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The International Spread of COVID-19 Stock Market Collapses

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Abstract

We identify periods of mildly explosive dynamics and collapses in the stock markets of 18 major countries during the first wave of the COVID-19 pandemic of 2020. We find statistical evidence of instability transmission from the Chinese stock market to all other markets. The recovery is heterogeneous and generally non-explosive.

JEL Classification: F3, G12, G15, C58

Keywords: Mildly Explosive Behavior, Stock Market Crashes, COVID-19

1 Introduction

By historical standards, the international stock market crash of March 2020 associated with the first major wave of COVID-19 pandemic due to a novel coronavirus appears exceptional, even if compared to other episodes of infection and disease spread. Using measurements of daily stock market swings based on contemporary journalistic accounts going back to 1900, Baker et al. (2020) show that the U.S. stock market volatility during the first half of 2020 is unprecedented. It surpasses that of the Great Depression, the Great Financial Crisis (GFC), and the Spanish Flu pandemic. The realized stock market volatility (VIX) in the USA during the first spell of the COVID-19 pandemic is in the same ballpark as that of the Great Crash of 1929, Great Depression Crash in 1933, and Black Monday Crash in 1987. Until March 2020, when they were activated 4 times, U.S. market-wide circuit breakers had been activated only once, in 1997 (Li and Yao, 2020). In other countries, volatility also increased dramatically (Cepoi, 2020; Okorie and Lin, 2020; Zhang et al., 2020).

Recent research shows that firms and industries are affected differently and that non-linear dynamics and responses are typical. Ramelli and Wagner (2020) provide a timeline of the initial stages of the epidemic and propose a breakdown in 3 phases: Incubation (January 2 to January 17), Outbreak (January 20 to February 21), and Fever (February 24 to March 20). They show that market analysts started paying attention to the epidemic only during the Outbreak period. They connect stock prices to corporate features and argue that the largest impact of the epidemic has been on companies with low cash and high refinancing risks and leverage. Pagano et al. (2020) argue that the stock returns of firms more resilient to social distancing tend to outperform those of firms with less resilience. Alfaro et al. (2020) demonstrate that day-to-day changes in the predictions of standard models of infectious disease forecast changes in aggregate stock returns during the 2003 SARS outbreak in Hong Kong and the COVID-19 pandemic in the USA. They document that industries more exposed to virus transition (such as entertainment) have experienced deeper stock market declines. Using data on futures on dividends, Gormsen and Koijen (2020) provide evidence of a link between the impact of COVID-19 and the revision of growth and dividend expectations in the USA and Europe. Croce et al. (2020) study the effect of news shocks related to local epidemic conditions and information diffusion through Twitter, and find a large market price of contagion risk.

We outline a statistical and descriptive analysis and use a novel testing approach pioneered by Phillips and Yu (2011) and Phillips et al. (2015) to detect episodes of mildly explosive behavior (statistical instability) in 18 major stock market indices between November 1, 2019 and May 31, 2020. This method has been used to identify bubbles in real estate markets (Pavlidis et al., 2016), detect distress in fixed income

markets (Contessi et al., 2020), and develop trading strategies based on bubbles detection (Milunovich et al., 2019).

First, we document the extent of instability and distress across stock markets. Second, we identify periods of instability in these markets. Third, we test for transmission of instability from market to market. We find evidence of instability in all countries, especially between the end of February and the beginning of April. We show that instability is associated with a sudden collapse of stock markets, while the recovery is smoother. The source of this worldwide instability is the Chinese crash, detected at the end of January. We provide evidence of statistical transmission of instability from China to all other economies during the first three months of 2020.

2 Data and Empirical Methods

We use a daily dataset (5-day weeks) of 18 major stock market indices. These indices exhibit the largest capitalization levels in the world and belong to countries that have been impacted by the epidemic. The adopted methods identify and date-stamp periods of statistical instability in stock markets and detect instability migration from market to market. We consider stock market indices for the following areas:

1. South-East Asia: China (SSEC, Shanghai SE Composite Index), Hong Kong (HSI, Hang Seng Composite Index), Singapore (FTFSTA, Singapore FTSE All-Share Index), South Korea (KS100, Korea KOSPI-100), Taiwan (TSE50, Taiwan FTSE/TSE-50 Price Index), and Thailand (SET100, Thailand SET-100 Index);

2. Europe: France (FCHI, Paris CAC-40 Index), Germany (GDAXIP, Germany DAX Price Index), Italy (MIBCI3, Milan COMIT 30 Index), Spain (IBEX, Madrid SE IBEX-35), Sweden (OMXS30, OMX Stockholm-30 Index), and Switzerland (SPIX, Switzerland Price Index);

3. Other Advanced Economies: Australia (AXJO, S&P/ASX 200 Composite Index), UK(FTAS, UK FTSE All-Share Index), USA (DJA3, Dow Jones Composite Average - Actual - Index), and Japan (N500, Nikkei 500 Index);

4. Other Emerging Economies: Brazil (IBX, Rio de Janeiro IBX-100 Index) and India (NSEI, NSE-50 Index).

Some of these countries have multiple indices. We choose the most widely used in the literature. All series start on November 1, 2019 and end on May 29, 2020. We run our methods on the full samples. Consistent with the growing COVID-19/asset pricing literature, we describe empirical results starting

from January 1, 2020 – the day after the Wuhan Municipal Health Commission in China reports a cluster of cases of pneumonia in Wuhan, Hubei Province.

