estimated effect is quite similar and significant for both the capital-to-assets and the regulatory-capital-to-risk-weighted-assets ratios, although the economic magnitude of the effect of contagion is somewhat smaller than that for financial variables—episodes of contagion involving all countries are followed by a one-quarter ahead deterioration of capital-to-assets and regulatory-capital-to-assets ratios of 1.09 and 1 percent, respectively.

Table 9 summarizes the results for several robustness tests for the predictive power of bad contagion for the alternative financial stability indicators. These robustness tests are similar to those for the predictive power of bad contagion for stock returns in table 5. The main result that episodes of bad contagion are followed by a statistically significant deterioration of financial stability conditions is robust to adding alternative control variables, except for the predictive power for regulatory-capital-to-assets ratios when country-level jumps are added. Although, for all indicators, country-level return jumps are not statistically significant, the coefficient of bad contagion changes considerably for this specification. For all specifications except that with country-level jumps, the gains in predictive power remain of a similar magnitude for all indicators.[13]

results, I provide preliminary evidence that bank indexes are more exposed to contagion than headline indexes. This evidence requires pooling headline and bank indexes and estimating equation 10. I add a dummy that takes the value of 1 only for bank indexes and have that dummy interact with bad contagion. I find that the coefficient associated with the interaction between the bank dummy and contagion is statistically significant at any standard confidence level.

[13]Country-level jumps are highly correlated with bad contagion, which might cause some multicolinearity issues for this particular specification. In unreported results, I have tried to orthogonalize the country-level jumps dummy by having the dummy take the value of zero when there are episodes of contagion (coincidence

Figures 5 to 7 explore the robustness of the market-based financial stability implications of contagion to alternative contagion measures. The results suggest that, irrespective of the contagion measures used, bad contagion is a useful predictor for future bank stock returns, CDS spreads, and SRISK-to-GDP ratios. For all market-based financial stability measures, the magnitude and significance of the coefficient associated with contagion are very similar to those in the benchmark setting when alternative specifications of the integration model are used. However, the results are more sensitive to changes in the threshold used to detect jumps. In particular, the effect of contagion for future bank stock returns is much smaller for the 10 percent threshold contagion measure and much larger for the 2 percent threshold contagion measure than for the benchmark contagion measure. For bank CDS spreads, the coefficient associated with the 2 percent threshold contagion measure is much larger for one-week to six-month horizons. Finally, for SRISK ratios, the coefficient associated with bad contagion is significant only for horizons of less than six months when the threshold used to detect jumps is increased to 2 percent.

In unreported results, I also explore the robustness of my main empirical findings to the pre-GFC sample for bank stock returns and SRISK, as all other financial stability measures are only available from 2005. The results suggest that, although the gains in predictive power are smaller for this sample, bad contagion is still a useful predictor for future bank stock returns and SRISK. Specifically, the coefficient associated with contagion is negative and significant for horizons up to nine months for bank stock returns—episodes of contagion are followed by a drop in bank stock prices—and the coefficient associated with SRISK is positive and significant, especially at horizons shorter than three months—episodes of contagion are followed by an increase in SRISK.[14]

4.3. Financial integration and exposure to contagion

The empirical evidence so far suggests that episodes of bad contagion are followed by a significant deterioration of several indicators of the health and stability of international financial systems. These results are obtained from a panel-data regression setting, which, although beneficial for the precision in the estimation of the parameters (Bansal and Dahlquist, 2000), ignores the potential heterogeneity in the exposure to contagion across countries. In this section, I explore the differential or heterogeneous predictive power of bad contagion for the alternative market-based financial stability measures.

The regression setting to test the heterogeneous exposure to contagion is the following:

$$\Delta FS_{j,t,t+h} = b_j(h) + b_{C,j,t}(h)C_t + \mathbf{B(h)W_t} + u_{j,t+h}, \tag{11}$$

where

$$b_{C,j,t} = \delta_0 + \delta_1 y_{j,t-1},$$

where $y_{j,t} \in \mathbf{Y_{j,t}}$ is each one of the variables in the set of country-specific determinants of international integration introduced in section 2.2 and explained in detail in appendix A. This setting allows me to test whether the variables in $\mathbf{Y_{j,t}}$ are useful at explaining the heterogeneous exposures to bad contagion across countries (see Hausman and Wongswan, 2011, and Bowman et al., 2015).

Table 10 summarizes the results for the global integration determinants with potential to

of jumps). The results for the predictive power of bad contagion remain robust to this specification.

[14]These results are available, upon request, from the author.

explain heterogeneous exposures to bad contagion across countries. The results suggest that a higher ratio of foreign currency reserves makes countries less vulnerable to a decrease in bank index stock prices. Also, two proxies for financial openness seem to explain the heterogeneous exposure to bad contagion. On the one hand, a higher ratio of market capitalization or a higher Chinn-Ito index (more-open economies) increases the exposure of a country's SRISK to contagion. On the other hand, however, more-open economies according to the Chinn-Ito index appear less vulnerable to a decrease in bank stock prices after episodes of contagion. Trade links, characterized by the ratio of total exports and imports to GDP, also explain the vulnerability of a country's SRISK to bad contagion. Finally, larger portfolio liabilities make a country's bank index less exposed to bad contagion. Overall, however, the results suggest that a very reduced number of variables driving international integration significantly explain the heterogeneity in the exposure to bad contagion. Moreover, the explanatory power of these variables is not robust across financial stability measures. Therefore, although some indicators suggest that more-open economies are more exposed to contagion, the effect of contagion on financial stability indicators seems to be mostly uniform across countries.

5. Conclusion

The transmission of shocks across international stock markets around market downturns is at the center of the contagion literature. Although "contagion" usually has a negative connotation, empirical evidence to support its negative implications is almost nonexistent in the literature. In this paper, I propose a measure of bad contagion as the coincidence of extreme unexpected returns in several international stock markets. Using a panel-data setting with data for 33 countries, I show that episodes of bad contagion are followed by a further deterioration of international stock prices. Moreover, I show that episodes of contagion do not have to be very severe to have predictive power for international stock returns. I also explore the predictive power of bad contagion for a set of country-specific financial stability indicators. I show that episodes of bad contagion are followed by a significant and economically meaningful deterioration of financial stability conditions: a decrease in bank index stock prices, an increase in banks' CDS spreads, an increase in SRISK, and a reduction of capital-to-assets ratios. This evidence is robust to alternative control variables, alternative specifications of the contagion measure, and, to a lesser extent, a sample removing the global financial crisis that started in 2008 and the euro-area crisis that immediately followed.

Appendix A. Data sources and definitions

Variable name	Description	Source	Frequency	Notes
Dividend yields	Dividends paid out to current price for the representative stock market index	Bloomberg	Daily	
GDP	Gross domestic product	World Bank, Haver analytics	Quarterly	Nominal and real depending on the ratio
Current account deficit*	Current account deficit	Haver analytics, IMF	Quarterly	
Foreign exchange reserves*	Central bank's reserves in foreign currency	IMF	Quarterly	
Market capitalization*	Total country's stock market capitalization	Bloomberg, World Bank	Daily	
Exports and imports*	Exports plus imports from and to the country	Haver analytics	Quarterly	
Bank international claims*	Banking total intl. claims by counterparty country	BIS	Quarterly	
Assets by foreigners	Proportion of total bond and stocks owned by foreigners	IMF	Annual	Starts in 2005 for China, Hong Kong, Ireland, Italy, Japan, Poland, Spain, and Thailand
Financial openness	Chinn-Ito index of financial openness (1=open)	Chinn-Ito website, IMF AEAER reports	Annual	See Chinn and Ito (2006)
Portfolio liabilities	Net stock and bond inflows	IMF	Quarterly	
Sovereign yields	Ten-year sovereign bond yields	Federal Reserve Board, central banks	Daily	Russia starts in 2010
SRISK*	Systemic risk measure in Brownless and Engle (2016): Capital shortfall of the banking system conditional on a severe market decline	V-Lab, NYU Stern	Daily	
U.S. VP	U.S. Variance risk premium calculated as the difference between the square of the VIX and the 22-day rolling window realized variance	Bloomberg	Daily	See Bollerslev, et. al (2009)
U.S. macro uncertainty	Citibank U.S. surprise index	Bloomberg	Daily	
GDP share	Country's GDP over cross-country sum of GDP	World Bank	Quarterly	
Stock market cap. share	Country's market capitalization over sum of market capitalization across countries	Bloomberg, World Bank	Daily	
CDS	Country's Credit Default Swap spread	Markit	Daily	Not available for New Zealand
Bank CDS	Value-weighted average of the CDS of a group of representative financial institutions	Markit, Federal Reserve Board	Daily	
Bank stock prices	Datastream bank index closing price	Datastream	Daily	Not available for New Zealand
CAR	Country average of banks' capital to assets ratio	IMF	Quarterly	Merged from Financial soundness indicator and GFSR
BCA	Country average of banks' regulatory capital to risk-weighted assets ratio	IMF	Quarterly	Same as CAR

*Expressed as a percentage of GDP

Appendix B. Global correlations

In this appendix, I describe the alternative measures of global correlation used in the set of control variables for the regressions in sections 3 and 4.

