

A Multicountry Measure of Comovement and Contagion in International Markets: Definition and Applications

by

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Abstract

This paper introduces a new measure of comovement and contagion of crises between countries, applies it to 16 world crises, including the current COVID-19 pandemic, and provides insights regarding the occurrence of contagion during these crises. Our measure demonstrates several important advantages over the extant measures of contagion. Traditional measures of contagion, such as increase in correlation, could be limited in scope since they are bivariate, whereas contagion is often a regional or global market phenomenon. The multiple comparisons that the binary correlations require in such cases could yield inconclusive or contradictory results and fail to capture the broad effects of the crisis on the regions. Moreover, during crises, a country's stock market volatility often increases, a phenomenon that could lead to a spurious indication of increased correlation with other countries (contagion). Corrections for this bias have been suggested, but they could adversely affect the power of the contagion tests and fail to detect genuine contagion. Using simulations, we show the robustness of our measure to changes in volatility and demonstrate its power to affirm instances of genuine contagion. Support for the power of our measure relative to an extant leading measure of contagion is also provided by analysis of the cases of the 1994 Mexican peso crisis, the 1997 East Asian crisis, and Black Monday, the 1987 US stock market crash.

JEL classifications: C12, C18, C58, G01, G15, G4, F36, F65

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I. Introduction

Correlation between the returns of stock markets around the world is a well-known phenomenon. This correlation, however, may take the form of contagion when a crisis in one country affects others, and may even lead to a world crisis.¹ There is a lack of consensus

¹ The literature related to this phenomenon relies on two concepts: comovement and contagion. Comovement, often measured by unconditional cross-market correlation between stock market indices, describes the simultaneous movement of financial markets in periods of both stability and crisis. Contagion is the change (increase) in the propagation mechanism of shocks between countries in periods of crisis. In

regarding the causes of contagion. Many of the hypotheses concerning the causes of contagion are economic. These include fundamental linkages between countries, trade relations, the international banking system, geographical proximity, and macro similarities (see, e.g., Rigobon, 2019). Behavioral explanations have also been offered. These theories contend that investor behavior during turbulent times may differ from behavior during stable times in ways that lead to contagion.² Researchers are usually not able to determine whether the underlying reason for a crisis is fundamental or behavioral because the contagion processes of crises seem to be similar regardless of the causes.

The traditional methods of testing for contagion consist of identifying the breakpoint that marks the outbreak of a crisis and examining whether there is a shift in correlation between markets immediately after it. However, correlation is a bivariate measure, while contagion is often a regional or even a global phenomenon. Using correlations to detect contagion within a regional framework requires many bilateral comparisons that could be too specific and thus fail to reveal global or regional insights.³ Moreover, correlations often yield conflicting or baffling results (such as finding that some countries within a region have been infected by a crisis and some were not, with no apparent reason).

Boyer, Gibson, and Loretan (1997), Forbes and Rigobon (2002) (henceforth FR), and Rigobon (2003) have pointed out another issue that affects traditional measures of contagion. They argue that during crises, when markets are volatile, estimates of correlation coefficients tend to be upward-biased and hence observed increased correlation during turbulent periods may be spurious. (A proof, following FR, is provided in Appendix 1).

In addition to the above concerns, other issues (i.e., omitted variables, simultaneous equations, and asymmetric behavior of stock returns) may affect the reliability of shifts in correlation as measures of contagion. To address these matters, researchers have expanded the set of methods used in modeling and testing comovement and contagion. Among these, one may find the multivariate ARCH and GARCH models, the multinomial logistic

other words, it is the increase in comovement (correlation) between the financial markets of one or more countries in crisis periods. This term was introduced by King and Wadhvani (1990).

² Barberis et al. (2005); Khan and Park, (2009); and Boyer, (2011) advocate behavioral explanations for contagion. Brzoza-Brzezina et al., (2018) and Park and Shin (2020) have emphasized the importance of the international banking system in the propagation of contagion. Contagion may also occur within a country when information from some firms affects investors' opinions about others (see, e.g., Cazier et al., 2020).

³ Most studies focus on a small number of countries (e.g., Aloui et al., 2011; Connolly and Wang, 2003). Dungey et al., (2005) introduced a joint residual test of contagion based on a factor structure approach. The authors controlled for common shocks that affect all asset returns. Although their proposed methodology supports regional testing, it is difficult to apply.

regression model, co-breaking analysis, and Granger-causality tail risk networks (see, e.g., Bae et al. 2003, Ahlgren and Antell, 2010, Dungey et al., 2005, Bekaert et al., 2009, Hodrick, and Zhang, 2009, Casarin et al., 2018, Corsi et al., 2018 and Londono, 2019). Nevertheless, these researchers have not reached a consensus regarding the appropriate measurement of contagion and many of the different measurement methods provide differing results regarding the occurrence and extent of contagion. (See, e.g., Rigobon, 2003, Bekaert et al., 2009, Hodrick, and Zhang, 2009, and Ahlgren and Antell, 2010).⁴ Moreover, the complex nature of these models makes them difficult to apply.

The above-mentioned inconclusive literature hints that alternatives to the correlation-based approaches to measuring and testing for contagion are needed.⁵ This study picks up the gauntlet and proposes a novel, non-correlation-based method for measuring comovement and contagion: the multicountry measure. The uniqueness of this measure is that instead of using correlations (including variations such as regressions) it relies on the frequency with which stock markets move in the same direction.⁶ This technique is based on the frameworks of herding measurement presented in articles by Lakonishok et al. (1992). Grinblatt et al. (1995). and Venezia et al. (2011).⁷

The multicountry measure we propose has several advantages. First, it can cover many countries simultaneously and provide one measure for their contagion rather than making multiple binational comparisons that may turn out to be country-specific and fail to capture the regional or global effects of crises. Second, as we show in the simulations below, it is robust to changes in volatility. FR suggest an adjustment to correlation that can control this bias. This adjustment, however, does not solve the problem of bilateral comparisons and requires the identification of the country in which the contagion originates, an issue that may be problematic if the origin is not clear, as in the case of the COVID-19 pandemic. Moreover, in the three crises analyzed by FR, the multicountry

⁴ On the pros and cons of the various methods, see Bekaert and Wu (2000), Ang and Chen (2002), Connolly and Wang (2003), Chiang et al. (2007), Kim et al. (2005), Wu (2005), Rodriguez (2007), Chollete et al. (2011), Kenourgios et al. (2011), Arakelian and Dellaportas (2011), and Aloui et al. (2011).

⁵ As Rigobon (2019, p. 96) has suggested, “More research is obviously needed. Continuing to use the standard methods is, however, more dangerous than having partial answers.”

⁶ This mitigates the sensitivity of the measure to large deviations, a problem that may arise with correlations, as Ronn et al. (2009) have pointed out.

⁷ Chiang and Zheng (2010) suggest a different approach to measuring how herding is affected by crises. According to it, the effect of fluctuations in returns on herding can be analyzed by their effects on the form of the market equilibrium. The disadvantage of this interesting approach is that it requires that the price indices of the various countries follow a global CAPM. In addition to some technical difficulties, this approach analyzes herding via the CAPM, a model that requires an efficient market, a type of market that does not allow for herding.

measure seems to possess more power to detect genuine contagion. Last, most of the new methods introduced are quite complex and difficult to apply. Thus, for implementation it is often needed to resort to plain correlations as they yield almost the same results as the complex structural models (see, e.g., FR). The multicountry measure, on the other hand, can be calculated in a straightforward manner and could serve as a daily measure of comovement and contagion, thus facilitating continuous monitoring of these phenomena around the world.

The remainder of this article is constructed as follows. In Section II, we describe the data and in Section III we present the methodology used for constructing the multicountry measure. Simulations that examine the robustness of our measure to changes in volatility as well as the power of the model are presented in Section IV. The results presenting our estimates of contagion for various international crises are presented in Section V, and in Section VI we further examine the power of our measure in three major crises relative to a prominent measure. In Section VII we present our conclusions.

II. Data

This study employed daily data consisting of 53 market price indices that cover the western European markets, the GIIPS/eastern European markets, the Asian/Oceanian markets, the Latin American markets, and other markets (Groups A, B, C, D, E, respectively in Appendix 2). The data spans the period from March 22, 1983, to December 31, 2020, for some countries, but for others the data was available only from a later date. (See Appendix 3 for detailed information on the first date of availability for the data of each country and the names of the leading indices representing each country used in this study.) All the data are taken from DataStream International. During periods when values were missing from certain indices, these indices were not used in the calculations.

