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# ARE STOCK MARKETS DISCONNECTED FROM THE REAL ECONOMY DURING THE COVID-19 PANDEMIC?

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## Summary

Stock indices throughout the world plunged at the onset of the Covid 19 outbreak, suggesting a global health crisis unlike any experienced in the past century. However, stock markets have recovered and continued to grow since April 2020, despite challenging market conditions. The purpose of this paper is to present empirical evidence of the divergence between the stock market and the real economy. We discover that the US stock market is more disconnected during the coronavirus outbreak, but European stock markets are more connected to the real economy. Our research illuminates the prospect that, under some circumstances, such as a global health crisis, stock markets may become isolated from the real economy.

<Inside Cover>

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# CHAPTER 1. INTRODUCTION

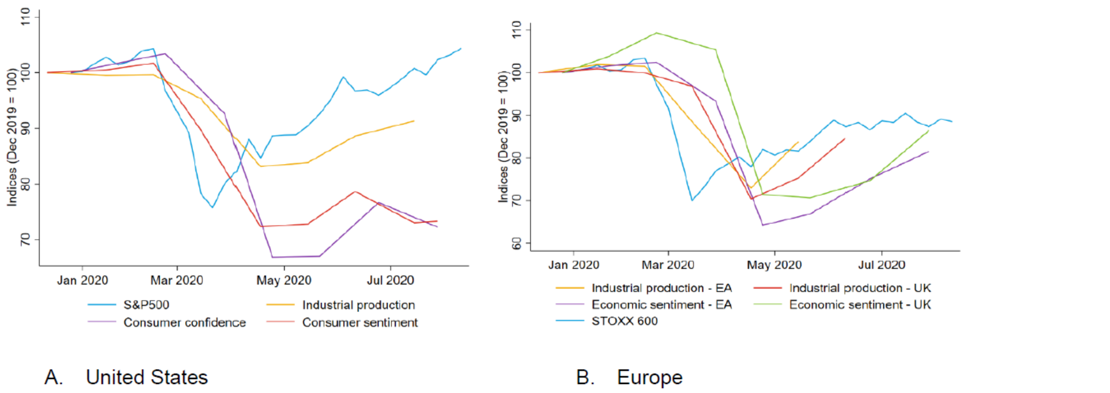
Since the beginning of 2020, the world economy has been experiencing a truly global crisis due to the covid-19 or coronavirus pandemic. Throughout history, we have been confronted with many highly contagious and deadly diseases, such as the Black Plague (1346 - 1352), the 1918 "Spanish Flu" pandemic, or the Severe Acute Respiratory Syndrome (SARS) outbreak at the beginning of the 21st century. Compared to these episodes, the novel coronavirus is a unique public health crisis in that it has affected all countries and people worldwide. The pandemic prompted the introduction of several non-pharmaceutical measures, such as city-wide lockdowns, border restrictions, and mandatory quarantine, all of which are more stringent than measures taken during previous episodes such as the 1918 pandemic.

The impact of the pandemic was and still is, very large and profound. According to International Labor Organization (ILO), the pandemic reduced 8.8% of global working hours in 2020 compared to the fourth quarter of 2019, with 4.5% due to a reduction in hours worked by currently employed workers, 3.4% due to unemployed workers not actively looking for a new job, and 0.9% due to those who are unemployed but actively looking for a new job. This amount is equivalent to approximately 255 million full-time jobs. Among all regions, the overall decline in working hours in 2020 compared with 2019 was largest in Europe (14.6%), followed by the Americas (13.7%), the Arab States (9.1%), Asia (7.9%), and Africa (7.6%)[1].

The United States was the world's pandemic center in 2020, with more than 20 million people infected[2]. There was also a very high unemployment rate due to the strict lockdowns. The Department of Labor reported that the weekly number of claims for unemployment insurance rose to more than 3 million in the third week of March 2020 and peaked the next week at nearly 7 million claims. From April 2020, it gradually declined and remained stable at less than 1 million claims per week. The total number of insured unemployed workers peaked in mid-May 2020 at 25 million cases

[1] ILO Monitor: COVID-19 and the World of Work, Seventh Edition, International Labor Organization, January 15, 2021, p. 2.
[2] Calculated from the data collected by Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE).

**Figure 1: Disconnection between stock markets and real economic indicators**




Sources: Bloomberg Finance L.P.; Conference Board; European Commission; Haver Analytics; Statistical Office of the European Communities; US Federal Reserve Board; University of Michigan Survey; and IMF staff calculations.
Note: All series are indexed to 100 as of the last observation prior to January 2020. Stock market index levels are shown weekly. Monthly industrial production and sentiment series are shown in the week of release.

Source: Igan, Kirti & Peria (2020), p.g. 2.

and then fell to 3.5 million in June 2021[3].

Despite the decline in unemployment rates, there was an increase in new daily confirmed cases in the United States in the fourth quarter of 2020, as well as in many other countries such as India and Japan. As a result, the recovery of the global economy is expected to be delayed in 2021. In early December 2020, Federal Reserve Chairman Jerome Powell commented that the outlook for recovery was “extraordinarily uncertain” and that “significant challenges and uncertainties remain” [4]. During this period of high uncertainty, it has been observed that there is a disconnect between the stock market and the real economy. This phenomenon seems to be more pronounced in the US compared to European markets (Igan, Kirti, and Peria 2020). As shown in Figure 1, the US stock market crashed in the period February-March 2020, but then recovered quickly and briskly, while real economic indicators showed no signs of a rapid recovery.

The connections between stock markets and our economy are important and have been explored in the literature. Morck, Shleifer, and Vishny (1990) suggest that the stock market may be a sideshow after all since fluctuations in the (U.S.) stock market are irrelevant to firms' investment

[3] Unemployment Insurance Weekly Claims, Department of Labor, June 17, 2021. https://www.dol.gov/
[4] Powell, Jerome H., Coronavirus Aid, Relief, and Economic Security Act, December 1 and 2, 2020. https://www.federalreserve.gov/newsevents/testimony/powell20201201a.htm.

decisions. Dow and Gorton (1997) show that in one of the equilibria, investment decisions are suboptimal even when stock prices are strong-form efficient. Bond, Edmans & Goldstein (2012) discuss possible channels through which secondary market prices influence real economic activity because of their informativeness. They also argue that the definition of price efficiency should be broadened to include “the extent to which prices reflect information that is useful for the efficiency of real decisions (rather than the extent to which they forecast future cash flows).” Thus, if the stock market is closely and dynamically linked to the real economy, prices should reflect market conditions during the Covid-19 health care crisis because they are important information for decision-makers during periods of high uncertainty.

This paper aims to answer the question of whether there is a disconnect between the stock market and the real economy during the Covid 19 pandemic. In doing so, we contribute to the line of research on the real effects of financial markets on the economy by providing empirical evidence on the possibility that the stock market may be disconnected from the real economy under special conditions, such as during a global pandemic. We also contribute to the new line of research on the impact of Covid-19 on the stock market.

The rest of the paper is organized as follows. Chapter 2 discusses existing theoretical and empirical work on the real effects of financial markets on the economy. Chapter 3 presents the main hypothesis, data, and methodology used in this paper. Chapter 4 discusses the empirical results and Chapter 5 concludes.

# CHAPTER 2. LITERATURE REVIEW

A very interesting research question in finance is whether secondary financial markets, namely the stock market, have real economic consequences. A traditional view in finance is that financial markets affect the real economy through their financing role in the primary channel. Any shock in the primary financial market that constrains a firm's ability to raise more capital would then reduce investment and real economic output. In contrast, secondary financial markets do not affect the real economy because capital does not flow into firms through this channel, or they affect only to the extent that the firm's liquidity in the secondary market affects its ability to raise capital in the primary market. However, Bond, Edmans & Goldstein (2012) argue that it is a mistake to treat secondary market prices as a sideshow and that prices have real economic effects because of their informational function. If we accept this idea, we could naturally explain various phenomena in finance, namely “manipulative short selling, the asymmetric dissemination of bad news and good news, financial market runs, information-based trading, and the presence of non-controlling blockholders that otherwise seem puzzling” (Bond, Edmans & Goldstein 2012).

The line of research on price efficiency focuses on whether the price of a particular security can accurately predict the future value of that security, while the research question on the real efficiency of secondary prices is whether “prices accurately convey information about underlying economic state or choice variables that are important for real efficiency” (Bond, Edmans & Goldstein 2012). These two concepts are referred to as forecasting price efficiency (FPE) and revelatory price efficiency (RPE) as defined by Bond, Edmans & Goldstein (2012). Price efficiency increases real efficiency because efficient real decisions can be made from informative prices. Nevertheless, price efficiency does not always lead to real efficiency. This may be the case when prices reflect the firm's investment level but do not provide information to guide real investment decisions (Dow & Gorton 1997).

Real decision-makers, such as firm managers, shareholders, or regulators, often learn from security prices to make real decisions and consequently influence the real economy (Baumol 1965).

Bond, Edmans & Goldstein (2012) document that there are three main reasons to explain this mechanism. First, a large amount of different information flows into securities prices when investors interact in the financial market. Although real decision-makers are the most informed about the firm, their knowledge is incomplete. To make optimal real decisions, they need more than just the information about the firm, such as the market conditions, the firm's competitors, the market demand, etc., so they would like to get such information from the prices for real decision making. A typical example is that a manager considering an acquisition deal may cancel it if he observes a negative market reaction of stock prices after the deal announcement (Luo 2005).

In addition, the idea that market participants have some information about the firm value that the firm managers do not know is supported by IPO empirical research, such as Jegadeesh, Weinstein & Welch (1993), and Michaely & Shaw (1994). Boot & Thakor (1997) and Subrahmanyam & Titman (1999) use the price’s feedback effect in this learning channel to explain the firm’s decision to choose equity financing over debt financing, which is not following the pecking order theory in corporate finance. Likewise, Foucault & Gehrig (2008) adopt the same line of reasoning for the firm’s crossing-listing shares in different markets. Cross-listing allows firms to get more information and thus increases the efficiency of making investment decisions.

Second, since the compensation of the firm managers is tied to the stock price, they are still concerned about it even when they do not actively learn additional information from it. Stock prices are often used as a performance indicator for the firm managers because shareholders believe that prices convey information about the firm's value. In this so-called "incentives channel," prices affect the real economy by inducing real decision-makers to take actual actions. This effect was first mentioned by Baumol (1965) and then was formalized by Fishman & Hagerty (1989). These papers document that higher price efficiency incentivizes the firm's managers to take favorable actions to maximize the firm's value and eventually increase real efficiency. Using this phenomenon, Fishman & Hagerty then justify the firm's motives for making the information about the firm available to the public to improve price efficiency.

Third, there is a possibility that the learning behavior of real decision-makers may result from irrationality. They may irrationally keep track of secondary market prices and use them as a benchmark, but the source of this behavior still originates from price informativeness.

There is sizeable empirical evidence for the real effects of secondary financial markets, particularly the stock market. As mentioned above, the corrective action of the firm managers to call off an acquisition deal when there is an adverse reaction from the stock market after the announcement of the agreement illustrates the real effects of prices through the learning channel. Jennings & Mazzeo (1991) find no evidence to support this hypothesis. However, using a considerably larger sample and designing the test as close as possible to the above idea, Luo (2005) finds supporting evidence and also points out that the probability of canceling the deal is notably higher when market participants are most likely to know more than the manager about the prospects of the deal and when the deal can be reversed. Kau, Linck & Rubin (2008) find a similar conclusion which shows that the learning effect is more significant if there are governance systems to alleviate the agency problem between managers and shareholders.

Chen, Goldstein & Jiang (2007) document that the sensitivity of investment to price (Tobin's Q) is strongly and positively related to the two measures of the amount of private information embedded in stock price, which is "price non-synchronicity" and " probability of informed trading (PIN)." It implies that managers use the new information in the stock price as an investment decision-making guideline. When accounting for measurement error in Q, Bakke & Whited (2010) show that the effect of price informativeness on investment sensitivity to Q remains the same. Nevertheless, the previously reported relationship between the sensitivity of investment to price and a measure of capital constraints, as documented by Baker, Stein, and Wurgler (2003), no longer holds when this correction is implemented. Foucault & Fresard (2011) find that cross-listing firms have a higher sensitivity to price, primarily when obtaining new information from prices. In addition, Durnev, Morck & Yeung (2004) find that price informativeness positively affects real investment efficiency, supporting the real effects through both learning and incentives channels.

Kang & Liu (2008) focus on studying the incentives channel and find that the sensitivity of CEO compensation to stock price changes is positively related to price informativeness. Ferreira,

Ferreira & Raposo (2011) propose that it is less necessary to have other governance mechanisms in the firm, such as board monitoring if the price informativeness can enhance the manager's incentives. Indeed, their results suggest that board independence is negatively related to price informativeness.

Fang, Noel & Tice (2009) research the impact of stock liquidity on firm performance during a period of a liquidity shock – the decimalization in the US stock market in 2001. They find that the improvement in liquidity increases the information aggregation of stock prices and then enhances firm performances, consistent with the theory in both learning and incentives channels. Remarkably, this positive effect is more substantial for firms with high manager's incentives, consistent with the incentives channel. Bharath, Jayaraman & Nagar (2012) also study the impact of liquidity shock (decimalization) on the value of the firms with large blockholders. They show that increased liquidity creates an exit threat from large blockholders, which puts pressure on managers to make productive efforts to improve the firm value. This effect is especially strong for firms with high managerial incentives, which follows the theory of the incentives channel.

