

Stock Prices, Lockdowns, and Economic Activity in the Time of Coronavirus

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Abstract

Stock prices and workplace mobility trace out striking clockwise paths in daily data from mid-February to late May 2020. Global stock prices fell 30 percent from 17 February to 12 March, *before* mobility declined. Over the next 11 days, stocks fell another 10 percentage points as mobility dropped 40 percent. From 23 March to 9 April, stocks recovered half their losses and mobility fell further. From 9 April to late May, both stocks and mobility rose modestly. This dynamic plays out across the 31 countries in our sample, with a few notable exceptions. We also find strong evidence that stricter lockdown policies, both in-country and globally, drove larger declines in national stock prices conditional on pandemic severity, workplace mobility, and income support and debt relief policies. In a closer look at the two largest economies, we find that the pandemic had greater effects on stock market levels and volatilities in the U.S. than in China. Narrative evidence confirms (a) the dominant role of pandemic-related developments for stock prices in both countries, and (b) no previous infectious disease outbreak (including the Spanish Flu and SARS) had stock market effects that resemble those of COVID-19.

JEL Classifications: E32, E44, E65, G12, G18, I18

Keywords: stock prices, lockdown policies, market shutdowns, coronavirus, COVID-19, workplace mobility, China

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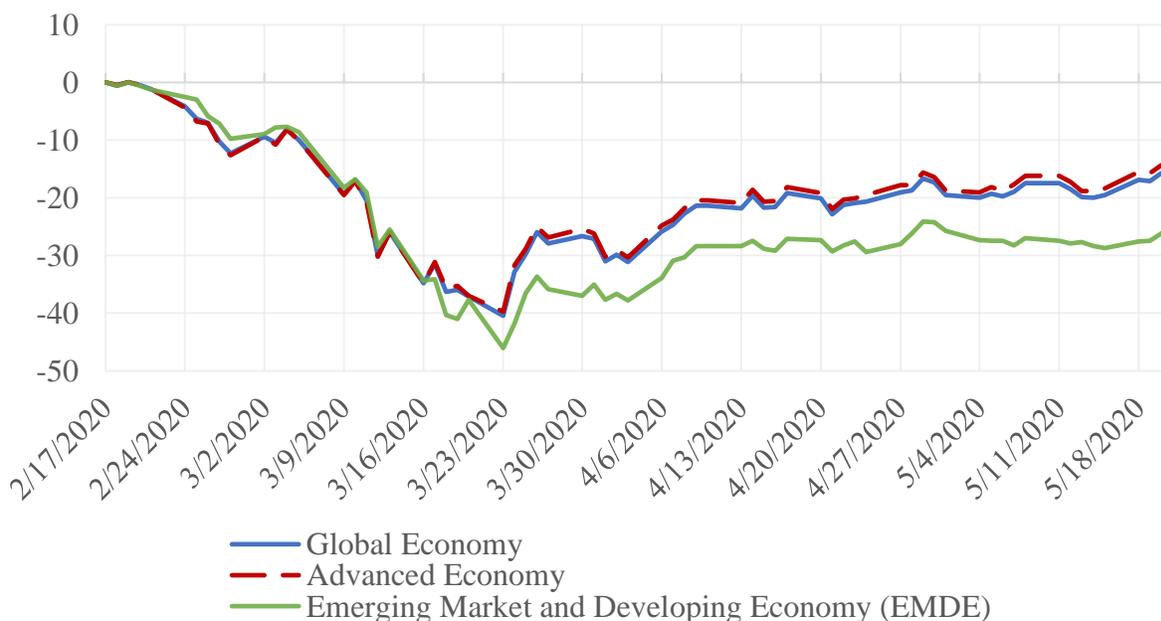
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1. Introduction

Stock markets cratered after mid-February in countries around the world, as the coronavirus pandemic spread beyond China. Value-weighted prices dropped 40 percent from 17 February to 23 March in the advanced economies (Figure 1). Emerging market and developing economies (EMDEs) saw an even steeper drop. This period also exhibits historically high levels of intraday, daily, and implied stock market volatility amidst extraordinarily high economic uncertainty¹.

Figure 1. Global Stock Prices, Percent Deviations from 17 February 2020



Notes: We plot the cumulative percent deviation in average equity prices from 17 February 2020 to the indicated dates. In computing averages, we weight each country's deviation by its market capitalization on 31 December 2018. Before averaging, we linearly interpolate country-level values between nearest trading dates to fill in missing values. Our sample contains 17 advanced economies (88.4% of overall market capitalization) and 14 EMDEs (11.6%).

In what many see as a puzzle, the global stock market recovered more than half its losses from 23 March to late May. U.S. stock market behavior, in particular, has prompted much head scratching: Despite a failure to control the pandemic, the U.S. stock market recovered 73 percent

¹ See Alan et al. (2020) for equity market volatility measures based on GARCH models and intraday prices for dozens of countries, Baker et al. (2020a) for U.S. volatility measures that stretch back to 1900, the website at www.PolicyUncertainty.com for newspaper-based economic uncertainty measures for more than 25 countries based on Baker, Bloom and Davis (2016), and Altig et al. (2020) for a variety of forward-looking measures of economic uncertainty for the United States and United Kingdom.

of its lost value by the end of May and 95 percent by 22 July.² Shiller (2020) attributes these and other aspects of recent market dynamics to “crowd psychology, the virality of ideas, and the dynamics of narrative epidemics.” He also asks why the stock market failed to predict the pandemic-induced recession before the downturn began.

Recent stock price behavior is also remarkable in other respects. Using text-based methods to characterize the drivers of stock market jumps and volatility, Baker et al. (2020a) find that previous pandemics, including the Spanish Flu, had little or no impact on the U.S. market. In one exercise, they examine all 1,143 daily U.S. stock market moves greater than 2.5 percent, up or down, since 1900. Next-day newspaper accounts attribute not a single jump before 2020 to pandemic-related developments. In glaring contrast, newspapers attribute 24 of 27 daily U.S. jumps between 24 February and 30 April to COVID-19 developments and policy responses to the pandemic. Other research also highlights the pandemic’s impact on the stock market. For example, Alfaro et al. (2020) find that unexpected changes in the anticipated trajectory of COVID-19 infections predict next-day stock returns in the United States. Amstad et al. (2020) find that a “COVID-19 risk attitude” index derived from internet searches helps explain national stock market moves from mid-February to late April. These studies help motivate our investigation into the joint dynamics of stock prices, economic activity, and policy actions during the coronavirus pandemic.

In our first set of results, we show that stock prices and workplace mobility (a proxy for economic activity) trace out striking clockwise paths in daily data from mid-February to late May 2020. Global stock prices fell 30 percent from 17 February to 12 March, *before* mobility declined. Over the next 11 days, stocks fell another 10 percentage points as mobility dropped 40 percent. From 23 March to 9 April, stocks recovered half their losses and mobility fell further. From 9 April to late May, both stocks and mobility rose modestly. The same dynamic plays out across the vast majority of the 31 countries in our sample, with a few notable exceptions that we highlight and discuss.

Common global dynamics are a pronounced feature of our data. Thus, we also ask whether national stock prices have predictive value for own-country economic activity, conditional on global developments. We find that they do. Another natural question is whether stock prices responded too slowly to information that presaged a pandemic-driven downturn. While we cannot rule out this possibility, we make several observations that suggest it was reasonable, as of early and mid-February 2020, for stock market investors to anticipate a modest impact of COVID-19 on economic activity and asset prices.

Perhaps because COVID-19 erupted first in China, the dynamic between stock prices and mobility played out differently there. In particular, China experienced coincident drops in stock prices and mobility during the early phase of its pandemic recession. The exact dynamics are obscured by an extended Spring Festival market closure in response to the pandemic. Unlike most other countries, our mobility measure for China returns to its pre-pandemic baseline by late April, and Chinese stock prices surpass pre-pandemic levels by the second half of April.

² Calculated from the Wilshire 5000 Total Market Full Cap Index [WILL5000INDFC], retrieved from FRED, Federal Reserve Bank of St. Louis on 25 July 2020. Because U.S. markets were closed on 17 February, our start date is 18 February in these calculations.

In a second set of results, we find that stock prices are lower when countries impose more stringent market lockdown measures. This association survives the inclusion of controls for global average outcomes and common time effects. In our preferred specification – which includes controls for own-country and global average values of economic activity, pandemic severity, and government income support and debt relief measures – national stock prices are 3.0 percentage points lower when the own-country lockdown stringency index is one standard deviation higher and 4.7 points lower when the global average stringency index is one standard deviation higher. These are separate effects, and both are highly statistically significant.

Next, we look more closely at stock prices in the world's two largest economies. As we show in various ways, the COVID-19 pandemic had much larger effects on stock prices and return volatilities in the U.S. than in China. At least in part, the greater impact on American stock prices reflects China's greater success in containing the pandemic. However, we stress that the U.S. stock market shows a much greater sensitivity to pandemic-related developments long before it became evident that its early containment efforts would flounder. That leads us to further investigations into the differences between Chinese and U.S. markets during the period from mid-February to late May 2020.

In one exercise, we use next-day newspaper accounts to classify the (perceived) reasons for large daily moves in Chinese stock markets from 1990 onwards. Before COVID-19, newspapers attribute not a single such move (out of hundreds) to pandemic developments or news about infectious diseases. From 2 January to 30 April 2020, Chinese newspapers attribute all 6 daily stock market moves greater than $|3\%|$ on the Shanghai Stock Exchange and all 8 daily moves greater than $|3.8\%|$ on the Hang Seng to the economic fallout of the pandemic or policy responses to the pandemic.³ These two results closely parallel findings in Baker et al. (2020a) for the United States. However, the incidence of large daily stock market moves during the coronavirus pandemic is about four times greater in the U.S. than in China. In a second exercise, we catalog interventions by Chinese regulatory authorities and the People's Bank of China that sought to support the stock market. Our event-study analysis of these interventions finds some evidence that they raised Chinese stock market volatility, at least temporarily.

Our study relates closely to a rapidly growing literature on the dynamics of stock prices, economic activity, and policy actions during the coronavirus pandemic. Notable contributions include Alan et al. (2020), Caballero and Simsek (2020), Chen and Spence (2020), Cox et al. (2020), and Deb et al. (2020).⁴ Compared to these papers, we contribute by documenting the predictive content of national stock prices for near-future economic activity and by providing

³ One might worry that newspaper accounts merely reflect the prevailing narrative of the day rather than meaningful information about the true reasons for large daily stock market moves. Baker, Bloom, Davis and Sammon (2020b) address this question at some length. They validate the newspaper-derived explanations in several ways. They also find that newspaper-based interpretations have predictive power for future stock market volatility, even when conditioning on a standard battery of controls for serial correlation in stock market volatility.

⁴ Another rapidly growing literature explores the distinctive effects of the coronavirus pandemic on the cross-sectional structure of firm-level equity returns. Examples include Albuquerque et al. (2020), Alfaro et al. (2020), Davis, Hansen and Seminario (2020), Ding et al. (2020), Hassan et al. (2020), Pagano et al. (2020), Papanikolaou and Schmidt (2020), and Ramelli and Wagner (2020).

evidence that stock prices fall sharply with the stringency of lockdown measures, conditional on a battery of controls for pandemic severity, mobility, and the generosity of income support and debt relief policies. We also provide some evidence on how other aspects of national policy relate to stock price behavior during the pandemic, particularly in China.

2. Stock Prices, Lockdowns, and Activity as the Pandemic Unfolded

A. Sources of Data for National Outcomes

We integrate data from multiple sources. Our main high-frequency proxy for national economic activity is the percent workplace mobility deviation from baseline in Google's *COVID-19 Community Mobility Reports*. This measure reflects the frequency and duration of visits to worksites relative to the own-country baseline. Google (2020) defines the baseline as the median value, for the corresponding day of the week, during the 5-week period from 3 January to 6 February 2020. These data are available from 17 February onwards for 31 countries in our many-country sample but not available for China.

We obtain national stock market index values on trading days from Global Financial Data (GFD) at <https://globalfinancialdata.com/>. For much of our analysis, we treat each country's value on 17 February 2020 as a baseline and measure percent deviations on date t as $r_{c,t} = \ln\left(\frac{P_{c,t}}{P_{c,0}}\right) \times 100$, where $P_{c,0}$ is the stock market index value of country c on 17 February. When aggregating over countries, we weight by stock market capitalization values as of 31 December 2018 from the World Bank's World Federation of Exchanges Database.

To quantify the strictness of government-mandated market lockdown measures adopted in response to actual and prospective COVID-19 outbreaks, we use the Oxford "Stringency" Index from Hale (2020). Our Economic Support Index, which reflects the extent of government measures to provide income support and debt relief, is also from Hale (2020). Our data on COVID-19 cases and deaths per million persons are from Johns Hopkins University (2020).

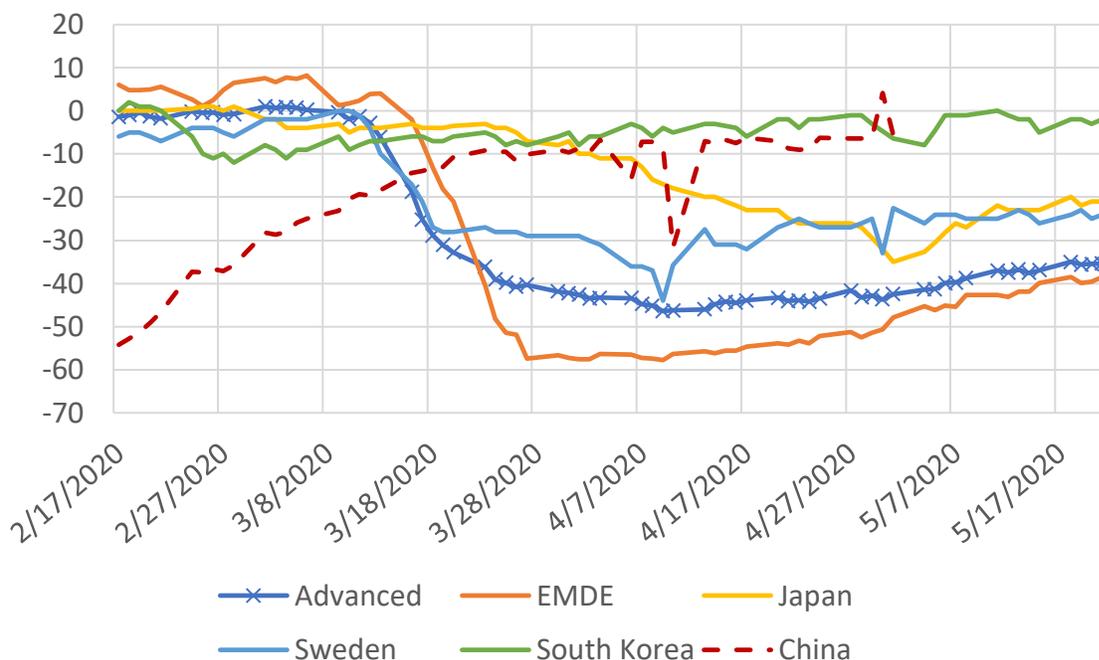
After merging these sources, we have daily data for 31 countries from 17 February to 21 May 2020. Ordered by stock market capitalization, there are 17 Advanced Economies (AE) in our sample: the United States, Japan, France, Canada, Switzerland, Germany, South Korea, Netherlands, Spain, Singapore, Sweden, Belgium, Taiwan, Poland, Ireland, Greece, Slovenia. There are 14 Emerging Market and Developing Economies (EMDEs): India, Brazil, South Africa, Thailand, Malaysia, Mexico, Chile, Qatar, Turkey, Romania, Argentina, Kazakhstan, Hungary, Croatia.⁵

Figure 2 displays percent workplace mobility deviations (WMD) for selected countries and regions. We linearly interpolate WMD values between market trading days to remove the effects of weekends and holidays. (Appendix Figure A.1 displays raw WMD values for all days.) Most countries experienced tremendous drops in economic activity after early March. From 9 March to 9 April, the weighted-average WMD value fell nearly half among the AEs and nearly

⁵ Our grouping follows the IMF at www.imf.org/external/pubs/ft/weo/2020/01/weodata/groups.htm.

60 percent among the EMDEs. Figure 2 also shows the WMD path for three “outlier” countries with relatively small drops in economic activity: Japan, Sweden and, especially, South Korea.

Figure 2. Workplace Mobility on Trading Days, Percent Deviation from Baseline



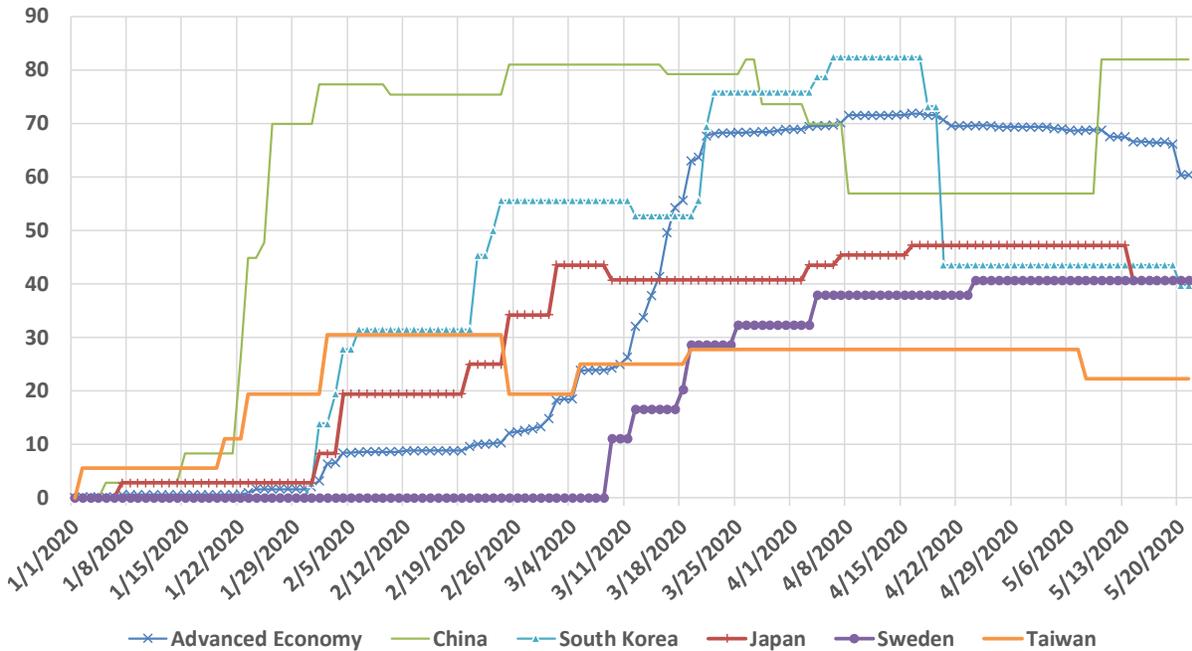
Note: We obtain national data from Google (2020) for trading days, interpolate the national data between trading days, and aggregate over countries using stock market capitalization. China’s mobility data are from Baidu.

Figure 3 and Appendix Figure A.2 summarize the stringency of market lockdown measures adopted by governments in reaction to the pandemic, as quantified in Hale (2020). These figures show that the timing and severity of lockdowns differ substantially across countries. The pandemic emerged first in China, and China also clamped down on economic activity sooner than other countries. South Korea, Japan, and Taiwan also responded faster than most other AEs but more lightly in Japan and Taiwan. Sweden responded later than other AEs and with relatively light restrictions. Except for Japan, Sweden, South Korea, Singapore and Taiwan, all countries in our sample eventually implemented a hard lockdown for at least one week, where we interpret “hard” to mean a lockdown stringency index value of 70 or greater.

B. The Time Paths of Stock Prices and Economic Activity

Figure 4 shows that stock prices and workplace mobility trace out striking clockwise paths in daily data from mid-February to late May 2020. Global stock prices fell 30 percent from 17 February to 12 March, *before* mobility declined. Over the next 11 days, stocks fell another 10 percentage points as mobility dropped 40 percent. From 23 March to 9 April, stocks recovered half their losses and mobility fell further. From 9 April to late May, both stocks and mobility rose modestly. The same dynamic plays out across the vast majority of the 31 countries in our sample (Figures 5 and A.3), with a few notable exceptions that we discuss later.

Figure 3. Economic Lockdown Stringency Index, 1 January to 21 May 2020.



Note: We obtain national data from Hale (2020) and aggregate over countries using stock market capitalization. The stringency index exceeds 70 at some point for all countries except Japan, Sweden and Taiwan.

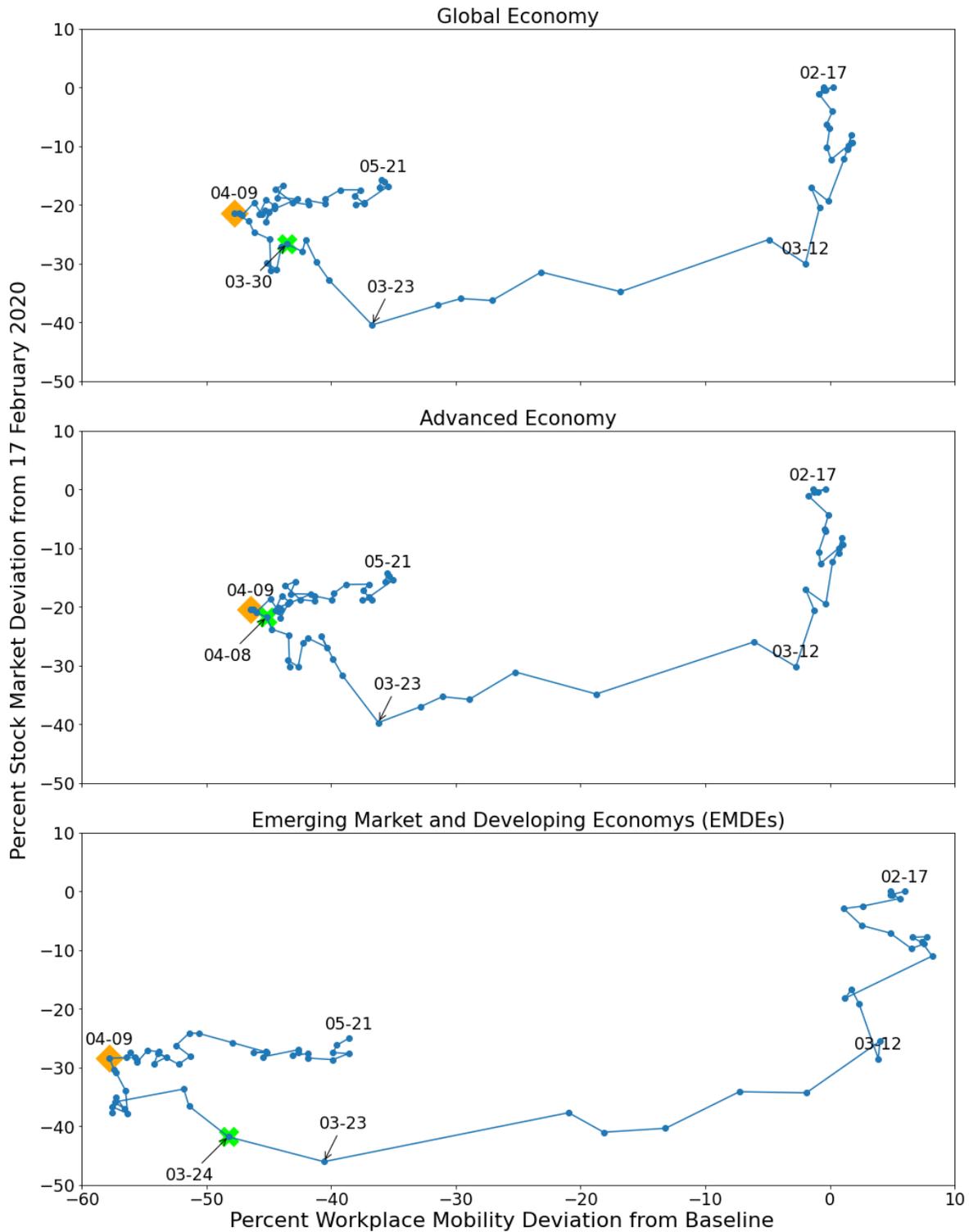
While our evidence shows that collapsing stock markets clearly preceded the collapse in economy activity, one could argue that a rational, forward-looking stock market would have reacted sooner. Indeed, Shiller (2020) writes: “[T]he World Health Organization (WHO) declared the new coronavirus ‘a public health emergency of international concern’ on January 30. Over the next 20 days, the S&P 500 rose by 3%, hitting an all-time record high on February 19. Why would investors give shares their highest valuation ever right after the announcement of a possible global tragedy? ... Why didn’t the stock market “predict” the coming recession by declining before the downturn started?”