2.1 Testing for Mild Explosiveness

The statistical detection of mild explosiveness evolves around a right-tail variation of the Augmented Dickey-Fuller (ADF) test and is based on a test equation, $y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t$. y_t is a time series of interest (a stock market index); μ is an intercept; p is the maximum number of lags (3 daily observations); and ε_t is an error term. The null and alternative hypotheses are $H_0 : \delta = 1$ and $H_1 : \delta > 1$, respectively. The original sample interval of T daily observations is rescaled to the interval $[0, 1]$. An ordinary least squares estimate of δ over the (rescaled) sample $[r_1, r_2] \subseteq [0, 1]$ is denoted as δ_{r_1, r_2}. The corresponding ADF test statistic is ADF_{r_1, r_2}. $r_w = r_2 - r_1$ is the (fractional) window size of the regression. The Generalized Supremum ADF ($GSADF$) test comes from a recursive procedure in which ADF test statistics are calculated over (overlapping) windows that roll over a forward moving and expanding sample. At each iteration, we estimate the test equation over a different (rescaled) sample and compute an ADF test statistic. The $GSADF$ test statistic is the supremum of ADF_{r_1, r_2} over all possible windows. $GSADF(r_0) = \sup\limits_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} \{ADF_{r_1, r_2}\}$, where r_0 is the smallest sample window width fraction (10%) and 1 is the largest window width fraction (full sample) in the recursion.

We first generate a random sample of T observations from a null model, a random walk with an asymptotically negligible drift, $y_t = dT^{-\eta} + \theta y_{t-1} + e_t$, $e_t \sim N(0, \sigma^2)$, $\theta = d = \eta = 1$. η is a localizing parameter that determines the size of the drift as $T \longrightarrow \infty$ and e_t is a normal error term. Then, we recursively estimate the test equation over the sample generated by the null model using the aforementioned recursive mechanism and store the $GSADF$ test statistic. First and second steps are repeated 1000 times. The p-value for the sample test statistic is $p(\hat{\tau}) = \frac{1}{1000} \sum_{j=1}^{1000} I(\tau_j > \hat{\tau})$. $\hat{\tau}$ is the sample $GSADF$ statistic; $I(\cdot)$ is an indicator function such that $I(\tau_j > \hat{\tau}) = 1$ if $\tau_j > \hat{\tau}$ and $I(\tau_j > \hat{\tau}) = 0$ if $\tau_j \leqslant \hat{\tau}$; and $\{\tau_j\}_{j=1}^{1,000}$ is the sequence of simulated $GSADF$ statistics.

2.2 Date-Stamping Periods of Mild Explosiveness

If the null hypothesis is rejected, origination and termination of mild explosiveness are estimated by a recursive ADF test on backward expanding samples based on an algorithm that mirrors the aforementioned procedure. The end point of each sample, r_2, now moves backwards. The start point varies from 0 to $r_2 - r_0$. For each r_2, we derive a sequence of ADF test statistics, $\{ADF_{r_1, r_2}\}_{r_1 \in [0, r_2 - r_0]}$ and a Backward

Supremum ADF test statistic, $BSADF_{r_2}(r_0) = \sup\limits_{r_1 \in [0, r_2 - r_0]} \{ADF_{r_1, r_2}\}$.

$\widehat{r}_e = \inf\limits_{r_2 \in [0,1]} \left\{ r_2 : BSADF_{r_2}(r_0) > cv_{r_2}^{\beta_T} \right\}$ is the beginning of mild explosiveness as a fraction of the full sample. $cv_{r_2}^{\beta_T}$ is the $100(1 - \beta_T)\%$ critical value of the $BSADF$ test statistic based on Tr_2 observations. $\beta_T \in (0, 1)$ indicates the level of the test (10%). The termination of mild explosiveness is $\widehat{r}_f = \inf\limits_{r_2 \in [\widehat{r}_e, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) < cv_{r_2}^{\beta_T} \right\}$. The origination (termination) date is the observation at which the $BSADF$ statistic exceeds (falls below) the critical value of the $BSADF$ statistic. $GSADF$ test and $BSADF$ test statistics are related to each other as $GSADF(r_0) = \sup\limits_{r_2 \in [r_0, 1]} \{BSADF_{r_2}(r_0)\}$.

2.3 Migration of Mild Explosiveness

Let $\theta_X(\tau)$ be the coefficient of an autoregressive model with an intercept term for $\{X_t\}_{t=1}^{\tau = Tr}$, with $r \in [r_0, 1]$. $\theta_X(\tau)$ is estimated by ordinary least squares as $\widehat{\theta}_X(\tau)$ over a recursively increasing window with a fixed starting date located as early as possible in the sample. $\theta_Y(\tau)$ and $\widehat{\theta}_Y(\tau)$ are defined in the same way. Time variation in $\theta_X(\tau)$ possibly means structural changes originating from turmoil or panic. When mild explosiveness reaches its peak in X_t (a maximum in the sequence of $BSADF$ test statistics), we can test for its transmission to Y_t. Under the alternative of transmission, mild explosiveness emerges in Y_t as it fades away in X_t. Therefore, the generating mechanism of Y_t has a recursive autoregressive coefficient, $\theta_Y(\tau)$, that (i) transitions from a unit root to a mildly explosive root and (ii) is negatively associated with the recursive autoregressive coefficient of X_t, $\theta_X(\tau)$.