Relatedly, Jayaraman & Milbourn (2011) also find that the CEO's equity compensation is positively related to stock liquidity. Edmans, Fang & Zur (2012) show that as the liquidity grows, blockholders are more likely to choose the governance through exit than through voice or intervention, resulting in positive returns and enhanced operating performances. Also, using decimalization as an exogenous shock, Kang & Kim (2011) find that the increase in liquidity causes a negative relation between the likelihood of CEO dismissals and corporate investments. Higher liquidity facilitates incorporating the benefits of R&D into stock prices, lowering the possibility of CEO turnover.

Edmans, Goldstein & Jiang (2012b) investigate the real effects of prices through the learning channel by utilizing a nonfundamental shock to market prices – mutual fund investors' withdrawals. They show that when the stock price of a particular firm falls due to a nonfundamental shock, the firm's likelihood of being acquired increases. In other words, it implies that acquirers learn from stock prices to identify their target firms. Furthermore, suppose the shareholders of the target firms also rely on stock prices to determine the firm values. In that case, they will accept the bid price that is closer to the stock prices, creating a profit takeover opportunity. Hence, the security price is not just "a sideshow" but does have real consequences on the economic activity through the learning channel.

As shown above, a large number of theoretical and empirical research papers have documented the connection between financial markets and the real economy. Surprisingly, the stock market seemed disconnected from the real economy since the onset of the covid-19 pandemic in early 2020. The disconnecting impact appears to be more pronounced in the United States and less in Europe (Igan, Kirti & Peria 2020). The goal of this study is to examine if there was a disconnect during the coronavirus pandemic. Our paper will contribute to the current literature by demonstrating that the real economy and financial markets may become separated in certain circumstances, such as during a global pandemic. In addition, we also contribute to the growing literature on the impact of Covid-19 on either stock markets or on the economy, such as Fernandes (2020), Al-Awadhi et al. (2020), Yousfi et al. (2021), and Smales (2021).

# CHAPTER 3. DATA AND METHODOLOGY

## Section 1. HYPOTHESIS AND METHODOLOGY

When the stock market is connected with the real economy, stock prices accurately reflect the information about the state of the economy or other essential variables for efficient real investment decisions. Conversely, suppose stock prices do not convey information for firm managers for their investment decisions in periods of high uncertainty, such as during the covid-19 pandemic. In that case, we may observe a disconnection between financial markets and the real economy.

In this paper, we hypothesize that as the coronavirus pandemic propagates around the globe, investors update their beliefs about the state of the economy downward on days that the number of newly confirmed cases is high (e.g., higher than the 7-day moving average reported in the JHU CSSE COVID-19 Data via Google). Then, they would rebalance their portfolios based on their revised beliefs by selling stocks that are more likely to be impacted and buying stocks that are less likely to be affected by the pandemic. Subsequently, the information about the state of the economy under the covid-19 pandemic will be incorporated into stock prices.

The following are the models that will be utilized in this paper:

$$VSML_t = \alpha + \beta_1 \ln(confirmed_t) + \beta_2 VSML_{t-1} + \beta_3 VSML_{t-2} + \beta_4 VSML_{t-3} + \varepsilon_t \quad (1)$$

$$VSML_t = \alpha + \beta_1 daily\ infection_t + \beta_2 VSML_{t-1} + \beta_3 VSML_{t-2} + \beta_4 VSML_{t-3} + \varepsilon_t \quad (2)$$

$$VS/VL_t = \alpha + \beta_1 \ln(confirmed_t) + \beta_2 VS/VL_{t-1} + \beta_3 VS/VL_{t-2} + \beta_4 VS/VL_{t-3} + \varepsilon_t \quad (3)$$

$$VS/VL_t = \alpha + \beta_1 daily\ infection_t + \beta_2 VS/VL_{t-1} + \beta_3 VS/VL_{t-2} + \beta_4 VS/VL_{t-3} + \varepsilon_t \quad (4)$$

$$VSML_{i,t} = \alpha + \beta_1 \ln\left(confirmed_{i,t}\right) + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (5)$$

$$VSML_{i,t} = \alpha + \beta_1\ daily\ infection_{i,t} + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (6)$$

$$VS/VL_{i,t} = \alpha + \beta_1 \ln\left(confirmed_{i,t}\right) + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (7)$$

$$VS/VL_{i,t} = \alpha + \beta_1\, daily\ infection_{i,t} + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (8)$$

The US data set is subjected to models (1) to (4), whereas the global data set is subjected to models (5) to (8). The first three lagged dependent variables are included in these models to decrease the influence of residual autocorrelation. Models (5) to (8) are two-way fixed-effect models used to account for the unobserved country- and time-specific factors.

Unlike other covid-19 research papers that study the impact of the pandemic on stock returns, we use industry-standard deviations in our model because covid-19 can have both negative and positive impacts on stock prices in different industries. The dependent variable $VSML_{i,t}$ (Volatility of Sensitive-Minus-Less sensitive) measures the difference between the average standard deviations of the pandemic-sensitive industries and the less sensitive industries in country *i* in day *t*. The dependent variable $VS/VL_{i,t}$ measures the ratio between the average standard deviations of the sensitive industries (VS) and the less sensitive industries (VL) in country *i* in day *t*. We compute 125-day, 60-day, and 30-day standard deviations for $VSML_{i,t}$ and $VS/VL_{i,t}$ as they can better capture the fluctuation of each industry in the short term. N-day standard deviation is the standard deviation of stock daily returns from day (t – n) to (t – 1).

The natural logarithm of the daily new confirmed cases and daily infection rate ($= confirmed_{i,t}\ /\ total\ population_i$) are used as proxies for the evolution of the pandemic. We then examine the relationship between each of these independent variables and the two dependent variables $VSML_{i,t}$ and $VS/VL_{i,t}$. During the pandemic, stocks in sensitive industries should experience more volatility than those in less sensitive businesses. As a result, if the stock market is linked to the real economy, $VSML_{i,t}$ and $VS/VL_{i,t}$ are anticipated to be positively associated to the proxies for the intensity of the Covid-19 pandemic.

### 3.1.1. Stock data

We want to confirm our hypothesis by looking at global stock markets since coronavirus is a worldwide pandemic. Because the effects of covid-19 vary by nation and area, we may compare the results between various marketplaces in different countries. Table 1 provides the list of 51 countries included in our sample. We obtain daily stock prices for 2019 and 2020 from COMPUSTAT Global.

Due to the difference in the industry classification, we divide all stocks into two data samples: the US and global data sets. The former utilizes the North American Industry Classification System (NAICS), whereas the latter, including all countries in our sample except the US, uses the Global Industry Classification System (GICS) developed by MSCI and S&P Down Jones Indices. Based on the macroeconomic model described in further detail in the next section, all industry sectors in each data set are classified into two categories: sensitive and less-sensitive groups to the pandemic. To mitigate the effects of vaccination rollout in early 2021, our sample only covers the year 2020 (2020/01/24[5] – 2020/12/31).

### 3.1.2. Covid-19 data

Covid-19 data was retrieved from the github.com website[6] on April 19, 2021, collected by Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE). The daily cumulative confirmed cases recorded in the file "time series covid19 confirmed global.csv" are used to determine the number of daily new confirmed cases for each nation. Following the matching of nations and provinces with their ISO3 codes, all records for each day for countries having numerous rows for various cities or territories, such as China, the United Kingdom, or France, are totaled to reflect the number of daily confirmed cases for that country in that day. Furthermore, there are mistakes due to changes in the original data sources over time, resulting in many negative daily confirmed cases. We convert all minor errors to zero and remove those that are very large.

[5] The start date of the Covid-19 data set is 2020/01/22. We take the date 2020/01/24 as the sample start date to remove days without data.
[6] https://github.com/CSSEGISandData/COVID-19

## Section 2. INDUSTRY CLASSIFICATION

To classify industries, we use the simulation results for the impacts of an influenza pandemic on industry performance produced by a macroeconomic model called the Regional Economic Model, Inc. (REMI) introduced by the US National Infrastructure Simulation & Analysis Center (NISAC), Infrastructure Analysis and Strategy Division, Office of Infrastructure Protection and Department of Homeland Security in October 2007. According to NISAC (2007), REMI is "a structural set of equations that model the U.S. macroeconomy, including the aggregate production of goods and services, employment levels and movement across industries, consumer spending, effects of wage and price changes, and international trade."

The model structure is illustrated in Figure 1. Each block represents a group of economic variables, and the direction of the arrows from one block to another describes the causal relationships both theoretically and empirically. "These relationships, developed into parameters with publicly available historical data, model the fundamentally dynamic and circular nature of the real economy: output generates employment, employment generates income, income generates demand for and spending on new output, new output generates new employment, and so on." (NISAC 2007, p. 11).

Though this model has some limitations in evaluating the economic consequences of a pandemic shock, it is the most comprehensive model to our knowledge for serving as a reference for projected industry performances as the economic ecosystem becomes more sophisticated and interconnected. Furthermore, the model uses NAICS for industry classification, making it easier to apply results to US stocks.

Figure 2 depicts the effects of an influenza pandemic on different industry sectors as evaluated by average GDP losses in the baseline scenario with no intervention, i.e. an unconstrained pandemic situation. Based on the overall GDP losses from all three shocks: demand, supply, and population, we rank all industries from most badly damaged to least impacted. Table 2 summarizes the findings. Group 1 consists of the nine industry sectors most impacted by the pandemic, with an average GDP loss of more than $10 billion, as well as the healthcare and social assistance sector,

**Table 1: List of countries**

| Country /area | ISO3 | Continent | Economy | # stock | Total confirmed cases | Population | Infection rate | Rank |
|---|---|---|---|---|---|---|---|---|
| Australia | AUS | Asia | Developed | 1991 | 28,515 | 25,499,884 | 0.1118% | 45 |
| Austria | AUT | Europe | Developed | 135 | 360,815 | 9,006,398 | 4.0062% | 10 |
| Bangladesh | BGD | Asia | Developing | 326 | 513,510 | 164,689,383 | 0.3118% | 37 |
| Belgium | BEL | Europe | Developed | 226 | 646,496 | 11,589,623 | 5.5782% | 3 |
| Bermuda | BMU | Europe | Small island developing state | 799 | 604 | 62,278 | 0.9698% | 30 |
| Brazil | BRA | South America | Developing | 503 | 7,675,973 | 212,559,417 | 3.6112% | 12 |
| Bulgaria | BGR | Europe | Developed | 147 | 202,266 | 6,948,445 | 2.9110% | 18 |
| Cayman Islands | CYM | Europe | Small island developing state | 1781 | 338 | 65,722 | 0.5143% | 34 |
| Chile | CHL | South America | Developing | 200 | 608,973 | 19,116,201 | 3.1856% | 16 |
| China | CHN | Asia | Developing | 6913 | 86,576 | 1,439,323,776 | 0.0060% | 49 |
| Denmark | DNK | Europe | Developed | 245 | 163,479 | 5,792,202 | 2.8224% | 20 |
| Egypt | EGY | Africa | Developing | 223 | 138,062 | 102,334,404 | 0.1349% | 42 |
| Finland | FIN | Europe | Developed | 283 | 36,115 | 5,540,720 | 0.6518% | 33 |
| France | FRA | Europe | Developed | 998 | 2,753,732 | 65,273,511 | 4.2188% | 8 |
| Germany | DEU | Europe | Developed | 1063 | 1,760,520 | 83,783,942 | 2.1013% | 24 |
| Greece | GRC | Europe | Developed | 176 | 138,850 | 10,423,054 | 1.3321% | 26 |
| Hong Kong | HKG | Asia | Developing | 594 | 8,846 | 7,496,981 | 0.1180% | 44 |
| India | IND | Asia | Developing | 4195 | 10,266,674 | 1,380,004,385 | 0.7440% | 32 |
| Indonesia | IDN | Asia | Developing | 705 | 743,198 | 273,523,615 | 0.2717% | 38 |
| Israel | ISR | Asia | Developing | 455 | 423,290 | 8,655,535 | 4.8904% | 5 |
| Italy | ITA | Europe | Developed | 529 | 2,107,314 | 60,461,826 | 3.4854% | 14 |
| Japan | JPN | Asia | Developed | 3945 | 235,809 | 126,476,461 | 0.1864% | 41 |
| Jordan | JOR | Asia | Developing | 206 | 294,604 | 10,203,134 | 2.8874% | 19 |
| Kuwait | KWT | Asia | Developing | 170 | 150,584 | 4,270,571 | 3.5261% | 13 |
| Luxembourg | LUX | Europe | Developed | 110 | 47,763 | 625,978 | 7.6301% | 1 |
| Malaysia | MYS | Asia | Developing | 951 | 113,010 | 32,365,999 | 0.3492% | 36 |
| Mexico | MEX | North America | Developing | 177 | 1,426,094 | 128,932,753 | 1.1061% | 27 |
| Netherlands | NLD | Europe | Developed | 266 | 804,122 | 17,134,872 | 4.6929% | 6 |
| New Zealand | NZL | Asia | Developed | 178 | 2,164 | 4,822,233 | 0.0449% | 46 |
| Nigeria | NGA | Africa | Developing | 165 | 87,607 | 206,139,589 | 0.0425% | 47 |
| Norway | NOR | Europe | Developed | 355 | 49,567 | 5,421,241 | 0.9143% | 31 |
| Oman | OMN | Asia | Developing | 117 | 128,867 | 5,106,626 | 2.5235% | 22 |
| Pakistan | PAK | Asia | Developing | 451 | 482,178 | 220,892,340 | 0.2183% | 39 |
| Peru | PER | South America | Developing | 123 | 1,015,137 | 32,971,854 | 3.0788% | 17 |
| Philippines | PHL | Asia | Developing | 274 | 474,064 | 109,581,078 | 0.4326% | 35 |
| Poland | POL | Europe | Developed | 755 | 1,294,878 | 37,846,611 | 3.4214% | 15 |