We take Shiller’s question to be why didn’t stock markets react earlier to the possibility of an impending economic disaster? And, in particular, why didn’t markets react shortly after the WHO’s declaration on 30 January? There is a ready answer to this question: Most investors did not see the novel coronavirus as a major risk to the economy of the sort that warranted a large devaluation in equity prices. Moreover, it is not obvious as of early February 2020, except in hindsight, that they should have regarded the virus as a major economic risk.

In this regard, we make four sets of observations. First, the WHO declared a “public health emergency of international concern” on five prior occasions since 2009.⁶ None of these declarations triggered a market crash, nor did any of the underlying disease outbreaks unfold in a manner that warranted a major devaluation in equity prices. Second, Baker et al. (2020a) show

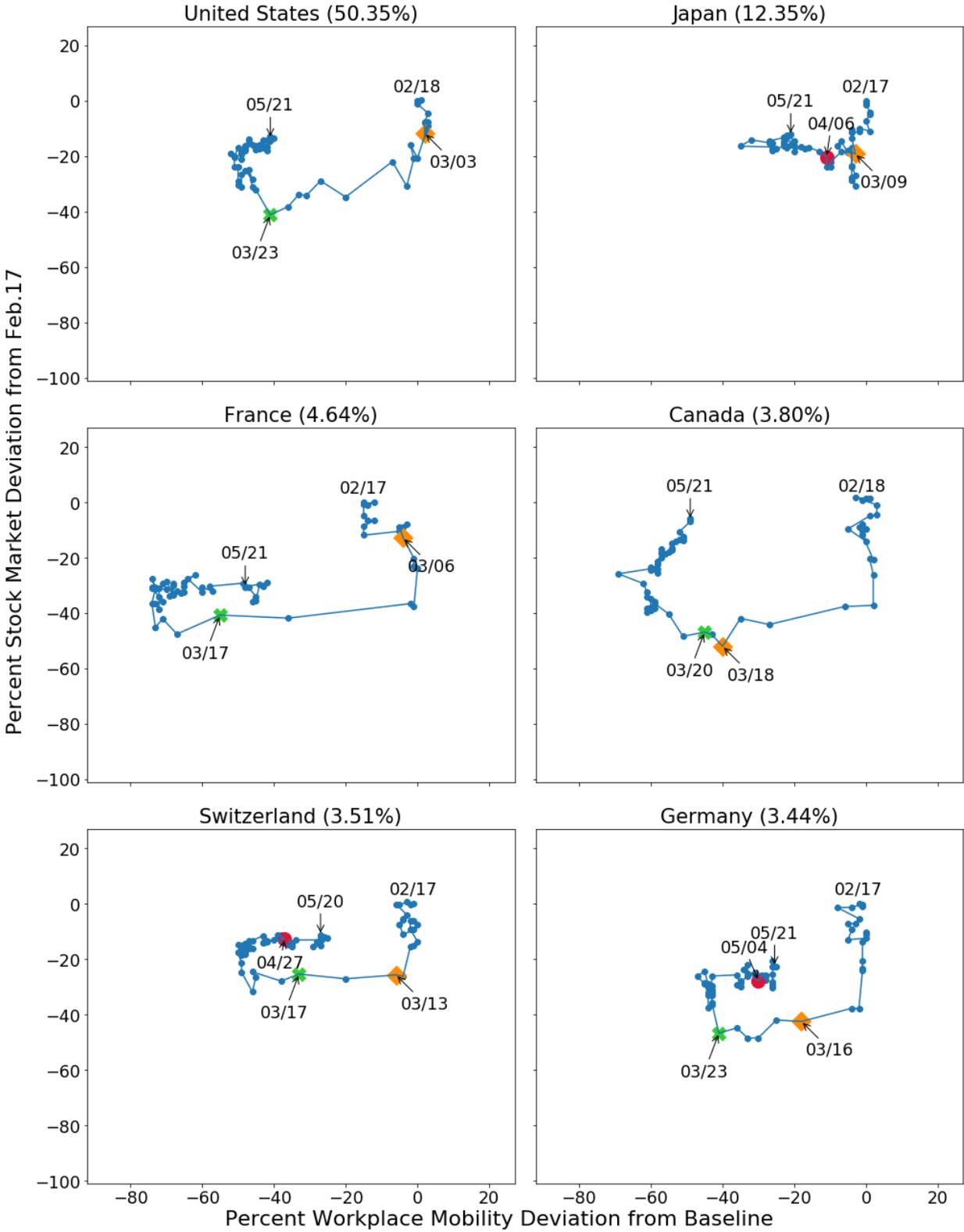
⁶ See the Wikipedia entry for [public health emergency of international concern](#), accessed 12 October 2020. The WHO formalized this type of emergency announcement in 2005, as discussed in WHO (2005).

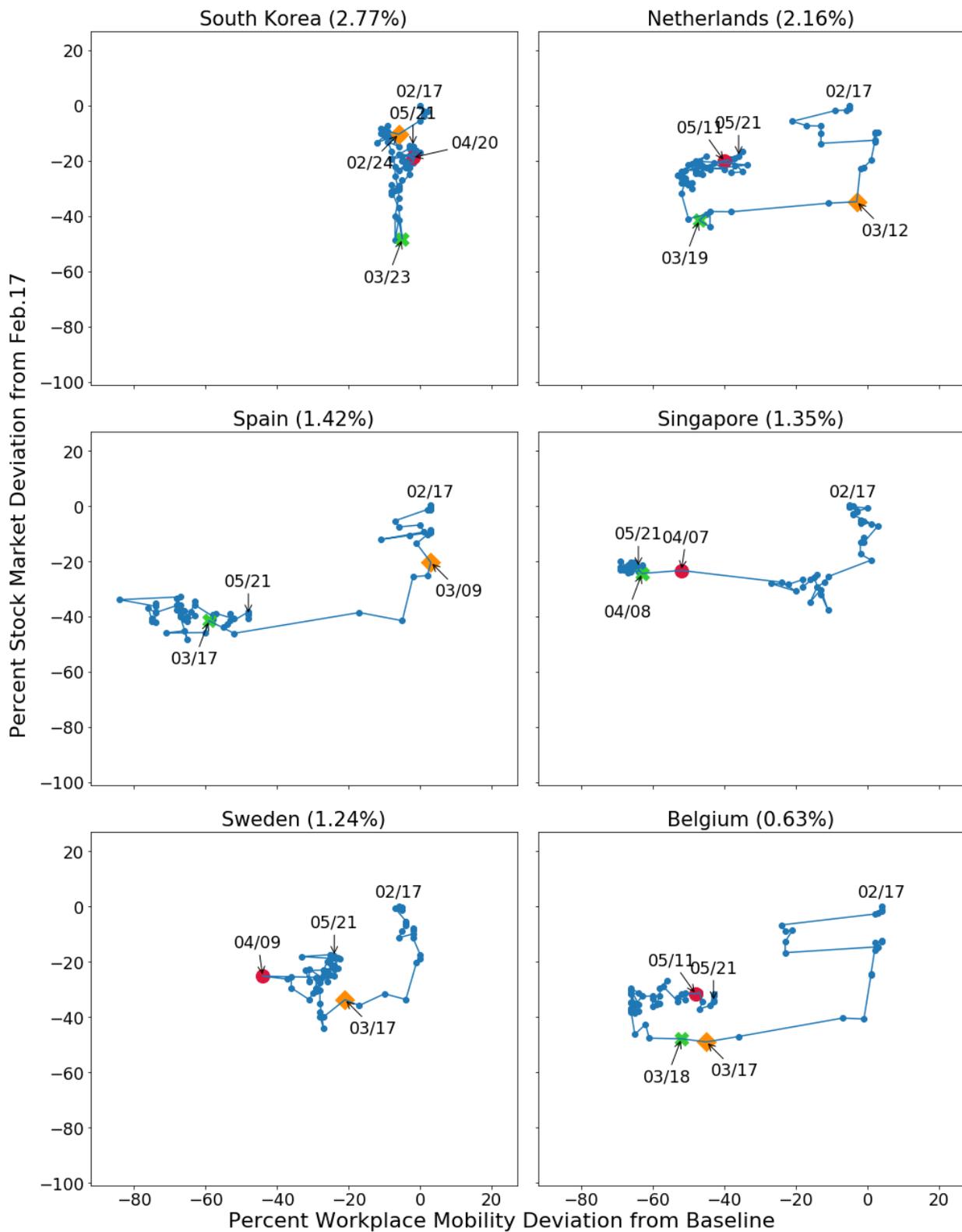
Figure 4. Time Path of Stock Prices and Workplace Mobility from 17 February to 21 May 2020

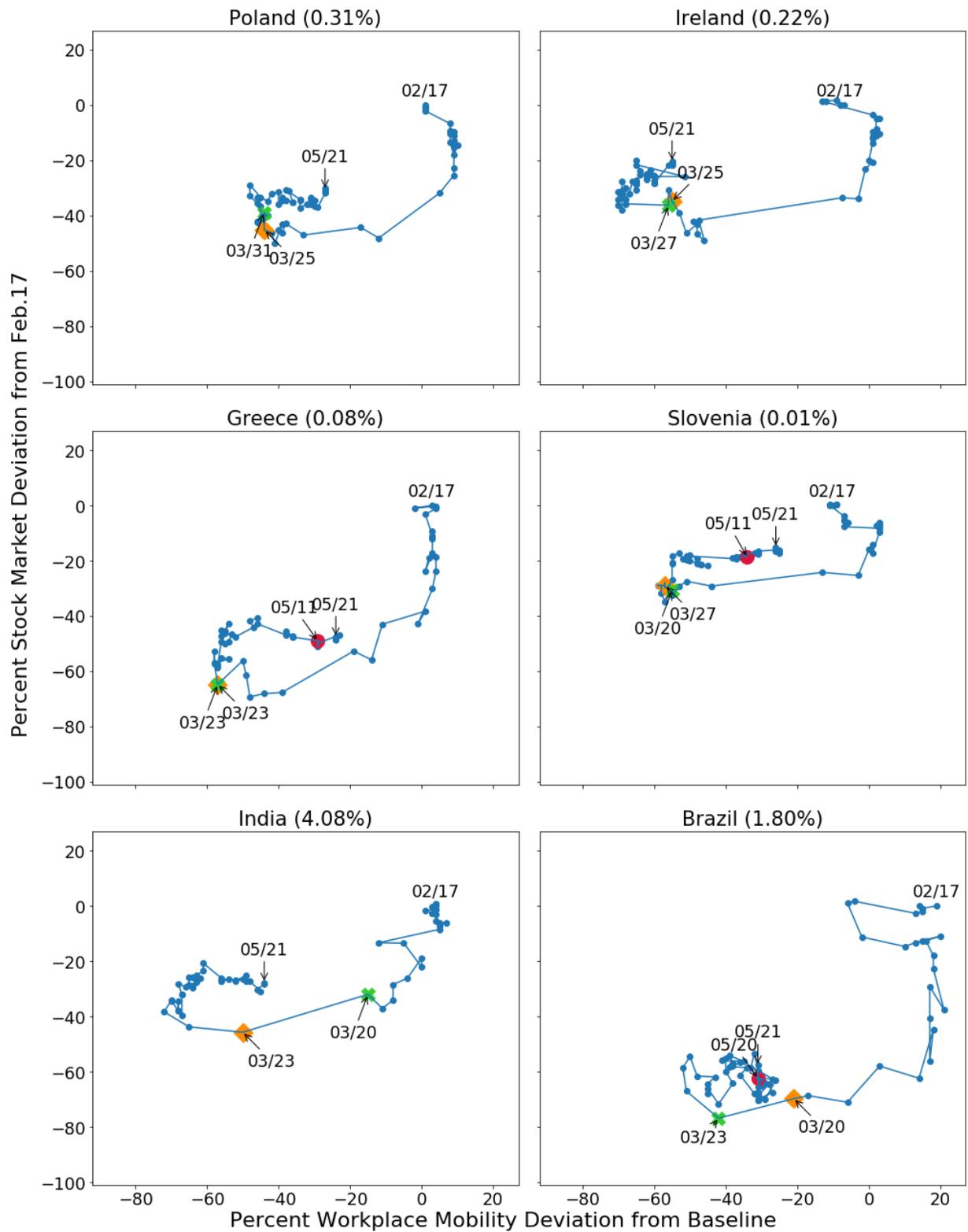


Note: The orange diamond shape marker represents the date when global weighted workplace mobility percentage change from the baseline reaches its lowest value. The green cross marker represents the first date when the average stringency index exceeds 70.

Figure 5. Time Path of Stock Prices and Workplace Mobility from 17 February to 21 May, Advanced Economies and EMDEs with Largest Market Capitalization







Note: An orange diamond marks the first confirmed COVID-19 death in the country, a green cross marks the first date with a stringency index value of 70 or more, and a red circle marks the date on which the stringency index first drops below 70.

that no previous infectious disease outbreak over the previous 120 years affected the U.S. stock market in a manner that resembles its response to COVID-19. That includes the Spanish Flu of 1918-19, which involved an excess mortality rates greater by an order of magnitude than that of COVID-19. It also includes the influenza pandemic of 1957-58, which involved an excess mortality rate similar to that of COVID-19 to date. Third, we provide evidence below that no previous infectious disease outbreak (back to 1990) affected stock markets in mainland China and Hong Kong in a manner that resembles their responses to COVID-19. That includes the SARS outbreak in 2003. Fourth, at least in the United States, the economic contraction triggered by COVID-19 has been much, much deeper than one would anticipate by extrapolating the impact of previous pandemics over the past 120 years.⁷ These observations suggest it was reasonable, as of early and even mid-February 2020, for stock market investors to anticipate a modest economic impact of COVID-19 on economic activity and asset prices.

C. National Stock Prices Predict Country-Specific Drops in Economic Activity

As we have shown, national stock price movements exhibit important co-movements in the period during which global-average values collapse. That raises the question of whether national stock prices have predictive value for own-country economic activity, conditional on global developments. We take up that question now.

To do so, we regress workplace mobility deviations on lagged stock price deviations in our panel of 31 countries. Our sample for this analysis contains all workdays from 12 March to 23 March, where “workdays” refer to dates on which the country’s stock market traded. For explanatory variables, we linearly interpolate between trading days to fill in weekend and holiday values. We choose 23 March as the sample endpoint, because that is when stock prices in most countries began to increase even as mobility fell further. We run two sets of regression:

$$WMD_{c,t} = \alpha \times SMD_{c,t-1} + I_c + I_t + \varepsilon_{c,t} \quad (1)$$

$$\Delta WMD_{c,t} = \sum_{j=1}^6 \beta^j \times \Delta SMD_{c,t-j} + I_t + \varepsilon_{c,t} \quad (2)$$

Table 1 reports the results. The first three columns provide strong statistical evidence that lower national stock prices yesterday foreshadow lower own-country workplace mobility deviations today. To interpret magnitudes, consider Column (3). The coefficient on the lagged own-country *SMD* variable says: If yesterday’s national stock price is 10 percentage points below its baseline value, the model predicts that today’s mobility deviation is 3 percentage points below its baseline, conditional on common global developments. This is a large effect, especially in light of the fact that many countries in our sample experienced *SMD* values 30 percentage points or more below baseline as of 22 March.⁸

⁷ See Baker et al. (2020a), Ferguson (2020), and Velde (2020) on this point.

⁸ Column (4) shows a statistically insignificant coefficient on lagged *SMD* when controlling for country and time effects. Since our sample entails a short panel dimension, with at most 8 observations per country, the inclusion of country and time effects pushes the data very hard. In this regard, recall that both *SMD* and *WMD* are already demeaned at the country level, given that they are expressed relative to country-specific baselines. So, we do not think Column (4) is informative. We include it here in case the reader has a different view.

Columns (5)-(6) implement versions of regression (2) and confirm the predictive power of national stock prices for own-country economic activity during mid-March period. In particular, the results say that *changes* in stock prices over the previous six days predict same direction *changes* in today’s economic activity. To interpret magnitudes, consider Column (6). The results say that a one-percentage drop in national stock prices on each of the previous six trading days predicts a 6.7 percentage point drop in today’s economic activity, as measured by *WMD*, conditional on common global developments. This is also a large effect.

Table 1. Regressions of Workplace Mobility Deviations on Lagged Stock Price Deviations, Daily Country-Level Data from 12 March to 23 March for the Dependent Variable

$WMD_{c,t}$ = Percent Workplace Mobility Deviation in Country c on Trading Day t

$SMD_{c,t}$ = Percent Stock Price Deviation in Country c on Trading Day t

$\Delta WMD_{c,t} = WMD_{c,t} - WMD_{c,t-1}$

Coefficient Estimates	Dependent Variable: $WMD_{c,t}$				Dependent Variable: $\Delta WMD_{c,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
α	0.78*** (0.10)	0.85*** (0.09)	0.30*** (0.08)	-0.07 (0.10)		
$\sum_{j=1}^6 \beta^j$					1.54*** (0.35)	1.12*** (0.34)
Intercept	3.87 (3.45)				-0.51 (1.22)	
Country Fixed Effects	NO	YES	NO	YES	NO	NO
Time Fixed Effects	NO	NO	YES	YES	NO	YES
Observation Count	241	241	241	241	241	241
Adjusted R^2	0.21	0.77	0.72	0.90	0.19	0.52

Notes: The sample includes all workdays from 12 March to 23 March for 31 countries, where “workdays” refers to dates on which the country’s stock market traded. For explanatory variables, we linearly interpolate between trading days to fill in weekend and holiday values. We use country-level stock price deviations prior to 12 March for lagged values of the explanatory variables. OLS Standard errors in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

D. What Accounts for National Stock Price Movements During the Pandemic?

Table 2 considers regression models that aim to account for national stock prices at a daily frequency during the period covered by Figures 4 and 5. (Table A.1 provides summary statistics for the variables.) We fit models to national data for 31 countries on trading days from 17 February to 21 May 2020. As we have seen, common global dynamics are a pronounced feature of stock prices and mobility during the sample period.⁹ Thus, we include common time

⁹ Regressing national stock price deviations from 17 February to 21 May on a full set of day fixed effects yields an adjusted R-squared value of 0.85. Analogous regressions yield an adjusted R-squared value of

effects in columns (1) to (3), and we adopt the common correlated effects (CCE) estimator advocated by Pesaran (2006) in columns (1) to (4). The CCE specification includes cross-country averages as explanatory variables.

The results provide strong evidence that the stringency of own-country and global lockdown measures have strong negative effects on national stock prices, conditional on (a) own and global pandemic severity, (b) own and global economic activity, and (c) own and global income support and debt relief policies. Consider the CCE specification in column (6). Estimated coefficients on the own-country and the global lockdown stringency indexes are negative and statistically significant at the 1 percent level. With respect to magnitudes, the -9.6 coefficient says a unit standard deviation increase in own-country lockdown stringency lowers national stock prices by 3.0 percentage points conditional on other variables. The results also say a unit standard deviation rise in global lockdown stringency lowers national stock prices by 4.7 percentage points conditional on other variables. These are large effects.

Turning to the other explanatory variables, the estimated effects of own-country economic support policies differ in sign across specifications, and the implied effect magnitudes are modest in all cases. There is weak evidence that increases in the extent of economic support policies globally raises national stock prices. According to Column (6), a unit standard deviation increase in global average economic support policies raises stock prices by 1 percentage point, conditional on the other variables.

There are two odd aspects of the results in Table 2. First, higher global average mobility is associated with lower stock prices in columns (4) to (6). Second, new COVID deaths per million are positively related to national stock prices, although the implied effects are modest in size. For example, using the estimates in Column (6), a unit standard deviation increase in the rate of own-country (global) new deaths is associated with a 0.28 (0.56) percentage point increase in national stock prices.

New COVID deaths per capita capture the current death rate but not the slope of its trajectory. To characterize the trajectory, we follow Mazumder et al. (2020) and calculate the time it takes for accumulated cases to double, as measured by

$$\text{Doubling Time}_{c,t,l} = \frac{t-l}{\log_2(N_{c,t}/N_{c,t-l})}, \quad (3)$$

where $N_{c,t}$ and $N_{c,t-l}$ are accumulated confirmed cases at times t and $t-l$ for country c . Figures A.4 plot national doubling times at a daily frequency calculated over one-day (i.e. $l = 1$), 3-day, and 7-day intervals. Those figures reveal great heterogeneity in doubling times across countries and within countries over time. We set $l = 7$ for use in our regression models.

National stock prices rise with own-country doubling time and with the product of own-country death rates and doubling time. Both results align with the idea that stock prices improve as pandemic severity diminishes. However, the signs are reversed for the coefficients on the global average doubling time and interaction variables.

0.85 for workplace mobility deviations, 0.94 for the stringency of market lockdown measures, and 0.24 for COVID-19 deaths per million persons.

Table 2. Accounting for National Stock Market Movements During the Pandemic
Panel Regressions, Daily Country-Level Data from 17 February to 21 May 2020

$WMD_{c,t}$ = Percent Workplace Mobility Deviation in Country c on Trading Day t

$SMD_{c,t}$ = Percent Stock Price Deviation from February 17 in Country c on Trading Day t

ω_c = Market capitalization share of country c using data as of 31 December 2018

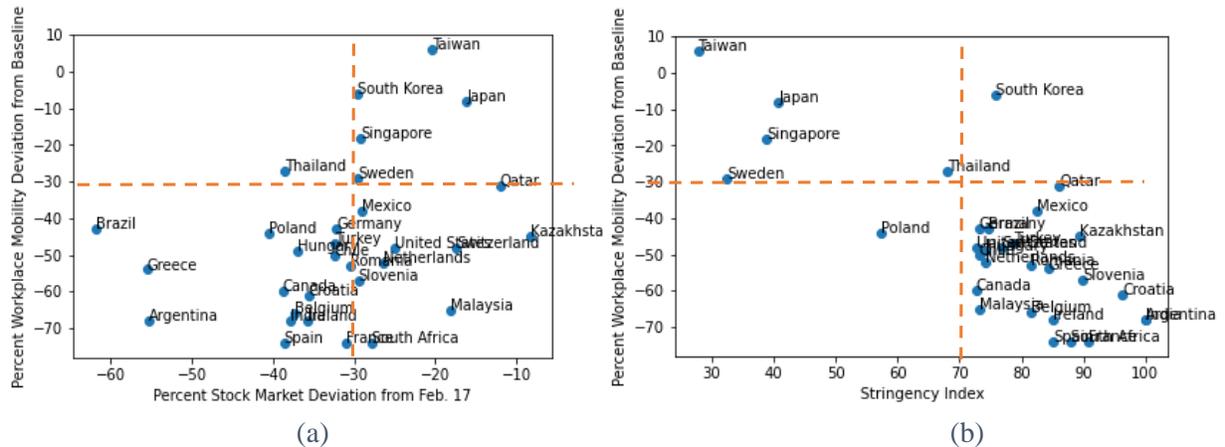
Explanatory Variables	Dependent Variable: $100 \times SMD_{c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$WMD_{c,t}$	2.9* (1.6)	2.7* (1.5)	3.4** (1.5)	2.6 (1.6)	1.8 (1.5)	2.5* (1.5)
$Deaths\ per\ million_{c,t}$	3.1 (5.1)	9.1** (4.5)	8.5* (4.4)	3.5 (5.0)	8.9** (4.4)	8.9** (4.4)
$\log(Doubling\ Time_{c,t})$		31.6** (15.9)	48.2*** (16.0)		40.7* (15.7)	57.5*** (15.9)
$Deaths\ per\ million_{c,t} \times \log(Doubling\ Time_{c,t})$			-21.8*** (3.7)			-22.5*** (3.7)
Stringency Index $_{c,t}$	-7.4*** (1.4)	-8.9*** (1.3)	-8.2*** (1.3)	-7.9*** (1.4)	-10.5*** (1.3)	-9.6*** (1.3)
Economic Support Index $_{c,t}$	-1.6** (0.8)	1.0 (0.7)	0.5 (0.7)	-1.3* (0.8)	1.3* (0.7)	0.8 (0.7)
$\sum_c \omega_c \times WMD_{c,t}$				-18.2*** (4.1)	-16.0*** (3.8)	-21.3*** (4.6)
$\sum_c \omega_c \times Deaths\ per\ Million_{c,t}$				24.9 (15.4)	12.2 (14.4)	31.2*** (11.8)
$\sum_c \omega_c \times \log(Doubling\ Time_{c,t})$					-80.8** (26.5)	-138.3*** (38.9)
$\sum_c \omega_c \times (Deaths\ per\ million_{c,t} \times \log(Doubling\ Time_{c,t}))$						31.2*** (11.8)
$\sum_c \omega_c \times Stringency\ Index_{c,t}$				-16.9*** (4.1)	-14.9*** (3.7)	-19.5*** (4.3)
$\sum_c \omega_c \times Economic\ Index_{c,t}$				2.1 (2.0)	2.1 (2.0)	2.8 (2.1)
$\sum_c \omega_c \times SMD_{c,t}$				87.4*** (3.1)	91.6*** (3.4)	91.4*** (3.3)
Country Fixed Effect	YES	YES	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	NO	NO	NO
N	2012	1773	1773	2012	1773	1773
adj. R^2	0.96	0.97	0.97	0.96	0.97	0.97

Note: The sample covers trading days from 17 February to 21 May 2020 for 31 countries. When calculating global means, we impute missing country-level values by linearly interpolating between trading days. The Stringency Index records the strictness of market lockdown measures, while the Economic Support Index captures the intensity of income support and debt relief policies. We calculate doubling times using 7-day intervals, and demean own-country and global $\log(Doubling\ Time)$ variables. The sample shrinks when we include $\log(Doubling\ Time)$, because it is undefined before a country's first COVID-19 death and we lack data for France. Columns (1)-(3) report OLS coefficient estimates with standard errors in parentheses. Columns (4)-(6) report estimates for Pesaran's (2006) Common Correlated Effects specification. * $p < .1$, ** $p < .05$, *** $p < .01$.