I use two measures of global correlation: a rolling-window Pearson correlation coefficient and a dynamic conditional correlation (DCC). The rolling-window global correlation is an equal-weighted average of pairwise rolling-window correlations. Specifically, I calculate the time-varying correlation between markets j and k as

$$\rho_{j,k,t} = \frac{\sum_{i=1}^{N} r_{j,t,i} r_{k,t,i}}{\sqrt{\sum_{i=1}^{N} r_{j,t,i}^2} \sqrt{\sum_{i=1}^{N} r_{j,t,i}^2}},$$

where N is fixed at 22 days, roughly the number of trading days per month.

To obtain DCC correlations, I follow Engle (2002). Specifically, I model a multivariate system for all countries' daily excess returns as follows:

$$\mathbf{r}_t \sim_{iid} N(\mu, \mathbf{H}_t), \tag{B.1}$$

where $\mathbf{r}_t$ contains excess daily returns for all countries, which are obtained by subtracting the one-month U.S. risk-free rate to the observed daily returns. I assume the vector of expected returns μ to be constant over time. The variance covariance matrix, $\mathbf{H}_t$, follows

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t, \tag{B.2}$$

where $\mathbf{D}_t$ is a diagonal matrix containing standard deviations for all countries and for the world portfolio ($D_{i,t}$ and $D_{m,t}$) and $\mathbf{R}_t$ is the time-varying correlation matrix.

To focus on correlations, the time-varying standard deviations are obtained using a GARCH(1,1) process. The (short-term) daily correlation between the returns of market j and that of market k is calculated as

$$\rho_{j,k,t} = \frac{q_{j,k,t}}{\sqrt{q_{j,j,t}} \sqrt{q_{k,k,t}}}, \tag{B.3}$$

with

$$q_{j,k,t} = \overline{\rho}_{j,k,\tau}(1 - a - b) + a\xi_{j,t-1}\xi_{k,t-1} + bq_{j,k,t-1}, \tag{B.4}$$

where $\xi_{j,t}$ and $\xi_{k,t}$ are the standardized residuals for the two markets, which are calculated using the GARCH(1,1) standard deviations (that is, $\xi_t = \mathbf{D}_t^{-1}(\mathbf{r}_t - \mu)$). The long-term correlation component $\overline{\rho}_{j,k,\tau}$ is specified as

$$\overline{\rho}_{j,k,\tau} = \sum_{l=1}^{L^c} \varphi_l(\omega^c) c_{j,k,\tau-l}, \tag{B.5}$$

where

$$c_{j,k,\tau} = \frac{\sum_{i=\tau-N_c}^{\tau} \xi_{j,i}\xi_{k,i}}{\sqrt{\sum_{i=\tau-N_c}^{\tau} \xi_{j,k}^2} \sqrt{\sum_{i=\tau-N_c}^{\tau} \xi_{k,i}^2}},$$

and the polynomial function φ_l is given by

$$\varphi_l(\omega) = (1 - l/L)^{\omega-1} / \sum_{i=1}^{L} (1 - i/L)^{\omega-1}). \tag{B.6}$$

I estimate the system of equations (B.1) to (B.6) using the two-step procedure introduced by Engle (2002).

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Table 1: One-week excess stock returns, summary statistics

This table reports the summary statistics for the time series of one-week excess log stock returns for each country's representative index. Returns are expressed in percent. Excess returns are calculated by subtracting one-month U.S. zero-coupon U.S. Treasury bond yields (turned into weekly equivalent). The sample considered runs from January 2000 until December 2014.

	World	Australia	Belgium	Brazil	Canada	China	Denmark	Finland	France	Germany	Greece
Mean	0.00	0.07	0.05	0.14	0.07	0.16	0.14	-0.07	-0.01	0.05	-0.25
St. Dev.	2.20	2.04	2.52	3.77	2.47	1.90	2.55	3.86	2.80	3.14	4.05
Median	0.23	0.29	0.55	0.43	0.34	0.25	0.39	0.27	0.23	0.33	-0.02
Skewness	-1.00	-0.81	-1.29	-0.52	-1.24	-1.16	-0.79	-0.81	-0.47	-0.54	-0.41
Kurtossis	9.86	6.48	0.77	4.80	11.04	10.03	6.36	6.63	5.65	6.44	4.78

	Hong Kong	Hungary	Indonesia	Ireland	Italy	Japan	Malaysia	Mexico	Netherlands	New Zealand	Norway
Mean	0.06	0.08	0.26	0.01	-0.06	-0.01	0.10	0.23	-0.05	0.16	0.05
St. Dev.	3.14	3.42	3.22	3.09	2.82	3.08	2.05	3.00	2.96	3.03	1.57
Median	0.24	0.16	0.43	0.32	0.27	0.23	0.20	0.40	0.25	0.40	0.14
Skewness	-0.10	-0.54	-1.05	-1.21	-0.60	-0.65	-0.33	-0.57	-0.79	-0.91	-0.69
Kurtossis	4.66	6.93	8.27	9.38	5.12	5.89	5.56	5.88	6.91	7.02	5.79

	Philippines	Poland	Portugal	Russia	South Africa	Spain	Sweden	Switzerland	Thailand	U.K.	U.S.
Mean	0.42	0.14	-0.11	0.27	0.23	0.04	0.01	0.03	0.16	0.00	0.05
St. Dev.	3.20	2.96	2.68	4.63	2.72	2.64	2.94	2.38	3.10	2.37	2.54
Median	0.70	0.33	0.14	0.67	0.49	0.15	0.31	0.25	0.35	0.19	0.28
Skewness	-1.07	-0.47	-0.76	-0.73	0.00	-0.13	-0.25	-0.70	-0.72	-0.67	-1.20
Kurtossis	7.21	4.65	5.96	9.07	6.19	7.41	4.46	7.41	5.64	6.43	14.89

Table 2: Factor model for interconnectedness

This table reports the estimated coefficients γ_1 and γ_2 in the following model:

$$r_{j,t} = \alpha X_{j,t} + \beta_{j,t} r_{m,t} + \mu_{j,t},$$

where $r_{i,t}$ and $r_{m,t}$ represent the excess return of country j's representative stock index and the world market portfolio, respectively, and

$$\beta_{j,t} = \gamma_1 \mathbf{Y_{j,t-1}} + \gamma_2 \mathbf{Z_{t-1}}.$$

Coefficients are estimated using panel-data (pooled) OLS in which all coefficients are restricted to be homogeneous across countries. Standard deviations are corrected by panel-data Newey West with 4 lags and are reported in parenthesis. *, **, and *** represent significance at the standard 10, 5, and 1 percent confidence levels, respectively. The variables in vectors $\mathbf{X_{j,t}}$, $\mathbf{Y_{j,t}}$, and $\mathbf{Z_{j,t}}$ are described in detail in Appendix A.

	Benchmark	Vulnerability	Uncertainty	Size
Dividend yield	-0.09***	-0.08***	-0.10***	-0.11***
	(0.02)	(0.02)	(0.02)	(0.02)
World returns	0.70***	0.68***	0.64***	0.51***
	(0.04)	(0.06)	(0.06)	(0.07)
Current account deficit	-0.16**	-0.23***	-0.32***	-0.33***
	(0.06)	(0.06)	(0.06)	(0.06)
Foreign currency reserves	-0.20*	-0.32***	-0.28**	-0.32***
	(0.08)	(0.08)	(0.09)	(0.09)
Market capitalization	0.04***	0.04***	0.03***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Exports and imports	-0.02	0.01	0.03	0.06*
	(0.02)	(0.02)	(0.03)	(0.03)
Bank intl. Claims	1.54	1.12	3.33	9.14*
	(3.62)	(3.70)	(4.00)	(4.13)
Assets by foreigners	0.98*	0.70	0.33	0.32
	(0.44)	(0.45)	(0.47)	(0.47)
Financial openness (Chinn Ito)	0.27***	0.28***	0.28***	0.27***
	(0.04)	(0.05)	(0.06)	(0.06)
Portfolio liabilities		-0.23	-0.45*	0.40
		(0.20)	(0.21)	(0.21)
Sovereign yields		0.14	0.24	0.83*
		(0.37)	(0.38)	(0.40)
SRISK		0.11	0.28	0.40*
		(0.16)	(0.19)	(0.19)
U.S. VP			0.78***	0.81***
			(0.14)	(0.14)
U.S. macro uncertainty			0.08***	0.08***
			(0.02)	(0.02)
GDP share				5.69***
				(0.97)
Stock market cap. Share				-4.38***
				(0.82)
Constant	0.30***	0.27***	0.34***	0.35***
	(0.07)	(0.07)	(0.08)	(0.08)
Adj. R-squared	30.93	31.44	29.56	29.70
N	21517	20213	17935	17935

Table 3: Alternative contagion indexes, summary statistics

This table reports a set of summary statistics for the alternative contagion measures described in section 2.2. In the benchmark contagion measure, unexpected returns are obtained from the benchmark factor model specification (see table 2) and jumps are detected using a 5% threshold. In measures 2 to 4, unexpected returns are obtained from the vulnerability, uncertainty, and size models, respectively (see table 2). In measure 5, unexpected returns are obtained from an international CAPM model in which the betas are constant over time. In measures 6 and 7, unexpected returns are obtained from the benchmark factor model specification, while the thresholds used to detect jumps are 10% and 2%, respectively. Specification 9 is the benchmark good contagion measure. AR(1) is the first-order autoregressive coefficient. *** represent significance at the 1% confidence level.