**Table 1 (Continued):**

| Country /area | ISO3 | Continent | Economy | # stock | Total confirmed cases | Population | Infection rate | Rank |
|---|---|---|---|---|---|---|---|---|
| Russia | RUS | Europe | In transition | 345 | 3,127,347 | 145,934,462 | 2.1430% | 23 |
| Saudi Arabia | SAU | Asia | Developing | 209 | 362,741 | 34,813,871 | 1.0419% | 28 |
| Singapore | SGP | Asia | Developing | 658 | 58,599 | 5,850,342 | 1.0016% | 29 |
| South Africa | ZAF | Africa | Developing | 321 | 1,057,161 | 59,308,690 | 1.7825% | 25 |
| South Korea | KOR | Asia | Developing | 2422 | 61,768 | 51,269,185 | 0.1205% | 43 |
| Spain | ESP | Europe | Developed | 322 | 1,938,671 | 46,754,778 | 4.1465% | 9 |
| Sri Lanka | LKA | Asia | Developing | 299 | 43,299 | 21,413,249 | 0.2022% | 40 |
| Sweden | SWE | Europe | Developed | 1085 | 437,379 | 10,099,265 | 4.3308% | 7 |
| Switzerland | CHE | Europe | Developed | 401 | 452,296 | 8,654,622 | 5.2261% | 4 |
| Taiwan | TWN | Asia | Developing | 1957 | 801 | 23,816,775 | 0.0034% | 50 |
| Thailand | THA | Asia | Developing | 1735 | 7,180 | 69,799,978 | 0.0103% | 48 |
| Turkey | TUR | Asia | Developing | 405 | 2,208,652 | 84,339,067 | 2.6188% | 21 |
| United Kingdom | GBR | Europe | Developed | 1742 | 2,492,768 | 67,886,011 | 3.6720% | 11 |
| United States | USA | North America | Developed | 6980 | 20,099,362 | 331,002,651 | 6.0723% | 2 |
| Vietnam | VNM | Asia | Developing | 808 | 1,465 | 97,338,579 | 0.0015% | 51 |

This table lists 51 countries that are included in our data set with 3-digit country codes published by the International Organization for Standardization (ISO). The economy is the country classification defined by United Nations (2020). Total confirmed cases are calculated from the Covid-19 data provided by Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE) as of 2020/12/31. The population is the total population of a country in 2020 retrieved from the worldpopulationreview.com website. The infection rate is computed by dividing the total confirmed cases by the total population in each country in 2020. Rank is the country ranking based on the infection rate.

whereas Group 2 consists of the other sectors that are less affected.

Despite being one of the least impacted businesses by the pandemic, the healthcare sector is classed as Group 1 for two reasons. First, the demand for healthcare products and services is positively related to the number of infected people. When the situation improves or the daily infection rate falls, demand falls, and vice versa. Second, a worldwide pandemic presents a huge chance for pharmaceutical corporations like Pfizer and Moderna to profit from new vaccine investments. However, if the pandemic is well under control when vaccine research is completed, the return may be smaller than anticipated. As a result, stocks in the healthcare business are thought to be more vulnerable to the pandemic or more volatile than those in Group 2.

Similarly, based on the results in Table 2, we divide the 11 GICS industry sectors into two groups, as shown in Table 3. Because the industry classification techniques employed by NAICS and GICS differ, the match is imprecise. Figure 2 does not indicate whether the energy industry is more or less affected than other industries. As the global economy faces border closures, cross-border travel restrictions, and quarantine, we believe the energy sector will be more affected than the industries in Group 2.

**Figure 2: Regional Economic Model, Inc. (REMI), model structure (NISAC 2007).**

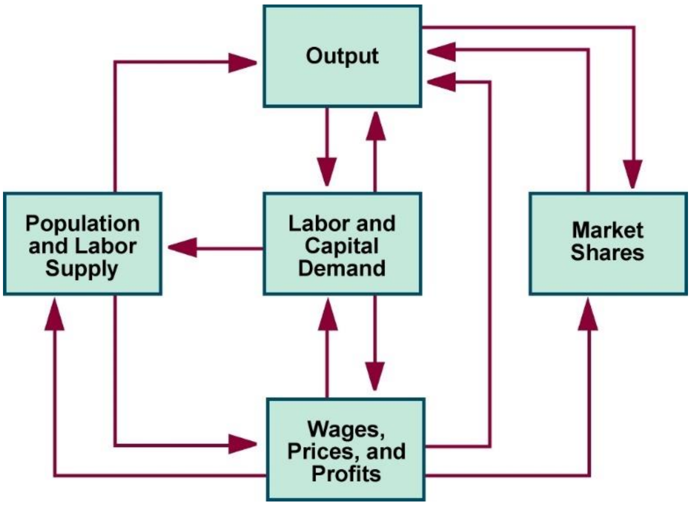



**Figure 3: Average gross domestic product (GDP) losses, by type of shock and industry: year 1, baseline scenario (NISAC 2007).**

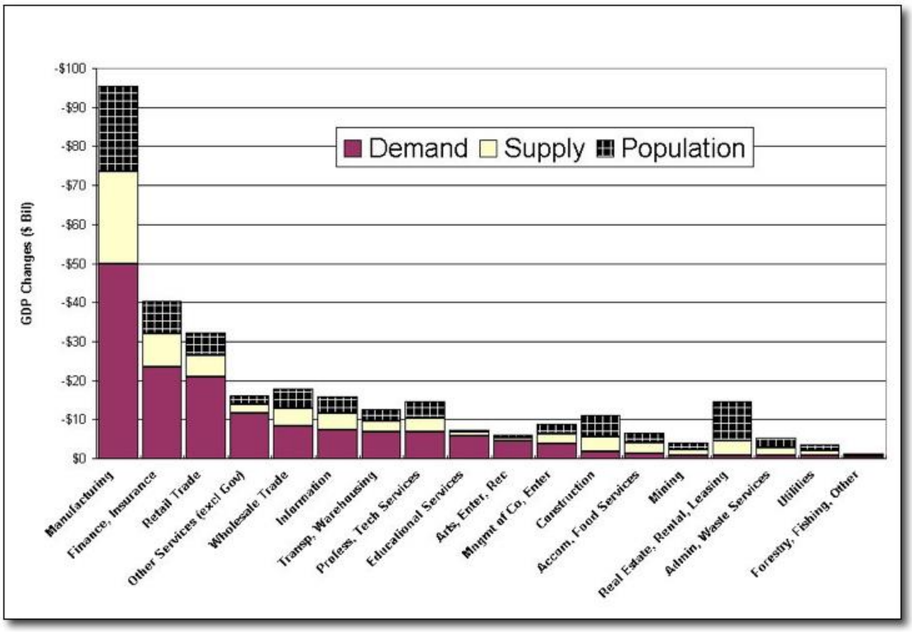


**Table 2: Industry classification for the US data.**

| Rank | Sector | NAICS sector code | Group |
|---|---|---|---|
| 1 | Manufacturing | 31, 32, 33 | 1 |
| 2 | Finance & Insurance | 55 | 1 |
| 3 | Retail Trade | 44, 45 | 1 |
| 4 | Wholesale Trade | 42 | 1 |
| 5 | Information | 51 | 1 |
| 6 | Professional, Scientific & Technical Services | 54 | 1 |
| 7 | Real Estate, Rental & Leasing | 53 | 1 |
| 8 | Transportation & Warehousing | 48, 49 | 1 |
| 9 | Construction | 23 | 1 |
| 10 | Management of Companies and Enterprises | 55 | 2 |
| 11 | Educational Services | 61 | 2 |
| 12 | Accommodation and Food Services | 72 | 2 |
| 13 | Arts, Entertainment, and Recreation | 71 | 2 |
| 14 | Administration Support, Waste Management and Remediation Services | 56 | 2 |
| 15 | Mining | 21 | 2 |
| 16 | Utilities | 22 | 2 |
| 17 | Agriculture, Forestry, Fishing and Hunting | 11 | 2 |
| 18 | Health Care & Social Assistance | 62 | 1 |

**Table 3: Industry classification for GICS sectors.**

| Group 1 | Sector | Group 2 | Sector |
|---|---|---|---|
| 10 | Energy | 30 | Consumer Staples |
| 15 | Materials | 40 | Financials |
| 20 | Industrials | 45 | Information Technology |
| 25 | Consumer Discretionary | 50 | Communication Services |
| 35 | Health Care | 55 | Utilities |
| 60 | Real Estate | | |

# CHAPTER 4. EMPIRICAL RESULTS

## Section 1. EMPIRICAL RESULTS FOR THE UNITED STATES

### 4.1.1. Summary statistics

The summary statistics for all industry groups and variables are presented in Table 4. Panel A reports the statistics for 125-day, 60-day, and 30-day standard deviations for each industry from January 24 to December 31, 2020. As the calculation window decreases from 125 days to 30 days, the mean of the industry standard deviations declines while their standard deviations, which describe the changes in the industry standard deviations, increase. It shows that the 60-day and 30-day standard deviations may depict the movement of the industry standard deviations better than the 125-day ones. From here onwards, the industry standard deviations shall be referred to as industry SD to avoid confusion. Correspondingly, we have 125-day, 60-day, and 30-day industry SD.

Compared to most of the industries in the Sensitive group, Group 12 (Accommodation and Food Services) and Group 13 (Arts, Entertainment and Recreation) have a more extensive spread in their industry SD, for example, 0.0165 and 0.0155 for Group 12 and 13's 125-day industry SD. The Accommodation and food services sector is composed of businesses that provide lodging services such as hotels, motels, resorts, and many types of camping sites, as well as businesses that provide meals, take-away food orders, and other food services[7]. The Arts, entertainment and recreation sector include businesses operating in three industries: Performing arts, spectator sports, and related industries, heritage institutions, and amusement, gambling, and recreation industries[8]. These industry sectors may be impacted more severely as a result of travel restrictions and changing consumer habits to avoid crowded areas.

Because our hypothesis and approach are highly dependent on assumptions about which industries are most affected by the pandemic, changes in the composition of each group may provide different findings. As a result, we define an alternative industry classification in which Group 2

[7] The detailed definition can be found at: www23.statcan.gc.ca
[8] The detailed definition can be found at: www23.statcan.gc.ca

(Finance and Insurance) and Group 5 (Information) are switched with Group 12 and 13. Thus, *VSML1* and *VS/VL1* represent the original classification (Table 2), and *VSML2* and *VS/VL2* represent the alternative classification. As can be seen from Panel B, on average *VSML2* and *VS/VL2* are higher than *VSML1* and *VS/VL1*, the excess volatility between the Sensitive and Less-Sensitive groups for the original classification. If we find similar results in both cases, our conclusion will be strengthened.

#### 4.1.2. Results

Table 5 reports the regression results for models (1) to (4) in Panel A to D. In each table, columns (1), (2), and (3) use 125-day, 60-day, and 30-day industry SD, respectively, to calculate *VSML1* and *VS/VL1*, and columns (4), (5), and (6) use 125-day, 60-day and 30-day industry SD to calculate *VSML2* and *VS/VL2*.

As shown in the first three columns in Panel A, *VSML1*, or the excess volatility, is negatively and significantly related to the log number of daily confirmed cases in the case of 125-day and 60-day industry SD. The coefficient of interest $\beta_1$, is not starkly different between models. On average, a 10% increase in the number of daily confirmed cases reduces the excess volatility by 0.019 basis points (= -0.00002*ln(1.1)). This inverse relationship implies that the volatility of the sensitive group grow less than that of the less insentive group. This is consistent with our hypothesis since it suggests that during the Covid-19 pandemic, the US stock market might be disconnected from the real economy.

In comparison with the first three columns, the coefficient $\beta_1$ in column (4) to (6) (Table 5) is negative but not statistically significant. It shows that there is no relationship between *VSML2* and $ln(confirmed)$. If Group 12 (Accommodation and Food Services) and Group 13 (Arts, Entertainment, and Recreation) are more affected, it makes the disconnection more serious in this case. We also find similar results in Panel C showing a negative relationship between *VS/VL1* and $ln(confirmed)$. A 10% growth in the number of daily confirmed cases decreases the volatility ratio *VS/VL1* by 0.95 basis points (= -0.01*ln(1.1)). In addition, *VS/VL2* is negatively and significantly related to $ln(confirmed)$ in the case of 125-day industry SD.

From Panel B and D, we find no connection between the dependent variables (*VSML* and *VS/VL*) and the daily infection rate in the US. While the US is the country with the highest total infection rate in 2020, scaling the daily new confirmed cases with the total population may render the values of the observations too small, and thus there is not much variation left after controlling for the lagged variables. Therefore, no conclusion can be drawn from the results in Panel B and D.