E. Outlier Countries

This section offers remarks on selected economies that exhibit highly distinctive, relatively favorable experiences with respect to workplace mobility, stock prices, or both. Figure 6 plots workplace mobility deviations against stock market deviations in panel (a) and stringency index values in panel (b) as of 30 March 2020, when the global stringency index first reaches 70. In the upper right corner of panel (a) are Taiwan, Singapore, South Korea, Japan and Sweden. These countries experienced relatively favorable stock price and workplace mobility deviations. All but South Korea also had comparatively low stringency index values. We note, however, that South Korea was slow to impose a hard lockdown. It took 60 days from the first confirmed case to a lockdown index value above 70 for South Korea, placing it among the bottom three countries by this measure of lockdown speed, along with Thailand and Singapore. Poland, Sweden, Japan and Taiwan did not implement a hard lockdown within our sample period.

Figure 6. Scatterplot of Workplace Mobility Deviation vs. Stock Market Deviation/Stringency Index on 30 March 2020



Note: We choose 30 March 2020 when the aggregated global stringency index first reaches 70, a hard lockdown by our definition.

Taiwan, Singapore, South Korea and Japan are East Asian economies that drew lessons from 2003 SARS epidemic. Before the COVID-19 outbreak, they had established comprehensive laboratory and medical surveillance systems to cope with pandemics. Taiwan, in particular adopted many containment measures at impressive speed in response to COVID. According to Cheng et al. (2020), “At the early stage of the outbreak, the strategy in Taiwan had three pillars: real-time surveillance with rapid risk assessment, border control and quarantine, and laboratory capacity building.”

Governments in South Korea and Singapore exploited access to mobile phone data of residents for contact tracing and virus containment. South Korea adopted an effective trace-test-treat policy. In these cases, fast government reactions, legal and technical infrastructures that supported rapid interventions, harsh penalties for violations of laws and regulations, and high-quality health care systems served as crucial enabling factors (Park et al., 2020). According to

Woo (2020), the later emergence of large infection clusters among Singapore's foreign workers overwhelmed hospital capacity, leading to high infection rates.

Japan is another country that successfully suppressed the initial spread of the disease. In addition to good governance and a strong health care system, the socially responsible and risk-aware behavior of its citizens enabled Japan to contain infection rates while also limiting economic damage, according to Tashiro and Shaw (2020).

The Swedish response has been highlighted as an exception due to its comparative leniency and its reliance on individuals to act responsibly and adhere to public recommendations. As Hensvik and Skans (2020) write, "Sweden's restrictions have been relatively mild compared to other European countries. The measures primarily rely on voluntary compliance with recommendations from the Public Health Agency regarding social distancing." Trust in the political and administrative system is a key to the Swedish approach, according to Dahlberg et al. (2020).

F. Additional Remarks on Related Literature

Alan et al. (2020) find that the daily number of active COVID-19 cases and the curvature of the active-case trajectory help predict stock market volatilities in a cross section of countries. Larger caseloads (relative to population) bring greater volatilities, according to their analysis. They also find that stricter lockdown policies bring lower stock market volatilities, while more frequent expressions of negative sentiment in corporate earnings conference calls bring higher volatilities. Our study is complementary to theirs in two respects: first, in its focus on stock price levels rather than volatilities, and second, in considering the dynamic relation of stock prices to workplace mobility in addition to measures of pandemic severity.

Cox et al. (2020) find that fluctuations in effective risk aversion or sentiment are the major driver of stock market volatility from February to April of 2020, while the Federal Reserve played a lesser role. Based on a theoretical analysis, Caballero and Simsek (2020) argue that an overshooting of asset prices and a temporary disconnect between Wall and Main street during the COVID-19 recession are features of an optimal monetary policy, because the central bank deliberately boosts asset prices to close the output gap as fast as possible.

Chen and Spence (2020) show that mobility-based proxies for economic activity align well with more standard measures of economic activity. They argue that fast policymaker response to COVID-19 outbreaks, coupled with strong detection and tracking abilities, enable a country to limit both infections and economic damage. Deb et al. (2020) estimate the effects of COVID containment measures on Nitrogen Dioxide emissions, flights, energy consumption, maritime trade, and mobility indices. They find that workplace closures and stay-at-home orders are effective in curbing infections (and more effective than other containment measures) but also involve large economic costs (larger than other measures). While they do not consider stock price behavior, we see their findings as broadly consistent with ours.

3. The China Experience

Thus far, we have said little about stock prices and activity in China. There are multiple reasons to separately examine the Chinese experience. First, the pandemic erupted first in China, when little was known about the SARS-COV-2 virus. Second, after initially suppressing information about the viral outbreak in Hubei province (Kynge et al., 2020, and Jacob, 2020), the Chinese government rapidly imposed aggressive containment measures. Third, as we will show, the dynamic between stock prices and economic activity played out differently in China than elsewhere, including other countries with relatively successful containment efforts. Finally, data for China present distinct challenges and opportunities.

A. Sources of Data for China

Our high-frequency proxy for economic activity in China relies on daily city-level data on residential commuting intensity from Baidu (2020),

$$RCI_{c,t} = \frac{\text{residents traveling within city } c \text{ on date } t}{\# \text{ of residents in city } c} \quad (4)$$

We obtain the daily city-level data from the Harvard Dataverse. To construct a national mobility measure, we compute the weighted-average $RCI_{c,t}$ values over 248 Chinese cities, using the number of residents in 2019 as weights. Consistent with Google’s construction of workplace mobility, we use the median value from 1 to 10 January 2020 as the baseline.

We consider stock prices for several share classes of Chinese listed firms, defined as follows:

- A shares are equity securities of companies listed on mainland China stock exchanges, denominated in RMB, and traded by investors in mainland China.
- B shares are equity securities traded on mainland exchanges but denominated in foreign currencies. On the Shanghai Exchange, B shares trade in U.S. dollars. On the Shenzhen Exchange, B shares trade in Hong Kong dollars.
- H shares are equity securities of companies listed on the Hong Kong Stock Exchange (HKEX), denominated in HKD, and traded by investors outside mainland China.

Companies can have multiple listings. We refer to companies with both A shares and H shares as AH firms, and companies with both A shares and B shares as AB firms.

Table 3 reports firm numbers and market capitalization in each category. Clearly, A shares dominate in terms of firm numbers and market cap. Firms that list on mainland exchanges in RMB and also list on the HKEX in HK Dollars (AH firms) account for 21% of the total market cap of A shares. The same set of firms account for 83% of the market cap of H shares.

Table 3. Number and Market Cap of Listed Chinese Firms

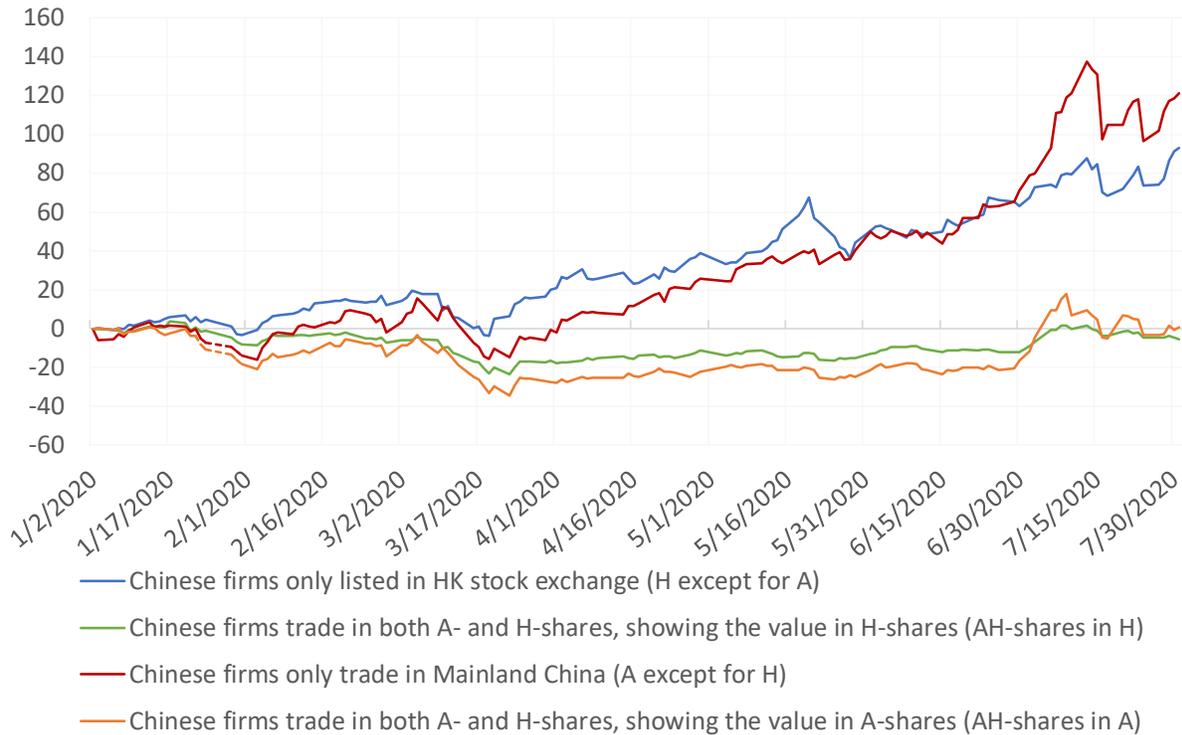
Firm Type	Number of Firms	Market Capitalization, Trillions of RMB	Market Cap % of Share Type
A Shares			
All Firms with A shares	3740	59.49	100
Those without H shares	3621	46.70	79
Those with H shares	119	12.79	21
B Shares			
All Firms with B shares	92	0.63	100
Those without A hares	16	0.07	11
Those with A shares	76	0.56	89
H Shares			
All Firms with H shares	258	5.09	100
Those without A shares	139	0.83	17
Those with A shares	119	4.26	83

Note: We select firms that trade actively from 2 January to 31 July 2020. The market capitalization value is based on the value of 7 August 2020. Data for A and B shares data are from CSMAR, accessed on 7 August 2020. Data for H shares are downloaded from Yahoo Finance. We use 1HKD = 0.9 RMB to convert currencies. The total Hong Kong market cap is 37.98 trillion RMB, and H shares account for 13.48%.

We compare the accumulated return of four categories (AH-share in A, AH-share in H, H except for A and A except for H) of public Chinese firms from 2 January 2020 in Figure 7. All four categories tended to move together from 2 January to 20 March. They started to diverge since 23 March, when the S&P 500 reached the lowest level due to the Covid-19 pandemic. AH-share firms underperform relative to other listed companies in both A-shares and H-shares.¹⁰ One possible explanation for this underperformance is that AH-share firms are more prone to global shocks. To test this hypothesis, we investigate each firm's revenue exposure by country through FactSet's Geographic Revenue Exposure (GeoRev). GeoRev represents each firm's revenue from a country as the percentage of its total revenue in that year. The weighted average GeoRev of mainland China for A except for H is 84%, and for AH-shares 86%. Thus, the underperformance is not due to AH-share companies' geographic revenue exposure. Another possible explanation is that AH-share companies are more sensitive to the pandemic compared to A except for H firms, a hypothesis we will test in the next section.

¹⁰ In Figure A.5, we also plot B share firms, finding that firms only listed in B-shares market performed very similarly as AH shares. AB shares firms behaved similarly as AH shares till late May, and afterwards increased much more than AH shares.

Figure 7. Chinese A-shares and H-shares Prices, Percent Deviations from 2 January 2020



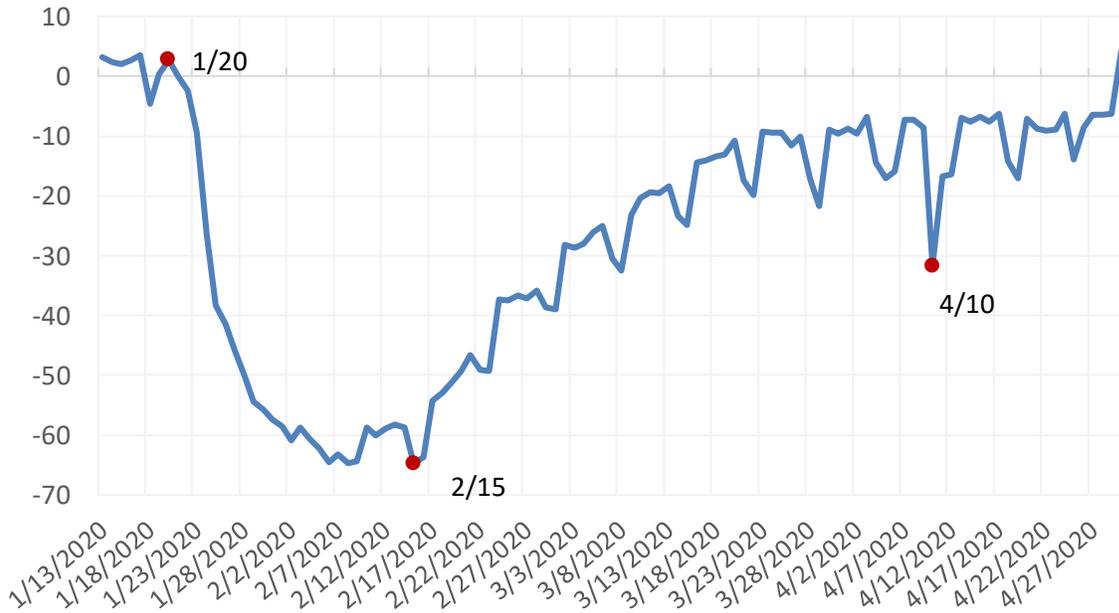
Note: We plot the cumulated percent deviations in average stock prices from 2 January 2020. While calculating the weighted average for each category, we use firm’s market capitalization on 7 August 2020 as the weight. Firms in all four categories operate in mainland China. “AH share” are firms listed in both A- and H-shares stock market, but with different stock prices in each market. The dashed line from 24 to 31 January 2020 represents the Spring Festival market closure in A-shares market. A-shares data are from CSMAR, the Chinese analogy of WRDS. H-shares data are downloaded from Yahoo Finance.

B. Stock Prices and Mobility in China

Figure 8 plots the evolution of China mobility, percent deviation from the baseline. The mobility sharply dropped since 20 January, reached the bottom on 15 February, and slightly rose afterwards. The decrease in the mobility on 10 April (Friday, non-holiday) was most likely due to new confirmed cases of COVID-19 of travelers from outside of China. Having heard this news, Chinese residents became cautious about going to public places.

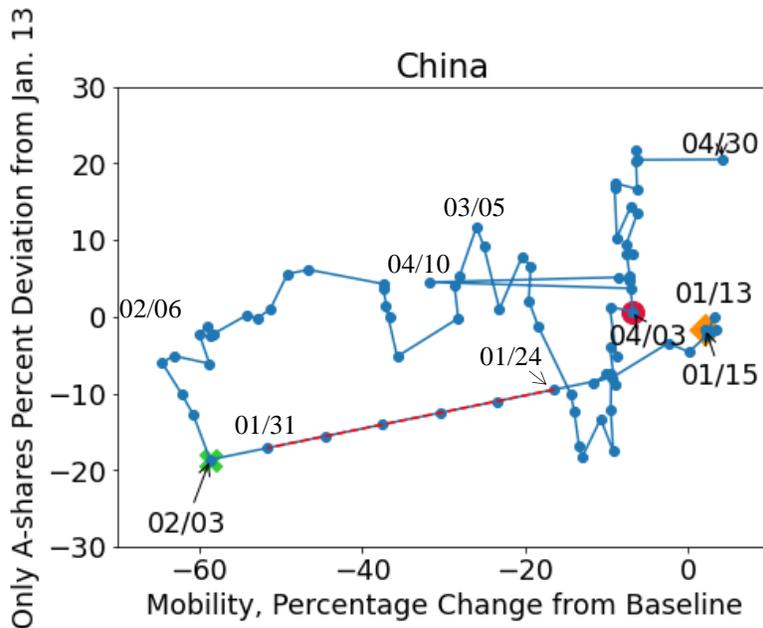
Figure 9 presents the time path of stock prices and mobility. Unlike other countries, we do not observe a sharp decline in stock prices before mobility drops in China. Indeed, China mobility plunged 29 percent from 15 to 24 January. During the market shutdown due to the Spring Festival, mobility dropped another 34 percent, and stock prices fell 11 percent. On 4 February, the second day after the stringency index surged above 70, stock prices started to climb up, while the mobility fell by another 6 percent. From 6 February to 4 March, mobility increased by 36 percent and stock prices rose by 11 percent. From 5 March to 30 April, mobility increased by 30 percent and got back to the original level, while stock prices increased by 9 percent.

Figure 8. China Mobility, Percent Deviation from the Baseline



Note: China mobility is defined as residents traveling at city c on date t over the number of residents at date t . In calculating the weighted average of China mobility, we use each city's number of residents in 2019 as the weight. The daily China mobility index for each city is recorded by Baidu, and we obtain the data from Harvard Dataverse, accessed on 15 August. The Baidu mobility data stopped updating since 2 May. We choose the median value of the mobility from 1 to 10 January 2020 as the baseline.

Figure 9. Time Path of China Stock Prices and Mobility from 13 January to 30 April 2020



Note: See Figure 8. We obtain the data of Chinese firms only traded in mainland China stock exchanges (only A-shares) from CSMAR dataset (Chinese analogy of WRDS). An orange diamond marks the first confirmed COVID-19 death, a green cross marks the first date with the stringency index value of 70 or more, and a red dot marks the date on which the stringency index first drops below 70. The red dashed line indicates the Spring Festival market closure, where we used linear interpolation for both stock prices and mobility. Mainland China stock market was closed from 27 to 31 January.

4. Analysis of China's Stock Market During the Pandemic

Unlike the American stock market, the Chinese stock market attracts millions of retail investors. This makes China's stock market more independent from the global system, but more sensitive to governmental influences (Yu and Ping, 2020). This section begins with a comparison of the world's two largest economies regarding the pandemic impact on their stock market levels and volatilities, and goes on to explain the differences.

A. Comparison of Chinese and American Stock Market Behavior

Figure 10 compares cumulative log returns on Chinese and American stocks during the first four months of 2020, and Figures 11 and 12 compare realized and implied stock market volatility over the same period. All three charts exhibit the same pattern: the coronavirus pandemic has so far had the largest impact on the S&P 500, a modest, yet noticeable, impact on the Shanghai Stock Exchange, and an intermediate effect on the Hang Seng. The improved situation regarding the coronavirus in China contributed to the lower market volatility in February 2020.

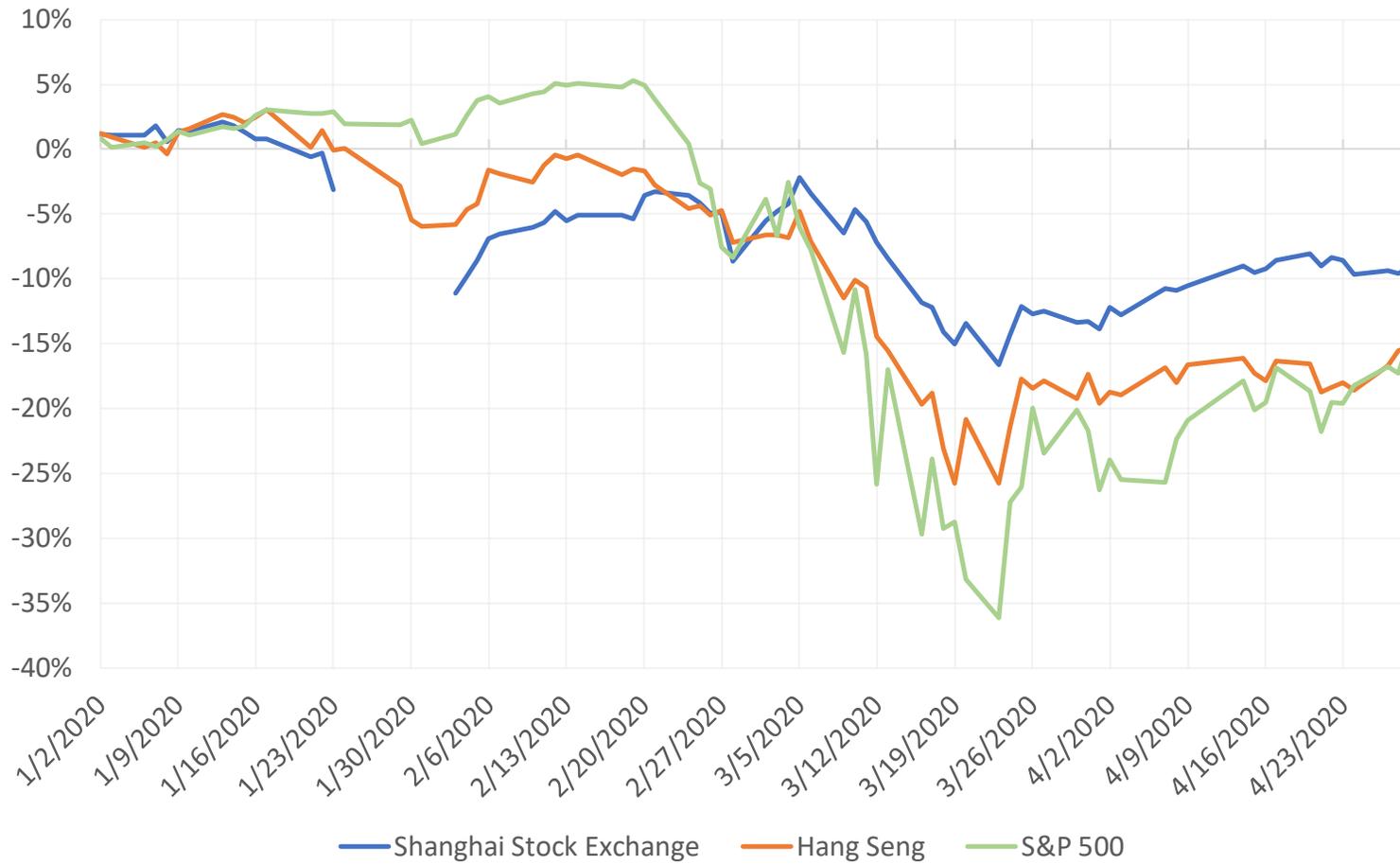
Due to the COVID-19, Chinese authorities extended the Spring Festival break by three more working days, which muted the stock markets response to the pandemic. Following this order, the Shanghai Stock Exchange announced on 27 January 2020 that the SSE would reopen on February 3 instead of 31 January.¹¹ As a result, no trading activity occurred from 24 January to 2 February. Because of the market closure, Chinese stock markets did not immediately register the impact of the mounting confirmed coronavirus cases, while U.S. markets reflected the skyrocketing domestic cases quickly. The market closure was important for the lower volatility observed in Chinese markets, since it prevented the short-term and immediate selling.