	1	2	3	4	5	6	7	8
	Benchmark	Vulnerability model	Uncertainty model	Size model	Unconditional beta	Treshold at 10%	Treshold at 2%	Good Contagion
Episodes of contagion	168	180	193	196	178	370	58	186
Mean	12.06	12.40	12.79	12.67	11.39	13.67	11.16	11.66
Maximum	56.25	54.84	54.84	54.84	56.25	65.63	43.75	56.25
Minimum	6.25	6.25	6.25	6.25	6.25	6.25	6.25	6.25
AR(1)	0.37***	0.36***	0.38***	0.36***	0.39***	0.31***	0.42***	0.31***
Coincidence in episodes with benchmark	100.00	95.83	94.64	92.86	85.71	100.00	34.52	47.02
Correlation with benchmark	1.00	0.96	0.92	0.91	0.93	0.82	0.83	0.34

Table 4: Predictive power of contagion for stock returns

This table reports the results for the following regression setting:

$$r_{j,t+h} = b_j(h) + b_C(h)C_t + \mathbf{B(h)W_t} + u_{j,t+h},$$

where $r_{j,t}$ is the excess log return of the headline index of country j and C_t is either the contagion index (panel A), the bad component of contagion (panel B), or the good component of contagion (panel C). $\mathbf{W_t}$ is a vector of global control variables that includes the U.S. stock index realized volatility, the U.S. variance risk premium (VP), and the global correlation (see appendix B). To facilitate the interpretation of the results, the coefficients are multiplied by 100 (if contagion were to increase from 0 to 100; that is, all countries simultaneously experience unusual returns). For all horizons, returns are converted to the weekly frequency, to make them directly comparable to the summary statistics in table 1. Gains in R^2 are calculated as the difference between the R^2 for the multivariate regression with all the variables and that with only the control variables. Standard deviations are corrected by panel-data Newey West with h lags and are reported in parenthesis. *, **, and *** represent significance at the standard 10, 5, and 1 percent confidence levels, respectively.

A. Contagion

Horizon (weeks)	1	4	8	12	26	52
Contagion	-2.03***	-0.44***	-0.64***	-0.60***	-0.54***	-0.40***
	(0.29)	(0.15)	(0.12)	(0.10)	(0.07)	(0.04)
U.S. Volatility	0.22	-0.67***	-0.32	-0.21	0.53**	0.64***
	(0.36)	(0.26)	(0.22)	(0.19)	(0.21)	(0.18)
VP	0.16	1.55***	2.29***	2.93***	2.02***	0.61**
	(0.69)	(0.44)	(0.36)	(0.30)	(0.26)	(0.24)
Avg. Correlation	0.46	1.37***	1.70***	1.67***	0.72***	-0.12
	(0.32)	(0.23)	(0.19)	(0.16)	(0.15)	(0.17)
Gains in R^2	0.31	0.07	0.32	0.41	0.63	0.65

B. Bad contagion

Bad contagion	-1.90***	-0.71***	-0.70***	-0.75***	-0.71***	-0.38***
	(0.37)	(0.18)	(0.13)	(0.11)	(0.08)	(0.05)
U.S. Volatility	-0.78**	-0.77***	-0.59***	-0.44**	0.34*	0.44**
	(0.34)	(0.24)	(0.21)	(0.19)	(0.20)	(0.18)
VP	-0.53	1.43***	2.08***	2.73***	1.84***	0.47**
	(0.68)	(0.42)	(0.35)	(0.29)	(0.25)	(0.24)
Avg. Correlation	0.75**	1.41***	1.79***	1.74***	0.77***	-0.06
	(0.31)	(0.22)	(0.19)	(0.17)	(0.15)	(0.18)
Gains in R^2	0.14	0.10	0.19	0.32	0.55	0.29

C. Good contagion

Good contagion	-2.14***	0.22	-0.47***	-0.38***	-0.33***	-0.35***
	(0.55)	(0.21)	(0.16)	(0.14)	(0.09)	(0.05)
U.S. Volatility	-0.60*	-1.13***	-0.66***	-0.56***	0.21	0.44**
	(0.33)	(0.24)	(0.21)	(0.19)	(0.20)	(0.19)
VP	-0.09	1.30***	2.16***	2.78***	1.89***	0.55**
	(0.68)	(0.44)	(0.36)	(0.30)	(0.26)	(0.24)
Avg. Correlation	0.70**	1.49***	1.80***	1.77***	0.80***	-0.06
	(0.32)	(0.22)	(0.19)	(0.17)	(0.15)	(0.17)
Gains in R^2	0.16	0.01	0.08	0.07	0.11	0.22

Table 5: Predictive power of bad contagion for stock returns, alternative control variables

This table reports the results for alternative specifications of the following regression setting:

$$r_{j,t+8} = b_j + b_C C_t + \mathbf{B W_t} + u_{j,t+8},$$

where $r_{j,t}$ is the log excess return of the headline index of country j and C_t is the bad component of contagion. $\mathbf{W_t}$ is a vector of control variables that changes in every specification. The specification in column 1 is that in panel B of table 4 (repeated here again for convenience). Country jumps is a dummy that takes a value of 1 if a jump is detected in country j, irrespective of whether or not there is contagion. The U.S. macro uncertainty is the Citibank macroeconomic uncertainty index. Avg. DCC Correlation is the equally-weighted average of pairwise DCC correlations, which are calculated as explained in appendix B. To facilitate the interpretation of the results, coefficients are multiplied by 100 (if contagion were to increase from 0 to 100; that is, all countries simultaneously experience unusual returns). For all horizons, returns are converted to the weekly frequency, to make them directly comparable to the summary statistics in table 1. To save space, I only report the parameters for the 2-month (8 weeks) horizon. The gains in R^2 are calculated as the difference between the R^2 for the multivariate regression with all the variables and that with only the control variables. Standard deviations are corrected by panel-data Newey West with 8 lags and are reported in parenthesis. *, **, and *** represent significance at the standard 10, 5, and 1 percent confidence levels, respectively.

	1	2	3	4	5
Bad contagion	-0.70***	-1.52***	-1.19***	-1.77***	-0.74***
	(0.13)	(0.21)	(0.17)	(0.21)	(0.14)
U.S. volatility	-0.59***	0.51**	-1.56***	0.79***	-0.27
	(0.21)	(0.26)	(0.19)	(0.23)	(0.20)
U.S. VP	2.08***	2.21***	0.87***	2.24***	1.79***
	(0.35)	(0.43)	(0.12)	(0.41)	(0.38)
Avg. Correlation	1.79***	0.17	0.00***	-0.06	
	(0.19)	(0.20)	(0.00)	(0.20)	
Dividend yields		-4.40			
		(2.74)			
Country jumps			2.84		
			(5.03)		
U.S. macro uncertainty				0.20**	
				(0.08)	
Avg. DCC Correlation					1.42***
					(0.34)
Gains in R^2	0.19	0.60	0.64	0.84	0.21

Table 6: Alternative financial stability indicators, summary statistics

This table reports a set of summary statistics for the alternative financial stability indicators described in appendix A. To save space, I only report the summary statistics for a subset of the 33 countries in the sample.

A. Annualized one-week excess returns for financial sector representative index

	World	Australia	Brazil	Canada	Germany	Ireland	Japan	Malaysia	Netherlands	Portugal	Spain	Sweden	Thailand	U.S.
Mean	-0.02	0.08	0.18	0.03	-0.21	-0.39	-0.14	0.08	-0.25	-0.37	-0.08	0.08	0.07	-0.05
St. Dev.	2.82	2.79	3.99	3.75	4.65	9.16	4.09	2.44	4.47	4.57	4.53	3.95	4.21	4.66
Median	0.15	0.32	0.21	-0.09	-0.05	-0.11	-0.15	0.12	-0.12	-0.10	0.10	0.14	0.14	0.07
Skewness	-1.38	-0.97	-0.40	0.51	-0.84	-0.66	-0.20	0.01	-0.79	-0.61	-0.30	-0.85	-0.49	0.04
Kurtossis	14.51	8.42	6.87	6.83	17.75	14.20	4.29	10.23	16.82	7.91	11.75	11.88	7.07	17.54

B. Country average of banks' CDS spreads

	World	Australia	Brazil	Canada	Germany	Ireland	Japan	Malaysia	Netherlands	Portugal	Spain	Sweden	Thailand	U.S.
Mean	129.75	69.09	202.15	58.84	83.57	343.63	69.27	81.98	71.23	249.59	131.91	70.35	123.81	102.03
St. Dev.	140.90	58.97	116.17	44.07	67.26	469.28	55.15	66.35	61.62	366.84	138.49	61.65	96.57	83.05
Median	88.42	68.42	158.24	56.98	87.55	152.45	62.19	81.08	65.02	83.46	100.87	70.66	124.55	105.77
Skewness	1.02	0.46	1.41	0.49	0.57	1.53	0.66	1.46	0.70	1.66	1.05	0.68	1.56	0.66
Kurtossis	3.36	2.04	4.30	2.05	2.52	4.29	2.28	5.47	2.50	4.50	3.11	2.39	5.18	2.65

Table 6: Alternative financial stability indicators, summary statistics, continued