**Table 4: Summary statistics for the US data.**

| *Panel A:* | | 125-day Standard Deviation | | | | 60-day Standard Deviation | | | | 30-day Standard Deviation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry Groups** | **Obs** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** |
| **Sensitive:** | | | | | | | | | | | | | |
| Group 1 | 238 | 0.0507 | 0.0086 | 0.0362 | 0.0606 | 0.0488 | 0.0122 | 0.0352 | 0.0715 | 0.0470 | 0.0140 | 0.0330 | 0.0860 |
| Group 2 | 238 | 0.0270 | 0.0094 | 0.0106 | 0.0379 | 0.0253 | 0.0128 | 0.0090 | 0.0490 | 0.0240 | 0.0140 | 0.0080 | 0.0620 |
| Group 3 | 238 | 0.0562 | 0.0107 | 0.0410 | 0.0699 | 0.0540 | 0.0155 | 0.0376 | 0.0832 | 0.0520 | 0.0180 | 0.0350 | 0.1020 |
| Group 4 | 238 | 0.0484 | 0.0086 | 0.0343 | 0.0590 | 0.0467 | 0.0132 | 0.0299 | 0.0721 | 0.0450 | 0.0160 | 0.0260 | 0.0860 |
| Group 5 | 238 | 0.0436 | 0.0089 | 0.0261 | 0.0554 | 0.0427 | 0.0121 | 0.0246 | 0.0643 | 0.0410 | 0.0140 | 0.0230 | 0.0800 |
| Group 6 | 238 | 0.0580 | 0.0090 | 0.0450 | 0.0701 | 0.0547 | 0.0126 | 0.0412 | 0.0768 | 0.0520 | 0.0140 | 0.0370 | 0.0900 |
| Group 7 | 238 | 0.0468 | 0.0163 | 0.0165 | 0.0656 | 0.0450 | 0.0216 | 0.0152 | 0.0839 | 0.0440 | 0.0240 | 0.0140 | 0.1070 |
| Group 8 | 238 | 0.0530 | 0.0124 | 0.0279 | 0.0685 | 0.0510 | 0.0171 | 0.0268 | 0.0830 | 0.0490 | 0.0210 | 0.0230 | 0.1040 |
| Group 9 | 238 | 0.0502 | 0.0135 | 0.0263 | 0.0662 | 0.0483 | 0.0187 | 0.0233 | 0.0828 | 0.0470 | 0.0210 | 0.0210 | 0.1030 |
| Group 18 | 238 | 0.0586 | 0.0098 | 0.0426 | 0.0724 | 0.0558 | 0.0153 | 0.0383 | 0.0854 | 0.0530 | 0.0200 | 0.0320 | 0.1050 |
| **Less sensitive:** | | | | | | | | | | | | | |
| Group 10 | 238 | 0.0456 | 0.0107 | 0.0232 | 0.0604 | 0.0448 | 0.0136 | 0.0213 | 0.0701 | 0.0440 | 0.0160 | 0.0190 | 0.0840 |
| Group 11 | 238 | 0.0458 | 0.0072 | 0.0336 | 0.0549 | 0.0448 | 0.0107 | 0.0308 | 0.0644 | 0.0430 | 0.0130 | 0.0280 | 0.0760 |
| Group 12 | 238 | 0.0519 | 0.0165 | 0.0201 | 0.0710 | 0.0506 | 0.0221 | 0.0179 | 0.0907 | 0.0490 | 0.0250 | 0.0170 | 0.1160 |
| Group 13 | 238 | 0.0506 | 0.0155 | 0.0243 | 0.0687 | 0.0488 | 0.0206 | 0.0223 | 0.0875 | 0.0480 | 0.0230 | 0.0230 | 0.1070 |
| Group 14 | 238 | 0.0480 | 0.0090 | 0.0289 | 0.0608 | 0.0468 | 0.0116 | 0.0252 | 0.0679 | 0.0460 | 0.0130 | 0.0240 | 0.0810 |
| Group 15 | 238 | 0.0679 | 0.0139 | 0.0405 | 0.0848 | 0.0665 | 0.0195 | 0.0383 | 0.1039 | 0.0640 | 0.0230 | 0.0360 | 0.1260 |
| Group 16 | 238 | 0.0346 | 0.0101 | 0.0157 | 0.0461 | 0.0333 | 0.0143 | 0.0145 | 0.0599 | 0.0320 | 0.0170 | 0.0130 | 0.0780 |
| Group 17 | 238 | 0.0506 | 0.0100 | 0.0310 | 0.0637 | 0.0491 | 0.0136 | 0.0307 | 0.0757 | 0.0470 | 0.0160 | 0.0280 | 0.0900 |
| *Panel B:* | | | | | | | | | | | | | |
| **Variables** | **Obs** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** |
| VSML1 | 238 | -0.0001 | 0.0021 | -0.0026 | 0.0044 | -0.0009 | 0.0022 | -0.0033 | 0.0052 | -0.0010 | 0.0020 | -0.0050 | 0.0030 |
| VSML2 | 238 | 0.0071 | 0.0030 | 0.0022 | 0.0114 | 0.0062 | 0.0040 | 0.0004 | 0.0135 | 0.0060 | 0.0040 | -0.0003 | 0.0180 |
| VS/VL1 | 238 | 1.0052 | 0.0592 | 0.9439 | 1.1597 | 0.9892 | 0.0693 | 0.9165 | 1.2019 | 0.9763 | 0.0529 | 0.8881 | 1.1276 |
| VS/VL2 | 238 | 1.1547 | 0.0579 | 1.0569 | 1.2379 | 1.1351 | 0.0671 | 1.0125 | 1.2650 | 1.1252 | 0.0594 | 0.9924 | 1.2193 |
| Daily infection | 238 | 0.00018 | 0.00020 | 0.00000 | 0.00076 | 0.00018 | 0.00020 | 0.00000 | 0.00076 | 0.00018 | 0.00020 | 0.00000 | 0.00076 |
| Ln(confirmed) | 238 | 9.4219 | 3.5411 | 0.0000 | 12.0000 | 9.4219 | 3.5411 | 0.0000 | 12.0000 | 9.4219 | 3.5411 | 0.0000 | 12.0000 |

This table reports the summary statistics for the US data. The pandemic-sensitive industries comprise group 1 (Manufacturing), group 2 (Finance & insurance), group 3 (Retail trade), group 4 (Wholesale trade), group 5 (Information), group 6 (Professional, scientific & techinical services), group 7 (Real estates, rental & leasing), group 8 (Transportation & warehousing), group 9 (Construction) and group 18 (Health care & social assistance). The less-sensitive industries comprise group 10 (Management of companies and enterprises), group 11 (Educational services), group 12 (Accomodation & food services), group 13 (Arts, entertainment & recreation), group 14 (Administration Support, Waste Management and Remediation Services), group 15 (Mining), group 16 (Utilities) and group 17 (Agriculture, Forestry, Fishing and Hunting). *VSML1* and *VS/VL1* are the excess industry volatility and the ratio of industry volatility calculated based on the original industry classification defined in Panel A. *VSML2* and *VS/VL2* are the excess industry volatility and the ratio of industry volatility calculated based on the alternative industry classification in which group 2 and 5 are switched with group 12 and 13.

**Table 5: Regression results for the US.**

**Panel A**: $VSML_t = \alpha + \beta_1 \ln(confirmed_t) + \beta_2 VSML_{t-1} + \beta_3 VSML_{t-2} + \beta_4 VSML_{t-3} + \varepsilon_t$ (1)

| | VSML1 | | | VSML2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(confirmed) | -0.00002*** | -0.00002** | -0.00002* | -0.00001* | -0.00000 | -0.00001 |
| | (0.00001) | (0.00001) | (0.00001) | (0.00000) | (0.00001) | (0.00001) |
| $VSML1_{t-1}$ | 1.031*** | 0.945*** | 0.940*** | | | |
| | (0.066) | (0.065) | (0.066) | | | |
| $VSML1_{t-2}$ | -0.012 | 0.129 | -0.014 | | | |
| | (0.095) | (0.090) | (0.091) | | | |
| $VSML1_{t-3}$ | -0.048 | -0.122* | 0.005 | | | |
| | (0.065) | (0.064) | (0.065) | | | |
| $VSML2_{t-1}$ | | | | 1.062*** | 1.047*** | 1.143*** |
| | | | | (0.063) | (0.064) | (0.065) |
| $VSML2_{t-2}$ | | | | 0.245*** | 0.214** | -0.021 |
| | | | | (0.093) | (0.093) | (0.100) |
| $VSML2_{t-3}$ | | | | -0.308*** | -0.266*** | -0.133** |
| | | | | (0.063) | (0.064) | (0.065) |
| Constant | 0.0001*** | 0.0002* | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| | (0.00005) | (0.0001) | (0.0001) | (0.00005) | (0.0001) | (0.0001) |
| Observations | 235 | 235 | 235 | 235 | 235 | 235 |
| $R^2$ | 0.995 | 0.989 | 0.947 | 0.996 | 0.993 | 0.984 |
| Adjusted $R^2$ | 0.995 | 0.989 | 0.946 | 0.996 | 0.993 | 0.983 |
| Residual Std. Error (df = 230) | 0.0001 | 0.0002 | 0.0004 | 0.0002 | 0.0003 | 0.001 |
| F Statistic (df = 4; 230) | 11,475.950*** | 5,103.000*** | 1,030.635*** | 13,427.850*** | 8,687.273*** | 3,431.109*** |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (1) for the US data from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent VSML2 is equal to the average industry standard deviation in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 5 (Continued):**

**Panel B**: $VSML_t = \alpha + \beta_1 daily\ infection_t + \beta_2 VSML_{t-1} + \beta_3 VSML_{t-2} + \beta_4 VSML_{t-3} + \varepsilon_t$ (2)

| | VSML1 | | | VSML2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (1) | (4) | (5) | (6) |
| Daily infection | 0.023 | 0.103 | 0.144 | -0.086 | 0.002 | -0.132 |
| | (0.063) | (0.085) | (0.138) | (0.087) | (0.123) | (0.193) |
| $VSML1_{t-1}$ | 1.077*** | 0.960*** | 0.949*** | | | |
| | (0.066) | (0.065) | (0.066) | | | |
| $VSML1_{t-2}$ | -0.011 | 0.131 | -0.014 | | | |
| | (0.097) | (0.091) | (0.091) | | | |
| $VSML1_{t-3}$ | -0.071 | -0.103 | 0.028 | | | |
| | (0.066) | (0.065) | (0.065) | | | |
| $VSML2_{t-1}$ | | | | 1.073*** | 1.048*** | 1.144*** |
| | | | | (0.063) | (0.064) | (0.065) |
| $VSML2_{t-2}$ | | | | 0.243*** | 0.214** | -0.021 |
| | | | | (0.093) | (0.093) | (0.100) |
| $VSML2_{t-3}$ | | | | -0.321*** | -0.266*** | -0.136** |
| | | | | (0.063) | (0.064) | (0.065) |
| Constant | -0.00002 | -0.00005** | -0.0001** | 0.00004 | 0.00002 | 0.0001 |
| | (0.00002) | (0.00002) | (0.00004) | (0.0001) | (0.0001) | (0.0001) |
| Observations | 235 | 235 | 235 | 235 | 235 | 235 |
| $R^2$ | 0.995 | 0.989 | 0.947 | 0.996 | 0.993 | 0.984 |
| Adjusted $R^2$ | 0.995 | 0.988 | 0.946 | 0.996 | 0.993 | 0.983 |
| Residual Std. Error (df = 230) | 0.0001 | 0.0002 | 0.0004 | 0.0002 | 0.0003 | 0.001 |
| F Statistic (df = 4; 230) | 11,009.950*** | 5,020.751*** | 1,021.811*** | 13,309.130*** | 8,672.807*** | 3,428.078*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (2) for the US data from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in day *t* divided by the 2020 US population. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 5 (Continued):**

**Panel C:** $VS/VL_t = \alpha + \beta_1 \ln(confirmed_t) + \beta_2 VS/VL_{t-1} + \beta_3 VS/VL_{t-2} + \beta_4 VS/VL_{t-3} + \varepsilon_t$ (3)

| | $VS/VL1$ | | | $VS/VL2$ | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(confirmed) | $-0.001^{***}$ | $-0.001^{**}$ | -0.0005 | $-0.0003^{**}$ | -0.00004 | -0.0001 |
| | (0.0002) | (0.0004) | (0.0003) | (0.0001) | (0.0002) | (0.0003) |
| $VS/VL1_{t-1}$ | $1.051^{***}$ | $1.033^{***}$ | $0.933^{***}$ | | | |
| | (0.066) | (0.064) | (0.066) | | | |
| $VS/VL1_{t-2}$ | 0.051 | 0.131 | 0.012 | | | |
| | (0.095) | (0.093) | (0.090) | | | |
| $VS/VL1_{t-3}$ | $-0.155^{**}$ | $-0.214^{***}$ | -0.006 | | | |
| | (0.063) | (0.063) | (0.065) | | | |
| $VS/VL2_{t-1}$ | | | | $0.967^{***}$ | $1.015^{***}$ | $1.160^{***}$ |
| | | | | (0.066) | (0.066) | (0.066) |
| $VS/VL2_{t-2}$ | | | | 0.096 | -0.042 | $-0.247^{**}$ |
| | | | | (0.091) | (0.094) | (0.100) |
| $VS/VL2_{t-3}$ | | | | -0.071 | 0.014 | 0.053 |
| | | | | (0.066) | (0.066) | (0.066) |
| Constant | $0.061^{***}$ | $0.055^{***}$ | $0.064^{***}$ | 0.011 | 0.015 | $0.038^{**}$ |
| | (0.013) | (0.020) | (0.024) | (0.008) | (0.013) | (0.018) |
| Observations | 235 | 235 | 235 | 235 | 235 | 235 |
| $R^2$ | 0.996 | 0.992 | 0.963 | 0.993 | 0.987 | 0.953 |
| Adjusted $R^2$ | 0.996 | 0.992 | 0.962 | 0.993 | 0.987 | 0.953 |
| Residual Std. Error (df = 230) | 0.004 | 0.006 | 0.010 | 0.005 | 0.008 | 0.013 |
| F Statistic (df = 4; 230) | $12{,}946.320^{***}$ | $7{,}213.683^{***}$ | $1{,}483.915^{***}$ | $7{,}931.899^{***}$ | $4{,}355.431^{***}$ | $1{,}174.590^{***}$ |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (3) for the US data from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 5 (Continued):**