Table 4 classifies the reason for the stock market jumps based on the explanation offered in the next-day newspaper, using the approach of Baker et al. (2020b). They examine next-day newspaper explanations to classify and characterize each daily move in the U.S. stock market greater than 2.5 percent, up or down, from 1900 to the present. Specifically, they read the lead article about each jump in next-day newspapers (or the same evening in the internet era) to classify the journalist's explanation into one of 16 categories, which include Macroeconomic News and Outlook, Government Spending, Monetary Policy, Unknown or No Explanation Offered, and Other – Specify.¹² Baker et al. (2020a) extended the approach to investigate the specific role of pandemics and infectious diseases.

¹¹ http://www.sse.com.cn/aboutus/mediacenter/hotandd/c/c_20200202_4991648.shtml

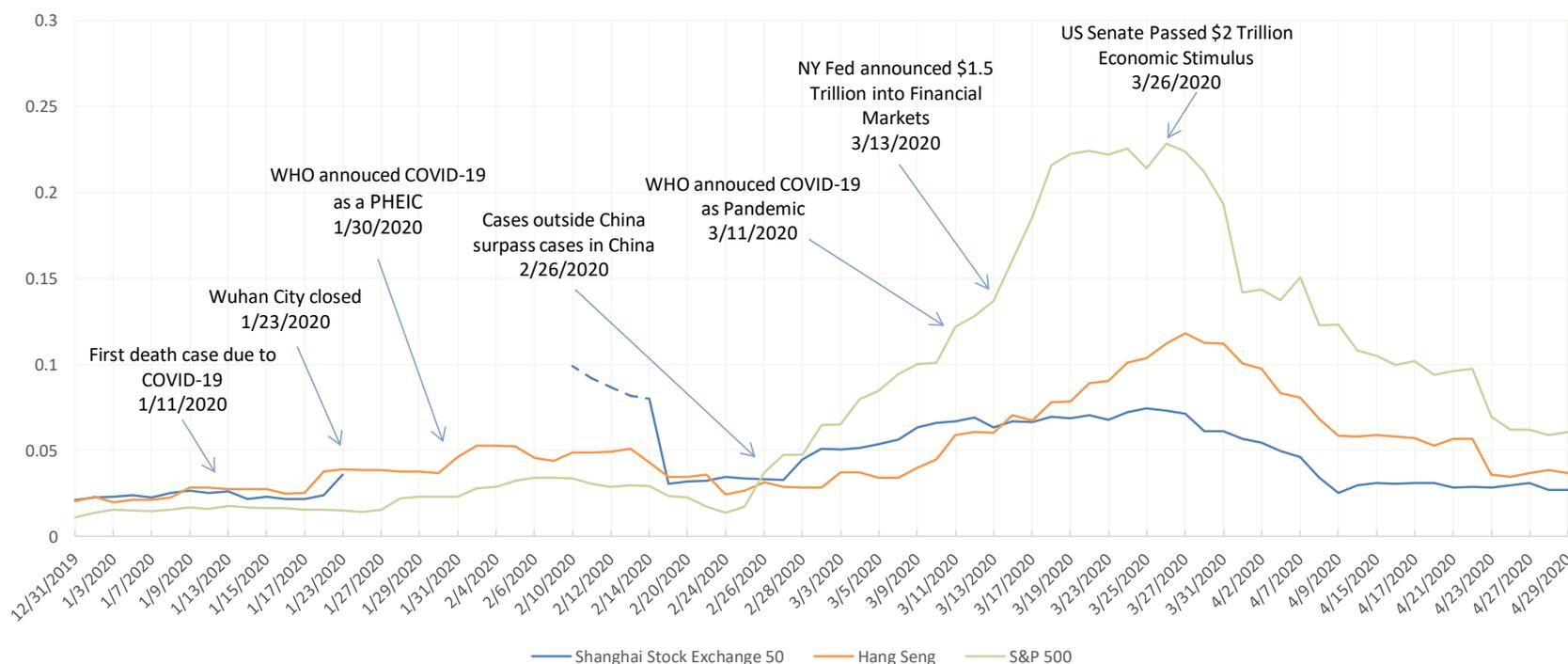
¹² The coding guide in Baker, Bloom, Davis, and Sammon (2018) describes the approach in detail.

Figure 10. Cumulative Log Returns on American and Chinese Stocks, 2 January to 29 April 2020



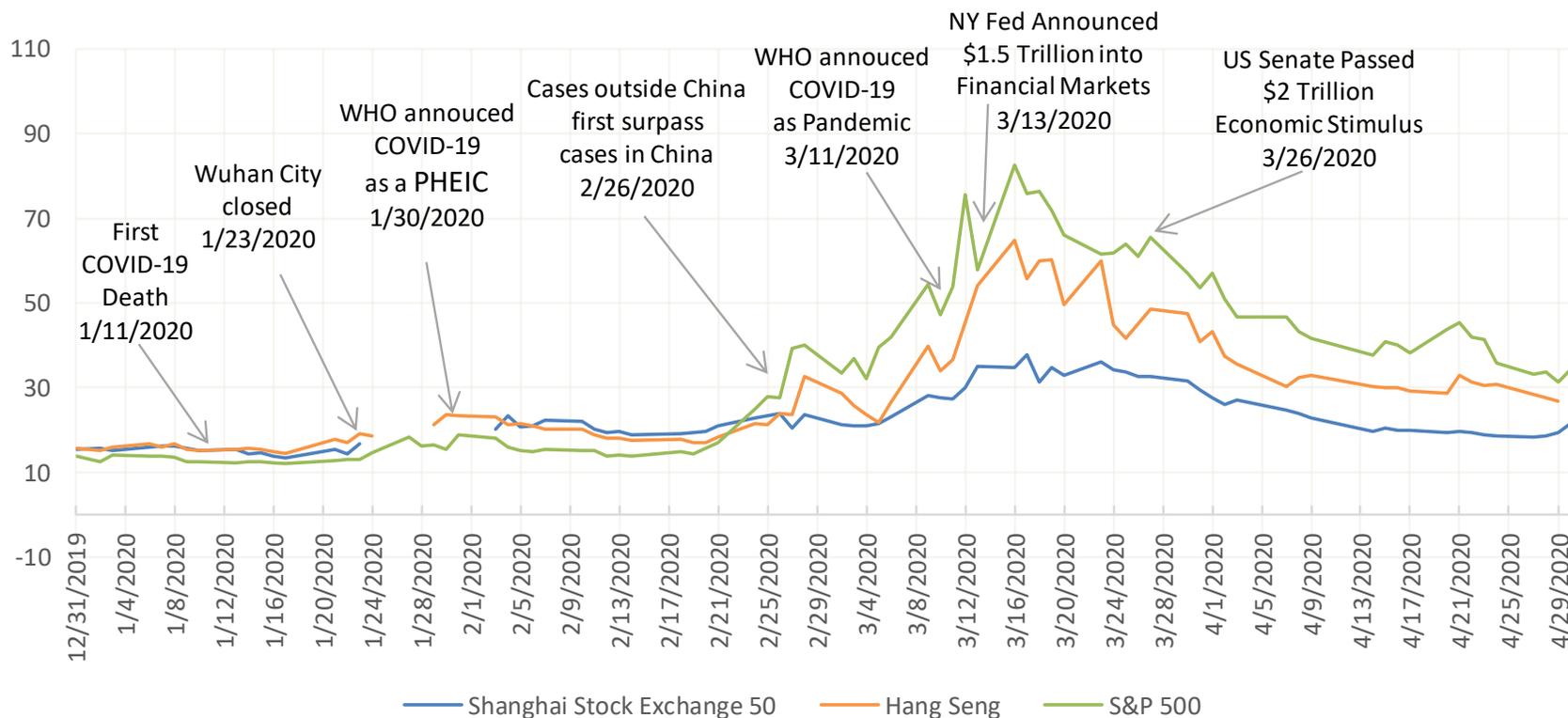
Note: The figure plots cumulative log changes from 31 December 2019 for the indicated stock market indexes, using daily closing values from Yahoo Finance, downloaded on 4 May 2020. The break in blue line indicates the Spring Festival market closure in Shanghai Stock Exchange, from January 24 (Friday) to February 2 (Sunday).

Figure 11. Realized Return Volatility Over Past 10 Trading Days, American and Chinese Stocks, 31 December 2019 to 29 April 2020



Notes: We measure realized volatility as the square root of the sum of squared returns over the past 10 trading days, calculating returns as log changes in closing-price index values. We linearly interpolate over weekends and other short market closures. The break in the series for the Shanghai Stock Index reflects an extended market closure for the Chinese Spring Festival and the coronavirus pandemic, which we handle as follows: (1) Let $j = 0, 1, 2, \dots, N^c$ index days, where $j = 1$ is the first closure day and $j = N^c$ the last closure day. (2) Treat the volatility data as missing for $j = 1$ to $N^c + 5$, and do not interpolate across these missing days. (3) For $j = N^c + k$ for $k = 6$ to 10 , compute past volatility by summing the squared returns over the past $k-1$ days (i.e., inclusive of the change from $k-1$ to k) and multiplying the sum by $(10/(k-1))$. This multiplication factor adjusts for the shorter volatility window. Then we take the square root. (4) When plotting the realized volatility data for the interval from $j = N^c + k$ for $k = 6$ to 10 , we use a dashed line.

Figure 12. Implied Volatilities, American and Chinese Stock Markets, 31 December 2019 to 30 April 2020



Note: Data for the Hang Seng Volatility Index (HSI Volatility Index) and the VIX (S&P 500) are from Yahoo Finance, downloaded on 4 May 2020. We calculated an implied volatility index for the Shanghai Stock Exchange 50 as explained in Appendix B, following the same approach as CBOE (2019) uses to calculate the VIX.

Panel C in Table 4 underscores the unprecedented impact of the COVID-19 pandemic on the U.S. stock market. In the period before 24 February 2020 – spanning 120 years and more than 1,100 jumps – next-day journalistic accounts attributed not a single daily stock market jump to infectious disease outbreaks or policy responses to such outbreaks. Perhaps surprisingly, even the Spanish Flu fails to register in next-day journalistic explanations for large daily stock market moves. There were 23 daily stock market jumps from March 1918 to June 2020, which spans the three major waves of the Spanish Flu. Next-day accounts in the *Wall Street Journal* attributed none of them to the Spanish Flu. Data since late February 2020 tell a remarkably different story. From February 24 through the end of April, there were 27 U.S. stock market jumps. Next-day newspaper accounts attribute 23 or 24 of them to news about COVID-19 developments and policy responses to the pandemic.

We take the same approach to the Shanghai Stock Exchange and the Hang Seng from 26 December 1990 to 30 April 2020. In doing so, we tap financially-oriented mainland Chinese newspapers for SSE jumps and the *South China Morning Post* for Hang Seng jumps. Before COVID-19, newspapers attribute zero jumps (out of hundreds) to news about infectious diseases. From 2 January to 30 April 2020, Chinese newspapers attribute all 6 daily stock market moves greater than $|3\%|$ on the Shanghai Stock Exchange and all 8 daily moves greater than $|3.8\%|$ on the Hang Seng to the economic fallout of the pandemic or policy responses to the pandemic. These two results closely parallel the U.S. results. However, the incidence of large daily stock moves during the coronavirus period is several times greater for the U.S. market than for the Chinese stock markets, in line with the extremely high volatility of the U.S. market during this period.

Table 4. Large Daily Moves in Chinese Stock Markets, Classifications Based on Next-Day Newspaper Accounts in Leading Chinese Newspapers

A. *Shanghai Stock Exchange*

Time Period	Jump Size	Number of Daily Stock Market Jumps	# Attributed to Economic Fallout of Pandemics	# Attributed to Policy Responses to Pandemics
26 December 1990 31 December 2019	$\geq 4\% $	384	0	0
2 January 2020 to 30 April 2020	$\geq 4\% $	1	1	0
	$\geq 3\% $ and $< 4\% $	5	4	1

B. *Hang Seng*

Time Period	Jump Size	Number of Daily Stock Market Jumps	# Attributed to Economic Fallout of Pandemics	# Attributed to Policy Responses to Pandemics
26 December 1990 31 December 2019	$\geq 3.8\% $	213	--	--
2 January 2020 to 30 April 2020	$\geq 3.8\% $	7	5	2
	$\geq 3\% $ and $< 3.8\% $	1	1	0

C. S&P 500 (Reproduced from Baker et al. 2020a)

	Number of Daily U.S. Stock Market Jumps Greater than $ 2.5\% $	Number Attributed to Economic Fallout of Pandemics	Number Attributed to Policy responses to Pandemics
2 January 1900 to 21 February 2020	1,116	0	0
26 December 1990 to 31 December 2019	254	0	0
2 January 2020 to 23 February 2020	0	0	0
24 February 2020 to 30 April 2020	27	13.4	10.4

Notes to Panel A: We consult next-day accounts of large daily stock market jumps in four official Chinese newspapers: *Security Times* (证券时报), *Security Daily* (证券日报), *Shanghai Security News* (上海证券报), and *China Security Journal* (中国证券报). These four major securities newspapers are the most authoritative and influential securities newspapers in China. They are the first to report the securities market information and government policies and thus are important sources of market information for investors. We classify the reason for the jumps based on the explanation offered in the next-day account, following the approach in Baker et al. (2020b). At least one paper contains a next-day article about each large daily stock market jump, as defined in the table. When multiple papers contain a next-day article about a given jump, they always agree as to the reason for the jump. On 3 February 2020, the first trading day after the Chinese Spring Festival, the Shanghai Stock Index fell 7.72%. On the next day, all four newspapers discussed the Shanghai Stock Market crash due to economic fallout of COVID-19 pandemics. The five dates with market jump greater than -or equal to $|3\%|$ and less than $|4\%|$ are: 28 February 2020 (-3.71%), 2 March 2020 (3.15%), 9 March 2020 (-3.01%), 16 March 2020 (-3.40%), and 23 March 2020 (-3.11%). The newspapers attributed the drops on 9, 19 and 23 March to the impact of Pandemics. On 24 March, *Shanghai Securities News* said that the Pandemics caused a shranked external demand from Europe and the U.S., who are China's first and second biggest trade partners. The A-share stock slipped in response to this demand shock. On 17 March, *Security Times* reported that major central banks' monetary policy surprised the market and caused the market to drop. On 10 March, *Securities Daily* attributed the A-share stock falls to reduced demand in overseas market due to panic on oil price and coronavirus. On 3 March, *China Securities Journal* ascribed the market increase to the improved situation in China compared to the rest of the world. On 29 February, according to *Security Times*, the A-share stock dropped along with the overseas stock markets which were affected by rising new COVID cases around the world.

Notes to panel B: To examine what drives HK stock market's reaction, we consult next-day accounts of large daily stock market jumps in *South China Morning Post*. Following the same methodology in Panel A, we classify the reason for the market jumps. The seven dates with market jump greater than $|3.8\%|$ in 2020 are: 9 March (-4.23%), 16 March (-4.03%), 18 March (-4.18%), 20 March (5.05%), 23 March (-4.86%), 24 March (4.46%) and 25 March (3.81%). The newspapers attributed the drops on 9, 16, 18, 20 and 23 March to the impact of the pandemics, while policy stimulation boosted the market on 24 and 25 March.

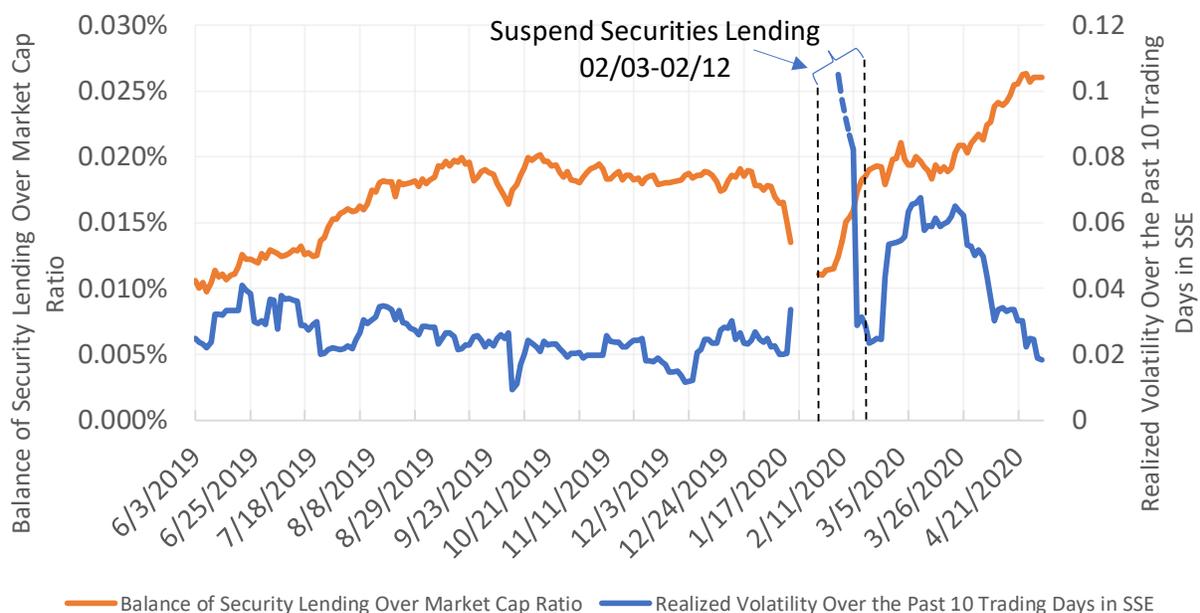
Notes to panel C: Based on the results in Baker et al. (2020a, 2020b), they consider all daily jumps in the U.S. stock market greater than 2.5%, up or down, since 1900. They classify the reason for each jump into 16 categories based on human readings of next-day (or same-evening) accounts in the *Wall Street Journal* (and *New York Times* in 2020). Fractional counts arise when newspapers differ in their jump attribution or human readers differ in their classification of the attribution, e.g. 12 and 16 March.

B. Explanations for the Relatively Muted Response of Chinese Stock Markets

On the first trading day after the Spring Festival, the Shanghai Stock Exchange (SSE) index decreased by 7.7%, but since then, increased for 7 consecutive days. The higher return and lower volatility in Chinese stock market contrast sharply with most developed countries. One possible explanation for this performance is that Chinese government might directly intervene, as was done in 2015 for the massive and direct buying orders. Yet, direct intervention did not occur this time. Rather, the regulators in China use window guidance to affect the market. Next, we explore this possibility.

Aside from extending market closure, the China Securities Regulatory Commission (CSRC) implemented a basket of regulations to limit the market selling power and encourage buying power. Examples include limiting brokers' securities lending businesses, encouraging insurers to buy more equities and asking mutual fund managers not to sell stocks. Furthermore, the Chinese authorities made a great effort to improve investors' confidence for the stock market and the outlook for the economy. Generally speaking, these regulations include four categories.

Figure 13. Balance of Securities Lending Over Market Cap Ratio and Realized Volatility Over the Past 10 Trading Day in Shanghai Stock Exchange (SSE)



Note: The Balance of Securities Lending Over Market Cap Ratio is the securities lending volume over Shanghai Stock Market's circulation market capitalization. The data is downloaded from [Shanghai Stock Exchange website](#), visited on May 1, 2020. The breaks in blue and orange series indicate the Spring Festival market closure in SSE, from January 24 (Friday) to February 2 (Sunday). We handle the realized volatility in SSE after the extended market closure as follows: (1) Let $j = 0, 1, 2, \dots, N^c$ index days, where $j = 1$ is the first closure day and $j = N^c$ the last closure day. (2) Treat the volatility data as missing for $j = 1$ to $N^c + 5$. (3) For $j = N^c + k$ for $k = 6$ to 10 , compute past volatility by summing the squared returns over the past $k-1$ days (i.e., inclusive of the change from $k-1$ to k) and multiplying the sum by $(10/(k-1))$. This multiplication factor adjusts for the shorter volatility window. Then we take the square root. (4) When plotting the realized volatility data for the interval from $j = N^c + k$ for $k = 6$ to 10 , we use a dashed line.

Restricted Securities Lending Businesses

Securities margin trading is the traditional intervention tool adopted by the authorities. It was used in 2015 during the China market turmoil. On 2 February 2020, the CSRC ordered that all brokers stop securities lending businesses.¹ The brokers cannot have security lending business till 12 February (there were slight variations regarding this date across different brokers), and they can only keep small trading volume afterwards, leading to weakened market selling power. In this way, investors cannot borrow shares to bet on the market crash by short selling. Figure 13 presents the security lending balance over market cap ratio and the realized volatility over 10 trading days of SSE index. The security lending balance in the SSE started to decrease from 20 January and remained at a level lower than pre-Spring Festival until 12 February 2020. Furthermore, a partial ban on short selling may start much earlier, from 22 January, "A few investors or brokers received calls telling them not to sell." This effectively mitigated the volatility in the market. This regulation is essential, as dating back to 2015, the authorities blamed short sales for exacerbating the crash. Chinese government has not used direct intervention in February 2020, partially because the state still holds \$144 billion of listed stocks, which was bought in 2015; see Howie (2020).

Restricting mutual funds selling activities

Mutual funds hold the highest portion of market cap among institutional investors. To ensure mutual funds' activity does not cause a panic in the stock market, the CSRC used window guidance and told funds managers not to sell their equities, unless they are faced with investor redemption.

To avoid investor redemption, major mutual funds announced that they would purchase the fund using their own money from the evening of 3 February 2020. Altogether, 39 fund managers announced a plan of 2.4 billion RMB purchasing of their own funds using their own capital to fight against the pandemic. Furthermore, many major shareholders as well as executives announced similar purchasing plans. For example, the well-known private offered fund, Kaifeng Investment, announced that they would not sell their equity holdings and would use their own capital to buy their own equity-funds for over 0.1 billion RMB; see Lin (2020). The CSRC's window guidance, together with institutional investors' spontaneous purchasing and

¹ This was not announced by the authorities but released to the media by several hedge fund managers and brokers; see Zhang, Thomson Reuters (2020).

repurchasing activities amid the market slide, sent a positive signal to the retail investors and helped to release negative market emotions.

Encouraging insurance companies to purchase equities

Knowing that institutional investors play an increasingly important role in the market, the Chinese banking and insurance regulator, China Banking and Insurance Regulatory Commission (CBIRC), encouraged insurers to buy more equities before the market reopening. The CBIRC considered raising the equity investment cap limit of 30% of assets. The state media also confirmed on 3 February 2020 that a group of Chinese insurers had 100 billion RMB ready to save the market if necessary. Doing so mitigated a market downturn by giving confidence to institutional investors and pressuring them to buy equities.

Guiding investors' expectations

The government made clear through many channels that state intervention is on the table. The People's Bank of China (PBOC) is known for not being transparent, as the PBOC rarely announces important policy changes ahead of time. However, the PBOC announced one day ahead of the stock market reopening that it would inject billions of dollars into the financial system by buying short-term bonds to keep bank lending flow. This announcement relieved the redemption pressure for mutual funds.

Similarly, the CSRC assured that it would “keep fully alert” and “study and launch hedging tools” to prevent investors from panicking. By boosting investors' confidence and expectations via the news media, the authorities managed the momentum. As the accumulated confirmation cases of COVID quickly flattened, investors believed that Chinese government had the situation under control and thus did not have a volatile outlook on the market.