C. SRISK to GDP ratio

	World	Australia	Brazil	Canada	Germany	Ireland	Japan	Malaysia	Netherlands	Portugal	Spain	Sweden	Thailand	U.S.
Mean	3.52	3.10	0.94	3.98	5.39	6.21	6.77	0.82	8.55	2.06	3.05	6.35	1.12	2.70
St. Dev.	3.61	3.92	1.10	3.81	2.48	5.04	4.55	0.60	5.47	2.66	4.00	4.90	1.03	1.72
Median	2.58	0.44	0.49	2.20	4.90	5.16	5.46	0.79	6.53	0.03	0.27	4.22	0.70	1.81
Skewness	1.46	1.06	1.48	0.84	0.16	0.75	0.39	1.37	0.05	0.75	0.96	0.58	0.94	0.85
Kurtossis	6.32	3.01	4.20	2.34	1.99	2.81	1.80	6.79	1.65	1.92	2.47	1.99	2.53	2.76

D. Country average of capital-to-assets ratios

	World	Australia	Brazil	Canada	Germany	Ireland	Japan	Malaysia	Netherlands	Portugal	Spain	Sweden	Thailand	U.S.
Mean	7.60	6.15	10.21	4.37	4.72	6.73	4.98	8.77	4.06	6.61	6.41	4.67	8.37	11.36
St. Dev.	0.95	0.39	0.66	0.49	0.55	3.09	0.58	0.89	0.77	0.69	0.52	0.33	0.69	1.06
Median	7.57	6.07	10.39	4.57	4.49	5.44	5.10	9.01	4.24	6.53	6.26	4.80	8.36	11.69
Skewness	-0.04	0.89	-0.45	-0.25	0.91	1.19	-0.85	-0.25	0.04	0.80	0.60	-0.81	0.07	-0.51
Kurtossis	2.35	3.75	2.22	1.40	2.40	3.06	3.52	1.69	1.74	3.16	2.30	2.60	2.27	2.07

E. Country average of regulatory-capital-to-risk-weighted-assets ratios

	World	Australia	Brazil	Canada	Germany	Ireland	Japan	Malaysia	Netherlands	Portugal	Spain	Sweden	Thailand	U.S.
Mean	14.63	11.48	16.94	14.70	15.37	15.94	13.55	15.72	14.17	11.26	12.30	13.13	15.21	13.82
St. Dev.	1.71	0.86	0.77	1.07	2.34	4.19	1.11	1.35	2.08	1.28	0.95	4.42	1.11	0.81
Median	14.51	11.74	16.96	14.82	15.01	13.46	13.30	15.31	13.72	11.78	11.99	11.55	15.40	14.10
Skewness	0.16	0.07	0.14	-0.73	0.03	0.49	0.60	0.33	1.06	-0.06	1.10	1.55	-0.40	-0.13
Kurtossis	2.24	2.07	2.58	2.89	1.49	1.56	2.24	1.71	3.08	1.64	2.91	3.69	2.17	1.39

Table 7: Predictive power of contagion for market-based financial stability indicators

This table reports the results for the following regression setting:

$$\Delta FS_{j,t,t+h} = b_j(h) + b_C(h)C_t + \mathbf{B(h)W_t} + u_{j,t+h},$$

where $\Delta FS_{j,t,t+h}$ is the change in each one of the market-based financial stability indicators in table 6 and C_t is the bad component of contagion. $\mathbf{W_t}$ is a vector of global control variables that includes the U.S. stock index realized volatility, the U.S. variance risk premium (VP), and the global correlation (see appendix B). To facilitate the interpretation of the results, coefficients for bank stock returns (panel A) are multiplied by 100 (if contagion were to increase from 0 to 100; that is, all countries simultaneously experience unusual returns), and presented at the weekly frequency. The gains in R^2 are calculated as the difference between the R^2 for the multivariate regression with all the variables and that with only the control variables. Standard deviations are corrected by panel-data Newey West with h lags and are reported in parenthesis. *, **, and *** represent significance at the standard 10, 5, and 1 percent confidence levels, respectively.

A. Bank index returns

Horizon (weeks)	1	4	8	12	26	52
Bad contagion	-6.47***	-2.53***	-1.93***	-1.24***	-1.21***	-0.52***
	(0.76)	(0.33)	(0.27)	(0.21)	(0.16)	(0.09)
U.S. Volatility	-6.28***	-2.13***	-1.25***	-0.91**	0.93***	1.01***
	(0.68)	(0.46)	(0.45)	(0.40)	(0.29)	(0.25)
VP	-24.55***	-3.93***	-0.11	2.67***	2.19***	0.61*
	(1.15)	(0.71)	(0.65)	(0.50)	(0.42)	(0.36)
Avg. Correlation	0.00	0.00	0.01**	0.01***	-0.15	-0.01***
	(0.38)	(0.30)	(0.28)	(0.26)	(0.22)	(0.24)
Gains in R^2	0.96	0.59	0.63	0.37	0.67	0.24

B. Bank CDS spreads

Bad contagion	28.16***	61.34***	97.05***	51.83***	45.91*	-35.50
	(5.40)	(11.49)	(15.98)	(18.02)	(26.60)	(32.16)
U.S. Volatility	-9.00***	-24.62***	-55.22***	-56.52**	-202.56***	-243.36***
	(3.27)	(9.49)	(18.02)	(25.35)	(42.14)	(59.74)
VP	6.11	31.42*	42.50	-24.19	-96.81	224.61
	(7.00)	(18.17)	(31.84)	(33.76)	(67.59)	(138.34)
Avg. Correlation	0.11***	0.40***	0.63***	0.73**	162.64***	3.60***
	(3.42)	(11.37)	(21.62)	(28.25)	(46.48)	(65.27)
Gains in R^2	0.52	0.66	0.78	0.15	0.05	0.02

C. SRISK to GDP ratio

Bad contagion	0.41***	0.74***	1.14***	0.77***	1.45***	1.38***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
U.S. Volatility	0.00	0.00***	-0.01***	-0.02***	-0.04***	-0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
VP	0.01***	0.00	-0.01***	-0.02***	-0.04***	-0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Avg. Correlation	0.00**	0.00**	0.00	0.00	0.91**	0.03***
	(0.03)	(0.11)	(0.19)	(0.25)	(0.46)	(0.85)
Gains in R^2	0.51	0.43	0.53	0.16	0.26	0.13

Table 8: Predictive power of contagion for capital-to-assets ratios

This table reports the results for the following regression setting:

$$\Delta FS_{j,t,t+1} = b_j(h) + b_C(h)C_t + \mathbf{B(1)W_t} + u_{j,t+1},$$

where $\Delta FS_{j,t,t+h}$ is the change in each one of capital-to-assets ratios in table 6 and C_t is the bad component of contagion. $\mathbf{W_t}$ is a vector of global control variables that includes the U.S. stock index realized volatility, the U.S. variance risk premium (VP), and the global correlation (see appendix B). The gains in R^2 are calculated as the difference between the R^2 for the multivariate regression with all the variables and that with only the control variables. Standard deviations are corrected by panel-data Newey West with 1 lag and are reported in parenthesis. *, **, and *** represent significance at the standard 10, 5, and 1 percent confidence levels, respectively.

	Capital to assets	Regulatory capital to risk-weighted assets
Bad contagion	-1.09***	-1.00***
	(0.00)	(0.00)
U.S. Volatility	0.01***	0.01***
	(0.00)	(0.00)
VP	0.02***	0.01*
	(0.01)	(0.00)
Avg. Correlation	0.00	-0.01***
	(0.33)	(0.21)
Gains in R^2	0.45	1.08

Table 9: Financial stability implications of bad contagion, alternative control variables

This table reports the results for alternative specifications of the following regression setting:

$$\Delta FS_{j,t,t+h} = b_j(h) + b_C(h)C_t + \mathbf{B(h)W_t} + u_{j,t+h},$$

where $\Delta FS_{j,t,t+h}$ is the change in each one of the market-based financial stability measures in table 6 and C_t is the bad component of contagion. $\mathbf{W_t}$ is a vector of control variables that changes in every specification. The specification in column 1 is that in tables 7 and 8 but, to save space, I only report the coefficients for the 2-month (8 weeks) horizon for the market-based variables and for the 1-quarter horizon for the capital-to-assets ratios. Country jumps is a dummy that takes a value of 1 if a jump is detected in country j, irrespective of whether or not there is contagion. The U.S. macro uncertainty is the Citibank macroeconomic uncertainty index. Avg. DCC Correlation is the equally-weighted average of pairwise DCC correlations, which are calculated as explained in appendix B. The gains in R^2 are calculated as the difference between the R^2 for the multivariate regression with all the variables and that with only the control variables. Standard deviations are corrected by panel-data Newey West with h lags for market-based measures and 1 lag for capital-to-assets ratios, and are reported in parenthesis. *, **, and *** represent significance at the standard 10, 5, and 1 percent confidence levels, respectively.