If the procedure has identified mild explosiveness in X_t between $\widehat{\tau}_{eX} = T\widehat{r}_{eX}$ and $\widehat{\tau}_{fX} = T\widehat{r}_{fX}$ and in Y_t between $\widehat{\tau}_{eY} = T\widehat{r}_{eY}$ and $\widehat{\tau}_{fY} = T\widehat{r}_{fY}$, assume that the two sequences of $BSADF$ statistics for X_t and Y_t peak at times $\widehat{\tau}_{\rho X} = T\widehat{r}_{\rho X}$ and $\widehat{\tau}_{\rho Y} = T\widehat{r}_{\rho Y}$, respectively, with $\widehat{r}_{\rho Y} > \widehat{r}_{\rho X}$. Let $m = \widehat{\tau}_{\rho Y} - \widehat{\tau}_{\rho X} = T\widehat{r}_{\rho Y} - T\widehat{r}_{\rho X}$ be the number of daily observations in $(\widehat{\tau}_{\rho X}, \widehat{\tau}_{\rho Y}]$. Migration can be detected by estimating

$$\left[\widehat{\theta}_Y(\tau) - 1\right] = \beta_0 + \beta_1 \left[\widehat{\theta}_X(\tau) - 1\right] \frac{\tau - \widehat{\tau}_{\rho X}}{m} + u_t, \ \tau = T\widehat{r}_{\rho X} + 1, ..., T\widehat{r}_{\rho Y},$$

over the period of gradual disappearance of mild explosiveness in X_t and the coincident emergence of explosiveness in Y_t. An asymptotically conservative and consistent test for $H_0 : \beta_1 = 0$ vs $H_1 : \beta_1 < 0$ is based on a standard normal test statistic,

$$Z_\beta = \frac{\widehat{\beta}_1}{L(m)}, \quad \text{where} \quad \frac{1}{L(m)} + \frac{L(m)}{T^\epsilon} \longrightarrow 0, \ \text{ as } T \longrightarrow \infty \ \text{ for any } \epsilon > 0,$$

for some slowly varying function $L(m)$, such as $a \log_{10}(m)$, with $a > 0$ and $m = O(T)$.

4

3 Empirical Results

We discuss the outcomes of a battery of tests of mild explosiveness on the stock market indices in the sample, describe the identified periods of mildly explosive behavior (length of at least 5 days) in each country, and report the results of tests of instability migration from China to all other countries.

MILDLY EXPLOSIVE BEHAVIOR. Table 1 reports the outcomes of the $GSADF$ tests. All stock markets exhibit statistical instability. Evidence of mild explosiveness is pervasive. It is detected at the 1% level in all cases but Hong Kong, where instability is found at the 5% level. Instability peaks in China first, on January 24, the day after the central government imposes a lockdown in Wuhan and other cities in Hubei. China is followed by Thailand, whose market instability peaks one month later, on February 26, and then again (with a peak about the same size as the first) between March 16 and 17.

All other stock market indices exhibit peaks of mild explosiveness between March 12 and March 23, shortly after the World Health Organization makes the assessment that COVID-19 can be characterized as a pandemic (March 11). The first phases of a harsh lockdown begin in Italy on February 21, but are limited to selected municipalities in the northern part of the country. Lockdown measures are extended to most of Northern Italy on March 8, and to the rest of the country and most of the economy on March 9. By then, other countries – such as France, Spain, and the UK – have experienced the effects of the epidemic and would lockdown the economy soon. The 12 days between March 12 and 23 represent the core of the COVID-19 outbreak around the world, as many countries introduce more stringent measures and impose broad stay-at-home orders.

Table 1 shows a clear separation across geographic regions. After China and Thailand, peaks of instability occur in Europe. Instability simultaneously peaks on March 12 in the 7 European countries in the sample (France, Germany, Italy, Spain, Sweden, Switzerland, and the UK). Brazil and Japan follow suit, with their peaks of instability occurring on March 16. Peaks of instability contemporaneously emerge on March 19 in the remaining 4 South-East Asian countries in the sample (Hong Kong, Singapore, South Korea, and Taiwan), in Australia, and in India. Finally, with an evident lag, a peak of instability appears in the USA on March 23. In all cases but Thailand and China, these peaks occur almost coincidentally with (or a few days earlier than) the lowest levels attained by the stock market indices as they collapse, and right before they start bouncing back. Such lowest index values are all clustered between March 16 and 23.

PERIODS OF MILD EXPLOSIVENESS. A mildly explosive collapse (a fall in the stock market index accompanied by statistical instability) starts on January 23 in China. The drop in the SSEC index occurs from

a local maximum of 3096 (January 20) to a local minimum of 2747 (January 24, the day before the start of the Chinese New Year, during the first days of which no trading occurs in Chinese financial markets).

Some evidence of the emergence of a mildly explosive collapse in Thailand appears on February 24. Similar evidence can be dated to the end of February in most other countries in the sample. On the one hand, stock market instability related to COVID-19 appears short-lived in China, maybe because of the timely beginning of the Chinese New Year. Chinese markets recover quickly, probably thanks to rapid and heavy-handed government interventions. On the other hand, instability seems to last longer in the other countries. It keeps developing until about the last week of March in Australia, the USA, Hong Kong, Spain, South Korea, Italy, France, Germany, the UK, Sweden, Switzerland, Japan, and Taiwan; and the first week of April in Singapore, India, and Thailand. Some instability is present at the end of May in Brazil and, maybe, Japan. During their respective worst periods of mildly explosive collapses, all countries experience pronounced declines in their stock markets, ranging from -9.7% and -10.2% (USA and Hong Kong, respectively) to -28.9% and -33.1% (Australia and Spain).[1] Except Brazil and possibly Japan, the countries in the sample are on a path of non-explosive recovery between April and May. In some of these economies (South Korea, Taiwan, Thailand, Sweden, Australia, Japan, and the USA), the recovery is proportionally more apparent. This evidence is reported in Table 2 and Figures 1, 2, and 3.