C. Policy Event-Study Analysis

To estimate how government policy interventions affected China's stock market during the pandemic, we consider monetary policy easing actions and regulatory actions that sought to boost or stabilize the stock market directly. Table 5 describes the identified policy interventions and their announcement and implementation dates. We delete duplicated dates to avoid bias. The time period is 25 December 2019 to 22 April 2020. As indicated by the table entries, the People's Bank of China relies on multiple monetary policy tools: Open Market Operation (OMO) (including reverse repo operations), Lending Facilities, Reserve Requirement Ratios (RRR), and loan rates.

Table 5. Policy Actions by Chinese Monetary and Financial Regulatory Authorities During the COVID-19 Pandemic

Local time, date, and day of announcement	First Trading Day: Shanghai, Hong Kong, New York	Implementation Date/ End Date (if applicable)	Policy
15:07, 1 January, Wednesday	2 Jan., 2 Jan., 2 Jan.	6 Jan.	PBOC cuts reserve ratio by 0.5%, freeing up 800 billion yuan (\$115 billion) in the financial system.
Evening, 27 January, Monday	3 Feb., 29 Jan., 27 Jan.	28 Jan./ 3 Feb.	CSRC extends the Spring Festival market break for three days.
15:00, 2 February, Sunday	3 Feb., 3 Feb., 3 Feb.	3 Feb./ 3 Feb.	PBOC injects 120 billion yuan (\$17 billion) via reserve repo operation.
09:46, 4 February, Tuesday	4 Feb., 4 Feb., 4 Feb.	4 Feb./ 4 Feb.	PBOC injects 50 billion yuan (\$7 billion) via reserve repo operation.
17:16, 13 March, Friday	16 Mar., 16 Mar., 13 Mar.	16 Mar.	PBOC says it will cut reserve requirement ratio (RRR) by 50-100 bps for banks that have met inclusive financing targets*. It will release 550 billion yuan (\$79 billion) to shore up the economy. Qualified joint-stock commercial banks will get an extra 100 bps cut.
16:57, 3 April, Friday	7 Apr., 7 Apr., 3 Apr.	7 Apr., 15 Apr., 15 May	PBOC to cut targeted RRR by 0.5 percentage points on April 15 and again on May 15. The cut only targets small banks, which releases 400 billion yuan (\$57 billion). PBOC will also lower the interest rate paid for excess reserves from 0.72% to 0.35% on April 7.
Early morning, 3 February, Monday	3 Feb., 3 Feb., 3 Feb.	3 Feb.	China Banking and Insurance Regulatory Commission (CBIRC) encourages insurers to buy more equities before the market reopens. *
Evening, 2 February, Monday	3 Feb., 3 Feb., 3 Feb.	3 Feb.	China Securities Regulatory Commission (CSRC) asked some brokerages, funds and insurers not to be net sellers for at least a week. Brokerages are only allowed to sell to meet redemptions by investors. *
Evening, 2 February, Sunday	3 Feb., 3 Feb., 3 Feb.	3 Feb.	CSRC asks all brokers to stop the securities lending business. *
Evening, 3 February, Monday	4 Feb., 4 Feb., 4 Feb.		To offset redemptions, major mutual funds announce they will purchase shares in their own funds. *

Note: Policy announcement date and time are locally based. We collect China's monetary policy announcements from the People's Bank of China's (PBOC) [official website](#). Policies come with

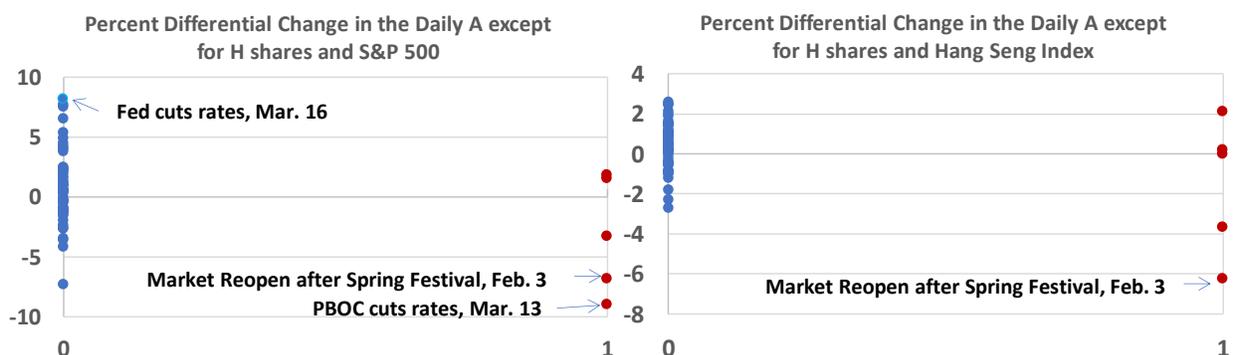
* represents the policies that are released by the media but never announced by the authorities. We see those as window guidance. U.S. Monetary Policy changes are from FOMC statements.

In order to more fully understand the causal factors behind China’s subdued market response to the pandemic, we conduct four event studies with the first two comparing different sets of companies and the last two focusing on the same set of companies. Specifically, we test the following hypotheses:

- Hypothesis 1: China’s policy actions have no impact on the returns on Chinese companies relative to U.S. companies
- Hypothesis 2: China’s policy actions have no impact on the returns on mainland China companies (A except for H shares) relative to Hong Kong companies.

Figure 14 shows daily return differentials for the Shanghai Stock Exchange relative to contemporaneous returns on the S&P 500 and the Hang Seng for five policy intervention dates (red dots) and the other trading days (blue dots) during our sample period. The stimulative Chinese government policy, however, brought down the return of the companies only listed in mainland China but not in HK stock exchange (A except for H shares) relative to the S&P 500 (left panel). A similar, but less noticeable, pattern holds when compared to the Hang Seng (right panel).

Figure 14. A except for H shares Return Differentials on Chinese Policy Announcement and Other Dates, 25 December 2019 to 22 April 2020



Note: Red dots show return differentials on Chinese policy announcement dates in Table 5, and blue dots show them on other dates. The sample covers all trading days from 25 December 2019 to 22 April 2020 on the Mainland China Stock Exchange (and matched trading days on the other two markets). A except for H shares represents companies who are only listed in mainland China stock exchange, and not in HK stock exchange.

To further explore the impact of Chinese government intervention and its effect on the stock market, we design the following OLS regression:

$$Return\ Differential_{i,t} = \alpha + \beta_1 \times Policy\ Announcement_t + Market\ Reopen\ after\ Spring\ Festival_t + \varepsilon_{i,t} \quad (5)$$

where *Return Differential* $_{i,t}$ represents return differential of the two sets of stock markets, and *Policy Announcement* $_t$ is a dummy variable, taking the value of 1 for the first trading day of policy announcement. If the announcement occurred in the morning on day t , we denote $PA_t = 1$ and 0 elsewhere. If the announcement occurred in the late afternoon or in the evening on day t , it would affect Chinese stock market on day $t + 1$ and affect U.S. stock market on day t . For this latter case, we calculate log return of A not H shares as $\ln(Price_{t+1}) - \ln(Price_{t-1})$. *Market Reopen after Spring Festival* $_t$ represents the first trading day after the Spring Festival market closure. For i , 1 represents A except for H shares – S&P 500 and 2 represents A except for H shares – Hang Seng Index.

Table 6 summarizes the result. We find some evidence that China’s policy actions decreased the returns (at least temporarily) on the A except for H shares relative to the S&P 500. The estimated effects are large and negative. In contrast, we do not see the contemporaneous effect of China’s policy actions on the A except for H shares relative to the Hang Seng. The dummy variable for *Market Reopen after Spring Festival* turns out to be significantly negative, as Chinese stock market registered the cumulative impact of the mounting confirmed coronavirus cases during the market closure period due to the Spring Festival and its three working day extension. The cut in the Federal funds rate resulted in higher returns on the A except for H shares relative to the S&P 500 – the opposite of what standard models imply about expansionary monetary policy shocks. The U.S. market participants may have contemplated that perhaps the Fed had formed a more pessimistic assessment of the economic outlook than they had, which in turn may have led the market participants themselves to update their own beliefs about the state of the economy.

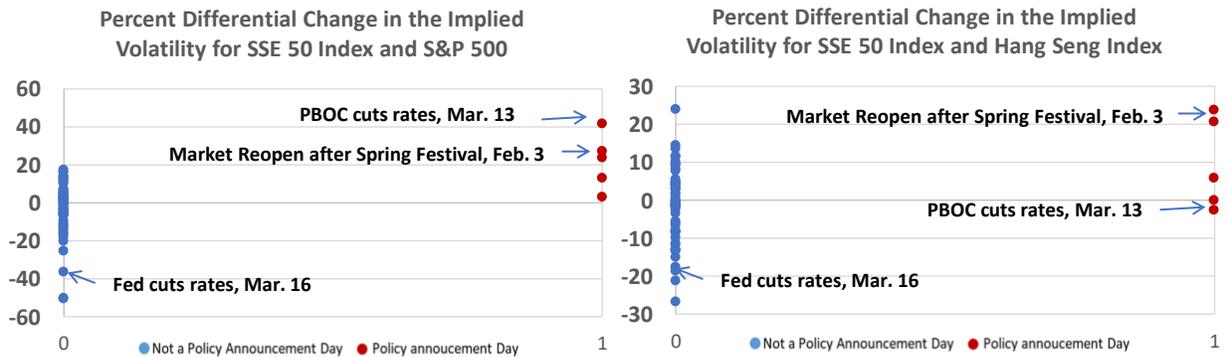
Table 6. OLS Regressions of Daily Return Differentials, 26 December 2019 to 22 April 2020

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Explanatory Variables	Dependent Variable: A except for H Shares Return – S&P 500 Return					Dependent Variable: A except for H Shares Return – Hang Seng Return			
Policy Announcement (PA) Dummy	-3.05*	-2.92*	-2.97*	-2.81*	-2.88*	-0.77	-0.72	-0.72	-0.68
	(1.60)	(1.54)	(1.60)	(1.53)	(1.60)	(0.63)	(0.65)	(0.63)	(0.65)
Market Reopen After Spring Festival	-4.61	-4.61	-4.55	-6.83*	-6.76*	-5.92***	-5.99***	-7.00***	-7.04***
	(3.47)	(3.33)	(3.39)	(3.75)	(3.80)	(1.37)	(1.39)	(1.54)	(1.55)
Fed cuts rates (16 March)		7.46**	7.23**	7.58**	7.26**		7.46**	7.23**	7.58**
		(3.00)	(3.51)	(2.99)	(3.49)		(3.00)	(3.51)	(2.99)
PA Lag			0.24		0.33		-0.27		-0.22
			(1.83)		(1.83)		(0.65)		(0.65)
PA Lead				2.22	2.23			1.07	1.06
				(1.76)	(1.77)				
Intercept	0.84**	0.72*	0.71*	0.60	0.59	0.44***	0.45***	0.38**	0.39**
	(0.40)	(0.39)	(0.40)	(0.40)	(0.41)	(0.16)	(0.17)	(0.16)	(0.17)
F value of Joint Coefficient test on (PA, PA Lag, PA Lead)			1.78	2.62*	1.73		0.82	1.87	1.27
N	64	64	64	64	64	63	63	63	63
$Adj. R^2$	0.10	0.17	0.16	0.18	0.17	0.31	0.30	0.33	0.32

Note: In the regression, the return differential is the percentage log return differential between two markets on the same day. We define day t as the stock market trading day. If the announcement occurred in the morning on day t , we denote $PA_t = 1$ and 0 elsewhere. If the announcement occurred in the late afternoon or in the evening on day t , it would affect Chinese stock market on day $t + 1$ and affect U.S. stock market on day t . For this latter case, we calculate log return of A except for H shares as $\ln(Price_{t+1}) - \ln(Price_{t-1})$. The joint coefficient test is on Policy Announcement Dummy, Policy Announcement Lag and Policy Announcement Lead. OLS Standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

In addition to market returns, we also examine the impact of Chinese government intervention on market volatilities. Figure 15 plots implied volatility change differentials for the SSE relative to the S&P 500 and the Hang Seng for the five policy intervention dates (red dots) and the other trading days (blue dots) during our sample period. China’s policy actions dramatically raised the volatilities of the SSE relative to the S&P 500, but had a much smaller impact on the volatilities of the SSE relative to the Hang Seng. On the other hand, following the Fed policy rate cut, the volatility of the SSE decreased by about 40% compared to the S&P 500, and by 20% relative to the Hang Seng.

Figure 15. Implied Volatility Change Differentials on Chinese Policy Announcement and Other Dates, 25 December 2019 to 22 April 2020



Note: See Figure 14. The percent change in the daily implied volatility is defined as: $\ln\left(\frac{Implied\ Volatility_t}{Implied\ Volatility_{t-1}}\right) \times 100$. There is no corresponding index option of SSE. We use SSE 50 Index option as a proxy to calculate the implied volatility.

Table 7 implements a similar statistical event-study analysis of policy interventions, but now on the differential of implied volatility between two markets. China’s policy actions significantly increased the implied volatility (at least temporarily) on the SSE relative to the S&P 500. However, we do not see the contemporaneous effect of China’s policy actions on the SSE implied volatility relative to the Hang Seng. The cut in the Federal funds rate resulted in lower implied volatility on the SSE relative to the S&P 500.

Our event-study analysis so far has compared the returns and volatilities of different sets of companies listed at different stock markets in response to China’s policy actions. Despite using high-frequency (i.e. daily) data, we cannot fully rule out the arrival of other news that

affects one market but not the other. To address this concern, we now focus on the same set of Chinese companies. Specifically, we test the following hypotheses:

- Hypothesis 3: China’s policy actions have no impact on the returns on Chinese companies listed in both mainland China and Hong Kong stock markets.
- Hypothesis 4: China’s policy actions have no impact on the returns on Chinese companies with their equity shares purchased by both domestic and foreign investors.

As illustrated in Figure 16, we do not observe any noticeable differences in the returns between policy announcement and non-policy announcement days. Further regression analysis in Table 8 confirms this observation.

Table 7. OLS Regressions of Differential Percent Changes in Daily Implied Volatility, 26 December 2019 to 22 April 2020

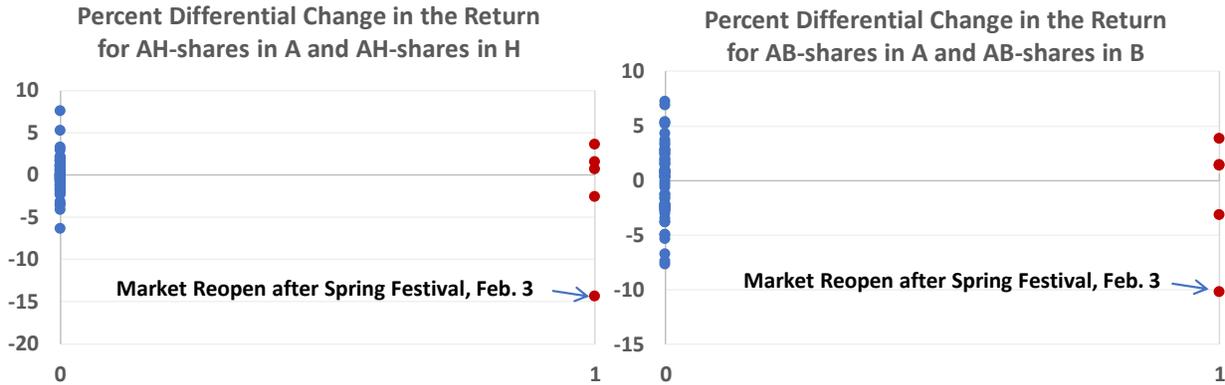
$$\Delta\text{Vol}\%_t = \ln\left(\frac{\text{Implied Volatility}_t}{\text{Implied Volatility}_{t-1}}\right) \times 100$$

Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: SSE 50 $\Delta\text{Vol}\%_t$ – S&P 500 $\Delta\text{Vol}\%_t$					Dependent Variable: SSE 50 $\Delta\text{Vol}\%_t$ – Hang Seng $\Delta\text{Vol}\%_t$				
Policy Announcement (PA) Dummy	23.7*** (7.3)	23.1*** (7.0)	24.3*** (7.2)	23.4*** (7.1)	24.5*** (7.2)	8.1 (5.1)	7.8 (5.0)	8.6 (5.2)	7.9 (5.1)	8.2 (5.2)
Market Reopen After Spring Festival	2.5 (15.2)	2.5 (15.2)	1.0 (15.3)	-1.3 (16.8)	-2.4 (16.9)	13.9 (11.0)	13.9 (10.8)	13.5 (11.0)	13.2 (12.1)	12.9 (12.2)
Fed cuts rates (Mar. 16)		-34.4** (13.7)	-28.8* (15.3)	-34.1** (13.8)	-28.8* (15.4)		-17.5* (9.8)	-15.9 (11.0)	-17.5* (9.9)	-15.9 (11.1)
PA Lag			-5.9 (7.2)		-5.7 (7.2)			-1.7 (5.2)		-1.7 (5.2)
PA Lead				3.8 (7.1)	3.5 (7.1)				0.7 (5.1)	0.6 (5.1)
Intercept	-2.6 (1.8)	-2.1 (1.8)	-1.8 (1.8)	-2.3 (1.9)	-2.0 (1.9)	-1.3 (1.3)	-1.0 (1.3)	-0.9 (1.3)	-1.1 (1.4)	-1.0 (1.4)
F value of Joint Coefficient test on (PA, PA Lag, PA Lead)			5.74***	5.52***	3.86**			1.25	1.20	0.82
N	64	64	64	64	64	62	62	62	62	62
adj. R ²	0.15	0.22	0.22	0.21	0.21	0.08	0.11	0.10	0.10	0.08

Note: In the regression, the dependent variable is the differential in percent log implied volatility changes between two markets. If the announcement occurred in the morning on day t , we denote $PA_t = 1$ and 0 elsewhere. If the announcement occurred in the late afternoon or in the evening on day t , it would affect Chinese stock market on day $t + 1$ and affect U.S. stock market on day t . For this latter case, we calculate log volatility of SSE as $\ln(\text{Implied Volatility}_{t+1}) -$

$\ln(\text{Implied Volatility}_{t-1})$. The joint coefficient test is on Policy Announcement Dummy, Policy Announcement Lag and Policy Announcement Lead. OLS Standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

Figure 16. Chinese Companies Percent Return Differentials on China’s Policy Announcement and Other Dates, 26 December 2019 to 22 April 2020



Note: Red dots show return differentials on Chinese policy announcement dates in Table 5, and blue dots show them on other dates. The sample covers all trading days from 26 December 2019 to 22 April 2020 for Chinese companies traded in both A-shares and H-shares (showing performance in A shares), Chinese firms traded in AH-shares (showing performance in H shares), Chinese firms traded in both A-shares and B-shares (showing performance in A-shares), and Chinese firms traded in AB-shares (showing performance in B-shares).

Table 8. OLS Regressions of Daily Return Differentials of Chinese Companies, 26 December 2019 to 22 April 2020

Explanatory Variables	Dependent Variable AH-shares in A Return – AH-shares in H Return				Dependent Variable AB-shares in A Return – AB-shares in B Return			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy Announcement (PA) Dummy	0.84 (1.10)	0.76 (1.12)	0.82 (1.11)	0.75 (1.13)	0.95 (1.71)	1.17 (1.74)	0.87 (1.72)	1.09 (1.75)
Market Reopen After Spring Festival	-15.21*** (2.37)	-15.11*** (2.40)	-14.94*** (2.63)	-14.87*** (2.66)	-11.06*** (3.70)	-11.35*** (3.74)	-9.73** (4.09)	-9.96** (4.12)
PA Lag		0.42 (1.01)		0.40 (1.02)		-1.17 (1.57)		-1.26 (1.58)
PA Lead			-0.27 (1.11)	-0.24 (1.12)			-1.32 (1.72)	-1.41 (1.73)
Intercept	-0.05 (0.27)	-0.08 (0.28)	-0.03 (0.28)	-0.06 (0.29)	-0.10 (0.42)	-0.03 (0.44)	-0.02 (0.44)	0.07 (0.46)
F value of Joint Coefficient test on (PA, PA Lag, PA Lead)		0.37	0.32	0.26		0.65	0.62	0.66
N	66	66	66	66	66	66	66	66
Adj. R ²	0.40	0.40	0.40	0.39	0.10	0.10	0.10	0.09

Note: In the regression, the return differential is the percentage log return differential between two markets on the same day. We define day t as the stock market trading day. If the announcement occurred in the morning on day t , we denote $PA_t = 1$ and 0 otherwise. If the

announcement occurred in the late afternoon or in the evening on day t , it would affect Chinese and Hong Kong stock market on day $t + 1$, and in this case, we calculate log return as $\ln(\text{Price}_{t+1}) - \ln(\text{Price}_{t-1})$. The joint coefficient test is on Policy Announcement Dummy, Policy Announcement Lag and Policy Announcement Lead. OLS Standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

5. Concluding Remarks

The early stages of the COVID-19 pandemic drove a spectacular rout in stock markets. Within the space of a few weeks, value-weighted share prices fell 20 to 50 percent in countries around the world. The stock market implosions preceded short-term collapses in economic activity in all but 2 of the 32 countries in our sample: South Korea saw only a modest drop in economic activity in the wake of the pandemic. China, the first country hit by the pandemic, experienced a simultaneous collapse in stock prices and economic activity.

Regarding policy, our evidence is broadly supportive of two propositions. First, more aggressive lockdown measures brought larger drops in national stock prices, conditional on pandemic severity, economic support policies, and then-current activity levels as measured by workplace mobility. The negative responses of stock prices to own-country and global-average lockdown stringency are large. Presumably, larger stock price drops reflected bigger downward revisions in the economic outlook, suggesting that investors saw harsher lockdowns as worse news about future economic performance. Second, countries that moved quickly to contain the spread of the virus – with or without aggressive market lockdown measures – enjoyed higher stock prices and better near-term economic performance. In short, relatively successful policy responses involved rapid implementation of virus containment efforts but not necessarily strict lockdowns on economic and social activity.

We have not delved into the factors that enabled some countries to rapidly implement an effective set of containment measures. Still, our discussion of “outlier” countries points to several elements that appear to have helped: encounters with major epidemics in the recent past (e.g., SARS in East Asia), the technical infrastructure needed to rapidly implement an effective test-trace-quarantine regime, a governance system that allowed for a rapid official response, an effective health-care system, governments that either enjoyed the trust and cooperation of their citizens or that had the means and will to compel compliance. It is perhaps understandable that many countries did not create the infrastructure to implement an effective test-trace-quarantine system in advance of the COVID-19 pandemic. That many rich countries still lack an adequate infrastructure for test-trace-quarantine points to political and institutional impediments rather than technical ones.

China sought to contain the pandemic and moderate its economic effects in many ways. These include government actions to support stock prices by limiting securities lending, restricting mutual fund selling, encouraging insurance agencies to buy equities, and managing investors’ expectations. The government also extended the annual Spring Festival market closure by several days during a critical period of the pandemic. Our investigation finds some evidence that these interventions generated greater market volatility.