**Panel D:** $VS/VL_t = \alpha + \beta_1 daily\ infection_t + \beta_2 VS/VL_{t-1} + \beta_3 VS/VL_{t-2} + \beta_4 VS/VL_{t-3} + \varepsilon_t$ (4)

| | $\boldsymbol{VS/VL1}$ | | | $\boldsymbol{VS/VL2}$ | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | 0.326 | 2.205 | 3.583 | 0.247 | 4.024 | 0.687 |
| | (1.721) | (2.295) | (3.409) | (2.791) | (3.061) | (4.344) |
| $VS/VL1_{t-1}$ | $1.138^{***}$ | $1.049^{***}$ | $0.939^{***}$ | | | |
| | (0.065) | (0.064) | (0.066) | | | |
| $VS/VL1_{t-2}$ | 0.050 | 0.132 | 0.013 | | | |
| | (0.099) | (0.094) | (0.090) | | | |
| $VS/VL1_{t-3}$ | $-0.195^{***}$ | $-0.192^{***}$ | 0.017 | | | |
| | (0.065) | (0.064) | (0.065) | | | |
| $VS/VL2_{t-1}$ | | | | $0.995^{***}$ | $1.007^{***}$ | $1.161^{***}$ |
| | | | | (0.066) | (0.066) | (0.066) |
| $VS/VL2_{t-2}$ | | | | 0.095 | -0.044 | $-0.248^{**}$ |
| | | | | (0.093) | (0.093) | (0.100) |
| $VS/VL2_{t-3}$ | | | | -0.089 | 0.031 | 0.057 |
| | | | | (0.067) | (0.066) | (0.066) |
| Constant | 0.006 | 0.010 | $0.029^{**}$ | -0.002 | 0.005 | $0.033^{**}$ |
| | (0.006) | (0.007) | (0.013) | (0.011) | (0.010) | (0.016) |
| Observations | 235 | 235 | 235 | 235 | 235 | 235 |
| $R^2$ | 0.995 | 0.992 | 0.963 | 0.993 | 0.987 | 0.953 |
| Adjusted $R^2$ | 0.995 | 0.992 | 0.962 | 0.992 | 0.987 | 0.952 |
| Residual Std. Error (df = 230) | 0.004 | 0.006 | 0.010 | 0.005 | 0.008 | 0.013 |
| F Statistic (df = 4; 230) | $12{,}005.610^{***}$ | $7{,}093.738^{***}$ | $1{,}476.275^{***}$ | $7{,}731.127^{***}$ | $4{,}387.825^{***}$ | $1{,}173.273^{***}$ |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (4) for the US data from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in day *t* divided by the 2020 US population. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

## Section 2. EMPIRICAL RESULTS FOR THE GLOBAL DATA

### 4.2.1. Summary statistics

Table 6 reports the summary statistics for the global data with the same structure as the US data. A similar pattern of industry SD for all GICS sectors can be observed from Panel A. When the estimation window declines from 125 days to 60 and 30 days, the average industry SD goes down and its standard deviation goes up. Similar to the US data, we assign the original industry classification defined in Table 3 to variables *VSML1* and *VS/VL1* and create an alternative classification for variables *VSML2* and *VS/VL2* in which the energy sector is moved to the Less Sensitive group. In the case of 125-day and 30-day industry SD, the average excess volatility becomes negative (-0.00001 and -0.00003), which may suggest that there were times during 2020 when the energy sector became more sensitive to the pandemic than industries in the sensitive group.

### 4.2.2. Results

In this section, we will discuss the regression results for the global data, which includes 50 countries from all continents and with different levels of economic growth. Furthermore, we investigate the disconnection phenomena in different areas of the world by repeating model (5) to (8) for stock markets in Europe, Asia & Pacific, America and Africa.

Table 7 summarizes the results for 50 countries in our data set, except the US, from January 24 to December 31, 2020. Panel A, B, C, and D report the results for models (5), (6), (7), and (8), respectively. In each panel, column (1) & (4), (2) & (5), and (3) & (6) correspond to 125-day, 60-day and 30-day industry SD, respectively. As shown in Panel A and C, the coefficient of interest $\beta_1$ is not statistically significant in all cases, which shows that there is no relationship between the dependent variables (*VSML* and *VS/VL*) and the number of daily confirmed cases. However, the results in Panel B show that the coefficient of interest $\beta_1$ is positively and significantly at least at 5% confidence level in 5 out of 6 cases. It implies that the excess volatility (*VSML*) is significantly and positively related to the daily infection rate. We can also observe a positive relationship between the ratio of industry volatility (*VS/VL*) and the daily infection rate in columns (3) and (6) of Panel D where the coefficient is positive and significant at 5% confidence level. Hence, stock markets in countries other than the US are shown to be more connected to the real economy.

It is worth noting that the industry classifications for both the US and the global data are based on the REMI model estimated by NISAC (2007). Though the application for GICS industry sectors is not entirely perfect, the fact that we obtain different results may suggest that the US stock market is more disconnected than the rest of the world. This is consistent with our hypothesis and the disconnect between the stock movement and the real economic indicators (Igan, Kirti & Peria 2020) as shown in Figure 1.

Next, we investigate whether this effect is present in different regions. Organized in the same structure with the results for the global data, Table 8 to Table 11 report the regression results for Europe, Asia and Pacific, America and Africa, respectively. Similar results are found in Table 8 for European countries. Though the dependent variables (*VSML* and *VS/VL*) is not related to the independent variable $ln(confirmed)$ as presented in Panel A and C, they are positively and significantly related to daily infection rate in Panel B and D. It can be concluded that the European stock markets are more connected than the US market.

From Table 9, we find no evidence to remark the connection between the stock market and the real economy in Asia and Pacific. There is a very small amount of statistical evidence in Table 10 and Table 11 supporting that the stock market is connected to the real economy during the Covid-19 pandemic in America and Africa. In Table 10, the ratio of industry volatility is only positively and significantly related to daily infection rate in the case of 30-day industry SD and for the alternative classification (column 6 in Panel D). In Table 11, the dependent variables (*VSML* and *VS/VL*) are only significantly positive in the case of 125-day industry SD and for the original classification (column 1 in Panel A and C).

To summarize, the connection between stock markes and the real economy is stronger in Europe, and there is not sufficient evidence to conclude whether stock markets are more or less connected to the real economy in other regions. The fact that we find strong statistical evidence for European countries and no evidence in Asia and Pacific, America, and Africa is probably due to our industry classification assumptions. They are built based on the REMI model, which was originally simulated for the US economy. Because of the differences in the economic development and the industrial structure between the developed and developing economies, those assumptions may be unsuitable for emerging countries.

**Table 6: Summary statistics for global data**

| *Panel A:* | | 125-day Standard Deviation | | | | 60-day Standard Deviation | | | | 30-day Standard Deviation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry Groups** | | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** |
| **Sensitive:** | | | | | | | | | | | | | |
| Sector 10 | | 0.0376 | 0.0185 | 0.0044 | 0.1128 | 0.0360 | 0.0194 | 0.0044 | 0.1371 | 0.0343 | 0.0200 | 0.0000 | 0.1850 |
| Sector 15 | | 0.0342 | 0.0132 | 0.0072 | 0.0797 | 0.0330 | 0.0142 | 0.0057 | 0.0946 | 0.0316 | 0.0150 | 0.0040 | 0.1176 |
| Sector 20 | | 0.0329 | 0.0108 | 0.0050 | 0.0838 | 0.0314 | 0.0115 | 0.0038 | 0.0733 | 0.0300 | 0.0121 | 0.0025 | 0.0804 |
| Sector 25 | | 0.0335 | 0.0129 | 0.0022 | 0.0766 | 0.0322 | 0.0139 | 0.0010 | 0.0903 | 0.0307 | 0.0144 | 0.0000 | 0.0892 |
| Sector 35 | | 0.0357 | 0.0168 | 0.0040 | 0.2066 | 0.0347 | 0.0206 | 0.0022 | 0.2967 | 0.0335 | 0.0256 | 0.0000 | 0.4190 |
| Sector 60 | | 0.0282 | 0.0107 | 0.0000 | 0.0718 | 0.0269 | 0.0116 | 0.0000 | 0.0812 | 0.0255 | 0.0123 | 0.0000 | 0.0855 |
| **Less Sensitive:** | | | | | | | | | | | | | |
| Sector 30 | | 0.0292 | 0.0111 | 0.0036 | 0.0660 | 0.0281 | 0.0120 | 0.0028 | 0.0879 | 0.0268 | 0.0125 | 0.0017 | 0.1096 |
| Sector 40 | | 0.0295 | 0.0108 | 0.0064 | 0.0646 | 0.0283 | 0.0114 | 0.0054 | 0.0642 | 0.0270 | 0.0119 | 0.0026 | 0.0747 |
| Sector 45 | | 0.0386 | 0.0137 | 0.0000 | 0.0782 | 0.0372 | 0.0146 | 0.0000 | 0.0863 | 0.0356 | 0.0153 | 0.0000 | 0.1053 |
| Sector 50 | | 0.0335 | 0.0117 | 0.0070 | 0.0681 | 0.0322 | 0.0127 | 0.0007 | 0.0738 | 0.0307 | 0.0137 | 0.0000 | 0.0868 |
| Sector 55 | | 0.0287 | 0.0126 | 0.0067 | 0.0717 | 0.0279 | 0.0140 | 0.0000 | 0.0991 | 0.0271 | 0.0153 | 0.0000 | 0.1394 |
| *Panel B:* | | | | | | | | | | | | | |
| **Variables** | **Obs** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** |
| VSML1 | 12004 | 0.001848 | 0.005016 | -0.01273 | 0.026029 | 0.001720 | 0.005536 | -0.01911 | 0.035869 | 0.001566 | 0.006398 | -0.03011 | 0.068658 |
| VSML2 | 12004 | -0.00001 | 0.004785 | -0.01652 | 0.030395 | 0.000017 | 0.005386 | -0.02267 | 0.045953 | -0.00003 | 0.006407 | -0.03226 | 0.077364 |
| VS/VL1 | 12004 | 1.068282 | 0.171367 | 0.587658 | 1.840009 | 1.071055 | 0.210244 | 0.556245 | 2.863033 | 1.075124 | 0.262552 | 0.442571 | 3.659761 |
| VS/VL2 | 12004 | 1.005688 | 0.160597 | 0.445937 | 1.952554 | 1.005954 | 0.185337 | 0.413266 | 2.326991 | 1.004798 | 0.222202 | 0.356264 | 3.674122 |
| Daily infection | 12004 | 0.00006 | 0.00019 | 0.00000 | 0.00976 | 0.00006 | 0.00019 | 0.00000 | 0.00976 | 0.00006 | 0.00019 | 0.00000 | 0.00976 |
| Ln(confirmed) | 12004 | 4.7989 | 3.2101 | 0.0000 | 14.0000 | 4.7989 | 3.2101 | 0.0000 | 14.0000 | 4.7989 | 3.2101 | 0.0000 | 14.0000 |

This table reports the summary statistics for the global data. The pandemic-sensitive industries comprise sector 10 (Energy), sector 15 (Materials), sector 20 (Industrials), sector 25 (Consumer discretionary), sector 35 (Health care), and sector 60 (Real estates). The less-sensitive industries comprise sector 30 (Consumer staples), sector 40 (Financials), sector 45 (Information technology), sector 50 (Communication services), and sector 55 (Utilities). *VSML1* and *VS/VL1* are the excess industry volatility and the ratio of industry volatility calculated based on the original industry classification defined in Panel A. *VSML2* and *VS/VL2* are the excess industry volatility and the ratio of industry volatility calculated based on the alternative industry classification in which sector 10 is moved to the less-sensitive group.

**Table 7: Regression results for global data**

**Panel A:**

$$VSML_{i,t} = \alpha + \beta_1 \ln(confirmed_{i,t}) + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (5)$$

| | **VSML1** | | | **VSML2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | 0.00001 | -0.00000 | 0.00000 | -0.00000 | -0.00000 | -0.00000 |
| | (0.00000) | (0.00001) | (0.00001) | (0.00000) | (0.00001) | (0.00001) |
| $VSML1_{t-1}$ | $0.731^{***}$ | $0.833^{***}$ | $0.903^{***}$ | | | |
| | (0.009) | (0.009) | (0.009) | | | |
| $VSML1_{t-2}$ | $0.154^{***}$ | $0.100^{***}$ | $0.060^{***}$ | | | |
| | (0.011) | (0.012) | (0.012) | | | |
| $VSML1_{t-3}$ | $0.062^{***}$ | $0.021^{**}$ | -0.013 | | | |
| | (0.009) | (0.009) | (0.009) | | | |
| $VSML2_{t-1}$ | | | | $0.796^{***}$ | $0.876^{***}$ | $0.927^{***}$ |
| | | | | (0.009) | (0.009) | (0.009) |
| $VSML2_{t-2}$ | | | | $0.152^{***}$ | $0.092^{***}$ | $0.046^{***}$ |
| | | | | (0.012) | (0.012) | (0.013) |
| $VSML2_{t-3}$ | | | | 0.007 | -0.009 | $-0.022^{**}$ |
| | | | | (0.009) | (0.009) | (0.009) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 12,001 | 12,001 | 12,001 | 12,001 | 12,001 | 12,001 |
| $R^2$ | 0.888 | 0.907 | 0.906 | 0.913 | 0.920 | 0.911 |
| Adjusted $R^2$ | 0.885 | 0.904 | 0.903 | 0.911 | 0.917 | 0.908 |
| F Statistic (df = 4; 11652) | $23{,}108.140^{***}$ | $28{,}327.540^{***}$ | $27{,}939.870^{***}$ | $30{,}672.860^{***}$ | $33{,}383.790^{***}$ | $29{,}693.620^{***}$ |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (5) for the global data from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 7 (Continued):**