TRANSMISSION. All countries experience other, less prolonged, episodes of mild explosiveness over the period under investigation. Given their temporal location, these episodes are likely not related to the development of the outbreak and the spread of the virus. Transmission of statistically unstable behavior related to COVID-19 is tested from the Chinese stock market to all other markets in the sample. As Table 3 shows, statistical evidence of migration of mild explosiveness from China (at its peak on January 24) to all countries is strong and extensive. Such empirical evidence suggests the existence of spill-over effects and the spread of market disturbances and financial contagion across major world stock markets during the first quarter of 2020. Heterogeneous country-level economic policies are likely to have heterogeneous effects on the shape and speed of recovery in each financial market. An aspect to consider for future research is the existence of financial contagion across countries and its extent during the pandemic.

COMPARISON WITH THE GFC. Unlike the COVID-19 economic crisis (which is initially triggered by a supply shock and then exacerbated by a combination of demand and financial shocks), the GFC is primarily caused by a financial shock that originates in the U.S. credit market in late July 2007 (Contessi et al., 2020). We test for mild explosiveness in the stock market indices of all countries in the sample

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[1]Relative declines are computed between the day before the beginning of instability and the last day of instability.

using daily data between January 1, 2008 and June 30, 2009 (see Table 4). In the United States, the epicenter of international instability in those months, the main GFC-related episode of mild explosiveness starts on September 29, 2008 and persists until December 24, 2008, with an overall decline of 25%. The impact of the crisis on the U.S. stock market is direct and immediate, although characterized by marked heterogeneity between sectors (Pagano et al., 2020). Mildly explosive stock market collapses also occur in China, Hong Kong, Singapore, South Korea, Thailand, Germany, Sweden, and Japan between September and December 2008. The relative magnitudes of these declines are comparable to those that are recorded in the first half of 2020. However, instability (i) does not appear to be as synchronized internationally during the GFC as during the first months of the COVID-19 pandemic; and (ii) is heterogeneous across countries in terms of duration. The remaining stock market indices do not exhibit statistically significant instability during the period under investigation.

4 Conclusions

We provide one of the first empirical investigations of the development and transmission of instability in stock markets in a cross-section of 18 major countries during the COVID-19 pandemic. We find robust evidence of instability and crashes spreading from China to other countries (especially European countries) during the most dramatic phases of circulation of the pandemic. The evidence is suggestive of an initially slow diffusion of stock market distress followed by rapid collapses, consistent with epidemiological models of diffusion of expectations.

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A Tables and Figures

Table 1: Right-Tail Augmented Dickey-Fuller (ADF) Tests on Stock Market Indices

Stock Market Index (Country)	GSADF Test Statistic	Peak Date	Date of Lowest Index Value
South-East Asian Economies			
SSEC (China)	3.989479***	01/24/2020	03/23/2020
HSI (Hong Kong)	2.678192**	03/19/2020	03/23/2020
FTFSTA (Singapore)	6.017338***	03/19/2020	03/23/2020
KS100 (South Korea)	4.48037***	03/19/2020	03/19/2020
TSE50 (Taiwan)	5.54893***	03/19/2020	03/19/2020
SET100 (Thailand)	4.477174***	02/26/2020	03/23/2020
Europe			
FCHI (France)	5.216905***	03/12/2020	03/18/2020
GDAXIP (Germany)	4.902948***	03/12/2020	03/18/2020
MIBCI3 (Italy)	4.667604***	03/12/2020	03/16/2020
IBEX (Spain)	5.053606***	03/12/2020	03/16/2020
OMXS30 (Sweden)	3.431591***	03/12/2020	03/23/2020
SPIX (Switzerland)	3.170666***	03/12/2020	03/23/2020
Other Advanced Economies			
AXJO (Australia)	3.753219***	03/19/2020	03/23/2020
N500 (Japan)	4.129232***	03/16/2020	03/16/2020
FTAS (UK)	4.525387***	03/12/2020	03/23/2020
DJA3 (USA)	4.297499***	03/23/2020	03/23/2020
Other Emerging Economies			
IBX (Brazil)	3.392524***	03/16/2020	03/23/2020
NSEI (India)	6.211307***	03/19/2020	03/23/2020

Notes. In this table, we report the outcomes of the right-tail ADF tests that we run individually on each index. We find statistical evidence of mildly explosive behavior in all of them. *** denotes statistical significance at the 1% level; ** denotes statistical significance at the 5% level. We use the Schwarz Information Criterion to select optimal lag in the test regressions. 3 days is maximum lag length considered when performing automatic lag length selection. Critical values are simulated using 1,000 replications. Initial window size: 10% of the full sample. Critical values (all indices; AXJO and IBX excluded): 3.0410 (99%), 2.3986 (95%), 2.0892 (90%). Critical values (AXJO): 3.1138 (99%), 2.3504 (95%), 2.0319 (90%). Critical values (IBX): 3.1005 (99%), 2.4285 (95%), 2.1101 (90%). Samples: 11/01/2019 - 05/29/2020. Peak Date: day on which the GSADF test statistic is located (i.e., where mildly explosive behavior peaks). Date of Lowest Index Value: day on which the index reaches its minimum value in the sample.