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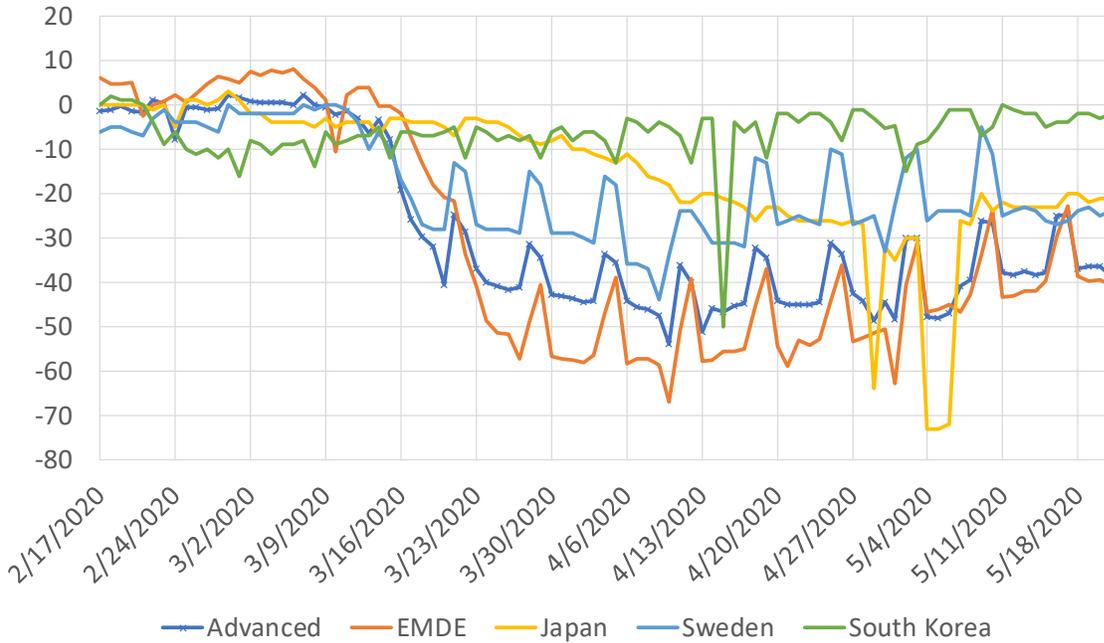
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Online Appendix A. Supplementary Material for Sections 2 and 3

Figure A.1. Workplace Mobility Deviation of Selected Economies

A. Raw Daily Data for All Days, Including Weekends and Holidays



B. Seven-Day Moving Average of All Days, Including Weekends and Holidays

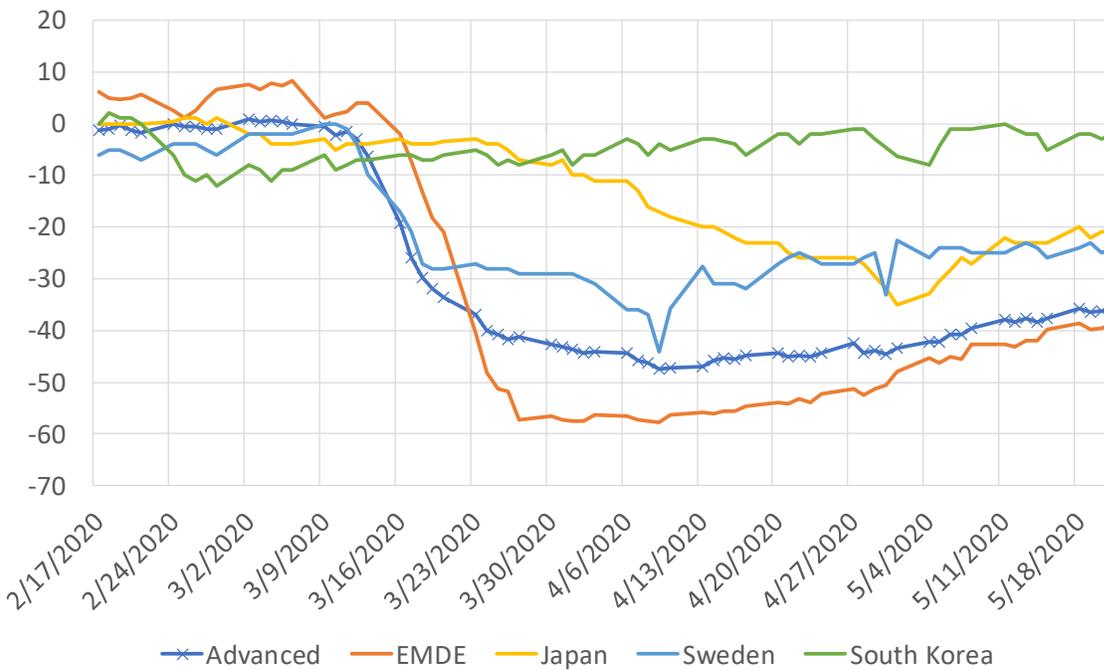
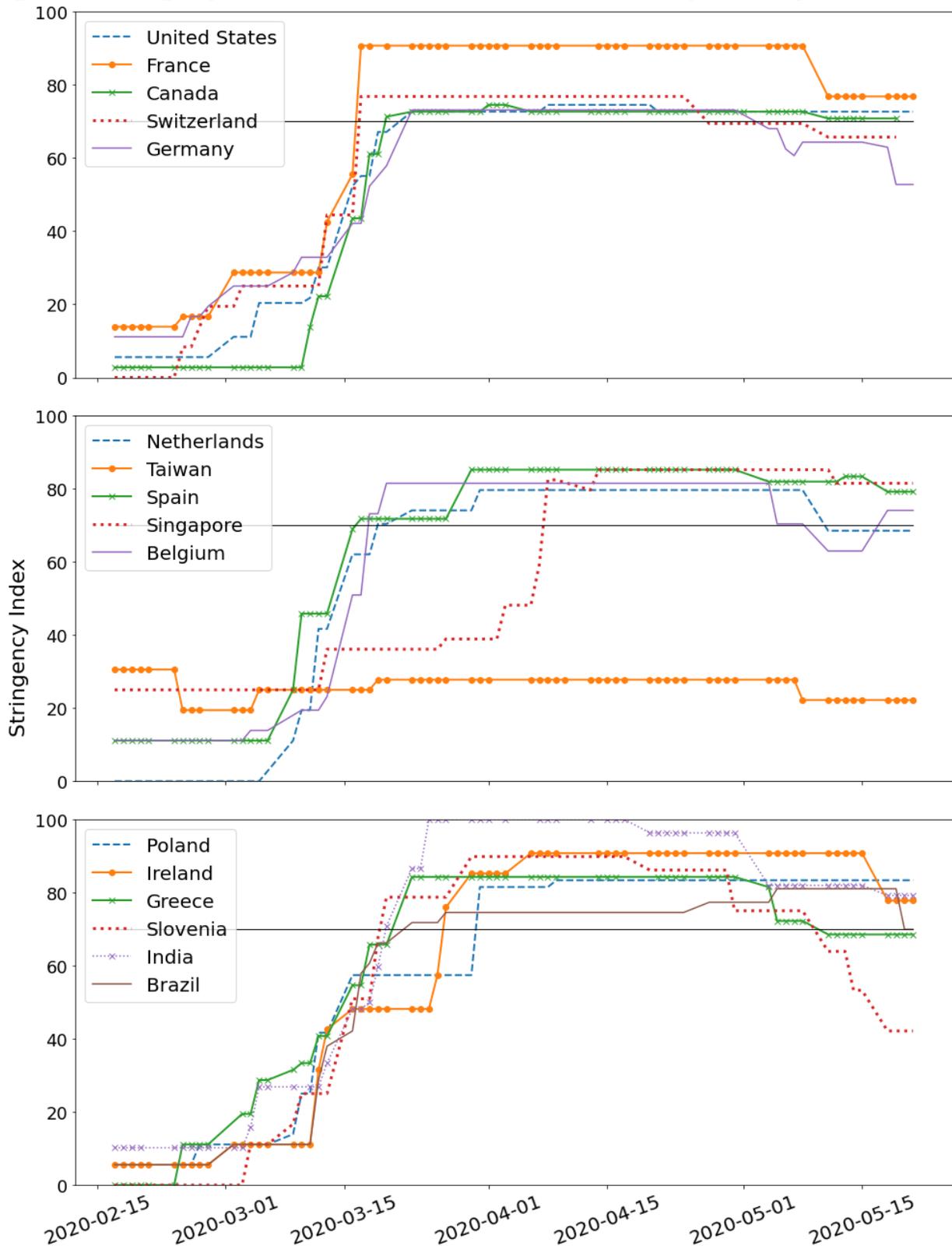
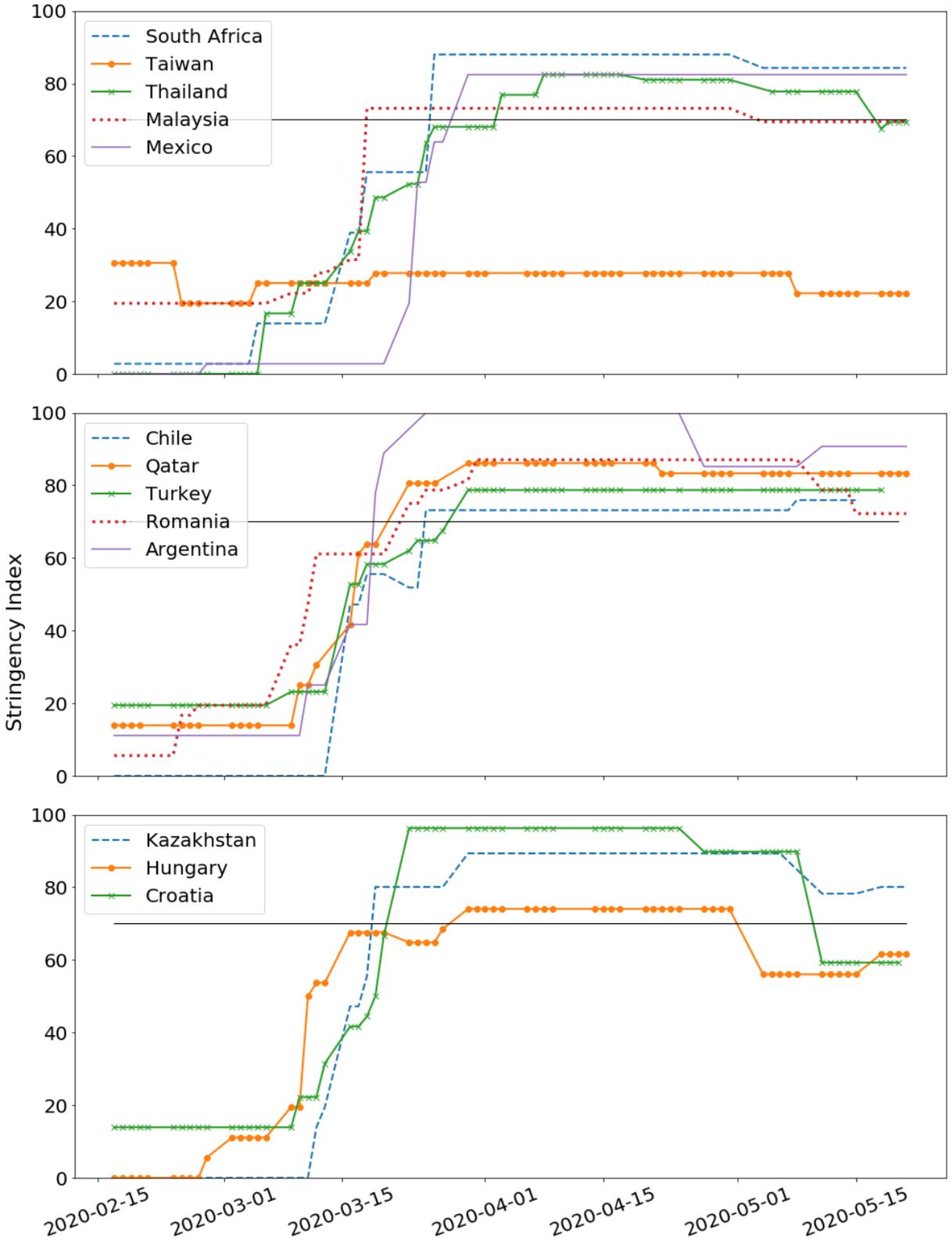


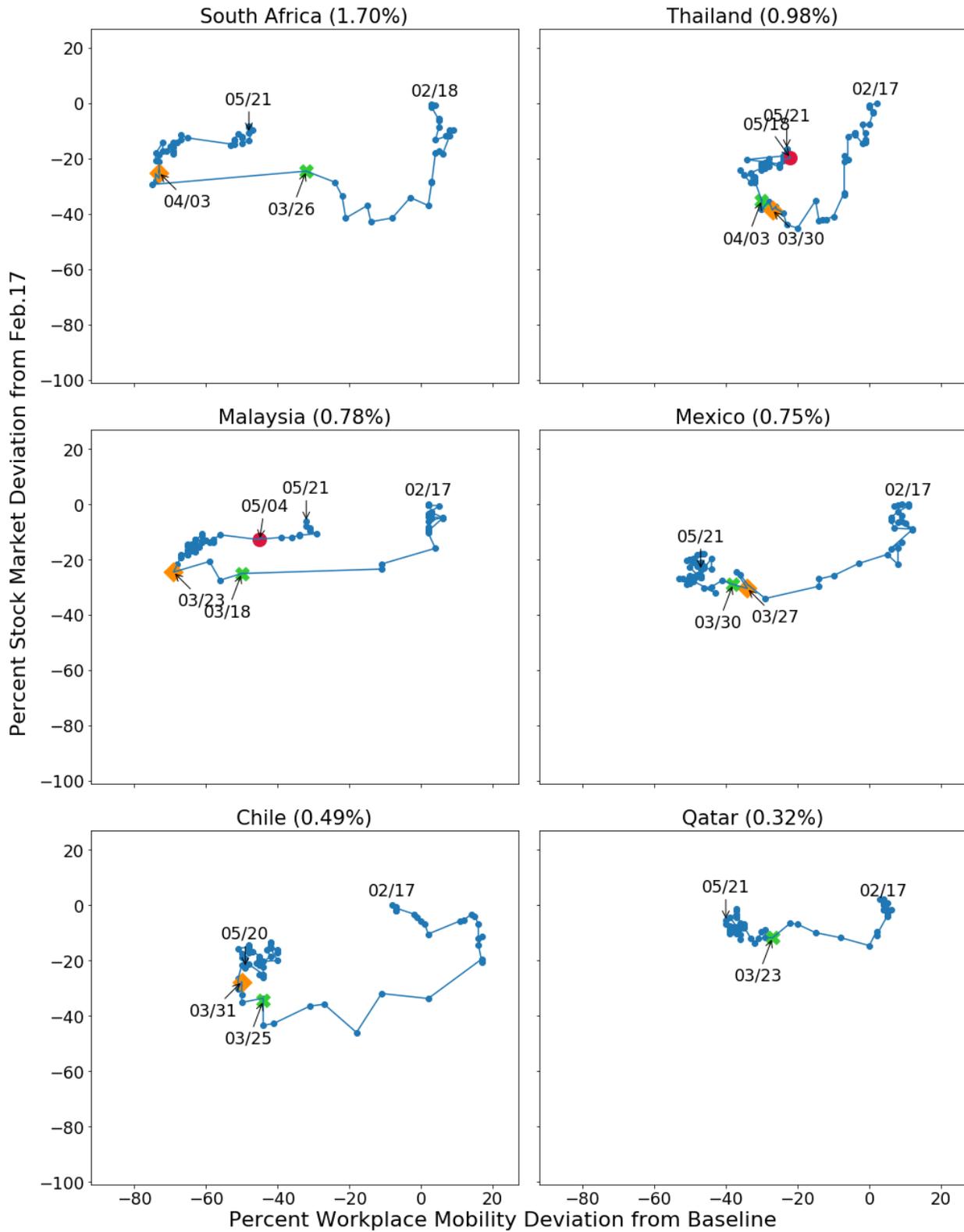
Figure A.2. Stringency of Economic Lockdown Measures, 17 February to 21 May 2020





Note: We plot the Stringency Index from 17 February to 21 May 2020. The horizontal black line indicates the Stringency Index level of 70. The order the countries is based on the market cap on 31 December.

Figure A.3. Time Path of Stock Prices and Workplace Mobility from 17 February to 21 May, Additional Countries