The data covers 16 crises and special events: Black Monday in 1987 (US), the creation of the Japanese zombie banks of 1990 (JP), Black Wednesday in 1992 (GB), the Mexican Peso crisis (the Tequila crisis) of 1994 (MX), the banking crisis of 1995 (MX), the Asian flu of 1997 (TH), the stock market mini-crash of 1997 (US), the Russian flu of 1998 (RU), the Brazil fever of 1999 (BR), the Nasdaq crash of 2000 (US), the Argentine crisis of 2000 (AR), the September 11, 2001 terrorist attack (US), the 2008 subprime crisis (US), the 2009 European sovereign debt crisis (GR), the 2019 election crisis (AR) and the Covid-19 pandemic in 2020. For each of these events, a specific breakpoint date is noted to enable the examination of the impact of the financial crisis. (A list of breakpoints paired

with the events is provided in Appendix 4.) The pairings of the breakpoints with the financial crises were obtained from various sources, including HSU (2017) and Razin (2014). To avoid a bias in empirical findings related to exchange rate fluctuation, as suggested by Mink (2009), returns data were denominated in local currency.

III. Methodology

The methodology used to construct the multicountry measure for contagion is based on the herding models of Lakonishok et al. (LSV) (1992); Grinblatt et al. (GTW) (1995); and Venezia et al. (VNS) (2011), where herding is defined as imitation of investment choices among market participants within a market. Proponents of herding behavior theory assume that investors tend to mimic the actions of others, suppressing their private information and personal beliefs about asset prices and basing their investment decisions mainly on the behavior of others. LSV, GTW, and VNS examined the herding behavior of analysts and/or other traders in the stock market by comparing their proportion of buy transactions of some individual or group of stocks during a particular period (of all their trades of these stocks; buy and sell), to their long-run proportion of buy transactions of these stocks. A statistically significant difference between these proportions would indicate the presence of (buy-side) herd behavior during that time.

Following LSV, GTW, and VNS, this study analyzed comovement/contagion by applying their methodology to the herding behavior of stock markets. For every day, t , we defined by P_t the proportion of rising stock market indices in all stock market indices in the sample:

$$P_t = \frac{\sum_{i=1}^N x_{it}}{N} \quad (2.1)$$

where P_t is the average number of countries with a rising stock index, N is the number of countries/indices in the sample, and $x_{it} = 1$ or $x_{it} = 0$ if the stock index of country i rose or declined during period t , respectively. The values of P_t range from 0 to 1. A value of P_t close to zero or one indicates that international stock markets comoved on that day. A P_t close to one indicates that countries comoved to the upside.

A graphical representation of P_t values before and after events' breakpoints is shown in Figure 1, which refers to Black Monday, which took place in 1987 in the US. The date of the breakpoint is marked by an oval. The chart reveals that there is a higher tendency of markets toward herd-like behavior after this point. The middle line, 0.4, exhibits the long

run of simultaneous movements (during the examined period). The synchronized movements after the breakpoint are stronger than those before it, suggesting the presence of stronger herding or contagion.

Figure 1: P_t values around Black Monday, which took place in 1987 in the US

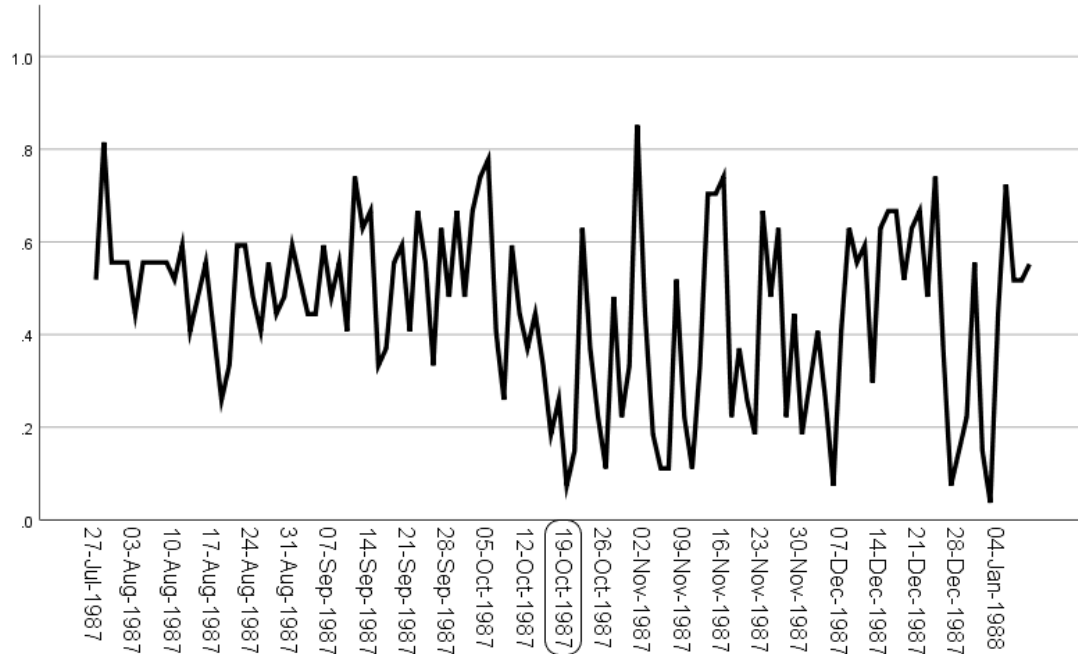


Figure 1 shows that the values of P_t drop after the breakpoint and become, on average, closer to 0, indicating a change in comovement behavior consistent with the intensification of downside comovement, i.e., contagion. Similar charts were created for other crises that emanated from the US (see Figures 2, 3, 4, 5 in Appendix 5) to assess whether they were also afflicted with contagion. Whereas visual inspection of the chart is a very illuminating way to determine whether contagion has occurred, this study also proposes formal measures of contagion that compare the comovement (herding) measures of the markets prior to the day of each crisis (the stable period) with the period after it (the turbulent period). The comovement measure was calculated as follows. For each period (or time window) of T trading days, we first calculated the average proportion of rising stock market indices

$$\bar{P}_T = \frac{\sum_{t=0}^T P_t}{T} \quad (2.2).$$

\bar{P}_T is considered the “normal” proportion of stock index increases in the relevant time window. A large deviation of P_t from “normal” on a given day, t , is indicative of

comovement on that day in the sense that stock markets move simultaneously in a positive direction. P_t significantly different from \bar{P}_T (the overall average of P_t) may indicate that international markets comoved on day t . Such frequent and sizeable deviations over a given prolonged period of time would indicate consistent herding behavior for that period. Accordingly, for each given crisis, we calculated these proportions for both stable and turbulent periods, which are the periods before and after the breakpoint, respectively, and explored whether there was a significant change in comovement (herding behavior) between them. Formally, we calculated \bar{P}_T for the turbulent and stable periods (applying the subscripts “stability” and “turbulence” to distinguish between them). That is, we calculated in (2.3) and (2.4) the average P_t for T days prior/after to the breakpoint ($t = 0$):⁸

$$\overline{P}_{stability} = \frac{\sum_{t=0-T+1}^0 P_t}{T} \quad (2.3)$$

and

$$\overline{P}_{turbulence} = \frac{\sum_{t=1}^T P_t}{T} \quad (2.4)$$

Based on these metrics, following LSV, GTW, and VNS, we defined substantial absolute deviation of P_t from \bar{P} , $|P_t - \bar{P}|$ as comovement (herding). We used the methodology of VNS to test whether the deviations of P_t from \bar{P} were due to chance or were systematic. We then calculated the following comovement (herding) multicountry measures:

$$CM_t = |P_t - \bar{P}| - E[|P_t - \bar{P}|] \quad (2.5).$$

We assumed that the number of rising stock market indices at time t , under the null hypothesis of no comovement, is binomially distributed with T “trials,” and “probability of success” P_t , where a rise in the stock market index is considered a “success.” In the above formula, we subtracted from the absolute value of the deviation $P_t - \bar{P}$ its expected value. Since the absolute value of $P_t - \bar{P}$ does not follow any known distribution for which exact formulas can be obtained, VNS suggested a method for a normal distribution approximation of the expectation $E[|P_t - \bar{P}|]$.⁹ The adjusted version of the approximation used in this study is the following:

⁸ The above calculations pertain to buy-side herding.