A. Bank index returns

	1	2	3	4	5
Bad contagion	-1.93***	-3.84***	-2.83***	-3.83***	-1.94***
	(0.27)	(0.50)	(0.35)	(0.48)	(0.28)
U.S. volatility	-1.25***	-0.66	0.35**	-0.28	-1.15***
	(0.45)	(0.51)	(0.17)	(0.50)	(0.41)
U.S. VP	-0.11	-0.10	-0.58***	0.35	-0.25
	(0.65)	(0.83)	(0.08)	(0.79)	(0.67)
Avg. Correlation	0.01**	0.03	0.00***	-0.11	
	(0.28)	(0.36)	(0.00)	(0.34)	
Dividend yields		1.44			
		(5.52)			
Country jumps			-5.50		
			(7.65)		
U.S. macro uncertainty				0.05	
				(0.16)	
Avg. DCC Correlation					0.64
					(0.51)
Gains in R^2	0.63	1.45	1.49	1.52	0.63

Table 9: Financial stability implications of bad contagion, alternative control variables, continued

B. Bank CDS spreads

	1	2	3	4	5
Bad contagion	97.05***	96.53***	41.70**	91.09***	92.77***
	(15.98)	(16.37)	(17.87)	(15.18)	(15.76)
U.S. volatility	-55.22***	-58.48***	39.40***	-117.25***	-15.41
	(18.02)	(21.02)	(12.17)	(22.29)	(19.45)
U.S. VP	42.50	39.67	-15.82***	11.30	74.23**
	(31.84)	(29.24)	(4.94)	(31.40)	(32.50)
Avg. Correlation	63.38***	63.39***	-0.05***	103.18***	
	(21.62)	(22.35)	(0.01)	(26.12)	
Dividend yields		51.47			
		(261.15)			
Country jumps			502.83		
			(513.82)		
U.S. macro uncertainty				-34.78***	
				(7.54)	
Avg. DCC Correlation					-28.40
					(33.65)
Gains in R^2	0.78	0.76	0.15	0.68	0.71

Table 9: Financial stability implications of bad contagion, alternative control variables, continued

C. SRISK to GDP ratio

	1	2	3	4	5
Bad contagion	1.14***	2.00***	0.70***	1.95***	1.11***
	(0.00)	(0.24)	(0.17)	(0.23)	(0.14)
U.S. volatility	-0.01***	-1.65***	1.00	-1.78***	-1.13***
	(0.00)	(0.27)	(0.98)	(0.26)	(0.21)
U.S. VP	-0.01***	-1.14***	0.73	-1.13***	-0.84**
	(0.00)	(0.42)	(0.48)	(0.39)	(0.34)
Avg. Correlation	0.00	0.69	-0.19***	0.64***	
	(0.19)	(0.22)	(0.00)	(0.22)	
Dividend yields		-2.50			
		(2.50)			
Country jumps			3.75		
			(4.60)		
U.S. macro uncertainty				-0.04	
				(0.09)	
Avg. DCC Correlation					-0.14
					(0.30)
Gains in R^2	0.53	1.00	0.23	1.02	0.50

Table 9: Financial stability implications of bad contagion, alternative control variables, continued

D. Capital-to-assets ratio

	1	2	3	4	5
Bad contagion	-1.09***	-1.10***	2.84**	-0.95**	-1.00***
	(0.00)	(0.40)	(1.25)	(0.41)	(0.39)
U.S. volatility	0.01***	1.49***	16.29	1.29***	1.55***
	(0.00)	(0.39)	(18.18)	(0.31)	(0.36)
U.S. VP	0.02***	1.52***	-48.55	1.61***	1.76**
	(0.01)	(0.57)	(29.70)	(0.58)	(0.73)
Avg. Correlation	0.00	-0.24	0.04***	-0.12	
	(0.33)	(0.34)	(0.01)	(0.35)	
Dividend yields		-0.50			
		(2.85)			
Country jumps			-1.04		
			(21.15)		
U.S. macro uncertainty				-0.08	
				(0.07)	
Avg. DCC Correlation					-0.49
					(0.49)
Gains in R^2	0.45	0.45	1.27	0.30	0.38

Table 9: Financial stability implications of bad contagion, alternative control variables, continued

E. Regulatory-capital-to-risk-weighted-assets ratio

	1	2	3	4	5
Bad contagion	-1.00***	-0.98***	2.84	-0.97***	-0.85***
	(0.00)	(0.28)	(10.33)	(0.29)	(0.28)
U.S. volatility	0.01***	0.88***	-52.57***	0.93***	0.78***
	(0.00)	(0.24)	(9.97)	(0.21)	(0.25)
U.S. VP	0.01*	0.58	0.32	0.62	0.62
	(0.00)	(0.36)	(5.23)	(0.38)	(0.45)
Avg. Correlation	-0.01***	-0.59***	0.00	-0.59***	
	(0.21)	(0.21)	(0.01)	(0.21)	
Dividend yields		1.06			
		(1.36)			
Country jumps			-1.26		
			(13.47)		
U.S. macro uncertainty				-0.02	
				(0.05)	
Avg. DCC Correlation					-0.30
					(0.30)
Gains in R^2	1.08	1.04	0.02	0.91	0.79

Table 10: Determinants of heterogeneous exposures to contagion

This table reports the estimate of coefficient δ_1 in the following regression setting:

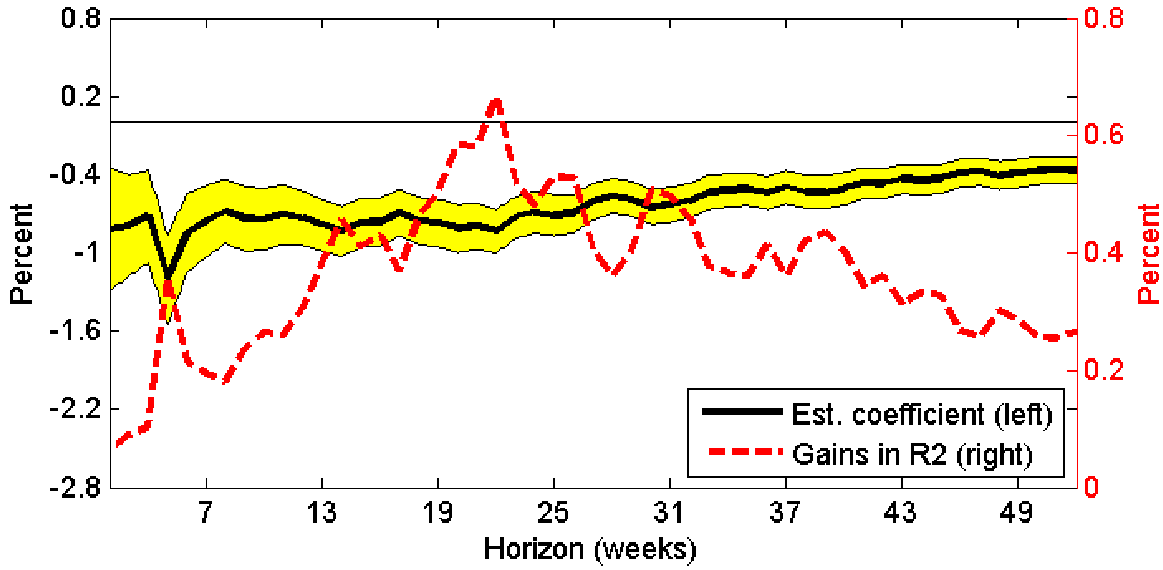
$$\Delta FS_{j,t,t+h} = b_j(h) + b_{C,j,t}(h)C_t + \mathbf{B(h)W_t} + u_{j,t+h},$$

where

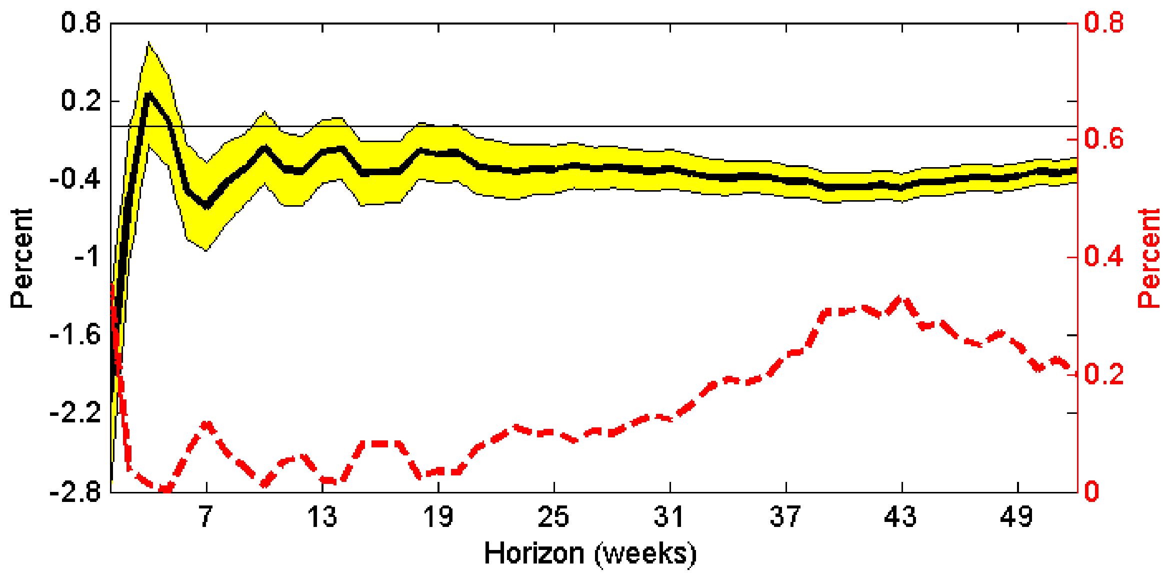
$$b_{C,j,t} = \delta_0 + \delta_1 y_{j,t-1},$$

where $y_{j,t}$ is each one of the variables in the set of country-specific determinants of international integration introduced in section 2.2 and explained in detail in appendix A. Standard deviations are corrected by panel-data Newey West with h lags and are reported in parenthesis. *, **, and *** represent significance at the standard 10, 5, and 1 percent confidence levels, respectively. To save space, I only report the coefficients for the 2-months horizon.