**Panel B**:

$$VSML_{i,t} = \alpha + \beta_1\, daily\ infection_{i,t} + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (6)$$

| | VSML1 | | | VSML2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | 0.125** | 0.144** | 0.263*** | 0.057 | 0.128** | 0.204** |
| | (0.049) | (0.063) | (0.085) | (0.048) | (0.064) | (0.089) |
| $VSML1_{t-1}$ | 0.730*** | 0.833*** | 0.902*** | | | |
| | (0.009) | (0.009) | (0.009) | | | |
| $VSML1_{t-2}$ | 0.154*** | 0.100*** | 0.061*** | | | |
| | (0.011) | (0.012) | (0.012) | | | |
| $VSML1_{t-3}$ | 0.062*** | 0.021** | -0.014 | | | |
| | (0.009) | (0.009) | (0.009) | | | |
| $VSML2_{t-1}$ | | | | 0.795*** | 0.875*** | 0.926*** |
| | | | | (0.009) | (0.009) | (0.009) |
| $VSML2_{t-2}$ | | | | 0.153*** | 0.093*** | 0.047*** |
| | | | | (0.012) | (0.012) | (0.013) |
| $VSML2_{t-3}$ | | | | 0.007 | -0.009 | -0.022** |
| | | | | (0.009) | (0.009) | (0.009) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 12,001 | 12,001 | 12,001 | 12,001 | 12,001 | 12,001 |
| $R^2$ | 0.888 | 0.907 | 0.906 | 0.913 | 0.920 | 0.911 |
| Adjusted $R^2$ | 0.885 | 0.904 | 0.903 | 0.911 | 0.917 | 0.908 |
| F Statistic (df = 4; 11652) | 23,120.190*** | 28,340.680*** | 27,964.500*** | 30,677.000*** | 33,395.090*** | 29,708.160*** |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (6) for the global data from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 7 (Continued):**

**Panel C**:

$$VS/VL_{i,t} = \alpha + \beta_1 \ln(confirmed_{i,t}) + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (7)$$

| | VS/VL1 | | | VS/VL2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | 0.0001 | -0.0003 | 0.0002 | -0.0001 | -0.0002 | -0.0001 |
| | (0.0002) | (0.0003) | (0.0004) | (0.0002) | (0.0002) | (0.0003) |
| $VS/VL1_{t-1}$ | 0.600*** | 0.758*** | 0.869*** | | | |
| | (0.009) | (0.009) | (0.009) | | | |
| $VS/VL1_{t-2}$ | 0.224*** | 0.145*** | 0.081*** | | | |
| | (0.010) | (0.011) | (0.012) | | | |
| $VS/VL1_{t-3}$ | 0.113*** | 0.043*** | -0.007 | | | |
| | (0.009) | (0.009) | (0.009) | | | |
| $VS/VL2_{t-1}$ | | | | 0.716*** | 0.796*** | 0.868*** |
| | | | | (0.009) | (0.009) | (0.009) |
| $VS/VL2_{t-2}$ | | | | 0.199*** | 0.146*** | 0.091*** |
| | | | | (0.011) | (0.012) | (0.012) |
| $VS/VL2_{t-3}$ | | | | 0.037*** | 0.010 | -0.015 |
| | | | | (0.009) | (0.009) | (0.009) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 12,001 | 12,001 | 12,001 | 12,001 | 12,001 | 12,001 |
| $R^2$ | 0.845 | 0.878 | 0.885 | 0.894 | 0.900 | 0.889 |
| Adjusted $R^2$ | 0.841 | 0.874 | 0.882 | 0.891 | 0.897 | 0.886 |
| F Statistic (df = 4; 11652) | 15,932.870*** | 20,920.990*** | 22,461.060*** | 24,644.000*** | 26,206.330*** | 23,412.840*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (7) for the global data from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 7 (Continued):**

**Panel D:**

$$VS/VL_{i,t} = \alpha + \beta_1\, daily\ infection_{i,t} + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (8)$$

| | VS/VL1 | | | VS/VL2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | 3.698$^{*}$ | 2.568 | 9.526$^{**}$ | 1.806 | 3.200 | 7.289$^{**}$ |
| | (2.216) | (2.941) | (3.829) | (1.834) | (2.392) | (3.244) |
| $VS/VL1_{t-1}$ | 0.600$^{***}$ | 0.758$^{***}$ | 0.868$^{***}$ | | | |
| | (0.009) | (0.009) | (0.009) | | | |
| $VS/VL1_{t-2}$ | 0.224$^{***}$ | 0.145$^{***}$ | 0.081$^{***}$ | | | |
| | (0.010) | (0.011) | (0.012) | | | |
| $VS/VL1_{t-3}$ | 0.113$^{***}$ | 0.043$^{***}$ | -0.007 | | | |
| | (0.009) | (0.009) | (0.009) | | | |
| $VS/VL2_{t-1}$ | | | | 0.716$^{***}$ | 0.796$^{***}$ | 0.867$^{***}$ |
| | | | | (0.009) | (0.009) | (0.009) |
| $VS/VL2_{t-2}$ | | | | 0.199$^{***}$ | 0.146$^{***}$ | 0.092$^{***}$ |
| | | | | (0.011) | (0.012) | (0.012) |
| $VS/VL2_{t-3}$ | | | | 0.037$^{***}$ | 0.010 | -0.015 |
| | | | | (0.009) | (0.009) | (0.009) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 12,001 | 12,001 | 12,001 | 12,001 | 12,001 | 12,001 |
| $R^2$ | 0.845 | 0.878 | 0.885 | 0.894 | 0.900 | 0.889 |
| Adjusted $R^2$ | 0.841 | 0.874 | 0.882 | 0.891 | 0.897 | 0.886 |
| F Statistic (df = 4; 11652) | 15,936.820$^{***}$ | 20,919.850$^{***}$ | 22,473.800$^{***}$ | 24,645.930$^{***}$ | 26,209.140$^{***}$ | 23,424.110$^{***}$ |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (8) for the global data from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 8: Regression results for Europe**

**Panel A:**

$$VSML_{i,t} = \alpha + \beta_1 \ln(confirmed_{i,t}) + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (5)$$

| | **VSML1** | | | **VSML2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | 0.00001 | 0.00000 | 0.00002 | 0.00001 | -0.00000 | 0.00002 |
| | (0.00001) | (0.00001) | (0.00002) | (0.00001) | (0.00001) | (0.00002) |
| $VSML1_{t-1}$ | $0.992^{***}$ | $1.001^{***}$ | $0.993^{***}$ | | | |
| | (0.015) | (0.015) | (0.015) | | | |
| $VSML1_{t-2}$ | -0.014 | -0.019 | -0.011 | | | |
| | (0.021) | (0.021) | (0.021) | | | |
| $VSML1_{t-3}$ | -0.017 | -0.021 | $-0.030^{**}$ | | | |
| | (0.015) | (0.015) | (0.015) | | | |
| $VSML2_{t-1}$ | | | | $0.981^{***}$ | $0.982^{***}$ | $0.979^{***}$ |
| | | | | (0.015) | (0.015) | (0.015) |
| $VSML2_{t-2}$ | | | | -0.016 | -0.011 | -0.010 |
| | | | | (0.021) | (0.021) | (0.021) |
| $VSML2_{t-3}$ | | | | -0.009 | -0.016 | -0.022 |
| | | | | (0.015) | (0.015) | (0.015) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,835 | 4,835 | 4,835 | 4,835 | 4,835 | 4,835 |
| $R^2$ | 0.940 | 0.937 | 0.920 | 0.928 | 0.924 | 0.910 |
| Adjusted $R^2$ | 0.936 | 0.934 | 0.916 | 0.924 | 0.920 | 0.905 |
| F Statistic (df = 4; 4567) | $17{,}770.220^{***}$ | $17{,}107.380^{***}$ | $13{,}169.880^{***}$ | $14{,}722.850^{***}$ | $13{,}949.850^{***}$ | $11{,}547.750^{***}$ |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (5) for European countries from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 8 (Continued):**

**Panel B:**

$$VSML_{i,t} = \alpha + \beta_1\ daily\ infection_{i,t} + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (6)$$

| | **VSML1** | | | **VSML2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | $0.173^{***}$ | $0.202^{**}$ | $0.405^{***}$ | $0.130^{*}$ | $0.239^{**}$ | $0.393^{**}$ |
| | (0.061) | (0.089) | (0.141) | (0.069) | (0.105) | (0.166) |
| $VSML1_{t-1}$ | $0.989^{***}$ | $0.999^{***}$ | $0.989^{***}$ | | | |
| | (0.015) | (0.015) | (0.015) | | | |
| $VSML1_{t-2}$ | -0.012 | -0.017 | -0.008 | | | |
| | (0.021) | (0.021) | (0.021) | | | |
| $VSML1_{t-3}$ | -0.018 | -0.021 | $-0.031^{**}$ | | | |
| | (0.015) | (0.015) | (0.015) | | | |
| $VSML2_{t-1}$ | | | | $0.980^{***}$ | $0.979^{***}$ | $0.975^{***}$ |
| | | | | (0.015) | (0.015) | (0.015) |
| $VSML2_{t-2}$ | | | | -0.014 | -0.008 | -0.007 |
| | | | | (0.021) | (0.021) | (0.021) |
| $VSML2_{t-3}$ | | | | -0.009 | -0.017 | -0.023 |
| | | | | (0.015) | (0.015) | (0.015) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,835 | 4,835 | 4,835 | 4,835 | 4,835 | 4,835 |
| $R^2$ | 0.940 | 0.938 | 0.920 | 0.928 | 0.924 | 0.910 |
| Adjusted $R^2$ | 0.936 | 0.934 | 0.916 | 0.924 | 0.920 | 0.905 |
| F Statistic (df = 4; 4567) | $17{,}795.680^{***}$ | $17{,}127.980^{***}$ | $13{,}191.020^{***}$ | $14{,}733.380^{***}$ | $13{,}966.850^{***}$ | $11{,}561.510^{***}$ |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (6) for European countries from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 8 (Continued):**

**<u>Panel C</u>:**

$$VS/VL_{i,t} = \alpha + \beta_1 \ln(confirmed_{i,t}) + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (7)$$

| | VS/VL1 | | | VS/VL2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | 0.0003 | -0.0001 | 0.001 | 0.0002 | -0.0001 | 0.0005 |
| | (0.0003) | (0.0004) | (0.001) | (0.0003) | (0.0004) | (0.001) |
| $VS/VL1_{t-1}$ | 0.993$^{***}$ | 0.997$^{***}$ | 0.984$^{***}$ | | | |
| | (0.015) | (0.015) | (0.015) | | | |
| $VS/VL1_{t-2}$ | -0.019 | -0.018 | -0.011 | | | |
| | (0.021) | (0.021) | (0.021) | | | |
| $VS/VL1_{t-3}$ | -0.016 | -0.021 | -0.027$^{*}$ | | | |
| | (0.015) | (0.015) | (0.015) | | | |
| $VS/VL2_{t-1}$ | | | | 0.970$^{***}$ | 0.967$^{***}$ | 0.967$^{***}$ |
| | | | | (0.015) | (0.015) | (0.015) |
| $VS/VL2_{t-2}$ | | | | -0.007 | -0.001 | -0.006 |
| | | | | (0.021) | (0.021) | (0.021) |
| $VS/VL2_{t-3}$ | | | | -0.013 | -0.019 | -0.020 |
| | | | | (0.015) | (0.015) | (0.015) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,835 | 4,835 | 4,835 | 4,835 | 4,835 | 4,835 |
| $R^2$ | 0.937 | 0.934 | 0.912 | 0.917 | 0.911 | 0.900 |
| Adjusted $R^2$ | 0.934 | 0.930 | 0.907 | 0.912 | 0.906 | 0.894 |
| F Statistic (df = 4; 4567) | 17,071.290$^{***}$ | 16,100.550$^{***}$ | 11,881.460$^{***}$ | 12,612.500$^{***}$ | 11,759.130$^{***}$ | 10,303.150$^{***}$ |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the regression results of model (7) for European countries from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 8 (Continued):**

**<u>Panel D</u>:**

$$VS/VL_{i,t} = \alpha + \beta_1\ daily\ infection_{i,t} + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (8)$$

| | VS/VL1 | | | VS/VL2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | 5.505*** | 5.669** | 15.766*** | 4.084* | 6.516** | 13.060** |
| | (1.988) | (2.883) | (4.981) | (2.252) | (3.255) | (5.309) |
| $VS/VL1_{t-1}$ | 0.991*** | 0.995*** | 0.981*** | | | |
| | (0.015) | (0.015) | (0.015) | | | |
| $VS/VL1_{t-2}$ | -0.017 | -0.017 | -0.008 | | | |
| | (0.021) | (0.021) | (0.021) | | | |
| $VS/VL1_{t-3}$ | -0.017 | -0.021 | -0.027* | | | |
| | (0.015) | (0.015) | (0.015) | | | |
| $VS/VL2_{t-1}$ | | | | 0.969*** | 0.965*** | 0.964*** |
| | | | | (0.015) | (0.015) | (0.015) |
| $VS/VL2_{t-2}$ | | | | -0.006 | 0.001 | -0.003 |
| | | | | (0.021) | (0.021) | (0.021) |
| $VS/VL2_{t-3}$ | | | | -0.014 | -0.020 | -0.021 |
| | | | | (0.015) | (0.015) | (0.015) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,835 | 4,835 | 4,835 | 4,835 | 4,835 | 4,835 |
| $R^2$ | 0.937 | 0.934 | 0.913 | 0.917 | 0.912 | 0.900 |
| Adjusted $R^2$ | 0.934 | 0.930 | 0.907 | 0.912 | 0.906 | 0.895 |
| F Statistic (df = 4; 4567) | 17,096.360*** | 16,114.900*** | 11,908.090*** | 12,621.300*** | 11,770.260*** | 10,317.200*** |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (8) for European countries from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 9: Regression results for Asia & Pacific**