⁹ See Appendix 1 in Venezia et al. (2011). The distribution is that of the absolute value of the difference between a binomial distribution and its mean. Other authors (e.g., GTW) have used simulations to approximate this distribution, a method that is computationally very time-consuming.

$$E[|P_t - \bar{P}|] = \sqrt{2\bar{P}(1 - \bar{P})/(\pi T)} \quad (2.6).$$

Inserting (2.6) into (2.5) we obtain:

$$CM_t = |P_t - \bar{P}| - \sqrt{2\bar{P}(1 - \bar{P})/(\pi T)} \quad (2.7).$$

Contagion is the increase in comovement (herding) between financial markets that are subject to a financial shock experienced in one or more countries and the expansion of the negative implications of that shock to other countries in crisis periods. To test for contagion, this study analyzed the extent to which the comovement (herding) mechanism changed after financial shock was experienced in one or more countries.

The CM measure can be used to test for the significance of the shift in comovement (herding), i.e., contagion. A comovement measure during a turbulent period, $\overline{CM_{turbulence}}$, that is significantly higher than the expected comovement (herding) measure during a stable period, $\overline{CM_{stability}}$, indicates contagion in financial markets during T first days of a crisis. Formally, we defined the multicountry contagion measure of episode (crisis), j , for market group m by

$$C_{j,m} = \overline{CM_{turbulence(j,m)}} - \overline{CM_{stability(j,m)}} > 0 \quad (2.8).$$

We tested for the significance of the difference between stable and turbulent periods using one-tailed t-tests under the null hypothesis of no contagion. The test hypotheses are as follows:

$$\begin{aligned} H_0: C_{j,m} &\leq 0 \\ H_1: C_{j,m} &> 0 \end{aligned} \quad (2.9).$$

Having described our methodology, in the next section we examine by simulations its robustness to changes in volatility and study its power.

IV. Simulations Testing the Multicountry Measure's Power and Sensitivity to Increased Variance

By simulating markets experiencing crises, we gauge the sensitivity of our measure to changes in variance and its power. In these simulations, the multicountry measures were calculated for hypothetical returns data and the standard deviations of returns were

manipulated to determine the extent to which the multicountry measures were giving a false indication of increased correlation when only the variances (but not the correlations) changed during the crises. The simulations were performed by generating several sets of returns data with basic parameters like those prevailing in the countries and the periods we studied and calculating our measure of contagion while varying the standard deviations between tranquil and turbulent periods but keeping the correlation constant. We then examined the number of false indications of contagion our measure of contagion yielded. We examined the power of our measure by simulating the extent to which our measure provided an indication of contagion when contagion occurred. For this we calculated our measure for the scenarios where the correlations between the countries increased after the breakpoint while maintaining the same variances.

The following considerations guided us in the choice of the parameters. The correlation parameters, ρ , were based on Aloui et al., (2011), who reported a high daily returns correlation of 0.6 between Brazil and the US and a low daily returns correlation in the range of 0.2–0.3 between the US and China, India, and Russia. The range of mean returns, μ , was chosen based on a daily mean returns calculated from random samples of our real data. We based our return standard deviation parameters on three leading financial indices, the S&P 500, the FTSE 100, and the Tokyo Stock Exchange.¹⁰ The standard deviations reported in Table A6. 1 in Appendix 6 were estimated from the 60 trading days before and the 60 trading days after each breakpoint. Panel A of this table pertains to crises that emanated from the US and Panel B to crises that originated from all other countries.

From this table one observes that in crises originating in the US, the standard deviations almost doubled in the turbulent periods compared to the stable ones. In crises originating elsewhere, the standard deviations did not always increase, and when increases occurred they were relatively minor. Accordingly, we chose the range of standard deviations, σ , in the simulated stable period to be 0.008–0.012 and 0.015–0.02 for the turbulent one. We summarize the parameters used in our four sets of simulations in Table A6. 2 in Appendix 6, below.

The simulations were run in two stages. In the first stage, two return matrices of 30 countries on 60 trading days were created. One return matrix was created with parameters suitable for the simulated before-breakpoint (stable) period and the other with parameters suitable for the simulated after-breakpoint (turbulent) period. All data were generated with

¹⁰ We chose these exchanges because they were the ones involved in all the crises we studied.

the parameters in Table A6.1 using the Mathematica program under the normal distribution assumption. In the second stage, the multicountry measures for contagion, $C_{j,m}$ (eq. 2.8), were calculated and the effect of increasing standard deviations on these measures was studied. The tests were executed 100 times on each set of parameters.

The results of the simulations, including a short description of the most important parameters, are reported in Table 1. In both sets 1 and 2, the variances of the returns increased after the breakpoint, whereas the correlations did not. The number of false indications of contagion, that is the number of $C_{j,m}$ s significantly different from zero at the 5% levels, was small (only 2 of 100), indicating the robustness of our measure to changes in variance. Set 2 repeats the analysis made in Set 1 but serves to examine whether the level of the correlation may affect the results. As in Set 1, also in Set 2 the number of instances of spurious contagion is small, and it appears that the higher level of the correlation did not alter the incidence of false indications of contagion. Sets 3 and 4 were designed to examine the power of the tests, i.e., to study their ability to recognize contagion when it occurs. In these sets we maintained the same standard deviations before and after the breakpoints but changed the correlations. We observe that the number of correct identifications is large (99 and 85 of 100 in sets 3 and 4, respectively) which supports the test's power. Not surprisingly, the more the correlation changes after the break the higher the number of genuine detections of contagion (99 when the correlation changes by 0.4 vs. 85 when it changes by 0.3).

Table 1: Simulation results

*This table shows the simulation results for four sets of parameters. The bottom line presents the number of cases of 100 where our measure produced an indication of contagion. The row $\rho_{after} - \rho_{before}$ reports the change in correlation and its statistical significance (** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$).*

Change in σ	Increase in σ after the breakpoint		No change in σ after the breakpoint	
	Set 1	Set 2	Set 3	Set 4
ρ_{before}	0.2	0.3	0.2	0.3
ρ_{after}	0.2	0.3	0.6	0.6
$\rho_{after} - \rho_{before}$	0	0	0.4***	0.3**

Number of calculated significant contagion measures, $C_{j,m}$ s, of 100 simulated crises	2	2	99	85
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Having shown the robustness of the multicountry measure to changes in variance and its power, we present our results in the next section.

V. Results: Multicountry Estimates of Contagion for Various International Crises

This section begins with our general observations on all the crises analyzed, then in subsections IV.1 and IV.2 these observations are refined to distinguish between crises that emanated from the US and those that originated elsewhere.

The values of the multicountry measures $C_{j,m}$ were estimated by utilizing a 60-trading-day window before and after the outbreak day of the crisis.¹¹ We calculated these values for all crises (j) listed in Section II and for the following affected groups (m): all markets, European markets, western European markets, GIIPS/eastern European markets, Asian/Oceanian markets, and Latin American markets. The European markets category includes the western European and GIIPS/eastern European market groups.¹²

In Table 2, we present only those $C_{j,m}$ s that were positive. Positive $C_{j,m}$'s indicate the possibility of the occurrence of contagion. For these cases, a measure of significance was added (** for $p < 0.01$, * for $p < 0.05$, and \cdot for $p < 0.1$). If $C_{j,m}$ was negative, there was no contagion and hence no need to test for significance. We therefore marked these entries as NEG in Table 2. Table 2 is divided into two panels. Panel A pertains to crises that emanated from the US, Panel B to those that emanated from all other countries.

We observe in Table 2 that only 14 of 64 entries are marked NEG.¹³ If crises did not matter, there would be a 50/50 chance for the $C_{j,m}$ for each episode each market pair (j, m) to be positive or negative. Under such a null hypothesis, a non-parametric test would

¹¹ The reason for choosing $T = 60$ is that some of the events are chronologically close to each other, and longer windows would cause the events and their effects to overlap. On the other hand, a period with fewer than 30 observations might unjustifiably not yield significant results.

¹² We repeated the analysis for a 40-day window to check for robustness. Since the qualitative results were quite similar, we do not present the results here, but they are available from the authors upon request.