	Bank index returns	CDS spreads	SRISK to GDP
Current account deficit	-1.35	1.24	0.87
	(3.31)	(1.06)	(1.15)
Foreign currency reserves	6.99***	-0.34	-0.59
	(2.67)	(0.94)	(0.91)
Market Capitalization	0.24	-0.11	0.31**
	(0.44)	(0.38)	(0.12)
Exports and imports	1.33	0.25	0.57**
	(0.95)	(0.32)	(0.25)
Bank intl. Claims	3.11	0.81	1.09**
	(3.39)	(1.15)	(0.49)
Assets by foreigners	0.11	-0.21	0.03
	(0.25)	(0.18)	(0.07)
Financial openness (Chinn Ito)	2.29*	0.56	1.35**
	(1.26)	(0.77)	(0.65)
Portfolio liabilities	37.05*	-3.32	0.96
	(19.01)	(3.71)	(6.23)
Sovereign yields	0.17	0.19	-0.06
	(0.26)	(0.18)	(0.06)



A. Bad contagion



B. Good contagion

Figure 1: Additional predictive power of bad and good contagion for stock returns

This figure reports the coefficients associated with each component of contagion from the following regression setting:

$$r_{j,t+h} = b_j(h) + b_{C^{bad}}(h)C_t^{bad} + b_{C^{good}}(h)C_t^{good} + \mathbf{B(h)W_t} + u_{j,t+h},$$

where $r_{j,t}$ is the log excess return of the headline index of country j and $\mathbf{W_t}$ is a vector of global control variables that includes the U.S. volatility, the U.S. variance risk premium (VP), and the global correlation (see appendix B). To facilitate the interpretation of the results, coefficients are multiplied by 100 (if contagion were to increase from 0 to 100; that is, all countries simultaneously experience unusual returns). For all horizons, returns are converted to the weekly frequency, to make them directly comparable to the summary statistics in table 1. The gains in R^2, the red dashed line, are calculated in this case as the difference between the R^2 for the multivariate regression with all the variables and that with only the control variables including either good contagion (panel A) or bad contagion (panel B). The shaded area corresponds to the 95 percent confidence interval calculated from Newey-West corrected standard deviations.

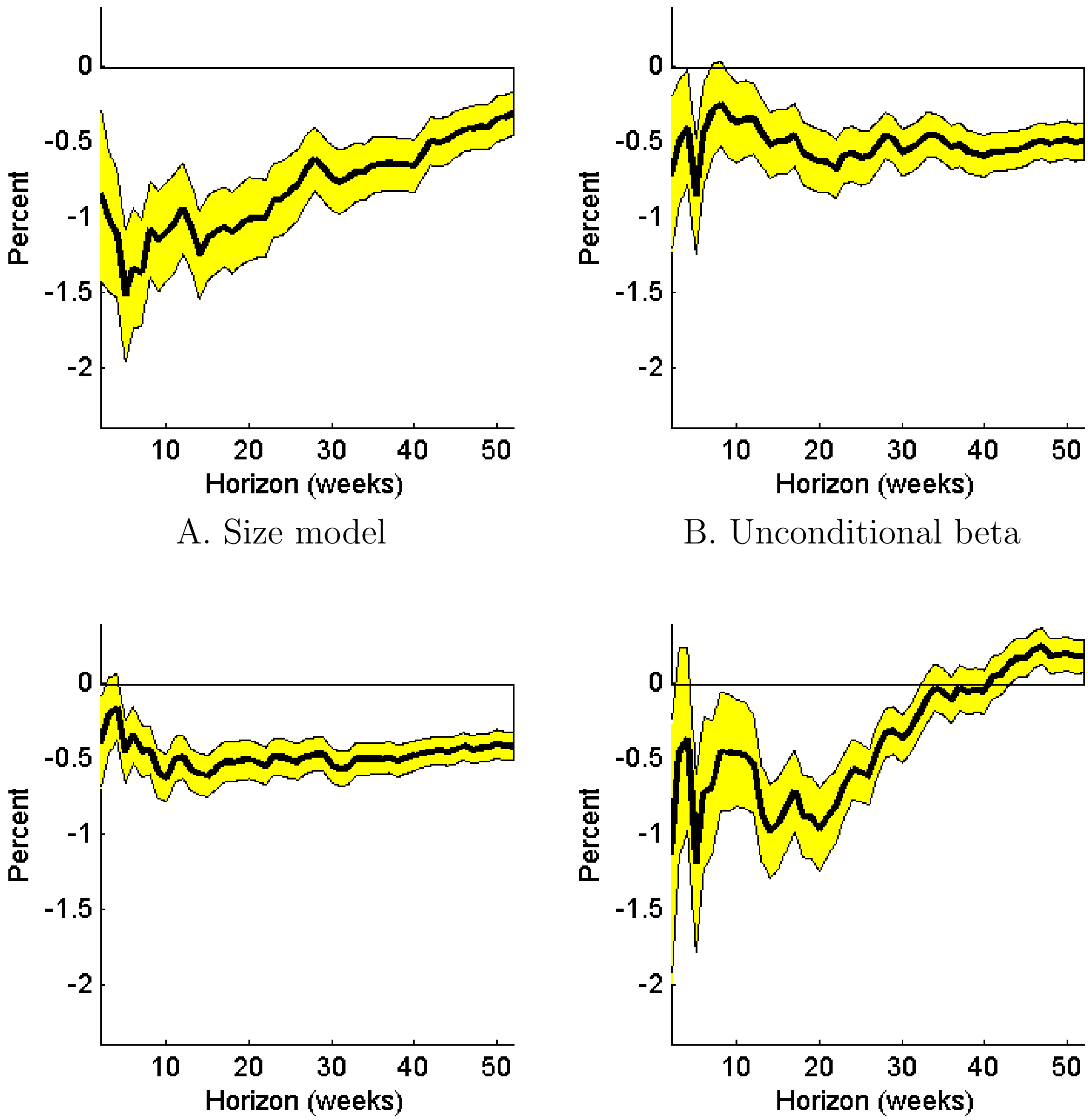


Figure 2: Predictive power of bad contagion for stock returns, alternative contagion measures

The figure shows the predictive power for stock returns of the alternative contagion measures introduced in section 2.2 (see also table 3). The shaded area corresponds to the 95 percent confidence interval calculated from Newey-West corrected standard deviations.

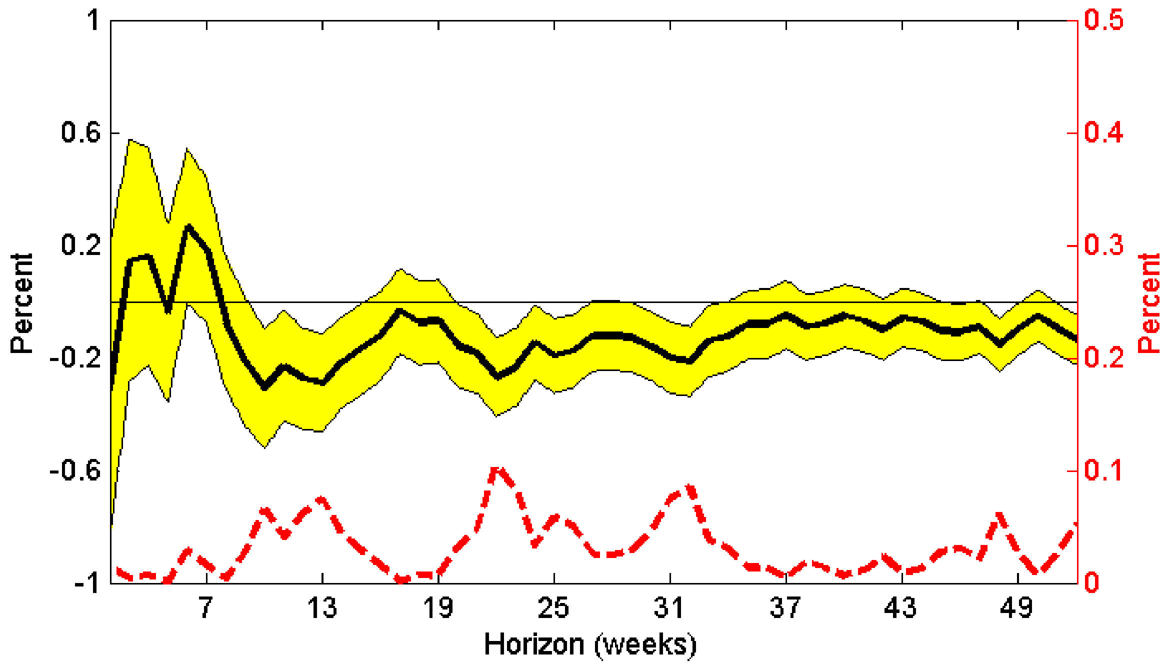
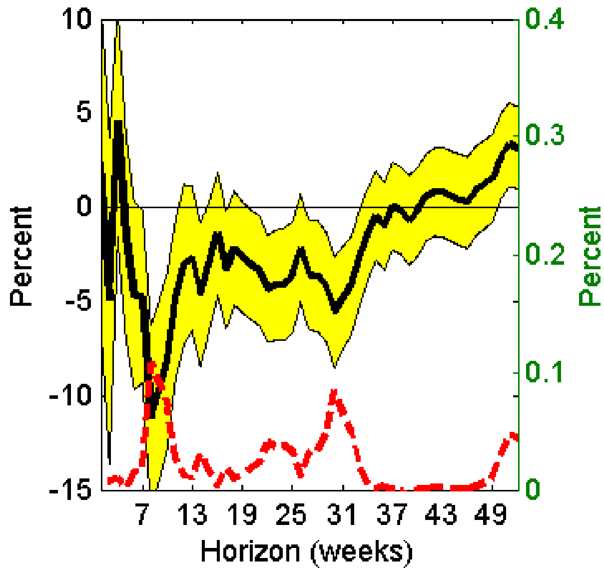
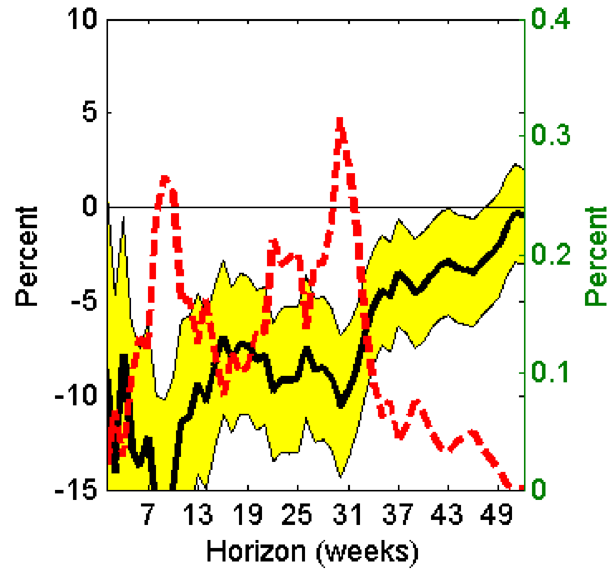