Table 2: Major Periods of Instability by Stock Market Index between January 1 and May 29, 2020 (length of at least 5 days)

Stock Market Index (Country)	Periods of Instability	Stock Market Index (Country)	Periods of Instability
South-East Asian Economies			**Europe**
SSEC (China)	01/02/2020-01/07/2020 **01/23/2020-01/28/2020* (-10.3%)**	FCHI (France)	**02/27/2020-03/03/2020** **03/05/2020-03/24/2020* (-25.4%)**
HSI (Hong Kong)	**03/12/2020-03/24/2020* (-10.2%)**	GDAXIP (Germany)	**02/27/2020-03/03/2020** **03/05/2020-03/25/2020* (-22.7%)**
FTFSTA (Singapore)	01/02/2020-01/07/2020 01/09/2020-01/20/2020 **03/06/2020-04/06/2020* (-20.0%)**	MIBCI3 (Italy)	**03/06/2020-03/23/2020* (-26.6%)**
KS100 (South Korea)	**02/27/2020-03/02/2020** **03/12/2020-03/24/2020* (-21.1%)**	IBEX (Spain)	**02/27/2020-03/03/2020** **03/06/2020-03/23/2020* (-33.1%)**
TSE50 (Taiwan)	**03/12/2020-03/24/2020* (-13.2%)**	OMXS30 (Sweden)	**02/27/2020-03/02/2020** **03/06/2020-03/24/2020* (-22.3%)**
SET100 (Thailand)	**02/26/2020-03/04/2020*** 03/06/2020-04/02/2020 (-21.1%)	SPIX (Switzerland)	**02/27/2020-03/02/2020** **03/09/2020-03/23/2020* (-22.2%)**
Other Advanced Economies			**Other Emerging Economies**
AXIO (Australia)	**02/28/2020-03/24/2020* (-28.9%)**	IBX (Brazil)	01/02/2020-01/08/2020 **03/06/2020-04/06/2020* (-27.9%)** 05/25/2020-05/29/2020
N500 (Japan)	**02/27/2020-03/24/2020* (-14.4%)**	NSEI (India)	**03/06/2020-04/03/2020* (-28.3%)**
FTAS (UK)	**02/25/2020-03/03/2020** **03/05/2020-03/25/2020* (-22.4%)**		
DJA3 (USA)	**03/12/2020-03/25/2020* (-9.7%)**		

Notes. In this table, we report major estimated periods of statistical instability between January 1 and May 29, 2020, for each index in the sample. Periods in bold are associated with an overall decline of the corresponding index. Periods denoted with an asterisk contain the peak dates reported in Table 1. The percentages in parentheses represent the relative changes in the stock market indices during the corresponding periods of mildly explosive collapse (they are computed between the day before the beginning of mild explosiveness and the last day of mild explosiveness). In the cases of South Korea, Thailand, France, Germany, Spain, Sweden, Switzerland, and the UK, such percentages are computed over two non-continuous (but close enough) periods of mildly explosive collapse. All periods of mild explosiveness are detected using 90% critical values.

Table 3: Tests of Migration from the SSEC Index (China)

| Migration to	Peak Date	m	β_1	Standard Error	T-Stat	L(m)				Z_β			
						a=1/10	a=1/5	a=1/4	a=1/3	a=1/10	a=1/5	a=1/4	a=1/3
South-East Asian Economies													
HSI (Hong Kong)	03/19/2020	39	-0.782	0.191	-4.106	0.159	0.318	0.398	0.530	**-4.917**	**-2.4585**	**-1.9668**	**-1.4751**
FTFSTA (Singapore)	03/19/2020	39	-3.510	0.406	-8.657	0.159	0.318	0.398	0.530	**-22.064**	**-11.032**	**-8.8254**	**-6.6191**
KS100 (South Korea)	03/19/2020	39	-0.944	0.237	-3.984	0.159	0.318	0.398	0.530	**-5.936**	**-2.968**	**-2.3744**	**-1.7808**
TSE50 (Taiwan)	03/19/2020	39	-1.535	0.321	-4.781	0.159	0.318	0.398	0.530	**-9.6445**	**-4.8223**	**-3.8578**	**-2.8934**
SET100 (Thailand)	02/26/2020	23	-1.054	0.236	-4.464	0.136	0.272	0.340	0.454	**-7.7408**	**-3.8704**	**-3.0963**	**-2.3222**
Europe													
FCHI (France)	03/12/2020	34	-3.369	0.278	-12.128	0.153	0.306	0.383	0.510	**-21.996**	**-10.998**	**-8.7983**	**-6.5988**
GDAXIP (Germany)	03/12/2020	34	-5.040	0.235	-21.494	0.153	0.306	0.383	0.510	**-32.912**	**-16.456**	**-13.165**	**-9.8737**
MIBCI3 (Italy)	03/12/2020	34	-2.326	0.296	-7.861	0.153	0.306	0.383	0.510	**-15.191**	**-7.5954**	**-6.0763**	**-4.5572**
IBEX (Spain)	03/12/2020	34	-2.178	0.222	-9.824	0.153	0.306	0.383	0.510	**-14.224**	**-7.1119**	**-5.6895**	**-4.2672**
SPIX (Switzerland)	03/12/2020	34	-0.729	0.176	-4.144	0.153	0.306	0.383	0.510	**-4.7633**	**-2.3816**	**-1.9053**	**-1.429**
OMXS30 (Sweden)	03/12/2020	34	-1.442	0.214	-6.739	0.153	0.306	0.383	0.510	**-9.4142**	**-4.7071**	**-3.7657**	**-2.8243**
Other Advanced Economies													
AXJO (Australia)	03/19/2020	39	-1.878	0.176	-10.659	0.159	0.318	0.398	0.530	**-11.802**	**-5.9009**	**-4.7208**	**-3.5406**
N500 (Japan)	03/16/2020	36	-3.722	0.301	-12.373	0.156	0.311	0.389	0.519	**-23.914**	**-11.957**	**-9.5658**	**-7.1743**
FTAS (UK)	03/12/2020	34	-1.929	0.218	-8.860	0.153	0.306	0.383	0.510	**-12.595**	**-6.2974**	**-5.0379**	**-3.7784**
DJA3 (USA)	03/23/2020	41	-1.217	0.197	-6.180	0.161	0.323	0.403	0.538	**-7.5479**	**-3.7739**	**-3.0192**	**-2.2644**
Other Emerging Economies													
IBX (Brazil)	03/16/2020	36	-0.823	0.191	-4.303	0.156	0.311	0.389	0.519	**-5.2906**	**-2.6453**	**-2.1163**	**-1.5872**
NSEI (India)	03/19/2020	39	-3.685	0.398	-9.265	0.159	0.318	0.398	0.530	**-23.158**	**-11.579**	**-9.2631**	**-6.9473**