¹³ Entries pertaining to "all markets" and "European markets" were excluded since such entries aggregate the contagion estimates from the subgroups and we wanted to consider the effects of the crises on mutually exclusive groups in our discussion.

conclude that the probability of obtaining 14 or fewer negative $C_{j,m}$ s is 0.0004%, hence it seems quite safe to assume that crises indeed affect comovement (herding) between countries' stock indices, i.e., contagion exists.¹⁴

¹⁴ This was calculated as the cumulative probability of obtaining 14 successes (non-positive $C_{j,m}$'s) of 64 tosses of a fair coin (the sign of $C_{j,m}$ when there is no difference between stable and turbulent periods).

Table 2: Multicountry Measure Estimation for 16 crises

*This table presents the results regarding contagion estimated by the multicountry measure. The entries denote the values of $C_{j,m}$. Positive $C_{j,m}$ indicates the occurrence of contagion. NEG appears when $C_{j,m}$ is zero or negative for contagion cases. The levels of significance were added (*** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$). The measures were calculated with a 60-trading-day window around the breakpoint day of the crisis.*

Panel A: Origin of the Event: US							
Event	Group of markets	All	European	Western European	GIIPS/ Eastern European	Asian/ Oceanian	Latin American
Black Monday (1987)		0.0870***	0.0966***	0.0617**	0.0551**	0.0817***	NEG
Stock Market Mini-Crash (1997)		0.0584***	0.0569**	0.0316	0.0746***	0.0489**	0.0452**
Nasdaq Crash (2000)		0.0211	0.0299	0.0359*	0.0319	0.0183	NEG
September 11 (2001)		0.0357**	0.0373*	0.0277	0.0396*	0.0405**	0.0074
Subprime Crisis (2008)		0.0501**	0.0141	0.0063	0.0465**	0.0505**	0.0597***
COVID-19 Pandemic (2020)		0.0591***	0.0912***	0.0807***	0.0985***	0.0180	0.0637***
Panel B: Origin of the Event: Non-US							
Japanese Zombie Banks (1990, JP)		0.0282*	0.0565**	0.0519**	0.0230	0.0113	NEG
Black Wednesday (1992, GB)		NEG	NEG	NEG	0.0071	0.0138	0.0361**
Tequila Crisis (1994, MX)		NEG	NEG	NEG	NEG	0.0215	0.0234
Banking Crisis (1995, MX)		0.0241*	0.0226	0.0457**	0.0135	0.0179	0.0191
Asian Flu (1997, TH)		0.0483***	0.0577***	0.0681***	0.0454**	0.0331*	0.0182
Russian Flu (1998, RU)		0.0390**	0.0534**	0.0515**	0.0470**	0.0148	NEG
Brazil Fever (1999, BR)		NEG	NEG	NEG	NEG	0.0076	NEG
Argentine Crisis (2000, AR)		0.0356**	0.0275	0.0665***	NEG	0.0368**	0.0238
European Sovereign Debt Crisis (2009, GR)		NEG	NEG	NEG	0.0015	NEG	0.0354*
Election Crisis (2019, AR)		0.0030	0.0291	0.0399*	0.0015	NEG	0.0228

V.1. Crises originated in the US

Panel A of Table 2 shows that crises that began in the US have had considerable impact on global financial markets. All events that originated in the US demonstrated a positive mean difference in $C_{j,m}$ in the all-markets group, with four of five of them demonstrating contagion statistically significant at conventional levels.

We start with the financial crisis starting with the break of the COVID-19 pandemic, in around February 2020, as it is the most recent one. Its origin is not as clear as other crises, but because of its global nature, we include it in this subsection. The contagious COVID-19 virus could be to blame also for contagion in the financial markets in the first few weeks of the pandemics as can be gleaned from the last row of Panel A of Table 2. In this row significant measures of contagion are detected for all regions except for one.

The Black Monday crisis seems to have been quite impactful with an immediate impact on the US market even more serious than that of September 11. The Dow Jones Industrial Average (DJIA) fell on that day by 22.61%, the largest one-day percentage fall of the DJIA, as compared to a fall of “only” 14% during the week after the September 11 attack (the stock market closed the day of the attack and reopened only a week later). There were no apparent reasons for Black Monday and despite the efforts of many researchers to explain this event, no single explanation has prevailed. Following the stock market crash, a group of 33 eminent economists from various countries met in Washington, D.C. and collectively predicted that “the next few years could be the most troubled since the 1930s” (see New York Times, 1987). However, the long run economy was barely affected, and growth increased throughout 1987 and 1988, with the DJIA regaining its pre-crash closing high of 2,722 points in early 1989.

The case of the 1997 stock market mini-crash (US) shows similar results, demonstrating an even more prominent impact on regional markets, with contagion in Latin American markets. Although the crisis was secondary, following the 1997 Asian flu (TH), the fact that it originated in the US led to contagion, especially in less developed financial markets such as GIIPS/eastern European, Asian/Oceanian, and Latin American ones.

The 2000 Nasdaq crash seems to have had the least impact (the data do not indicate a significant effect in any of the subgroups or in the “all markets” group). These results can be explained by the existence of serious vulnerabilities associated with the cascade of financial crises since the 1997 Asian flu (TH). In 2000, the Nasdaq crash joined a series of

financial events that included earlier crises around the world and took place simultaneously with the Brazil fever of 1999 (BR) and the Argentine crisis of 2000 (AR). The difficulty of isolating financial crises could be the reason for these results not being significant. The p-value of the t-test on the all-markets group is 0.119, very close to the conventional 10% statistical significance level, that is, in a less vulnerable period significant contagion would have been evident.

The importance of the US in the financial arena is demonstrated by the example of a non-economic event such as the September 11 terrorist attack in 2001. The event had an immediate effect on the US financial market, which in turn affected global financial markets, as reported in Table 2. Analysis of estimations made at the regional level demonstrated that the European and Asian/Oceanian markets experienced the main impact of that event.

With globalization, the importance of the US market in the financial arena has grown. Markets across the globe are connected to the US financially and through trade. These close connections are reflected in the contagion that resulted from the subprime crisis in 2008. The findings reported in Table 2 indicate contagion for the all-markets group and almost all regional groups' estimations, specifically in less developed financial markets such as the GIIPS/eastern European, Asian/Oceanian, and Latin American ones.¹⁵

The subprime crisis in 2008 had a contagion effect, even though it was not a surprise (since the exact breakpoint date is unclear) and was a continuous crisis, although some of its events, such as the collapse of Lehman Brothers, did surprise many. The 2000 Nasdaq crash seems to have been the least contagious, but it was also the least surprising.

V.2. Crises originated in countries other than the US

While the US is the most influential market in the world and it is intuitively plausible that crises there will affect other countries, Panel B of Table 2 shows that crises that originated in other countries were also contagious. The immediate impact of events such as the creation of the Japanese zombie banks in 1990 (JP), the 1995 banking crisis (MX), the 1997 Asian flu (TH), the 1998 Russian flu (RU), and the 2000 Argentine crisis (AR) on global financial markets is intuitively clear.

¹⁵ In a similar vein, Park and Shin (2020) found that emerging market economies that were more exposed to banks in the crisis-affected countries suffered more capital outflows during the global financial crisis.

An examination of regional markets in Table 2 regarding the creation of the Japanese zombie banks in 1990 (JP) reveals that European markets experienced the main impact of this crisis. Caution must be exercised when interpreting the empirical results in this case and drawing conclusions about which country initiated the financial shock, since in the early 1990s the European markets experienced several crises, beginning with the Western European Exchange Rate Mechanism crisis of 1992, which resulted from the unforeseen reunification of Germany, and ending with the Nordic countries' crisis, which resulted from premature financial liberalization. Since determining the exact dates of these events is exceedingly difficult, they were not included in this study.

An examination of regional markets regarding the 1995 banking crisis (MX) reveals that western European markets experienced the main impact of this event. The 1995 banking crisis (MX) was a secondary crisis followed by the Tequila Crisis in 1994 (MX), which stemmed from financial liberalization and political events.