**Panel A:**

$$VSML_{i,t} = \alpha + \beta_1 \ln\left(confirmed_{i,t}\right) + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (5)$$

| | **VSML1** | | | **VSML2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | -0.00000 | -0.00000 | -0.00001 | -0.00001 | -0.00001 | -0.00001 |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| $VSML1_{t-1}$ | 0.620*** | 0.734*** | 0.823*** | | | |
| | (0.014) | (0.014) | (0.014) | | | |
| $VSML1_{t-2}$ | 0.246*** | 0.205*** | 0.145*** | | | |
| | (0.016) | (0.017) | (0.018) | | | |
| $VSML1_{t-3}$ | 0.081*** | 0.022 | -0.016 | | | |
| | (0.014) | (0.014) | (0.014) | | | |
| $VSML2_{t-1}$ | | | | 0.728*** | 0.847*** | 0.911*** |
| | | | | (0.014) | (0.014) | (0.014) |
| $VSML2_{t-2}$ | | | | 0.197*** | 0.135*** | 0.070*** |
| | | | | (0.017) | (0.018) | (0.019) |
| $VSML2_{t-3}$ | | | | 0.040*** | -0.009 | -0.020 |
| | | | | (0.014) | (0.014) | (0.014) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,427 | 5,427 | 5,427 | 5,427 | 5,427 | 5,427 |
| $R^2$ | 0.885 | 0.916 | 0.906 | 0.929 | 0.946 | 0.927 |
| Adjusted $R^2$ | 0.877 | 0.910 | 0.900 | 0.924 | 0.942 | 0.923 |
| F Statistic (df = 4; 5105) | 9,775.823*** | 13,872.040*** | 12,272.810*** | 16,630.220*** | 22,218.170*** | 16,305.990*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (5) for Asian and Pacific countries from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 9 (Continued):**

**Panel B:**

$$VSML_{i,t} = \alpha + \beta_1\, daily\ infection_{i,t} + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (6)$$

| | VSML1 | | | VSML2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | -0.059 | -0.067 | -0.040 | -0.073 | -0.078 | -0.025 |
| | (0.072) | (0.082) | (0.102) | (0.065) | (0.076) | (0.098) |
| $VSML1_{t-1}$ | 0.620*** | 0.734*** | 0.823*** | | | |
| | (0.014) | (0.014) | (0.014) | | | |
| $VSML1_{t-2}$ | 0.246*** | 0.205*** | 0.145*** | | | |
| | (0.016) | (0.017) | (0.018) | | | |
| $VSML1_{t-3}$ | 0.081*** | 0.022 | -0.016 | | | |
| | (0.014) | (0.014) | (0.014) | | | |
| $VSML2_{t-1}$ | | | | 0.728*** | 0.847*** | 0.912*** |
| | | | | (0.014) | (0.014) | (0.014) |
| $VSML2_{t-2}$ | | | | 0.197*** | 0.135*** | 0.070*** |
| | | | | (0.017) | (0.018) | (0.019) |
| $VSML2_{t-3}$ | | | | 0.039*** | -0.009 | -0.020 |
| | | | | (0.014) | (0.014) | (0.014) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,427 | 5,427 | 5,427 | 5,427 | 5,427 | 5,427 |
| $R^2$ | 0.885 | 0.916 | 0.906 | 0.929 | 0.946 | 0.927 |
| Adjusted $R^2$ | 0.877 | 0.910 | 0.900 | 0.924 | 0.942 | 0.923 |
| F Statistic (df = 4; 5105) | 9,776.478*** | 13,873.060*** | 12,271.380*** | 16,631.250*** | 22,217.580*** | 16,297.920*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (6) for Asian & Pacific countries from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 9 (Continued):**

**Panel C:**

$$VS/VL_{i,t} = \alpha + \beta_1 \ln(confirmed_{i,t}) + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (7)$$

| | **VS/VL1** | | | **VS/VL2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | -0.001$^{*}$ | -0.001 | -0.001 | -0.0005$^{*}$ | -0.0004 | -0.001$^{*}$ |
| | (0.0003) | (0.0004) | (0.0005) | (0.0002) | (0.0003) | (0.0003) |
| $VS/VL1_{t-1}$ | 0.460$^{***}$ | 0.602$^{***}$ | 0.759$^{***}$ | | | |
| | (0.014) | (0.014) | (0.014) | | | |
| $VS/VL1_{t-2}$ | 0.293$^{***}$ | 0.268$^{***}$ | 0.178$^{***}$ | | | |
| | (0.015) | (0.016) | (0.017) | | | |
| $VS/VL1_{t-3}$ | 0.181$^{***}$ | 0.083$^{***}$ | 0.001 | | | |
| | (0.014) | (0.014) | (0.014) | | | |
| $VS/VL2_{t-1}$ | | | | 0.617$^{***}$ | 0.741$^{***}$ | 0.864$^{***}$ |
| | | | | (0.014) | (0.014) | (0.014) |
| $VS/VL2_{t-2}$ | | | | 0.251$^{***}$ | 0.210$^{***}$ | 0.107$^{***}$ |
| | | | | (0.016) | (0.017) | (0.018) |
| $VS/VL2_{t-3}$ | | | | 0.095$^{***}$ | 0.018 | -0.022 |
| | | | | (0.014) | (0.014) | (0.014) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,427 | 5,427 | 5,427 | 5,427 | 5,427 | 5,427 |
| $R^2$ | 0.809 | 0.872 | 0.863 | 0.908 | 0.931 | 0.901 |
| Adjusted $R^2$ | 0.796 | 0.864 | 0.855 | 0.902 | 0.926 | 0.895 |
| F Statistic (df = 4; 5105) | 5,389.383$^{***}$ | 8,693.662$^{***}$ | 8,069.945$^{***}$ | 12,580.490$^{***}$ | 17,162.950$^{***}$ | 11,625.470$^{***}$ |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the regression results of model (7) for Asian & Pacific countries from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 9 (Continued):**

**Panel D:**

$$VS/VL_{i,t} = \alpha + \beta_1\ daily\ infection_{i,t} + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (8)$$

| | **VS/VL1** | | | **VS/VL2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | -7.555* | -7.086 | -5.832 | -4.422 | -4.227 | -1.944 |
| | (4.078) | (4.778) | (5.547) | (2.829) | (3.299) | (4.077) |
| $VS/VL1_{t-1}$ | 0.460*** | 0.602*** | 0.759*** | | | |
| | (0.014) | (0.014) | (0.014) | | | |
| $VS/VL1_{t-2}$ | 0.293*** | 0.268*** | 0.178*** | | | |
| | (0.015) | (0.016) | (0.017) | | | |
| $VS/VL1_{t-3}$ | 0.181*** | 0.083*** | 0.001 | | | |
| | (0.014) | (0.014) | (0.014) | | | |
| $VS/VL2_{t-1}$ | | | | 0.617*** | 0.741*** | 0.865*** |
| | | | | (0.014) | (0.014) | (0.014) |
| $VS/VL2_{t-2}$ | | | | 0.251*** | 0.210*** | 0.107*** |
| | | | | (0.016) | (0.017) | (0.018) |
| $VS/VL2_{t-3}$ | | | | 0.094*** | 0.018 | -0.022 |
| | | | | (0.014) | (0.014) | (0.014) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,427 | 5,427 | 5,427 | 5,427 | 5,427 | 5,427 |
| $R^2$ | 0.809 | 0.872 | 0.863 | 0.908 | 0.931 | 0.901 |
| Adjusted $R^2$ | 0.797 | 0.864 | 0.855 | 0.902 | 0.926 | 0.895 |
| F Statistic (df = 4; 5105) | 5,389.864*** | 8,693.936*** | 8,068.216*** | 12,577.410*** | 17,159.960*** | 11,616.470*** |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression results of model (8) for Asian & Pacific countries from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 10: Regression results for America**

**Panel A:**

$$VSML_{i,t} = \alpha + \beta_1 \ln(confirmed_{i,t}) + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (5)$$

| | **VSML1** | | | **VSML2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | 0.00001 | 0.00000 | 0.00002 | -0.00002 | -0.00001 | 0.00002 |
| | (0.00002) | (0.00003) | (0.00004) | (0.00002) | (0.00003) | (0.00004) |
| $VSML1_{t-1}$ | 0.779$^{***}$ | 0.789$^{***}$ | 0.796$^{***}$ | | | |
| | (0.037) | (0.037) | (0.037) | | | |
| $VSML1_{t-2}$ | 0.112$^{**}$ | 0.068 | 0.099$^{**}$ | | | |
| | (0.047) | (0.047) | (0.048) | | | |
| $VSML1_{t-3}$ | -0.005 | 0.068$^{*}$ | 0.024 | | | |
| | (0.036) | (0.037) | (0.037) | | | |
| $VSML2_{t-1}$ | | | | 0.729$^{***}$ | 0.741$^{***}$ | 0.771$^{***}$ |
| | | | | (0.037) | (0.037) | (0.037) |
| $VSML2_{t-2}$ | | | | 0.145$^{***}$ | 0.103$^{**}$ | 0.123$^{***}$ |
| | | | | (0.046) | (0.046) | (0.047) |
| $VSML2_{t-3}$ | | | | 0.037 | 0.085$^{**}$ | 0.034 |
| | | | | (0.036) | (0.037) | (0.037) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 964 | 964 | 964 | 964 | 964 | 964 |
| $R^2$ | 0.817 | 0.866 | 0.845 | 0.866 | 0.882 | 0.869 |
| Adjusted $R^2$ | 0.754 | 0.820 | 0.791 | 0.819 | 0.841 | 0.824 |
| F Statistic (df = 4; 715) | 799.360$^{***}$ | 1,156.502$^{***}$ | 974.760$^{***}$ | 1,154.380$^{***}$ | 1,338.485$^{***}$ | 1,186.513$^{***}$ |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the regression results of model (5) for American countries, except the US, from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 10 (Continued):**

**Panel B:**

$$VSML_{i,t} = \alpha + \beta_1\, daily\ infection_{i,t} + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (6)$$

| | **VSML1** | | | **VSML2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | 0.246 | -0.036 | 0.347 | 0.001 | 1.056 | 1.511 |
| | (0.513) | (0.690) | (0.886) | (0.518) | (0.737) | (0.948) |
| $VSML1_{t-1}$ | 0.778*** | 0.790*** | 0.798*** | | | |
| | (0.037) | (0.037) | (0.037) | | | |
| $VSML1_{t-2}$ | 0.112** | 0.068 | 0.098** | | | |
| | (0.047) | (0.047) | (0.048) | | | |
| $VSML1_{t-3}$ | -0.004 | 0.067* | 0.025 | | | |
| | (0.036) | (0.037) | (0.037) | | | |
| $VSML2_{t-1}$ | | | | 0.729*** | 0.737*** | 0.768*** |
| | | | | (0.037) | (0.037) | (0.037) |
| $VSML2_{t-2}$ | | | | 0.146*** | 0.104** | 0.124*** |
| | | | | (0.046) | (0.046) | (0.047) |
| $VSML2_{t-3}$ | | | | 0.037 | 0.088** | 0.034 |
| | | | | (0.036) | (0.037) | (0.037) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 964 | 964 | 964 | 964 | 964 | 964 |
| $R^2$ | 0.817 | 0.866 | 0.845 | 0.866 | 0.883 | 0.869 |
| Adjusted $R^2$ | 0.754 | 0.820 | 0.791 | 0.819 | 0.842 | 0.824 |
| F Statistic (df = 4; 715) | 799.582*** | 1,156.461*** | 974.260*** | 1,151.648*** | 1,342.679*** | 1,190.886*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (6) for American countries, except the US, from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 10 (Continued):**

**Panel C:**

$$VS/VL_{i,t} = \alpha + \beta_1 \ln(confirmed_{i,t}) + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (7)$$

| | **VS/VL1** | | | **VS/VL2** | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | -0.0001 | 0.001 | 0.004 | -0.002 | 0.001 | 0.002 |
| | (0.001) | (0.002) | (0.003) | (0.001) | (0.002) | (0.002) |
| $VS/VL1_{t-1}$ | 0.809*** | 0.919*** | 0.927*** | | | |
| | (0.037) | (0.037) | (0.037) | | | |
| $VS/VL1_{t-2}$ | 0.111** | -0.050 | 0.008 | | | |
| | (0.048) | (0.051) | (0.051) | | | |
| $VS/VL1_{t-3}$ | 0.0001 | 0.065* | 0.005 | | | |
| | (0.037) | (0.037) | (0.037) | | | |
| $VS/VL2_{t-1}$ | | | | 0.746*** | 0.704*** | 0.711*** |
| | | | | (0.037) | (0.037) | (0.037) |
| $VS/VL2_{t-2}$ | | | | 0.135*** | 0.126*** | 0.172*** |
| | | | | (0.046) | (0.045) | (0.045) |
| $VS/VL2_{t-3}$ | | | | 0.023 | 0.086** | 0.043 |
| | | | | (0.036) | (0.036) | (0.037) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 964 | 964 | 964 | 964 | 964 | 964 |
| $R^2$ | 0.851 | 0.869 | 0.890 | 0.858 | 0.857 | 0.857 |
| Adjusted $R^2$ | 0.799 | 0.824 | 0.851 | 0.809 | 0.808 | 0.808 |
| F Statistic (df = 4; 715) | 1,020.854*** | 1,186.623*** | 1,440.204*** | 1,080.354*** | 1,073.781*** | 1,074.458*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (7) for American countries, except the US, from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 10 (Continued):**