Figure 3: Predictive power of bad contagion, pre-GFC sample

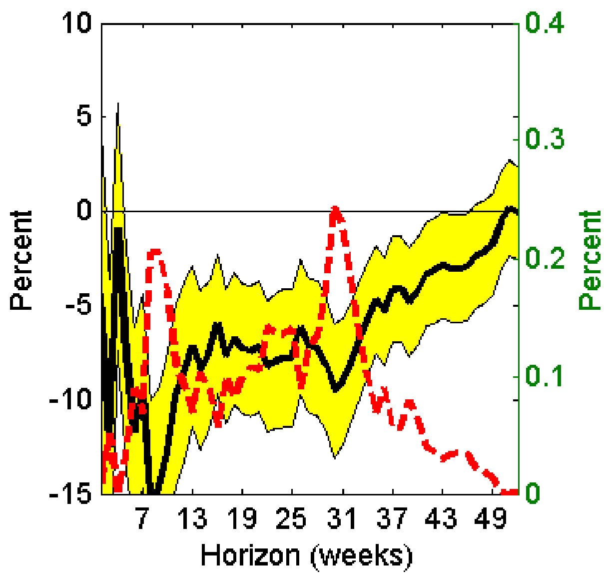
This figure reports the coefficients in the benchmark regression setting for the predictive power of bad contagion for stock returns (see table 4) for a subsample that ends in July 2008, just before the collapse of Lehman Brothers. The red dashed line represents the gains in predictive power from adding bad contagion to a multivariate regression including only the control variables. The shaded area corresponds to the 95 percent confidence interval calculated from Newey-West corrected standard deviations.



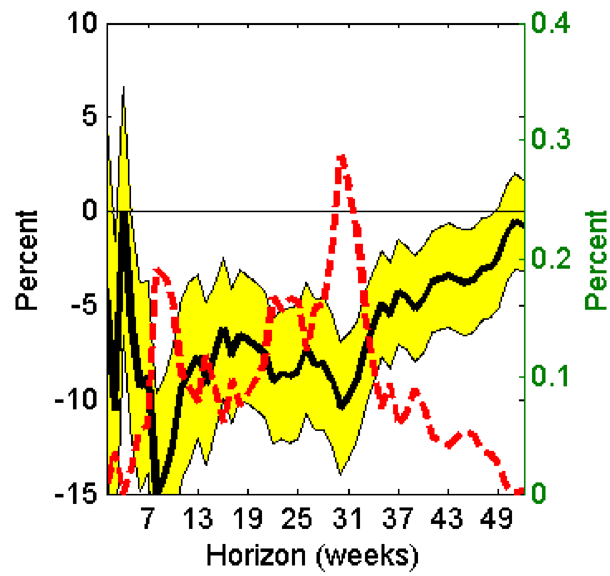
A. 10 % of countries



B. 25% of countries



C. 40% of countries



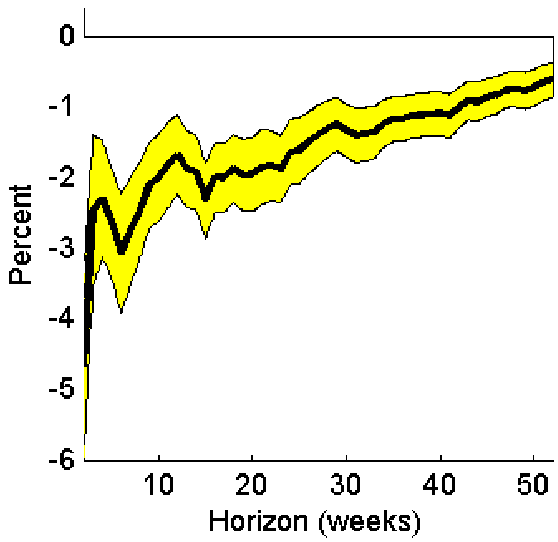
D. 50% of countries

Figure 4: Predictive power of bad contagion for stock returns, alternative contagion thresholds

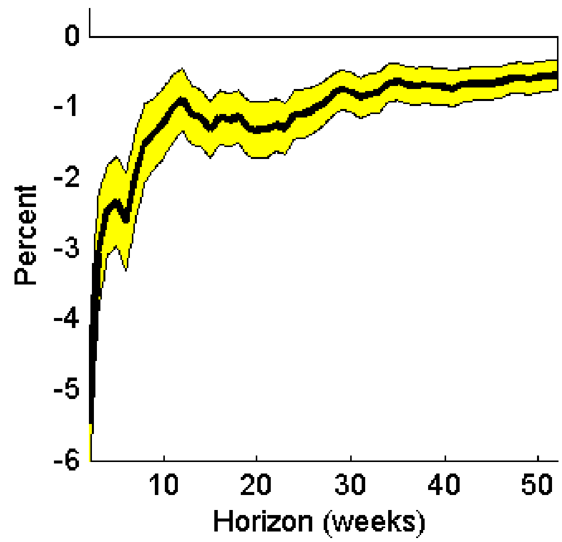
This table reports the results from the following regression setting:

$$r_{j,t+h} = b_j(h) + b_D(h)D_t + \mathbf{B(h)W_t} + u_{j,t+h},$$

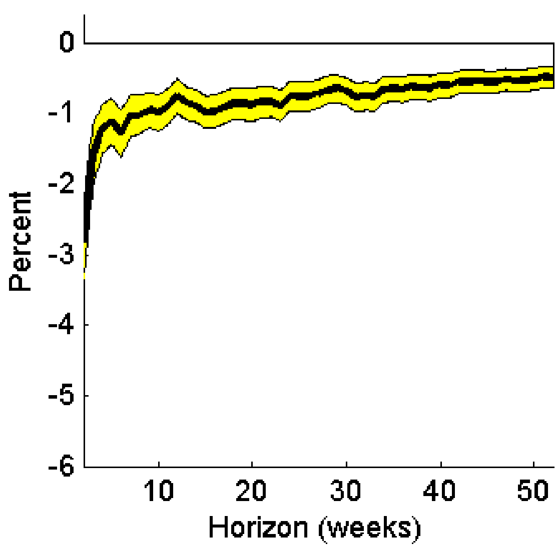
where D_t is a dummy that takes a value of 1 when contagion is lower than a certain threshold (proportion of countries involved in the contagion episode) and zero otherwise. The red dashed line represents the gains in predictive power from adding bad contagion to a multivariate regression including only the control variables. The shaded area corresponds to the 95 percent confidence interval calculated from Newey-West corrected standard deviations.