One of the most prominent and painful crises that originated outside of the US was the 1997 Asian flu (TH). It was quite unexpected in terms of both timing and scale. The crisis began in Thailand as a response to the financial collapse of the local currency and set off a domino effect in the region. The items relevant for the 1997 Asian flu (TH) in Table 2 show that contagion occurred in all country groups except for the Latin American one. The contagion we find here is remarkable in terms of both statistical significance and scale.¹⁶

Among other outcomes of the 1997 Asian flu (TH) are several crises that were impacted in the long run by contagion from it and by one another to varying degrees. The 1997 stock market mini-crash (US), the 1998 Russian flu (RU), and the 2000 Argentine crisis (AR) in their turn led to short-term contagion, as Table 2 shows. The 1999 Brazil fever (BR) however, as reported in Table 2, shows no contagion.

The 2009 European sovereign debt crisis (GR) that followed the 2008 subprime crisis (US) exhibits no contagion in almost any market group. These results are like those of Caporin et al. (2019), who used bond yield spreads to test the propagation of shocks. The western European markets group exhibited statistically significant contagion during the 2019 election crisis (AR).

¹⁶ For example, the effect of the Asian flu on the rest of the world is 0.0483, the highest among all crises of non-US origin, and has the highest significance level: 0.01.

VI. Comparison of the multicountry measure to FR's measure

The most prevalent techniques currently used to detect contagion between two markets consist of observing whether the correlation between them has increased following a crisis. However, as mentioned above, the increased variances that usually occur during crises may lead to a spurious increase in correlation. FR suggest that this bias can be corrected by using the following adjusted correlation, ρ , (unconditional of variance) given by

$$\rho = \frac{\rho^*}{\sqrt{1 + \delta[1 - (\rho^*)^2]}} \quad (6.1)$$

where, ρ^* is the unadjusted correlation and δ , the measure of increased variance of the infecting country during the turbulent period, is given by:

$$\delta \equiv \frac{\sigma_{xx}^h}{\sigma_{xx}^l} - 1 \quad (6.2).$$

In (6.2), σ_{xx}^h and σ_{xx}^l denote the variance of the infecting country, x , during the calm and the turbulent periods, respectively.

In what follows, we compare the results obtained by our method to those obtained by FR for the three crises they cover: the 1997 East Asian crisis, the 1994 Mexican peso crisis (often called the Tequila Crisis), and the 1987 US stock market crash (Black Monday). Like FR's adjusted correlation, our measure is robust to changes in variance, but we would also like to compare the two measures' power. FR find in many bivariate comparisons during these episodes that unadjusted correlations between the infecting country (the source of the crisis) and other countries changed after the crisis, but the adjusted correlation did not, thus showing that the failure to correct for the change in variance resulted in many spurious claims of contagion. Their results imply that, contrary to many other findings, no contagion occurred during these three crises.¹⁷ While the adjustment that FR propose helps to overcome the problem of increased variance during crises, one may wonder whether it may be too stringent and consequently diminish the power of their tests to detect true contagion.¹⁸ Observing the righthand columns of FR's Tables III, IV, VI, VII, VIII, and XI (*ibid.*, pp. 2240–2250), we note that without

¹⁷ See for example King and Wadhvani (1990), Lee and Kim (1993) and Calvo and Reinhart (1996).

¹⁸ Exact measures of power are difficult to obtain since for this a specific measure of contagion must be defined.

adjustments, 23 statistically significant instances of contagion, 45.1% of the 51 correlations examined, are registered, whereas after making the adjustment, only one remains (2%). This is indicative of a radical adjustment. It comes as no surprise to observe in FR that no contagion was found between Hong Kong and European and Latin American countries (FR's Table IV) or between Mexico and Southeast Asian countries (FR's Table VII) because of the large geographical distance and the weak economic ties between them.¹⁹ However, what we find remarkable and what may indicate that FR's adjustment is too severe, is their sweeping rejection of any contagion, especially the rejection of intraregional contagion for all three crises.

The multicountry measure, on the other hand, while overcoming the variance bias, demonstrates more power by detecting contagion that probably occurred in the above-mentioned episodes.²⁰ One important indication of the power of our measure, in addition to that demonstrated by the simulations, is its ability to differentiate between contagion that is more likely to occur and contagion that is less intuitively plausible. In particular, our measure was able to detect instances of intraregional contagion, which are more liable to occur, and reject instances of interregional contagions, which are less probable. For the East Asian crisis, the multicountry measure, C , showed intraregional contagion ($C = 0.043^{**}$) but no contagion to OECD countries ($C = 0.0041$) or to "other countries" ($C = 0.0376$).²¹ For the Mexican peso crisis, it showed only intraregional contagion ($C = 0.0529^{**}$) but none outside the region. For the 1987 US stock market crash, which had a remarkable global effect, our measure shows, as we expected, significant contagion ($C = 0.0015^{***}$) among the countries analyzed, all close economic allies of the US.

Additionally, our measure demonstrates an advantage by summarizing contagion across entire regions, whereas binary comparisons may be puzzling and difficult to interpret. This problem did not arise for FR since when using the adjusted correlations, which they recommended, all binary correlations except one indicated no contagion. Consider

¹⁹ On the importance of geographical proximity in the channels of propagation of crises, see, for example: De Gregorio and Valdes (2001), who argue that proximity of countries or regional effects are more important than trade links and/or macroeconomic similarities (*ibid.*, p. 311), Glick and Rose (1999), Amidi and Majidi (2020), Tobler (1979), and Sabkha et al. (2019).

²⁰ It is debatable whether contagion occurred and, if so, how to measure it precisely (explaining why this topic is still researched). Thus, economic intuition and plausibility are needed to assess the power of a measure to detect actual contagion. In our simulations, however, as shown above, the multicountry measure exhibited considerable power, which adds to its usefulness as an important test in the real world as well.

²¹ The measures of C appearing in this section differ somewhat from those presented in Table 2 because for this section we defined the country groups slightly differently to correspond with FR's groupings. Qualitatively, however, the results presented here are like those provided in Table 2.

however, for the sake of argument, what conclusions would have been reached if FR's unadjusted measure had been adopted for the 1997 East Asia crisis. One would then infer from the leftmost column of Table III that three countries had been infected (Indonesia, Korea, and the Philippines) and that the other five (Japan, Malaysia, Singapore, Taiwan, and Thailand) were not. This would also raise, in addition to the big picture question of whether intraregional contagion had occurred, minor questions such as, for example, why Korea was infected while Thailand was spared. FR did not face these dilemmas, but they are not merely hypothetical; other researchers have had to confront similar quandaries. For example, Sabkha et al. (2019) show in their Table 7 that during the global financial crisis of 2008, which emanated from the US, Lithuania was infected, yet Latvia was not, and when focusing on developed countries during this crisis, six of 16 countries were infected, while the others were spared. Many bilateral analyses may, therefore, fail to take into account the broader issue of the effect of a crisis on an entire region, whereas the multicountry measure we offer focuses on this matter.

VII. Conclusions

We offer a new measure, the multicountry measure, for assessing comovement and testing for contagion in international markets. We used this metric to analyze several crises, including the recent financial crisis that accompanied the outbreak of the COVID-19 pandemic, and found that, by and large, contagion is a common phenomenon. The measure we propose exhibits several advantages compared with existing ones. First, being a multicountry metric, it facilitates the capture of the global or regional effects of crises rather than making many bilateral observations regarding possible contagion that may be too specific and thus masking global and regional insights. Second, our simulations show that the multicountry measure is robust to increases in variances; an important feature since during crises, a country's stock market volatility often increases, a phenomenon that could lead to a spurious indication of contagion. Third, our simulations show that the measure is powerful enough to confirm genuine contagion. Moreover, we demonstrated its greater ability, relative to a leading extant contagion measure, to detect seemingly genuine contagion during three crises. Lastly, the measure is easy to implement and hence could be used as a standard daily measure of comovement.

The issue of contagion is still relevant today as ever, as our analysis of the COVID-19 pandemic shows, and extends beyond stock markets and macroeconomic crises to

involve the transmission of crises in other sectors such as the CDS market and cryptocurrencies.²² Given the continued interest in contagion, the expanding scope of this topic and the controversy surrounding the extent to which current tests can accurately detect such phenomena, we suggest that the multicountry measure, which provides a novel approach to contagion tests, be added to the tools used in the analysis of the potential spread of contagion. We leave it for upcoming research to further study this measure and use it in the analysis of future crises.

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²² Sabkha et al. (2019) consider the spread of crises in the credit default swap (CDS) and provide support for the hypothesis that contagion was widespread during the global 2007–2008 subprime market crises and the European sovereign debt crisis, and Da Gama Silva et al. (2019) evaluate contagion in the cryptocurrency market.