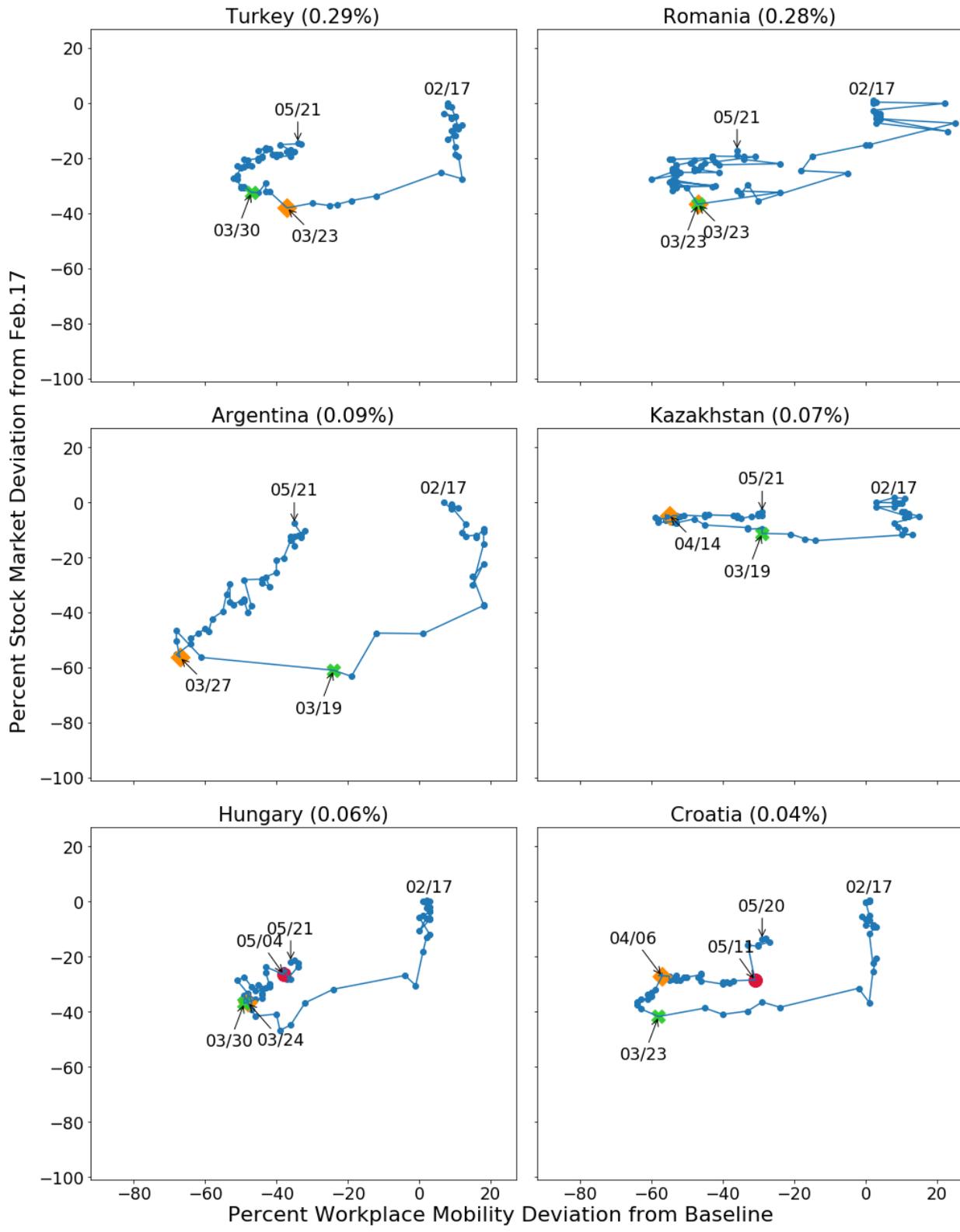
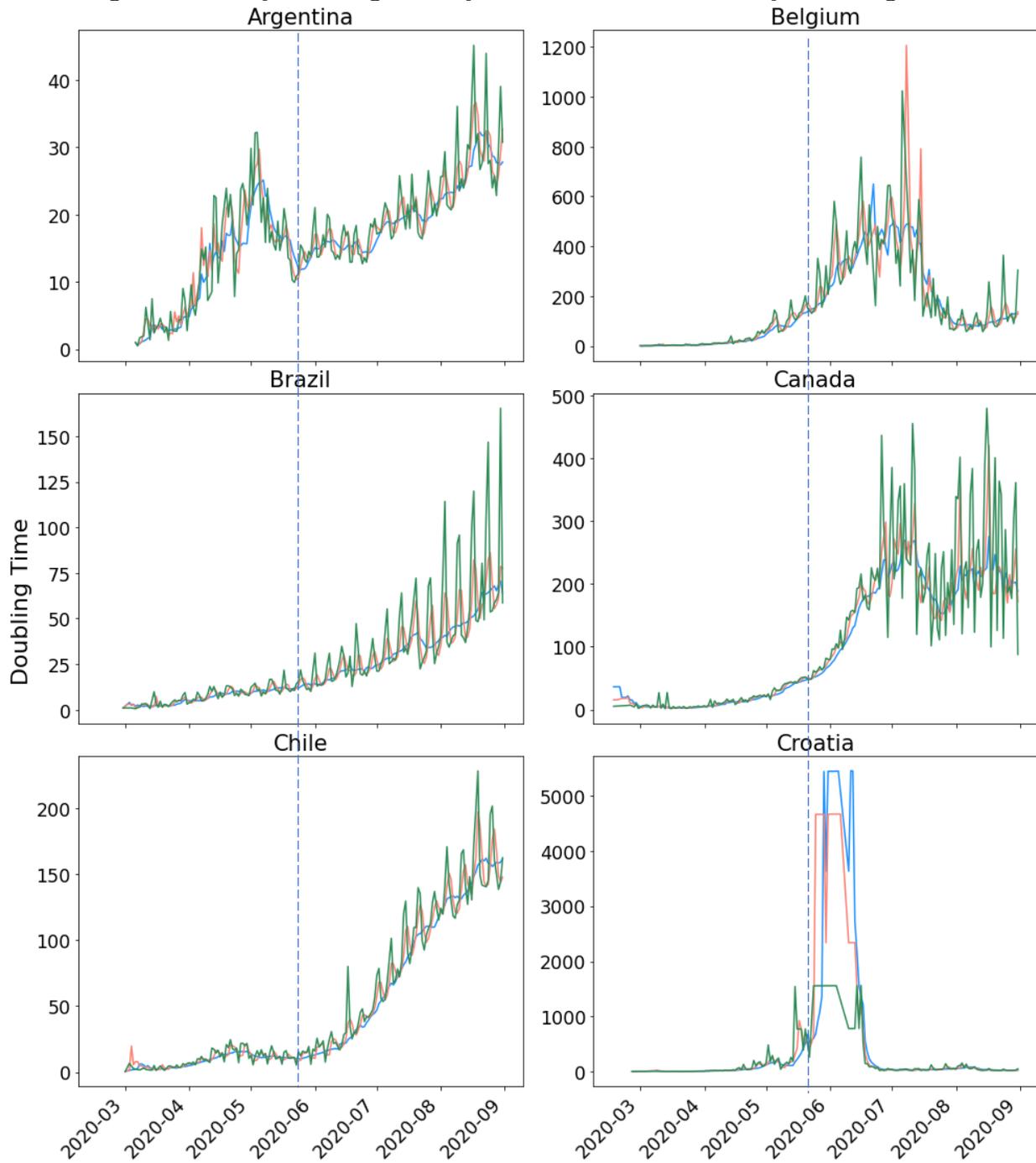
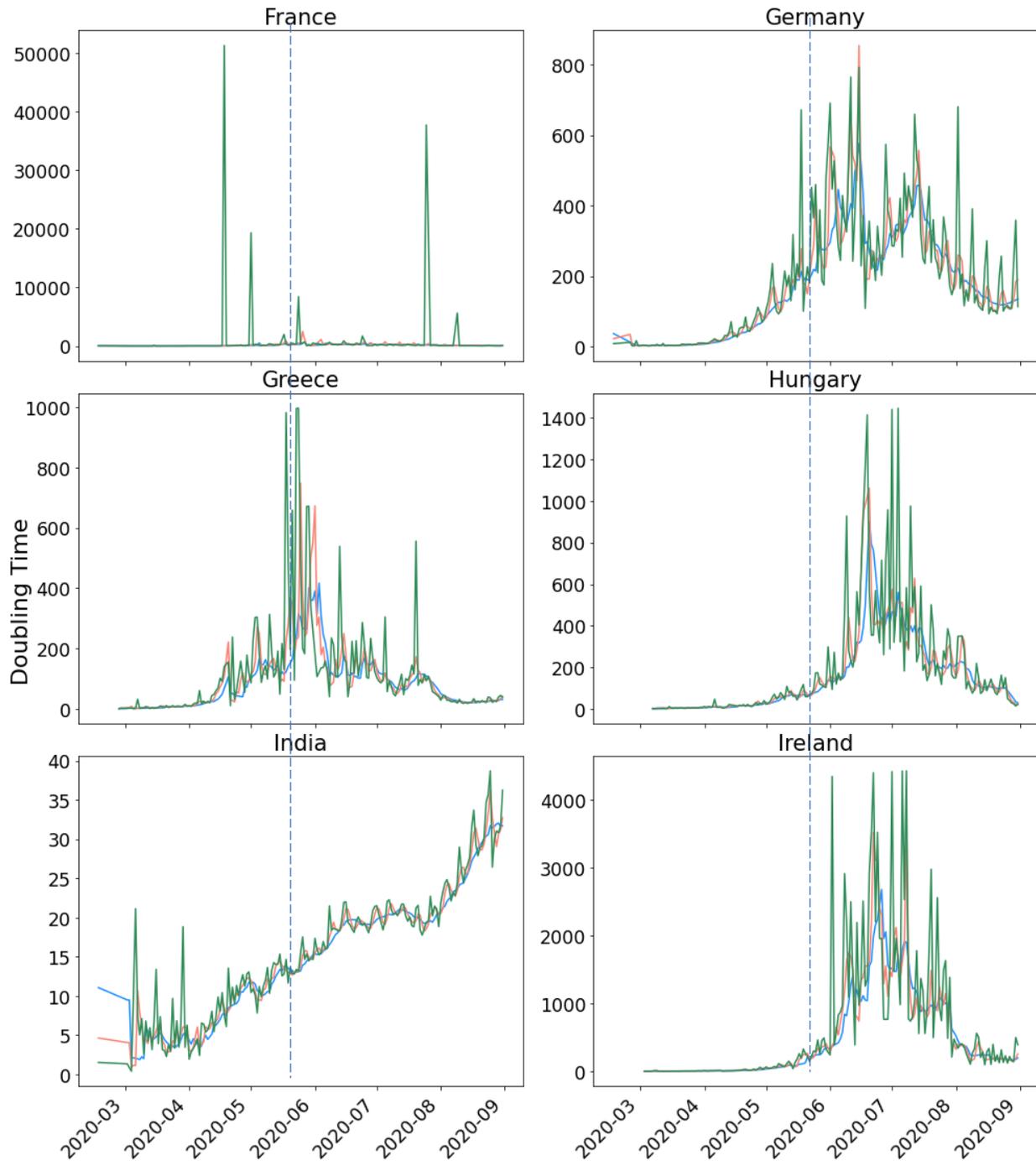
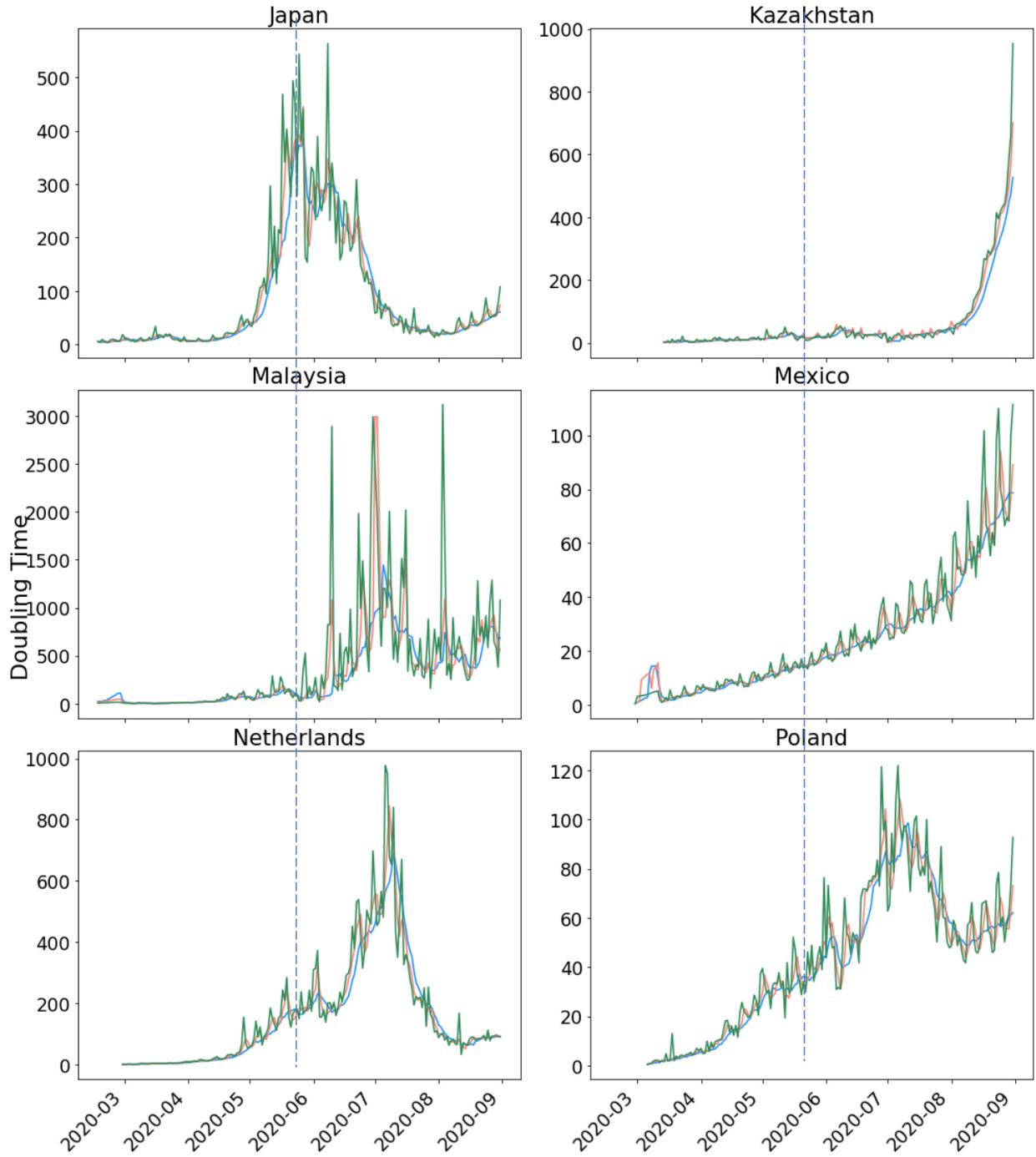
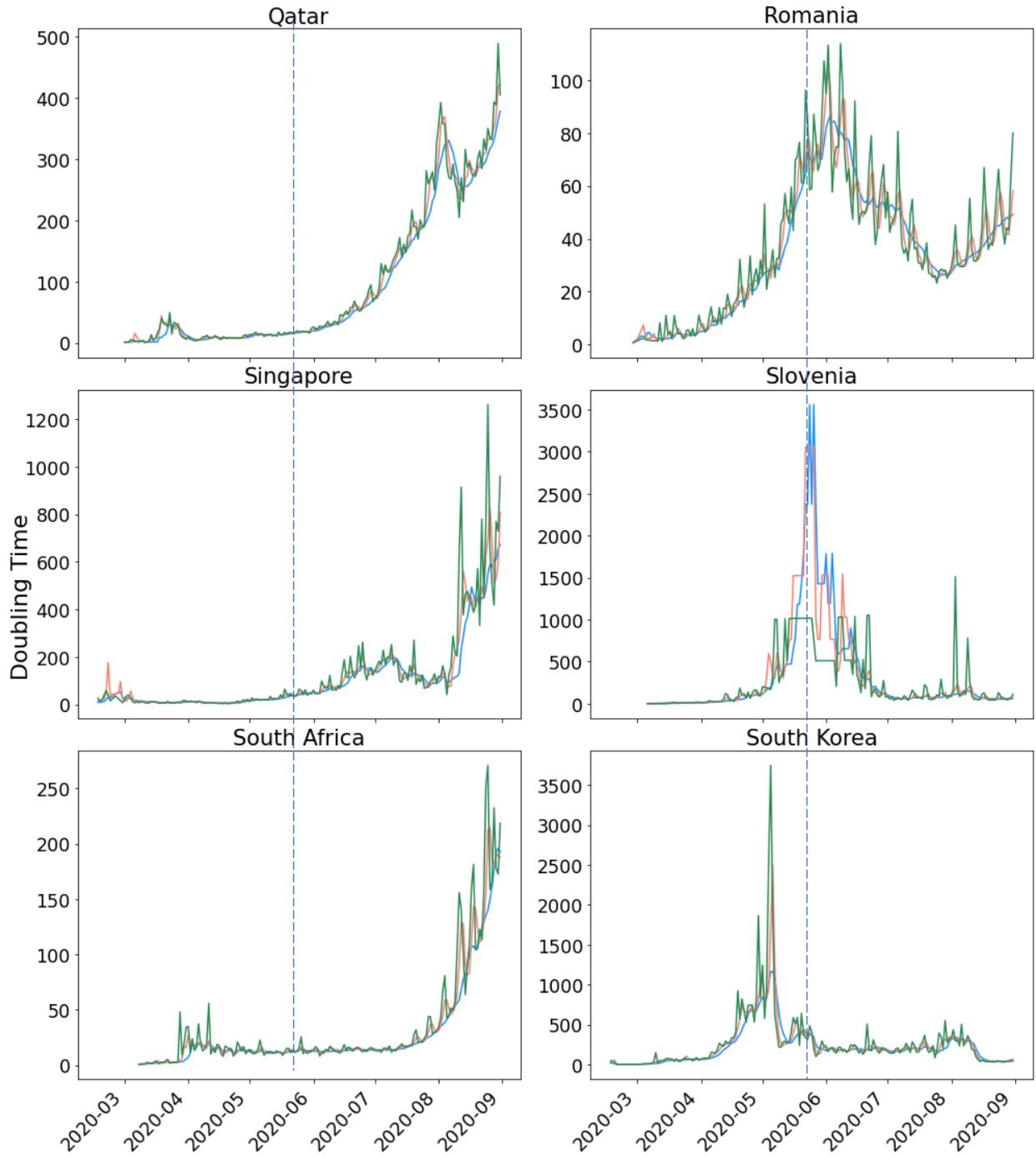


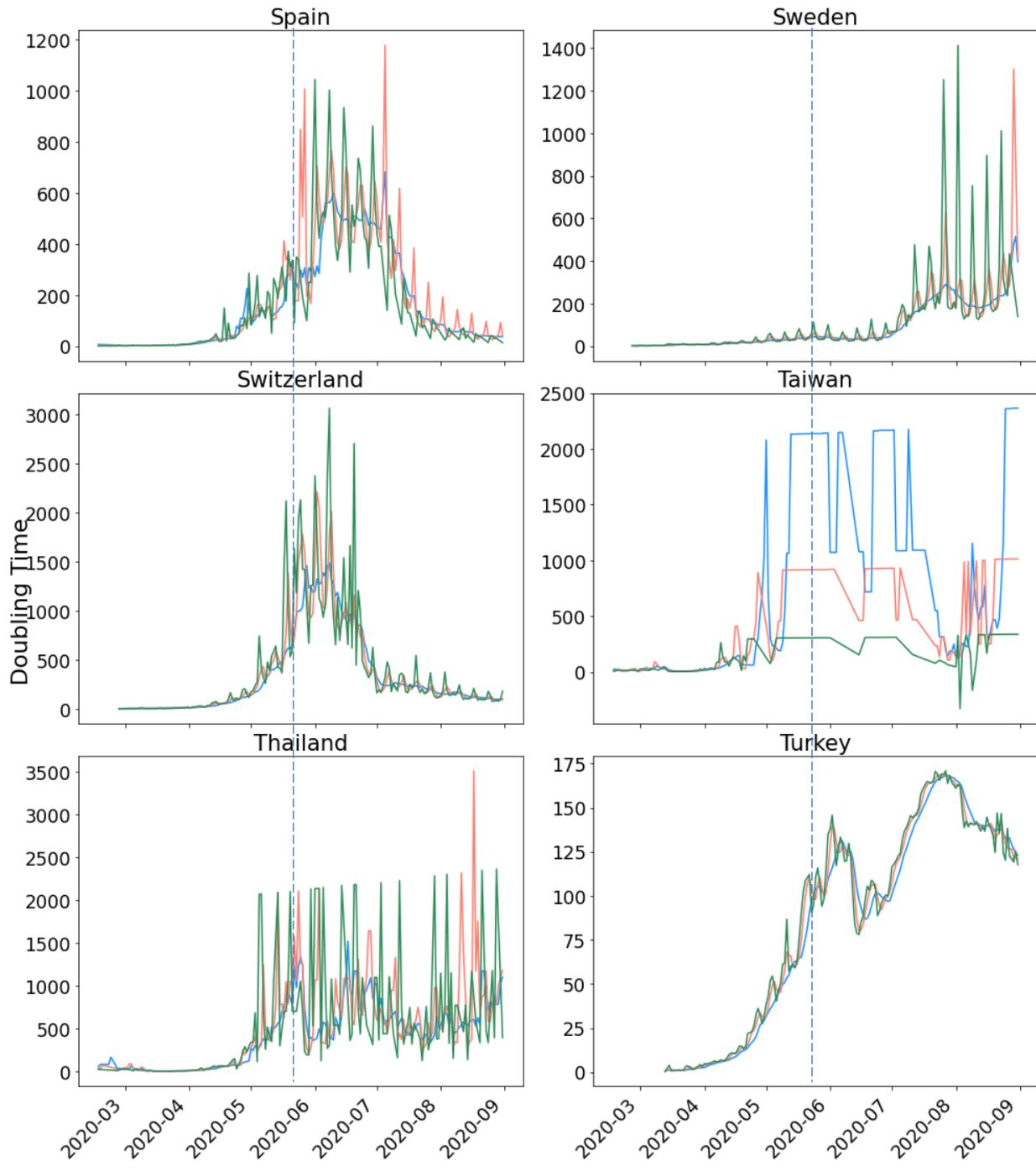
Figure A.4. Daily Doubling Time by Countries from 17 February to 31 August 31

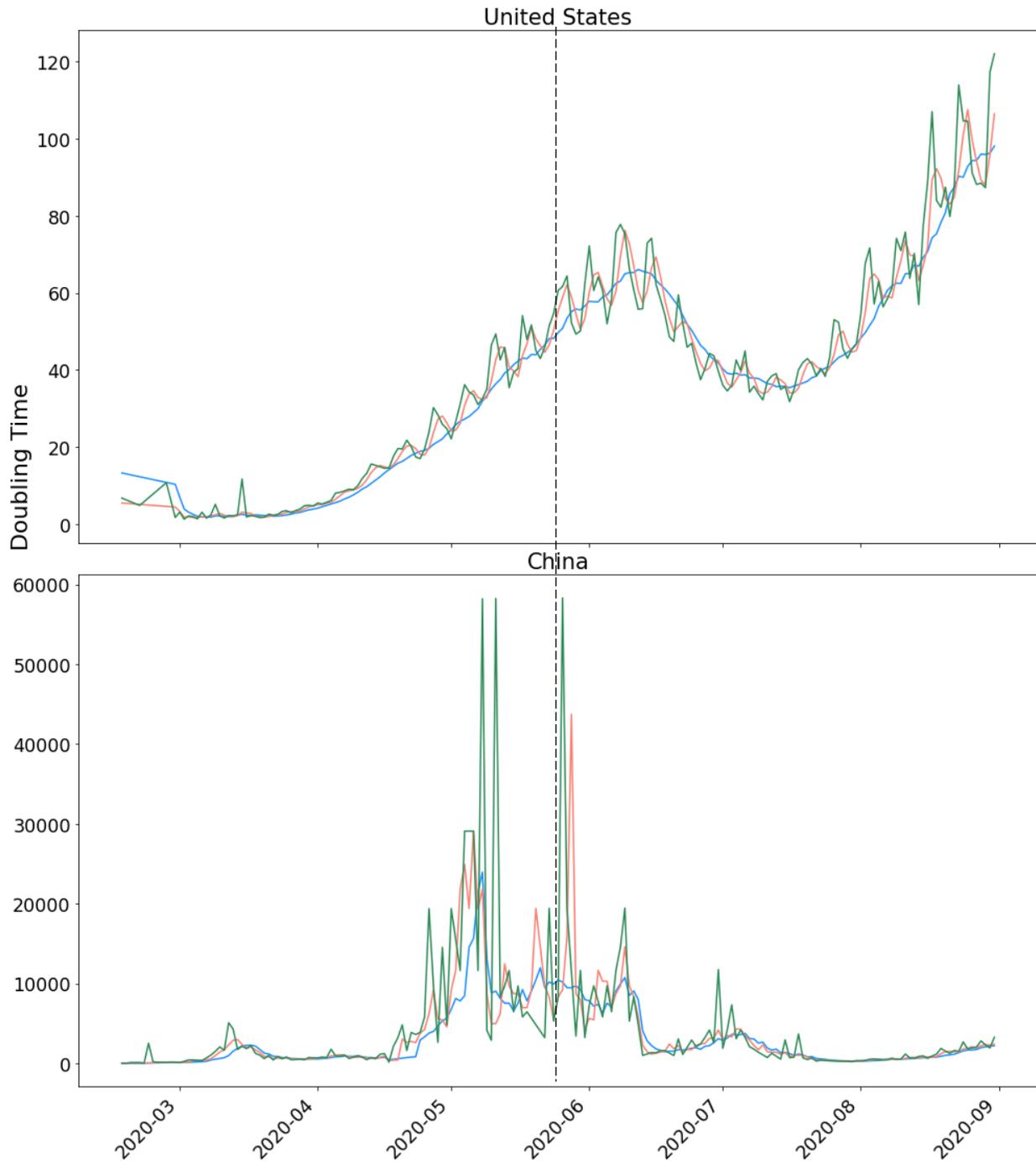






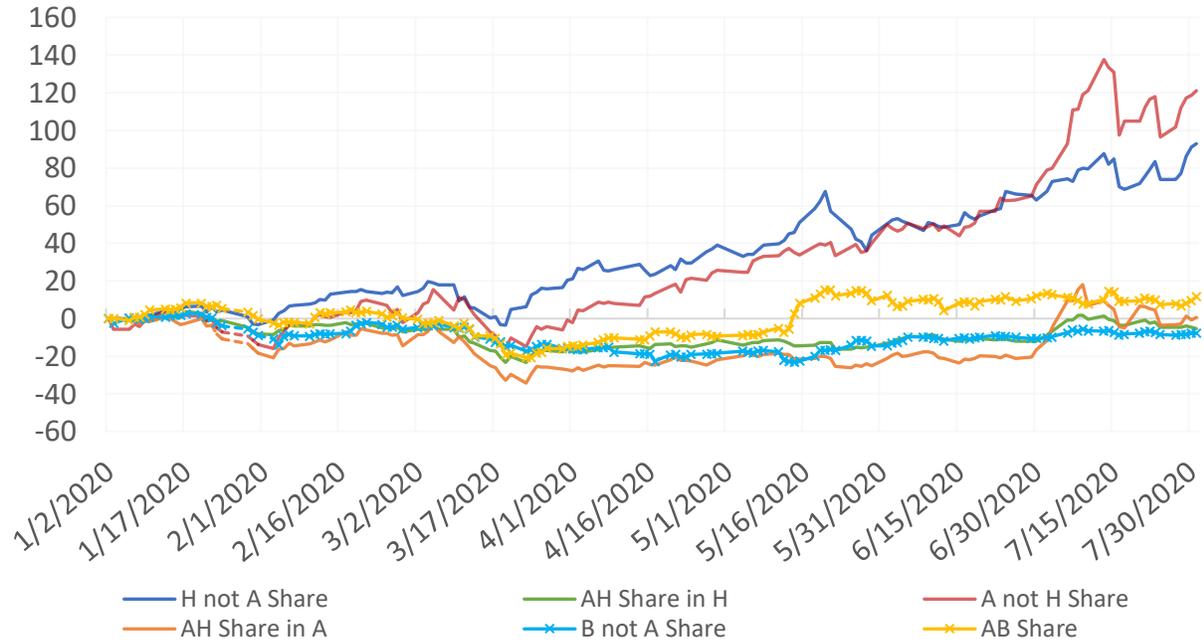






Note: We use Johns Hopkins Covid-19 [database](#) for confirmed cases. Blue line represents the doubling time based on the growth rate of the past seven days. Orange line shows the doubling time according to the past three days' growth rate. Green line presents the doubling time from the daily growth rate. Spain, France and Japan modified the methods of counting confirmed cases, resulting in decreased number of cases and a negative doubling time for some days. To fix this issue, we interpolate the doubling time for these days. When no new confirmed cases occur for a few days, there are missing values in the constructed doubling time and we impute these values using interpolation.

Figure A.5. Chinese A-Shares, B-Shares and H-Shares Prices,
Percent Deviations from 2 January 2020



Note: We plot the cumulated percent deviations in average stock prices from 2 January 2020. In calculating the weighted average for each category, we use firm's market capitalization on 7 August as the weight. Firms in all six categories operate in mainland China. "AH share" are firms listed in both A- and H-shares stock market, but with different stock prices in each market. "AH share in H" stands for "AH share" listed in H-shares market. "H not A share" are firms only listed in H-shares market. "A not H share" are firms only listed in A-shares market. "B not A share" are firms only listed in B-shares market. The dashed line from 24 to 31 January represents the Spring Festival market closure in A-shares market. A-, B-shares data are from CSMAR, the Chinese analogy of WRDS. H-shares data are downloaded from Yahoo Finance.

Table A.1. Summary Statistics for Variables Used in Table 2 Regressions

	mean	St. Dev.	min	25 th centile	Median	75 th centile	max
$WMD_{c,t}$	-29.6	25.1	-84	-50	-35	-4	25
$SMD_{c,t}$	-22.4	14.5	-76.89	-31.3	-21.3	-11.4	2.1
Deaths per Million	1.3	3.1	0	0	0.0	0.9	29
Log (Doubling Time)	2.6	1.52	-1.1	1.5	2.4	3.5	7.7
Economic Support Index	40.4	35.6	0	0	38.0	75	100
Stringency Index	55.7	31.1	0	25	70.8	81.5	100
$\sum_c \omega_c WMD_{c,t}$	-28.5	19.3	-47.9	-44.6	-38.1	-1.1	1.6
$\sum_c \omega_c SMD_{c,t}$	-19.4	9.3	-40.0	-25.7	-19.7	-15.9	0.1
$\sum_c \omega_c \text{Deaths per Million}_{c,t}$	2.0	1.8	0	0.01	2.4	3.8	4.8
$\sum_c \omega_c \text{Stringency Index}_{c,t}$	52.5	24.2	8.5	23.9	67.9	70.2	72.5
$\sum_c \omega_c \text{Economic Support Index}_{c,t}$	39.7	28.3	0.7	3.3	60.9	65.7	65.9

Notes:

1. The sample covers 2012 daily observations for 31 countries in the period from 17 February to 21 May 2020. The sample size is somewhat smaller (and excludes France) for Log(Doubling Time), as explained in the notes to Table 2.
2. ω_c is the country- c share of aggregate stock market capitalization of the 31 countries as of 31 December 2018. The countries are listed in Section 2.A in the main text.
3. See Section 2.A in main text for variable definitions and data sources.

Appendix B. Supplementary Material for Section 4

Following CBOE (2019) and consulting SSE's methodology of constructing iVIX, we construct China VIX by following the steps below:

- 1) Select SSE 50ETF options to be used in the China VIX Index calculation. The components of China VIX are near- and next-term put and call SSE 50ETF options. SSE 50ETF Options provide four expiration months: Current month, next month and the following consecutive quarters. We select SSE 50ETF options with expiration day longer than 7 days as near-term, and options with the second shortest expiration day as next-term. For example, on May 19, 2020, the China VIX Index would be calculated using SSE 50ETF options expiring 8 days later (i.e., "near-term") and 36 days later (i.e., "next-term"). On the following day, the SSE 50ETF options that expire in 7 days would become the "near-term" options and SSE 50ETF that expire in 35 days later would be the "next-term" options. The final selected options are out-of-the-money SSE 50ETF calls and puts centered around the at-the-money strike price, K_0 ². We only select options with non-zero bid prices, thus the number of options used in China VIX calculation may vary.
- 2) Calculate time to expiration T_1 and T_2 for near- and next-term options using the same following expression:

$$T = \frac{M_{current\ day} + M_{settlement\ day} + M_{other\ days}}{\text{Minutes in a year}}$$

Where $M_{current\ day}$ represents minutes remaining until midnight of the current day, $M_{settlement\ day}$ calculates the minutes from midnight until 9:15 am (GMT+8), $M_{other\ days}$ counts the total minutes in the days between current day and expiration day.