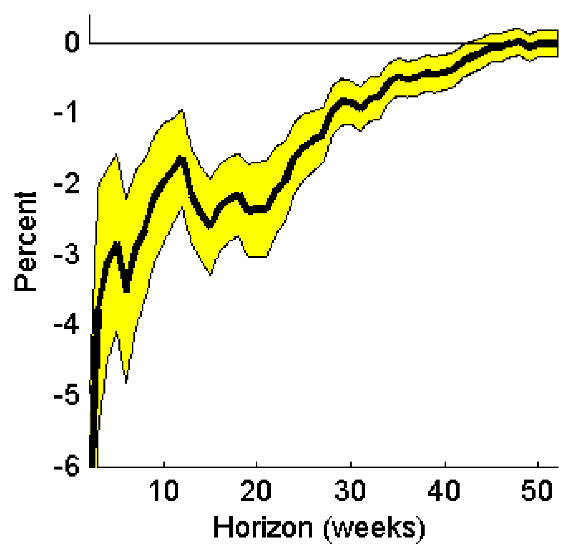
A. Size model



B. Unconditional beta



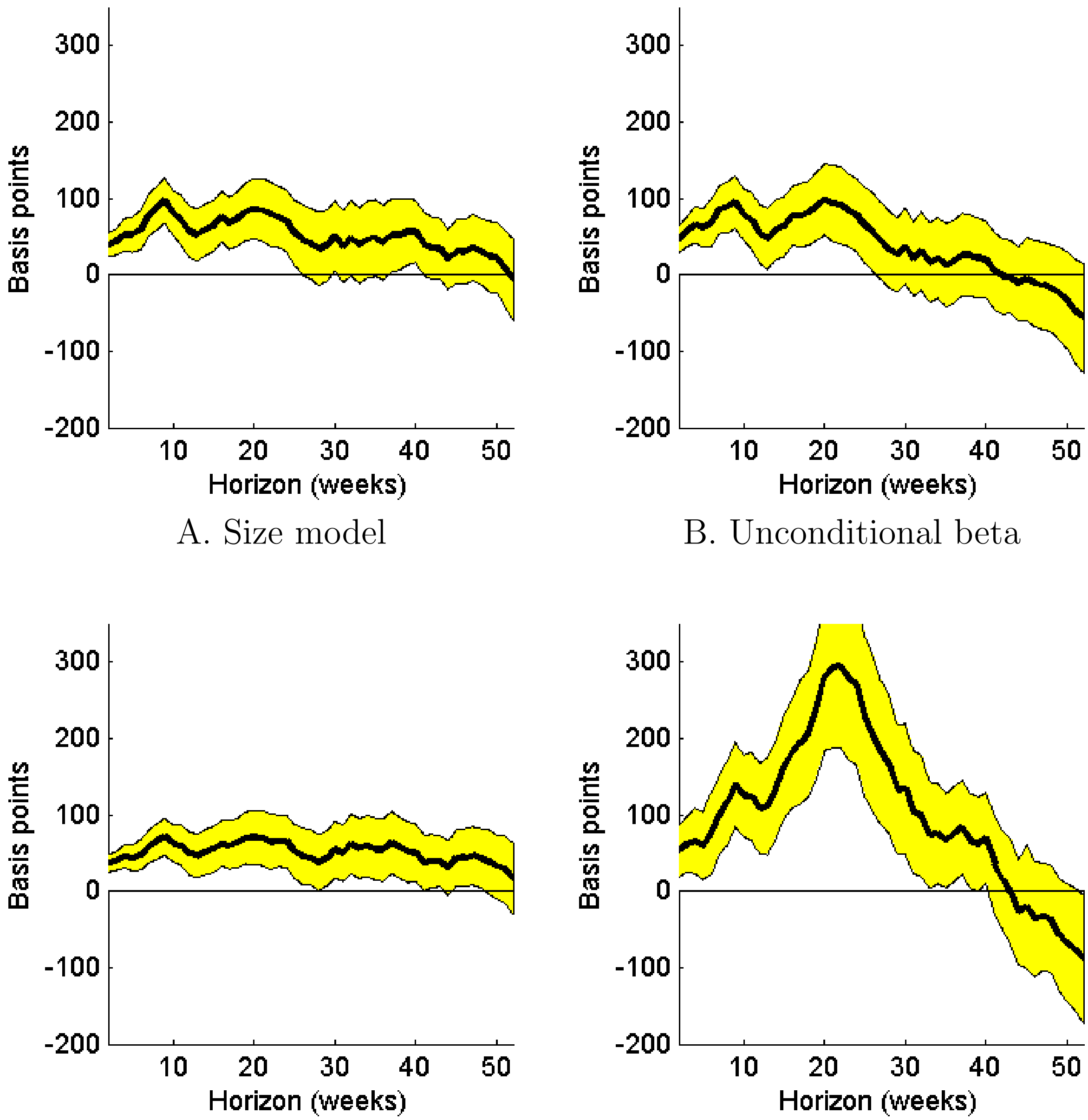
C. Threshold 10%



D. Threshold 2%

Figure 5: Predictive power of bad contagion for bank stock returns, alternative contagion measures

The figure shows the predictive power for bank stock returns of the alternative contagion measures introduced in section 2.2 (see also table 3). The shaded area corresponds to the 95 percent confidence interval calculated from Newey-West corrected standard deviations.

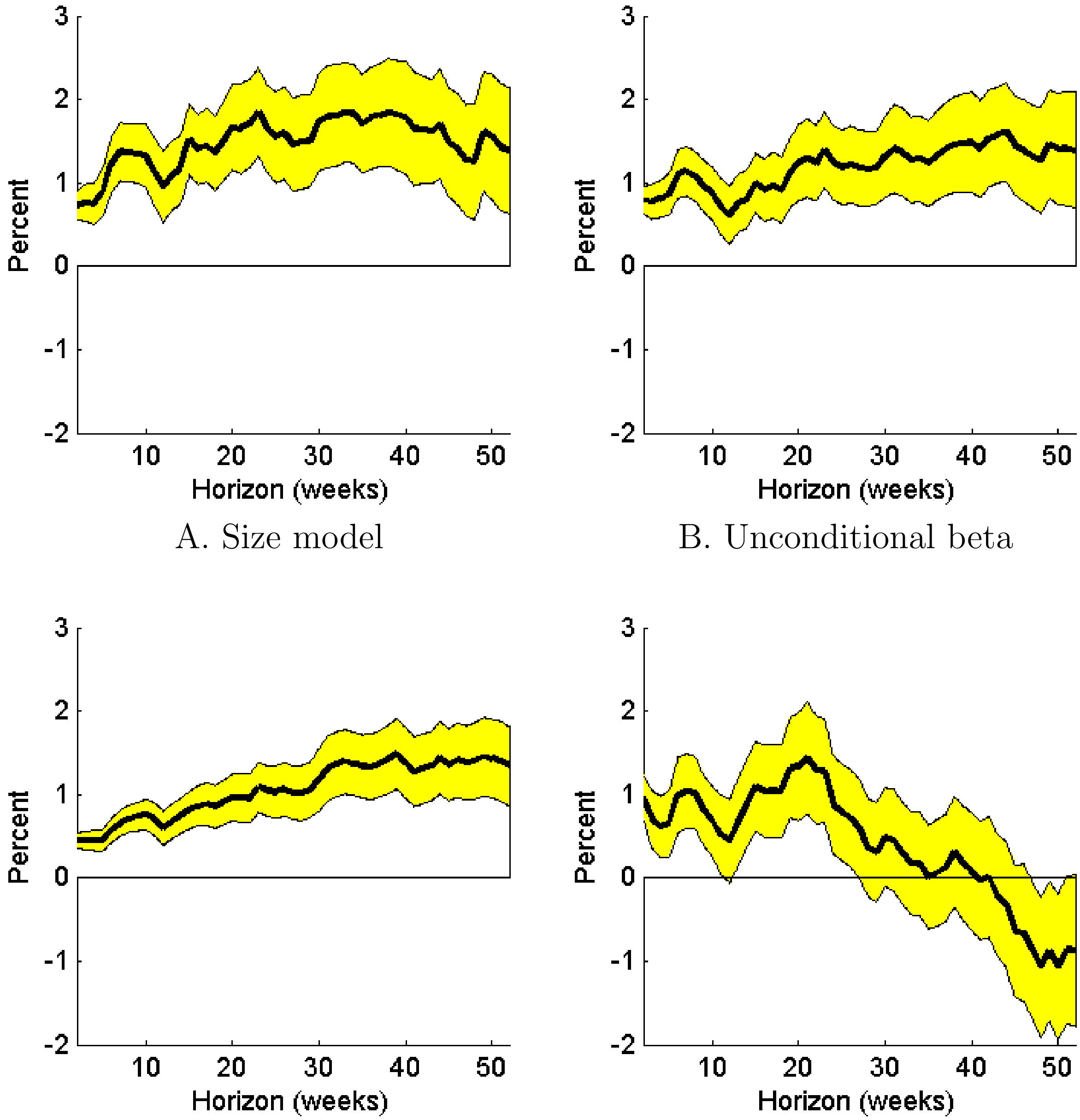


A. Size model　B. Unconditional beta

C. Threshold 10%　D. Threshold 2%

Figure 6: Predictive power of bad contagion for bank CDS spreads, alternative contagion measures

The figure shows the predictive power for bank CDS spreads of the alternative contagion measures introduced in section 2.2 (see also table 3). The shaded area corresponds to the 95 percent confidence interval calculated from Newey-West corrected standard deviations.



A. Size model B. Unconditional beta

C. Threshold 10% D. Threshold 2%

Figure 7: Predictive power of bad contagion for bank aggregate SRISK, alternative contagion measures

The figure shows the predictive power for SRISK ratios (SRISK to GDP) of the alternative contagion measures introduced in section 2.2 (see also table 3). The shaded area corresponds to the 95 percent confidence interval calculated from Newey-West corrected standard deviations.