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Appendix 1

Proof of the effect of increased variance on the correlation between countries

Following Rigobon, 2003, we show that the correlation between two countries could change not only because there is a greater effect of one country on the other, but also because their relative variability changes. Consider two countries and suppose one country's stock market returns are denoted by x_t and the other's by y_t . Assume country x affects country y by β . It can then be shown (see the algebra below) that the correlation coefficient between the countries is positively related to the variability of the influencing country. If the variability of this country increases, so does the correlation coefficient between the two countries. Thus, an increased correlation between the countries does not necessarily imply that country y was infected by the crisis (increased variance) of country x . This increased correlation could be a mere statistical artifact that stems from the increased variance of country x .

$$x_t = \eta_t$$

$$y_t = \beta x_t + \varepsilon_t$$

$$\text{var}(x_t) = \sigma^2_{\eta,t}$$

$$\text{var}(y_t) = \beta^2 \text{Var}(x_t) + \sigma^2_{\varepsilon,t}$$

$$\text{cov}(x_t, y_t) = \beta^2 \sigma^2_{\eta,t}$$

$$\rho_t = \frac{\beta^2 \sigma^2_{\eta,t}}{[\beta^2 \sigma^2_{\eta,t} + \sigma^2_{\varepsilon,t}]^{.5} [\sigma^2_{\eta,t}]^{.5}} = \frac{\beta^2 \sigma^2_{\eta,t}}{[\beta^2 \sigma^2_{\eta,t} + \sigma^2_{\varepsilon,t}]^{.5} [\sigma^2_{\eta,t}]^{.5}}$$

$$\rho_t = \frac{\beta}{(\beta^2 + \theta_t)^{1/2}}$$

where

$$\theta_t = \sigma^2_{\varepsilon,t} / \sigma^2_{\eta,t}$$

is the relative variance of the news in x and y .

In this model, x_t and y_t are stock market returns in two countries, with x affecting y linearly, and ε_t and η_t are the independent news in each country with variances $\sigma^2_{\varepsilon,t}$ and $\sigma^2_{\eta,t}$, respectively. The interrelationship between the countries runs only through β . Yet when there is new information on x or, alternatively, the idiosyncratic noise in x increases (that is, $\sigma^2_{\eta,t}$ increases), the correlation coefficient between x and y increases, although the covariance remains the same. The intuition behind the above algebra is that as the variance

of x increases, relatively more of the variance of y comes from x rather than from its own idiosyncratic variability. Hence, the correlation coefficient that represents the dependence between the variation in x and the variation in y increases.

Appendix 2

Attribution of the Countries to Regional Groups

Group	Group Name	Countries
A	Western European Markets	Germany (DE), United Kingdom (UK), France (FR), Denmark (DK), Netherlands (NL), Norway (NO), Sweden (SE), Austria (AT), Finland (FI), Switzerland (CH), Belgium (BE), Iceland (IS)
B	GIIPS/Eastern European Markets	Italy (IT), Ireland (IE), Spain (ES), Portugal (PT), Hungary (HU), Poland (PL), Greece (GR), Czech Republic (CZ), Slovakia (SK), Russia (RU), Turkey (TR). GIIPS refers to Greece (GR), Italy (IT), Ireland (IE), Portugal (PT), and Spain (ES)
C	Asian/Oceanian Markets	Japan (JP), Hong Kong (HK), China (CN), India (IN), Singapore (SG), South Korea (KR), Australia (AU), Pakistan (PK), Thailand (TH), Malaysia (MY), New Zealand (NZ), Indonesia (ID), Sri Lanka (LK), Philippines (PH)
D	Latin American Markets	Argentina (AR), Brazil (BR), Mexico (MX), Colombia (CO), Venezuela (VE), Chile (CL), Peru (PE), Panama (PA), Jamaica (JM)
E	Other Markets	United States (US), Canada (CA), Israel (IL), Jordan (JO), South Africa (ZA), Kuwait (KW), Kenya (KE)

Appendix 3

List and description of the stock market indices, including the first date of data availability for this index

Country	Abbreviation	Index Name	First date of data availability for this index
United States	US	S&P 500 COMPOSITE	3/22/1983
Germany	DE	DAX 30 PERFORMANCE	3/22/1983
United Kingdom	UK	FTSE 100	3/22/1983
Canada	CA	S&P/TSX COMPOSITE INDEX	3/22/1983
France	FR	FRANCE CAC 40	7/9/1987
Japan	JP	TOPIX	3/22/1983
Denmark	DK	OMX COPENHAGEN (OMXC20)	12/4/1989
Italy	IT	MSCI ITALY	3/22/1983
Netherlands	NL	AEX INDEX (AEX)	3/22/1983
Hong Kong	HK	HANG SENG	3/22/1983
Norway	NO	OSLO EXCHANGE ALL SHARE	3/22/1983
Ireland	IE	IRELAND SE OVERALL (ISEQ)	3/22/1983
Sweden	SE	OMX STOCKHOLM 30 (OMXS30)	1/2/1986
Austria	AT	ATX	1/7/1986
Finland	FI	OMX HELSINKI (OMXH)	1/2/1987
Spain	ES	IBEX 35	1/5/1987
Switzerland	CH	SWISS MARKET (SMI)	7/1/1988
Belgium	BE	BEL 20	1/2/1990
Portugal	PT	PORTUGAL PSI-20	12/31/1992
Russia	RU	MSCI RUSSIA	12/30/1994
Turkey	TR	ISTANBUL SE NATIONAL 100	1/4/1988
Hungary	HU	BUDAPEST (BUX)	1/2/1991
Poland	PL	WARSAW GENERAL INDEX	4/16/1991
Czech Republic	CZ	PRAGUE SE PX	4/6/1994

Country	Abbreviation	Index Name	First date of data availability for this index
Slovakia	SK	SLOVAKIA SAX 16	9/14/1993
Iceland	IS	OMX ICELAND ALL SHARE	12/31/1992
Greece	GR	ATHEX COMPOSITE	9/30/1988
Israel	IL	ISRAEL TA 100	4/23/1987
Jordan	JO	AMMAN SE FINANCIAL MARKET	11/21/1988
South Africa	ZA	MSCI SOUTH AFRICA	12/31/1992
Kuwait	KW	KUWAIT KIC GENERAL	12/28/1994
Kenya	KE	KENYA NAIROBI SE (NSE20)	1/11/1990
China	CN	SHANGHAI SE A SHARE	1/2/1992
India	IN	S&P BSE (100) NATIONAL	1/2/1987
Singapore	SG	MSCI SINGAPORE	3/22/1983
South Korea	KR	KOREA SE COMPOSITE (KOSPI)	3/22/1983
Australia	AU	S&P/ASX 200	5/29/1992
Pakistan	PK	KARACHI SE 100	12/30/1988
Thailand	TH	BANGKOK S.E.T.	3/22/1983
Malaysia	MY	FTSE BURSA MALAYSIA KLCI	3/22/1983
New Zealand	NZ	MSCI NEW ZEALAND	3/22/1983
Indonesia	ID	IDX COMPOSITE	4/4/1983
Sri Lanka	LK	COLOMBO SE ALL SHARE	1/2/1985
Philippines	PH	PHILIPPINE SE I(PSEi)	1/2/1986
Argentina	AR	ARGENTINA Merval	10/19/1989
Brazil	BR	FTSE 100	12/20/1989
Mexico	MX	MEXICO IPC (BOLSA)	1/4/1988
Colombia	CO	MSCI COLOMBIA	12/31/1992
Venezuela	VE	VENEZUELA SE GENERAL	4/1/1993
Chile	CL	CHILE SANTIAGO SE GENERAL (IGPA)	1/2/1987
Peru	PE	LIMA SE GENERAL(IGBL)	1/2/1991

Country	Abbreviation	Index Name	First date of data availability for this index
Panama	PA	PANAMA SE BVPSI	1/1/1992
Jamaica	JM	JAMAICA SE MAIN INDEX	6/11/1987