Notes. In this table, we test for migration of mildly explosive behavior from the SSEC index (China) to all other indices. Negative Z statistics (all estimated coefficients, in this table) indicate migration. Critical values for one-sided (left-tailed) test of migration (from a standard normal distribution): -2.326 (1% level test), -1.645 (5% level test), -1.282 (10% level test). m: length of the sample over which the test regression is run; number of daily observations between the observation immediately after the peak of mildly explosive behavior (excluded) in the SSEC index (from which migration is tested) and the peak of mildly explosive behavior (included) in the index to which migration is tested. L(m)=a*log₁₀(m), a>0. $Z_\beta=\beta_1/L(m)$. Z_β figures in bold (all figures, in this table) denote statistically significant migration at least at the 10% level. Peak date for the SSEC index (China) is 01/24/2020.

Table 4: Major Periods of Instability by Stock Market Index between January 1, 2008 and June 30, 2009 (length of at least 5 days)

Stock Market Index (Country)	Periods of Instability	Peak Date
South-East Asian Economies		
SSEC (China)	**03/24/2008-04/02/2008 (-11.8%)** **09/11/2008-09/18/2008 (-11.9%)** 02/06/2009-02/17/2009	02/16/2009
HSI (Hong Kong)	**06/27/2008-07/08/2008 (5.5%)** **10/06/2008-11/25/2008 (-27.2%)**	10/27/2008
FTFSTA (Singapore)	**06/27/2008-07/08/2008 (-4.1%)** **08/18/2008-12/31/2008 (-39.5%)** **01/15/2009-01/23/2009 (-4.8%)** **03/02/2009-03/12/2009 (-6.9%)** 05/01/2009-06/15/2009	10/27/2008
KS100 (South Korea)	**07/02/2008-07/18/2008 (-9.5%)** **09/01/2008-09/05/2008 (-4.4%)** **10/08/2008-10/30/2008 (-17.5%)** **11/18/2008-11/25/2008 (-8.8%)**	10/24/2008
TSE50 (Taiwan)	No overall instability	
SET100 (Thailand)	**07/03/2008-08/06/2008 (-12.2%)** **09/02/2008-12/15/2008 (-36.4%)** 04/29/2009-06/19/2009	05/13/2009
Other Advanced Economies		
AXJO (Australia)	No overall instability	
N500 (Japan)	**10/02/2008-10/31/2008 (-20.4%)** **06/10/2009-06/16/2009 (-0.2%)**	10/10/2008
FTAS (UK)	No overall instability	
DJA3 (USA)	**09/29/2008-12/24/2008 (-25.0%)** **02/17/2009-03/20/2009 (-6.0%)**	10/09/2008

| Stock Market Index (Country)	Periods of Instability	Peak Date
Europe		
FCHI (France)	No overall instability	
GDAXIP (Germany)	**06/20/2008-07/16/2008 (-8.4%)** **10/06/2008-10/27/2008 (-25.2%)**	10/24/2008
MIBCI3 (Italy)	No overall instability	
IBEX (Spain)	No overall instability	
OMXS30 (Sweden)	**06/24/2008-07/16/2008 (-9.6%)** **10/08/2008-10/29/2008 (-12.9%)**	07/01/2008
SPIX (Switzerland)	**06/27/2008-07/16/2008 (-5.9%)** **02/23/2009-03/09/2009 (-10.8%)**	10/10/2008
Other Emerging Economies		
IBX (Brazil)	No overall instability	
NSEI (India)	No overall instability	

Notes. In this table, we report major estimated periods of statistical instability between January 1, 2008 and June 30, 2009, for each index in the sample. Periods in bold are associated with an overall decline of the corresponding index. The percentages in parentheses represent the relative changes in the stock market indices during the corresponding periods of mildly explosive collapse (they are computed between the day before the beginning of mild explosiveness and the last day of mild explosiveness). Peak Date: day on which the GSADF test statistic is located (i.e., where mildly explosive behavior peaks). No overall instability (in a statistical sense) in a given country does not imply no decline in the corresponding index during the months of the Great Financial Crisis. All periods of mild explosiveness are detected using 90% critical values.