**Panel D:**

$$VS/VL_{i,t} = \alpha + \beta_1\ daily\ infection_{i,t} + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (8)$$

| | VS/VL1 | | | VS/VL2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | 37.754 | -19.072 | 86.418 | 14.041 | 70.879$^{*}$ | 108.292$^{**}$ |
| | (29.986) | (56.151) | (76.889) | (25.814) | (38.971) | (53.476) |
| $VS/VL1_{t-1}$ | 0.805$^{***}$ | 0.919$^{***}$ | 0.929$^{***}$ | | | |
| | (0.037) | (0.037) | (0.037) | | | |
| $VS/VL1_{t-2}$ | 0.110$^{**}$ | -0.049 | 0.008 | | | |
| | (0.048) | (0.051) | (0.051) | | | |
| $VS/VL1_{t-3}$ | 0.002 | 0.064$^{*}$ | 0.007 | | | |
| | (0.037) | (0.037) | (0.037) | | | |
| $VS/VL2_{t-1}$ | | | | 0.745$^{***}$ | 0.699$^{***}$ | 0.707$^{***}$ |
| | | | | (0.037) | (0.037) | (0.037) |
| $VS/VL2_{t-2}$ | | | | 0.136$^{***}$ | 0.126$^{***}$ | 0.172$^{***}$ |
| | | | | (0.046) | (0.045) | (0.045) |
| $VS/VL2_{t-3}$ | | | | 0.024 | 0.090$^{**}$ | 0.043 |
| | | | | (0.036) | (0.036) | (0.037) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 964 | 964 | 964 | 964 | 964 | 964 |
| $R^2$ | 0.851 | 0.869 | 0.889 | 0.858 | 0.858 | 0.858 |
| Adjusted $R^2$ | 0.800 | 0.824 | 0.851 | 0.808 | 0.809 | 0.809 |
| F Statistic (df = 4; 715) | 1,023.502$^{***}$ | 1,186.612$^{***}$ | 1,438.722$^{***}$ | 1,076.758$^{***}$ | 1,079.348$^{***}$ | 1,079.790$^{***}$ |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the regression results of model (8) for American countries, except the US, from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 11: Regression results for Africa**

**Panel A:**

$$VSML_{i,t} = \alpha + \beta_1 \ln(confirmed_{i,t}) + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (5)$$

| | VSML1 | | | VSML2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | 0.0003*** | 0.00003 | 0.0001 | 0.0001 | -0.00001 | 0.00003 |
| | (0.0001) | (0.0001) | (0.0001) | (0.00005) | (0.0001) | (0.0001) |
| $VSML1_{t-1}$ | 0.415*** | 0.490*** | 0.677*** | | | |
| | (0.031) | (0.033) | (0.040) | | | |
| $VSML1_{t-2}$ | 0.217*** | 0.233*** | 0.168*** | | | |
| | (0.034) | (0.038) | (0.047) | | | |
| $VSML1_{t-3}$ | 0.281*** | 0.235*** | 0.123*** | | | |
| | (0.029) | (0.031) | (0.036) | | | |
| $VSML2_{t-1}$ | | | | 0.516*** | 0.587*** | 0.700*** |
| | | | | (0.026) | (0.031) | (0.039) |
| $VSML2_{t-2}$ | | | | 0.315*** | 0.295*** | 0.238*** |
| | | | | (0.023) | (0.031) | (0.041) |
| $VSML2_{t-3}$ | | | | 0.172*** | 0.114*** | 0.060* |
| | | | | (0.024) | (0.030) | (0.036) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 766 | 766 | 766 | 766 | 766 | 766 |
| $R^2$ | 0.871 | 0.894 | 0.903 | 0.972 | 0.951 | 0.941 |
| Adjusted $R^2$ | 0.791 | 0.828 | 0.843 | 0.955 | 0.921 | 0.904 |
| F Statistic (df = 4; 472) | 795.539*** | 993.592*** | 1,097.852*** | 4,144.148*** | 2,308.759*** | 1,874.855*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (5) for African countries from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 11 (Continued):**

**Panel B:**

$$VSML_{i,t} = \alpha + \beta_1\, daily\ infection_{i,t} + \beta_2 VSML_{i,t-1} + \beta_3 VSML_{i,t-2} + \beta_4 VSML_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (6)$$

| | VSML1 | | | VSML2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | 2.573 | -1.221 | -0.518 | 0.268 | 0.134 | 0.362 |
| | (1.635) | (1.822) | (2.448) | (0.916) | (1.244) | (1.759) |
| $VSML1_{t-1}$ | 0.427*** | 0.490*** | 0.678*** | | | |
| | (0.031) | (0.033) | (0.040) | | | |
| $VSML1_{t-2}$ | 0.230*** | 0.235*** | 0.169*** | | | |
| | (0.034) | (0.038) | (0.047) | | | |
| $VSML1_{t-3}$ | 0.284*** | 0.236*** | 0.122*** | | | |
| | (0.030) | (0.031) | (0.036) | | | |
| $VSML2_{t-1}$ | | | | 0.520*** | 0.587*** | 0.701*** |
| | | | | (0.026) | (0.031) | (0.039) |
| $VSML2_{t-2}$ | | | | 0.318*** | 0.295*** | 0.238*** |
| | | | | (0.023) | (0.031) | (0.041) |
| $VSML2_{t-3}$ | | | | 0.172*** | 0.114*** | 0.060* |
| | | | | (0.024) | (0.030) | (0.036) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 766 | 766 | 766 | 766 | 766 | 766 |
| $R^2$ | 0.869 | 0.894 | 0.903 | 0.972 | 0.951 | 0.941 |
| Adjusted $R^2$ | 0.787 | 0.828 | 0.843 | 0.955 | 0.921 | 0.904 |
| F Statistic (df = 4; 472) | 780.074*** | 994.406*** | 1,097.367*** | 4,131.000*** | 2,308.724*** | 1,874.463*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (6) for African countries from 2020/01/24 to 2020/12/31. The dependent variable *VSML1* is equal to the average industry standard deviation in country *i* in day *t* of the sensitive industries minus that of the less-sensitive industries defined by the original classification. The dependent *VSML2* is equal to the average industry standard deviation in country *i* day *t* of the sensitive industries minus that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VSML1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VSML2*, respectively.

**Table 11 (Continued):**

**Panel C:**

$$VS/VL_{i,t} = \alpha + \beta_1 \ln\left(confirmed_{i,t}\right) + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (7)$$

| | VS/VL1 | | | VS/VL2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(confirmed) | 0.010*** | 0.002 | 0.0002 | 0.002 | -0.00001 | -0.002 |
| | (0.003) | (0.003) | (0.003) | (0.002) | (0.002) | (0.003) |
| $VS/VL1_{t-1}$ | 0.349*** | 0.429*** | 0.544*** | | | |
| | (0.029) | (0.030) | (0.034) | | | |
| $VS/VL1_{t-2}$ | 0.212*** | 0.240*** | 0.229*** | | | |
| | (0.031) | (0.034) | (0.039) | | | |
| $VS/VL1_{t-3}$ | 0.291*** | 0.260*** | 0.193*** | | | |
| | (0.027) | (0.029) | (0.032) | | | |
| $VS/VL2_{t-1}$ | | | | 0.523*** | 0.560*** | 0.582*** |
| | | | | (0.028) | (0.031) | (0.034) |
| $VS/VL2_{t-2}$ | | | | 0.292*** | 0.284*** | 0.281*** |
| | | | | (0.026) | (0.030) | (0.034) |
| $VS/VL2_{t-3}$ | | | | 0.165*** | 0.115*** | 0.131*** |
| | | | | (0.026) | (0.029) | (0.032) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 766 | 766 | 766 | 766 | 766 | 766 |
| $R^2$ | 0.813 | 0.873 | 0.905 | 0.932 | 0.909 | 0.920 |
| Adjusted $R^2$ | 0.697 | 0.795 | 0.846 | 0.890 | 0.852 | 0.871 |
| F Statistic (df = 4; 472) | 513.800*** | 814.405*** | 1,120.669*** | 1,620.845*** | 1,177.742*** | 1,360.747*** |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression results of model (7) for African countries from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *ln(confirmed)* is the natural logarithm of the daily confirmed cases in country *i* in day *t*. Any zero value is converted to one before taking the log. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

**Table 11 (Continued):**

**<u>Panel D</u>:**

$$VS/VL_{i,t} = \alpha + \beta_1\ daily\ infection_{i,t} + \beta_2 VS/VL_{i,t-1} + \beta_3 VS/VL_{i,t-2} + \beta_4 VS/VL_{i,t-3} + countryFE + day\&monthFE + \varepsilon_{i,t} \quad (8)$$

| | VS/VL1 | | | VS/VL2 | | |
|---|---|---|---|---|---|---|
| | (125-day SD) | (60-day SD) | (30-day SD) | (125-day SD) | (60-day SD) | (30-day SD) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Daily infection | 78.030 | -42.982 | -88.479 | 7.077 | -8.647 | -24.760 |
| | (52.966) | (60.425) | (69.377) | (38.766) | (48.651) | (55.855) |
| $VS/VL1_{t-1}$ | $0.365^{***}$ | $0.430^{***}$ | $0.543^{***}$ | | | |
| | (0.029) | (0.030) | (0.034) | | | |
| $VS/VL1_{t-2}$ | $0.230^{***}$ | $0.244^{***}$ | $0.231^{***}$ | | | |
| | (0.031) | (0.034) | (0.039) | | | |
| $VS/VL1_{t-3}$ | $0.296^{***}$ | $0.261^{***}$ | $0.194^{***}$ | | | |
| | (0.027) | (0.029) | (0.032) | | | |
| $VS/VL2_{t-1}$ | | | | $0.526^{***}$ | $0.561^{***}$ | $0.581^{***}$ |
| | | | | (0.028) | (0.031) | (0.034) |
| $VS/VL2_{t-2}$ | | | | $0.295^{***}$ | $0.285^{***}$ | $0.281^{***}$ |
| | | | | (0.025) | (0.030) | (0.034) |
| $VS/VL2_{t-3}$ | | | | $0.166^{***}$ | $0.115^{***}$ | $0.131^{***}$ |
| | | | | (0.026) | (0.029) | (0.032) |
| Day-month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 766 | 766 | 766 | 766 | 766 | 766 |
| $R^2$ | 0.809 | 0.873 | 0.905 | 0.932 | 0.909 | 0.920 |
| Adjusted $R^2$ | 0.690 | 0.795 | 0.846 | 0.890 | 0.852 | 0.871 |
| F Statistic (df = 4; 472) | $498.854^{***}$ | $814.506^{***}$ | $1{,}124.929^{***}$ | $1{,}618.235^{***}$ | $1{,}177.829^{***}$ | $1{,}359.545^{***}$ |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the regression results of model (8) for African countries from 2020/01/24 to 2020/12/31. The dependent variable *VS/VL1* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the original classification. The dependent *VS/VL2* is the ratio of the average industry standard deviation in country *i* in day *t* of the sensitive industries over that of the less-sensitive industries defined by the alternative classification. The independent variable *daily infection* is equal to the daily confirmed cases in country *i* in day *t* divided by country *i*'s population in 2020. Column (1) to (3) reports the results for 125-day, 60-day, and 30-day *VS/VL1*, respectively. Column (4) to (6) reports the results for 125-day, 60-day, and 30-day *VS/VL2*, respectively.

# CHAPTER 5. CONCLUSION

The real effects of financial markets on the economy through price informativeness have been documented in many research papers, such as Luo (2005), Chen, Goldstein & Jiang (2007), Fang, Noel & Tice (2009), Edmans, Goldstein & Jiang (2012b), etc. Since many speculators trade in secondary financial markets and try to profit from their information, a wide range of information is transmitted to prices. Thus, real decision-makers often learn from prices to make real investment decisions because their knowledge is imperfect and prices contain new information necessary for efficient real decision making. Consequently, secondary market prices affect real economic activity.

The coronavirus pandemic is an exogenous shock to the global economy whose impact is huge, surpassing any other health crisis in the last 100 years. Naturally, in 2020, the first year of the outbreak, investors would want to pay closer attention to any Covid 19 news given the still uncertain recovery outlook. As they revise their portfolios based on their Covid 19 information, prices should reflect the state of the economy during the pandemic, which is very important to actual decision-makers. Nevertheless, we note that there may be a disconnect between the stock market and the real economy, particularly in the United States, as shown in Figure 1.

Our paper aims to answer the question of whether the stock market is decoupled from the real economy during the Covid 19 pandemic by examining the relationship between industry excess volatility, the ratio of industry volatility, and proxies for the severity of the Covid 19 pandemic. The results show that there is a high probability that the U.S. stock market was disconnected from the real economy in 2020, while European stock markets were more connected. Due to the limitation in the model REMI, which only provides a simulation of the impact of pandemic influenza on the U.S. economy, we could not find statistical evidence of linkage in the American, except for the U.S., African, and Asia-Pacific stock markets.

The results of our work shed light on a phenomenon that the stock market may be disconnected from the real economy under certain conditions. A new question that arises is what causes this disconnect. Igan, Kirti, and Peria (2020) discuss several hypotheses about the causes of the disconnect between financial markets and the real economy, of which unprecedented monetary policy is the most likely culprit. Future research can further explore and investigate this issue. Understanding the real causes behind the disconnect is of great importance for real decision-makers and for the future empirical line of research on “how feedback effects from prices to cash flows affect the price formation process” (Bond, Edmans & Goldstein 2012).

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