Appendix 4
Breakpoint Date of All the Crises Analyzed

Event	Breakpoint Date
Black Monday in 1987 (US)	19/10/1987
Japanese Zombie Banks in 1990 (JP)	01/01/1990
Black Wednesday in 1992 (GB)	16/09/1992
Tequila Crisis in 1994 (MX)	22/12/1994
Banking Crisis in 1995 (MX)	12/09/1995
Asian Flu in 1997 (TH)	02/07/1997
Stock Market Mini-Crash in 1997 (US)	27/10/1997
Russian Flu in 1998 (RU)	17/08/1998
Brazil Fever in 1999 (BR)	18/01/1999
Nasdaq Crash in 2000 (US)	10/03/2000
Argentine Crisis in 2000 (AR)	01/11/2000
September 11 Terrorist Attack in 2001 (US)	11/09/2001
Subprime Crisis in 2008 (US)	19/09/2008
Euro Sovereign Crisis in 2009 (GR)	05/11/2009
Election Crisis in 2019 (AR)	12/08/2019
COVID-19 Pandemic 2020 (US)	17/02/2020

Appendix 5

Graphs of P_t Values for all Crises Emanating from the US

Figure A5.1: P_t values before and after event's breakpoint (October 27, 1997) for the US stock market mini-crash

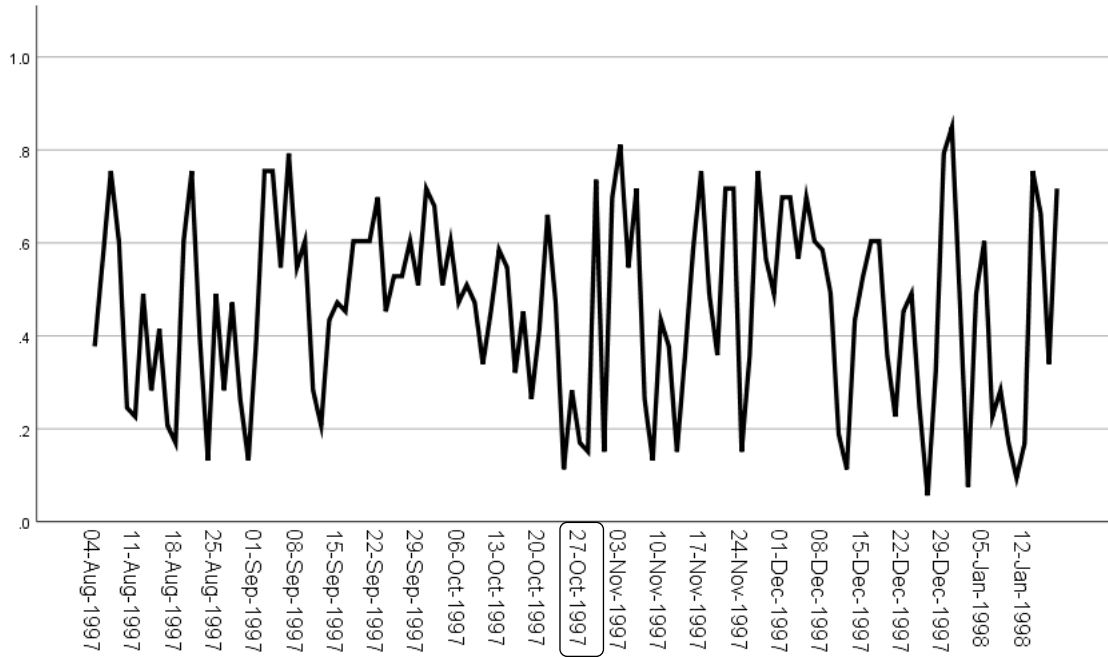


Figure A5.2: P_t values before and after event's breakpoint (March 10, 2000), which refers to the Nasdaq crash

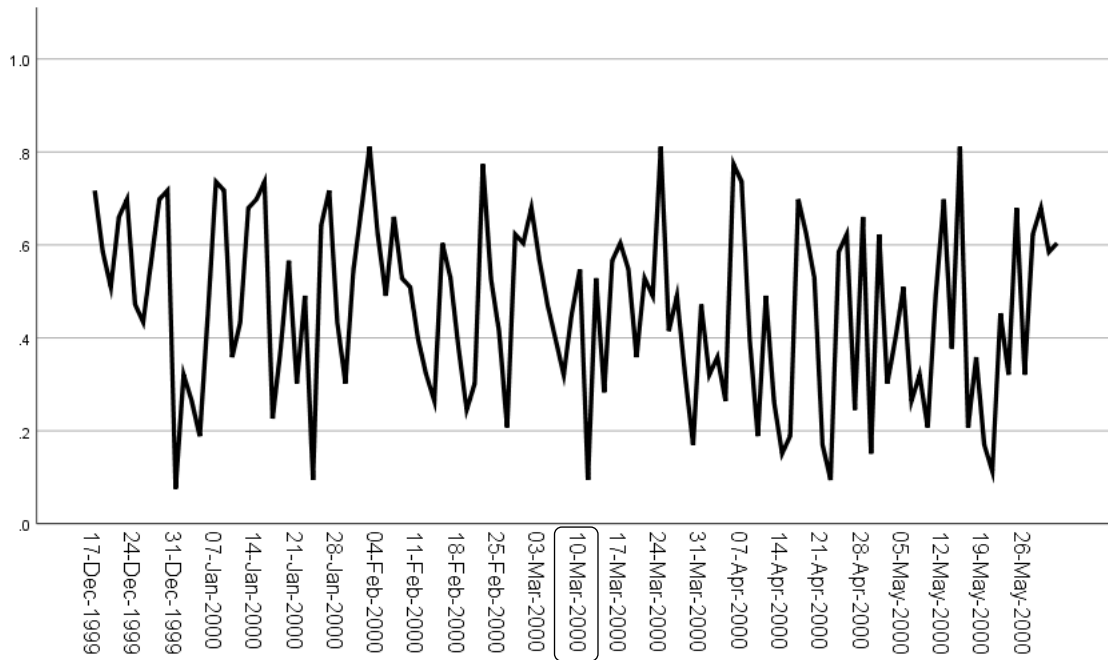


Figure A5.3: P_t values before and after event's breakpoint (September 11, 2001), which refers to the September 11 terrorist attack

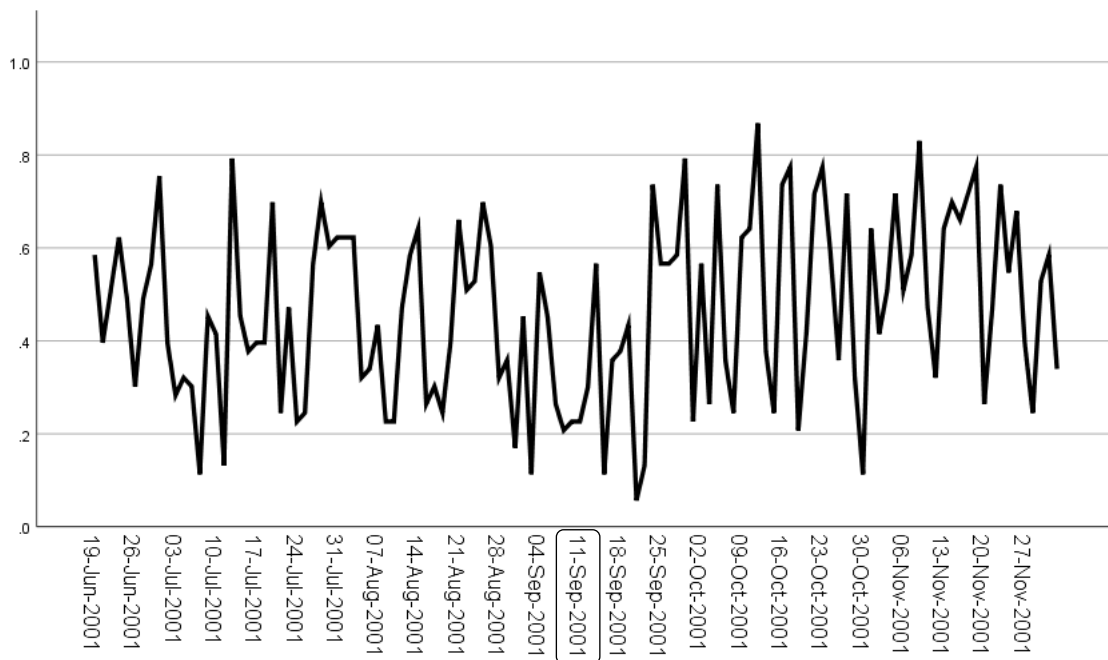


Figure A5.4: P_t values before and after event's breakpoint (September 19, 2008), which refers to the subprime crisis