Figure 1: Stock Market Indices, Sequences of $BSADF$ Test Statistics, Sequences of Critical Values, and Periods of Mild Explosiveness (1) – South-East Asian Economies
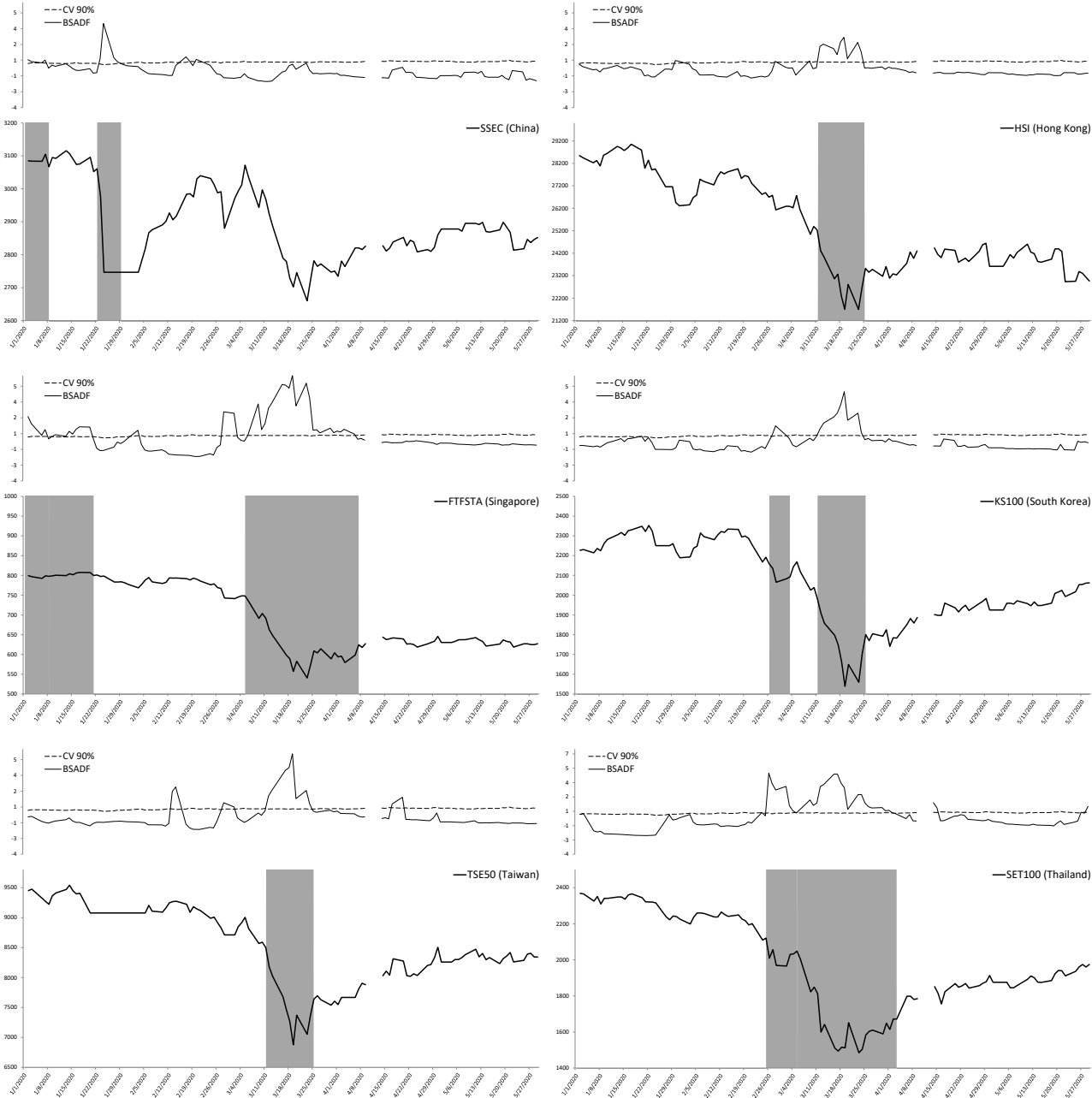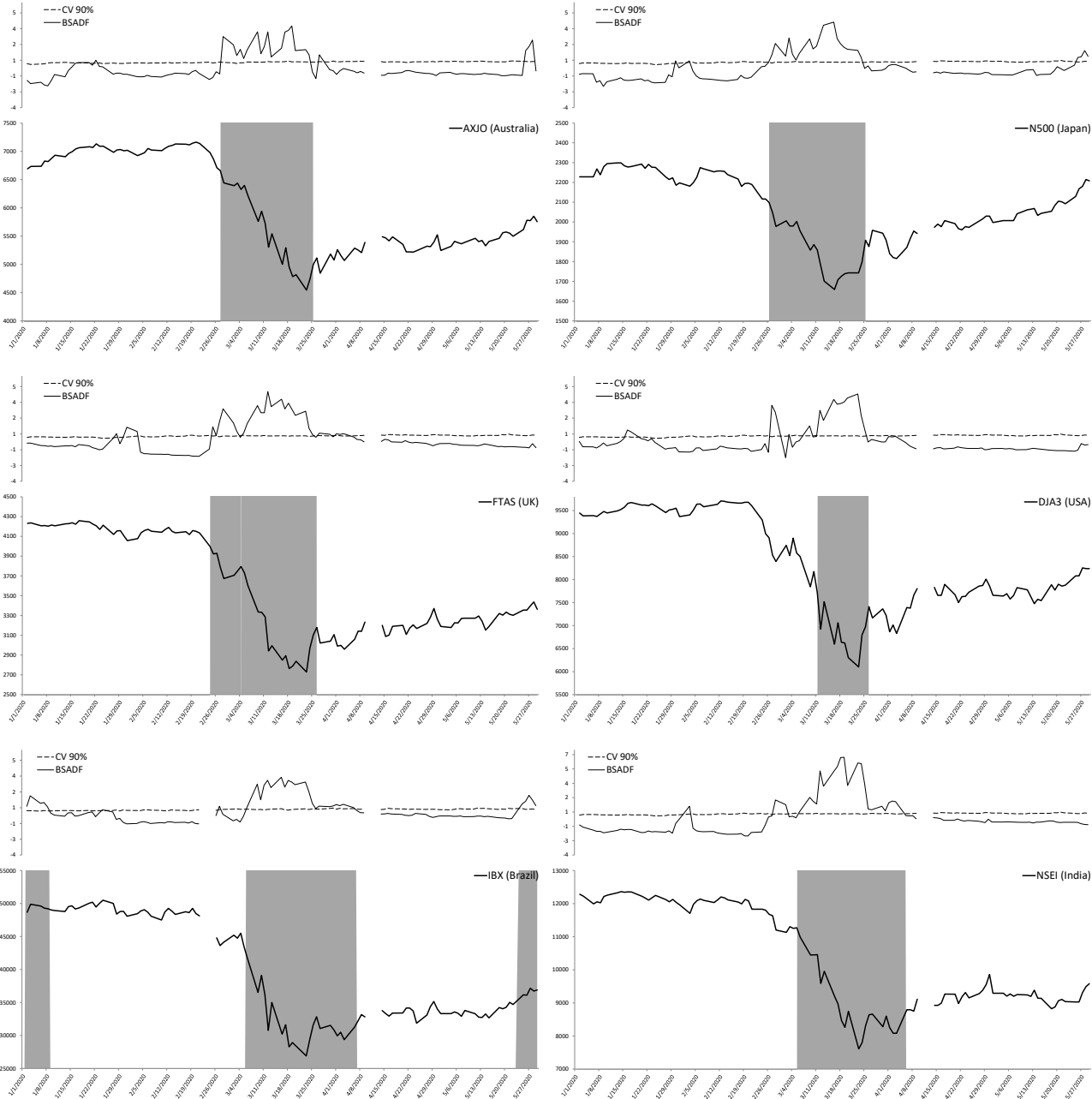