- 3) Determine the risk-free interest rates, R_1 and R_2 for near- and next-term options. The risk-free interest rates are yields based on Shanghai Interbank Offered Rate (SHIBOR). We apply a cubic spine to derive yields on the expiration dates of relevant SSE 50ETF options.
- 4) Determine the forward SSE 50ETF level, F_1 and F_2 , by identifying the strike price $K_{0,1}$ and $K_{0,2}$ at which the absolute difference between the call and put prices is smallest for near- and next-term options.

$$F_1 = K_{0,1} + e^{R_1 \times T_1} \times (\text{Call Price}_1 - \text{Put Price}_1)$$

$$F_2 = K_{0,2} + e^{R_2 \times T_2} \times (\text{Call Price}_2 - \text{Put Price}_2)$$

- 5) We select the out-of-the-money put options with strike prices less than $K_{0,1}$ for near-term option and put options with strike prices less than $K_{0,2}$ for next-term option. Similarly, we select the out-of-the-money call options with strike prices more than $K_{0,1}$ for near-term option and put options with strike prices more than $K_{0,2}$ for next-term option. We exclude call and pull options with zero bid price. Finally, we select both the put and call with strike price K_0 .
- 6) Calculate volatility for both near-term and next-term options with the following formula:

$$\sigma_1^2 = \frac{2}{T_1} \sum_i \frac{\Delta K_i}{K_i^2} e^{R_1 \times T_1} Q(K_i) - \frac{1}{T_1} \left[\frac{F_1}{K_{0,1}} - 1 \right]^2$$

$$\sigma_2^2 = \frac{2}{T_2} \sum_i \frac{\Delta K_i}{K_i^2} e^{R_2 \times T_2} Q(K_i) - \frac{1}{T_2} \left[\frac{F_2}{K_{0,2}} - 1 \right]^2$$

² SSE 50ETF Options offer nine strike prices (1 at-the-money, 4 out-of-the-money and 4 in-the-money), see <http://english.sse.com.cn/markets/derivatives/overview/>

Where ΔK_i is half the difference between the strike prices on either side of K_i . $Q(K_i)$ is the midpoint of the bid-ask spread for each option with strike K_i .

- 7) Calculate the 30-day weighted average of σ_1^2 and σ_2^2 . Then take the square root of that value and multiply by 100 to get the VIX Index value.

$$VIX = 100 \times \sqrt{\left\{ T_1 \sigma_1^2 \times \frac{M_{T_2} - M_{30}}{M_{T_2} - M_{T_1}} + T_2 \sigma_2^2 \times \frac{M_{30} - M_{T_1}}{M_{T_2} - M_{T_1}} \right\} \times \frac{M_{365}}{M_{30}}}$$

Where M_{T_1} is the number of minutes to settlement of the near-term options, M_{T_2} is the number of minutes to settlement of the next-term options, M_{30} represent the number of minutes in 30 days and M_{365} is the number of minutes in a 365-day year.

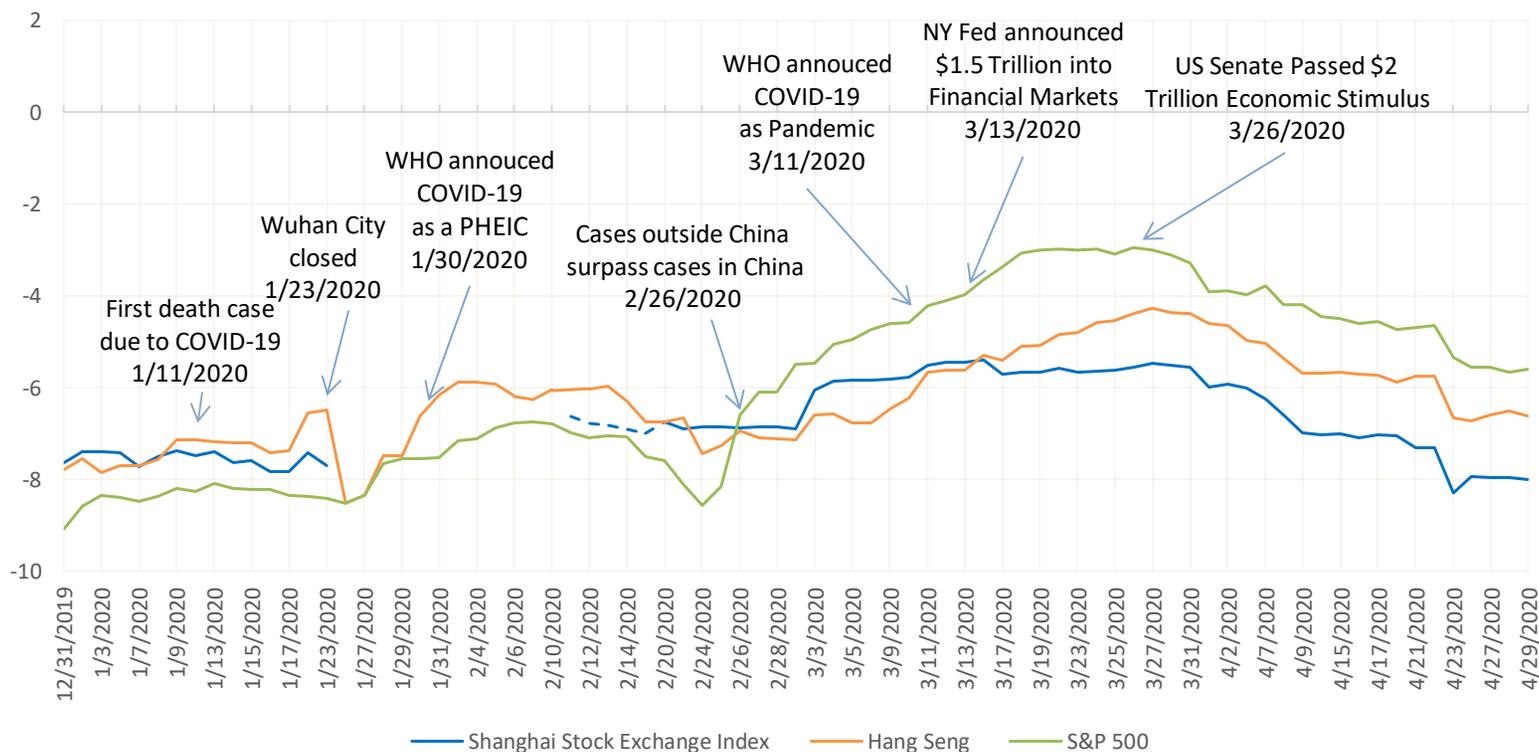
Shanghai Stock Exchange and China Securities Index Co (CSI) once published an official China VIX (iVX). But the authorities suspended publication of the volatility index in 2018 due to a technical upgrade. Reuters (2018) suspect it was the regulators' effort to curb speculative trading and shore up investor confidence. To measure the implied volatility of China's stock market, we consult CBOE VIX White Paper and Shanghai Stock Exchange's methodology of constructing iVX, we construct China VIX based on the Shanghai Stock Exchange 50ETF options. The details are included in Appendix B. Our China VIX replication is very close to iVX, as the overlapped part correlation is 0.99. The comparison can also be seen from Figure A.6 and A.7 in Appendix A.

Table B.1. The History of adjusting stock exchange stamp rate

Time Period	Stock Exchange Stamp Rate
1991-05/09/1997	0.3%
05/10/1997-06/11/1998	0.5%
06/12/1998-11/15/2001	0.4%
11/16/2001-01/23/2005	0.2%
01/24/2005-05/29/2007	0.1%
05/30/2007-04/23/2008	0.3%
04/24/2008-09/18/2008	0.1%
09/19/2008-present	0.1% sell side only

Note: Stock exchange stamp rate was used to intervene the market in history. Before September 19, 2008, the stamp duty was imposed on both buy and sell sides. After September 19, 2008, the stamp duty started to be levied upon the sell side only.

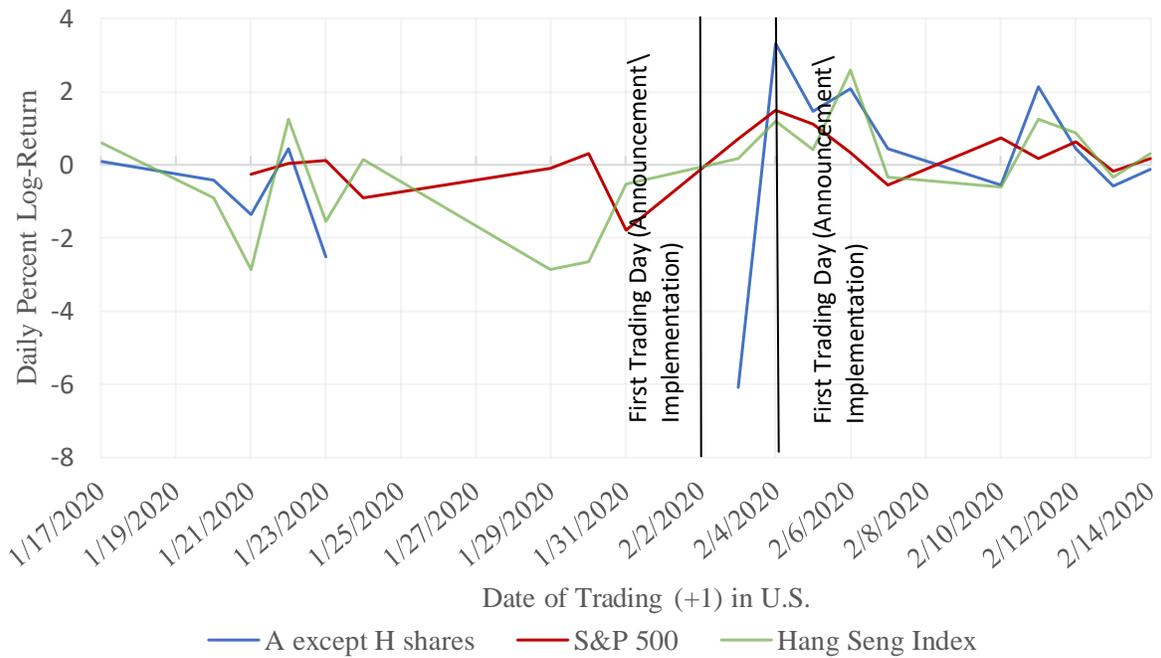
Figure B.1. Natural Log of Realized Volatility of Returns (Standard Deviation) over the Past 10 Trading Days, American and Chinese Stocks, 31 December 2019 to 29 April 2020



Note: The breaks in the line reflect different market closure time. The realized volatility over the past 10 trading days is the sum of squared returns over the past 10 trading days. To account for the impact of Chinese spring festival vacation, we normalize the realized volatility by taking the following steps: 1) Let $j = 0, 1, 2, \dots, N^c$, index days, where $j = 1$ corresponds to the first closure day and $j = N^c$ is the last closure day. 2) Treat $j=0$ like any other trading day. 3) Treat the volatility data as missing for $j = 1$ to $j = N^c + 5$. Show a gap in the series for each closure period. 4) For $j = N^c + k$ for $k = 6$ to 10 , compute past volatility by summing the squared returns over the past $k-1$ days (i.e., inclusive of the change from $k-1$ to k) and multiplying the sum by $(10/(k-1))$. This multiplication factor adjusts for the shorter volatility window. 5) When plotting the realized volatility data for the interval from $j = N^c + k$ for $k = 6$ to 10 , use a dashed line for these five days.

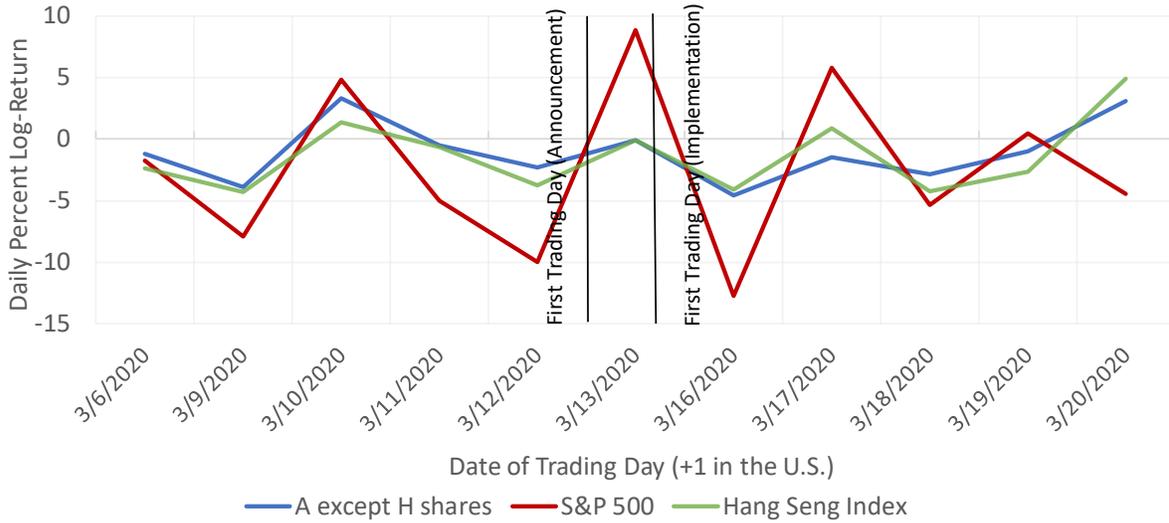
Figure B.2. Daily Log Returns in Windows Around Selected Chinese Policy Actions

Event: 1. PBOC injects \$17 billion via reverse repo operation; CSRC asked some brokerages, funds and insurers not to be net sellers for at least a week; CSRC asks all brokers to stop securities lending business, in the evening on Feb. 2, 2020; 2. CBIRC encourage insurers to buy more equities before the market reopens; To offset redemptions, major mutual funds announce they will purchase their own funds' shares, in the early morning on Feb. 3, 2020; 3. PBOC injects \$7 billion via reverse repo operation, announced at 9:46 AM on Feb. 4, 2020.

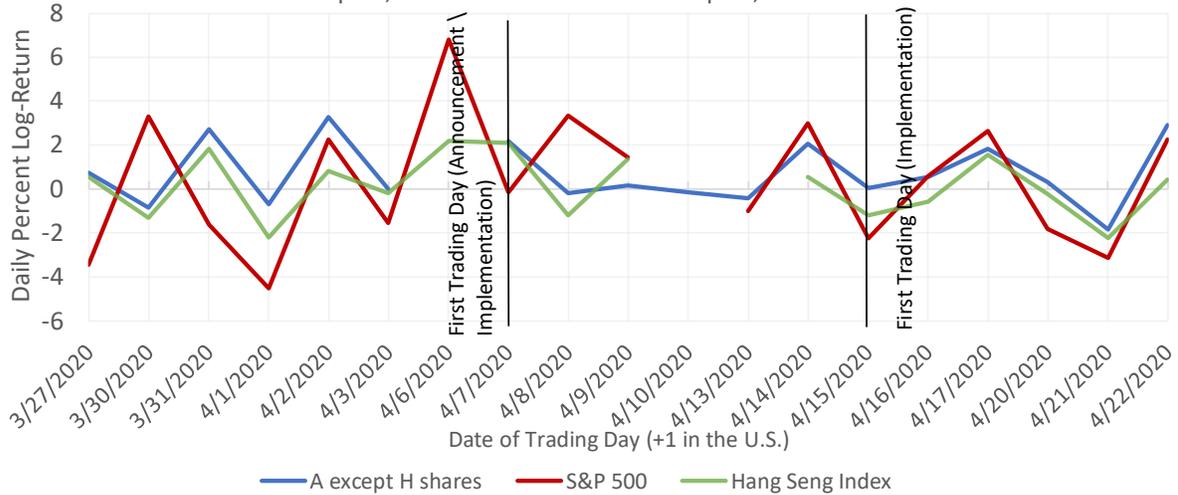


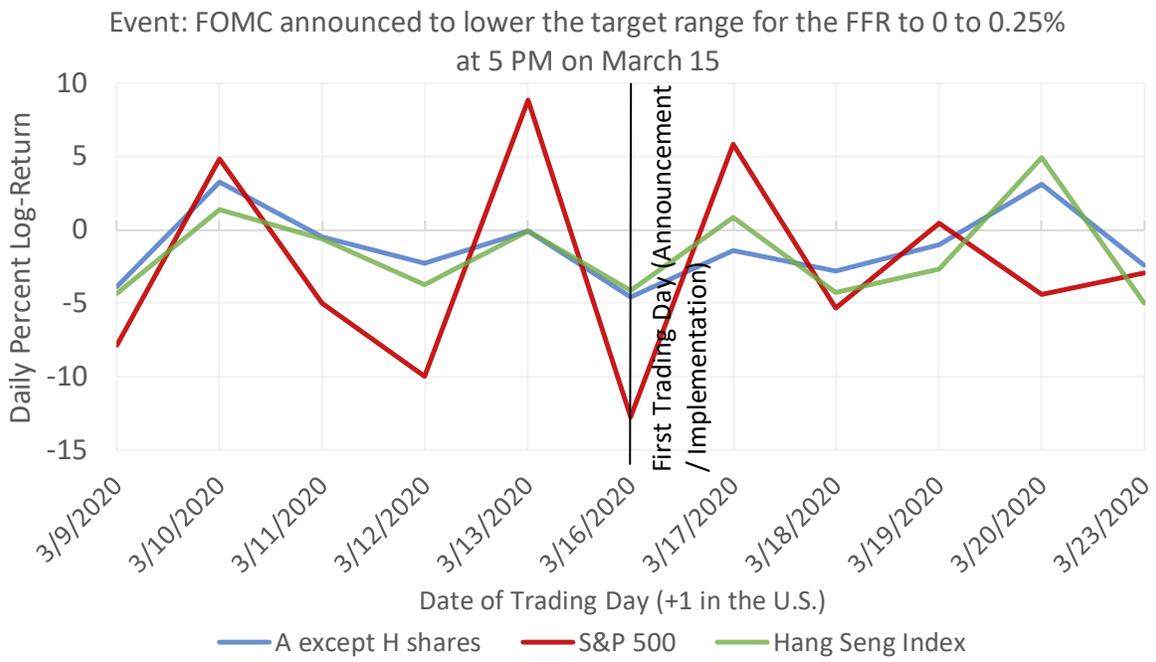
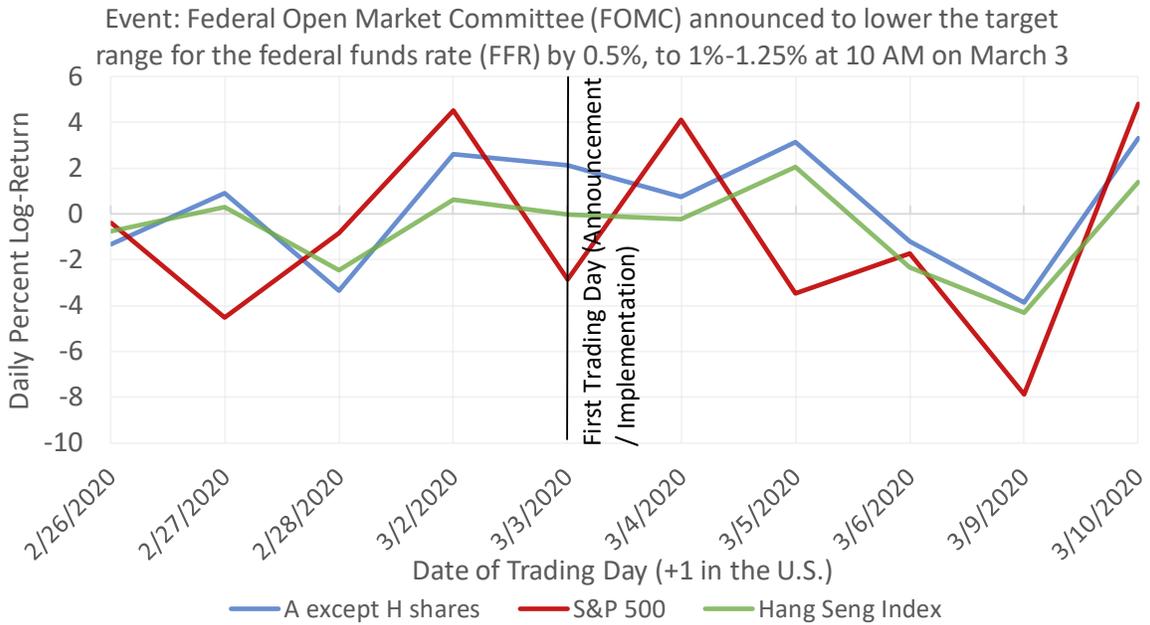
Note: We use A except H shares index for the Mainland China stock market, Hang Seng index for the H.K. stock market and S&P 500 for the U.S. stock market. We calculate the Daily log-return as the percentage daily log return in each stock market, according to the first trading day indicated in Table 1. The breaks represent market closure. Traditionally, PBOC doesn't announce reverse repo operation ahead of time. This announcement is the forward guidance to change investors' expectation.

Event: PBOC says it will cut the reserve requirement ratio (RRR) by 50-100 bps for banks that have met inclusive financing targets, announced at 5:16 PM on Mar.13, 2020

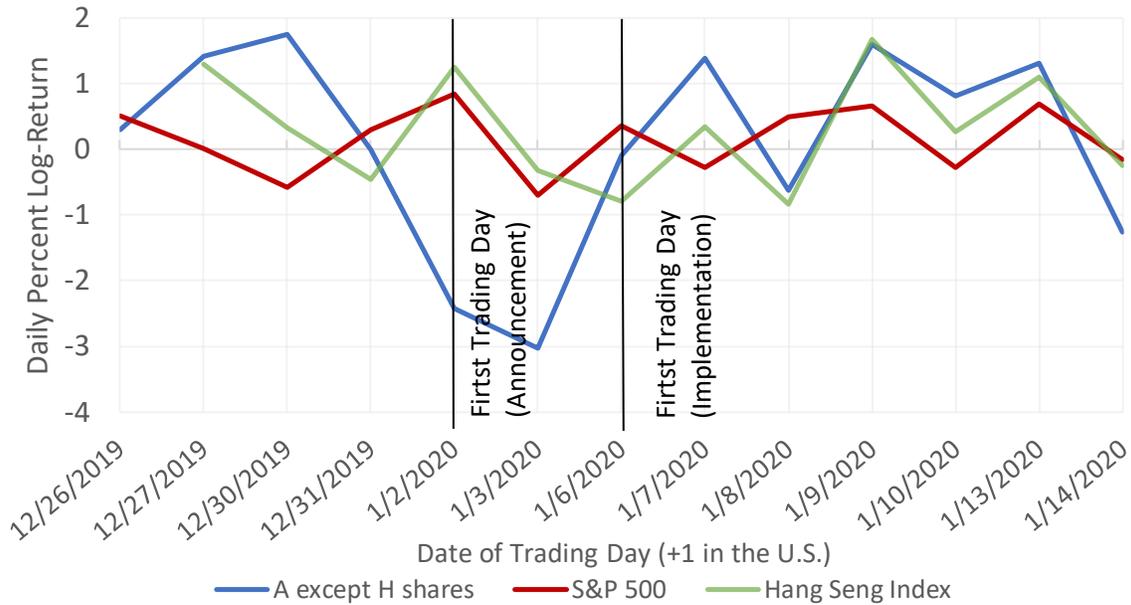


Event: PBOC will cut the targeted reserve requirement ratio (RRR) by 50 bps on Apr. 15 and May 15 separately, and will lower the interest rate paid for excess reserves from 0.72% to 0.35% on Apr. 7, announced at 4:57 PM on Apr. 3, 2020





Event: PBOC cuts Reserve Requirement Ratio by 0.5%,
announced at 3:07 PM on 1 January 2020



Note: We use A except for H shares index for the Mainland China stock market, Hang Seng index for the H.K. stock market and S&P 500 for the U.S. stock market. We calculate the Daily log-return as the percentage daily log return in each stock market, according to the first trading day indicated in Table 4. Breaks in the plotted data reflect extended market closures.