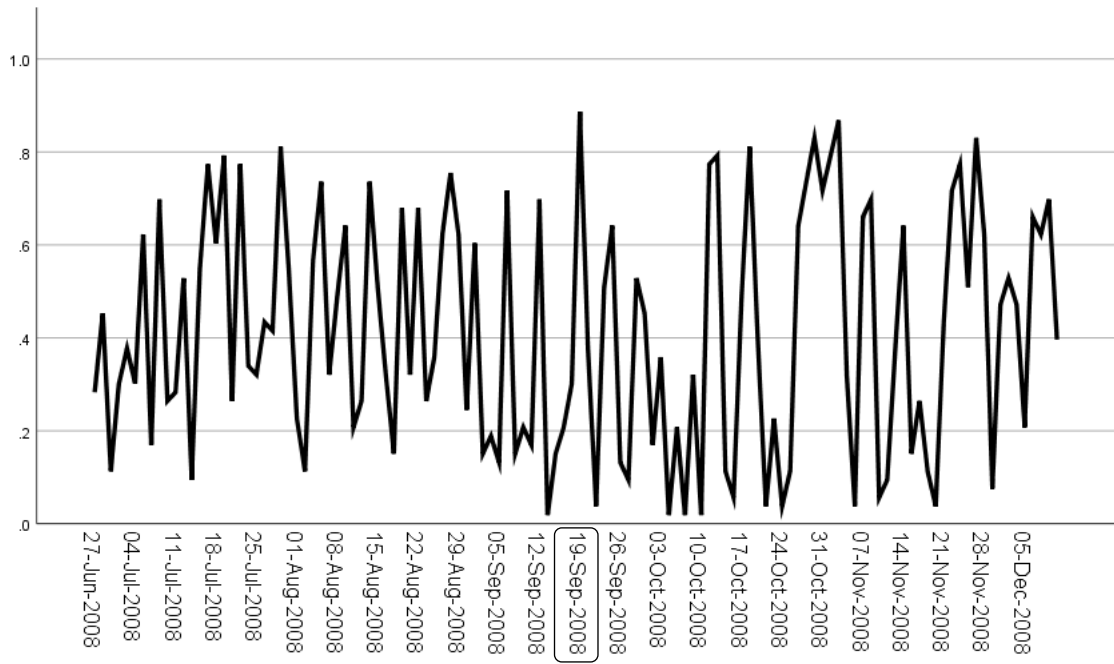
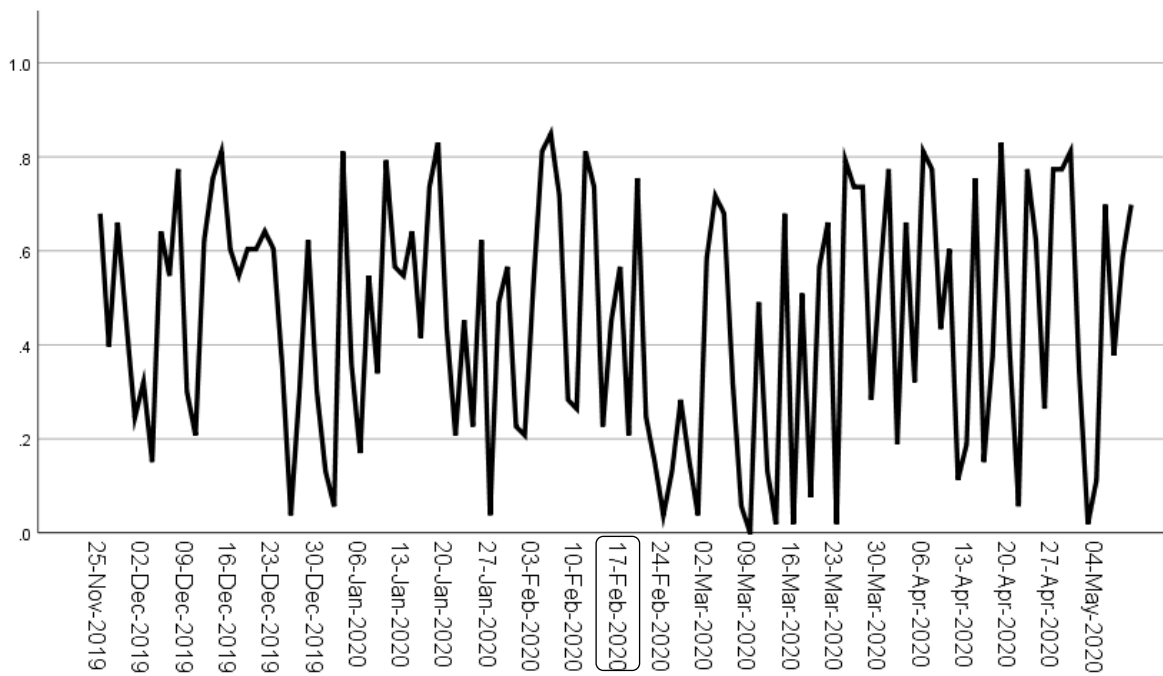


Figure A5.5: P_t values before and after event's breakpoint (February 17, 2020), which refers to the COVID-19 crisis



Appendix 6

Description of the Data Used in our Simulations

Table A6.1: Standard deviations during various crises

This table shows the daily returns standard deviations for three leading indices: S&P 500, the FTSE 100, and the Tokyo Stock Exchange. The standard deviations were calculated 60 trading days before and 60 trading days after each breakpoint.

Panel A: Origin of the event: US						
Event	S&P 500		FTSE 100		TOKYO SE	
	σ_{before}	σ_{after}	σ_{before}	σ_{after}	σ_{before}	σ_{after}
Black Monday (1987)	0.01310	0.03783	0.00877	0.03148	0.00895	0.02919
Stock Market Mini-Crash (1997)	0.01060	0.01558	0.01079	0.01268	0.01088	0.02149
Nasdaq Crash (2000)	0.01342	0.01754	0.01394	0.01368	0.01437	0.01745
September 11 (2001)	0.01039	0.01412	0.01034	0.01859	0.01350	0.01750
Subprime Crisis (2008)	0.01711	0.04566	0.01631	0.04018	0.01629	0.04277
COVID-19 Pandemic (2020)	0.00603	0.03968	0.00792	0.03044	0.00725	0.02198
Panel B: Origin of the event: Non-US						
Japanese Zombie Banks (1990, JP)	0.01104	0.00897	0.00991	0.00787	0.00603	0.01304
Black Wednesday (1992, GB)	0.00578	0.00562	0.01070	0.01165	0.02016	0.00951
Tequila Crisis (1994, MX)	0.00674	0.00418	0.00901	0.00634	0.00574	0.01226
Banking Crisis (1995, MX)	0.00483	0.00477	0.00649	0.00608	0.01226	0.00865
Asian Flu (1997, TH)	0.01034	0.01065	0.00750	0.00943	0.00941	0.00983
Russian Flu (1998, RU)	0.01065	0.01960	0.01080	0.02003	0.01097	0.01944

Brazil Fever (1999, BR)	0.01123	0.01199	0.01339	0.01140	0.01182	0.01150
Argentine Crisis (2000, AR)	0.01156	0.01502	0.00938	0.01122	0.01051	0.01215
European Sovereign Debt Crisis (2009, GR)	0.01107	0.00883	0.01073	0.01007	0.01130	0.01127
Election Crisis (2019, AR)	0.00803	0.00910	0.00743	0.00769	0.00859	0.00723

Table A6.2. Description of the Simulation Parameters

This table presents the range of four sets of parameters used to simulate returns before and after the breakpoint. Daily correlations between returns, means, and standard deviations are denoted by ρ , μ , and σ , respectively. Indices of before and after are added to differentiate between the values of these parameters before and after the breakpoint.

	Set 1	Set 2	Set 3	Set 4
ρ_{before}	0.2	0.3	0.2	0.3
Range of σ_{before}	(0.008, 0.012)			
Range of μ_{before}	(-0.002, 0.0025)			
ρ_{after}	0.2	0.3	0.6	0.6
Range of σ_{after}	0.015–0.02	0.015–0.02	0.008–0.012	0.008–0.012
Range of μ_{after}	(-0.004, 0.002)			