Notes. Shaded areas represent periods of mildly explosive behavior of at least 5 days.

Figure 2: Stock Market Indices, Sequences of $BSADF$ Test Statistics, Sequences of Critical Values, and Periods of Mild Explosiveness (2) – Europe
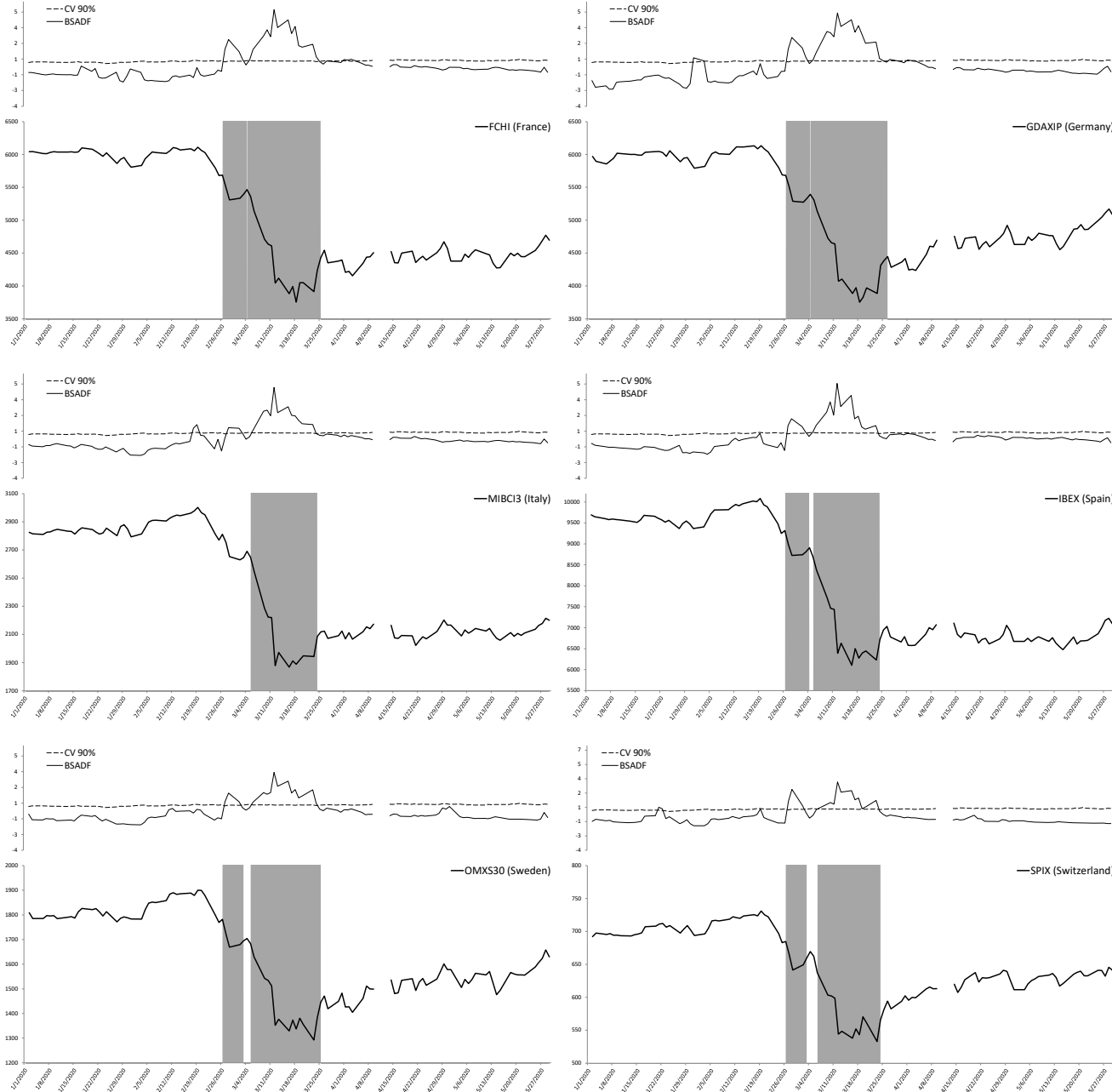
Notes. Shaded areas represent periods of mildly explosive behavior of at least 5 days.

Figure 3: Stock Market Indices, Sequences of $BSADF$ Test Statistics, Sequences of Critical Values, and Periods of Mild Explosiveness (3) – Other Advanced Economies and Other Emerging Economies

Notes. Shaded areas represent periods of mildly explosive behavior of at least 5 days.