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Stock market volatility and the COVID-19 reproductive number

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ABSTRACT

The media has prominently featured the totemic reproductive number $R$ in its COVID-19 coverage despite being an imperfect measure of the degree of infectivity of the virus. As such, it conveys information to the public regarding the state of the pandemic that affects market sentiment. We analyze how news about $R$ affects the volatility in stock markets worldwide and find that when $R$ is greater than one, which means the spread of the disease should soar, it has a positive and significant effect on volatility. Our results hold after controlling for government interventions and several robustness checks.

1. Introduction

The financial literature has identified factors that significantly affect the volatility in stock markets. They point to institutional arrangements and government characteristics (Antonakakis et al., 2013; Liu and Zhang, 2015; Hartwell, 2018; Chen and Chiang, 2020) as well as macroeconomic aspects such as economic policy (Onan et al., 2014; Baker et al., 2019) and the behavior of output and inflation volatility (Beltratti and Morana, 2006). Others point to trading activities by institutional investors (Gabaix et al., 2006), noise trading and investors’ sentiment (Verma and Verma, 2007), and the economy’s risk aversion (Bekaert and Hoerova, 2014).

Most of these factors have overlapped during the ongoing COVID-19 pandemic, to the extent that their effects on uncertainty and volatility are the largest in the history of pandemics (see Baker et al., 2020; David et al., 2021). Naturally, such an event has boosted academic debate and fed a growing literature on the effects of the evolution of the global pandemic and the subsequent policy responses, on financial markets (see Goodell, 2020, for a review).

We contribute to this debate by studying the relationship between stock market volatility and the so-called effective (or time-varying) reproductive number that is commonly referred to as $R$; this number has become a totemic figure in the COVID-19 pandemic. Broadly speaking, $R$ is a measure of the coronavirus’s capacity to spread and is the average number of people who become infected by an infectious person. Thus, when $R$ is greater than one the virus is at a high-contagion state and the number of infected people is expected to increase; by contrast, $R$ less than one corresponds to a low-contagion state, and the spread of the virus is...
expected to decline and eventually stop. Thus, from the viewpoint of public health policy, a widespread recommendation is to ease measures to contain the pandemic, such as lockdowns, only as long as  is less than one.\footnote{It is worth stressing that  is time-varying, since susceptible individuals change their behavior as the pandemic evolves (e.g., social distancing). See Fernández-Villaverde and Jones (2020), Arroyo-Marioli et al. (2021) and Li et al. (2021). It must not be confused with the basic reproductive number  that has the same interpretation as  but in the absence of actions against the pandemic and is a deep parameter in epidemiological models.}

While  may be a rough summary of the actual status of the pandemic (see Adam, 2020, for further discussion), it has featured prominently in media coverage and public policy discussions.\footnote{For example, see www.bbc.com/news/health-52473523 or www.weforum.org/agenda/2020/05/covid-19-what-is-the-r-number. Also, several research centers and government institutions provide daily updates of . For instance, https://rt.live. The report https://royalsociety.org/news/2020/09/set-c-covid-r-rate is a very useful public resource.} Thus, news about  can affect market sentiment regarding the state of the pandemic and economic perspectives; therefore, we hypothesize that  predicts volatility in the stock market. This prediction is in line with Yarovaya et al. (2020) and Salisu and Vinh Vo (2020) who emphasize the role of media coverage and social media as channels of financial contagion. To address this hypothesis, we gather information from a large sample of countries around the globe and compare the volatility between two pandemic states, as determined by the value of . We find that  is actually priced into stock markets, as volatility is higher and more sensitive to news in high-contagious states.

Furthermore, the effect of  on volatility is not only statistically significant and economically meaningful but can be orders of magnitude higher than the effect of policy responses. One interpretation of this finding is that  conveys more relevant information about the pandemic’s dynamics than policy interventions. Alternatively, Arroyo-Marioli et al. (2021) find that policy responses eventually reduce , so another reading of our results is that market participants are more responsive to news on the current  than to news on the expected future  that is represented by policy interventions in a context of undue uncertainty.

The rest of the article is organized as follows: Section 3 presents the data and identifies a positive association between volatility and . Section 4 refines the analysis by allowing  to affect volatility nonlinearly and by controlling for fixed effects, policy responses, and serial correlation. Section 5 concludes. All data and replication files are available as supplementary material.

2. Literature review

The COVID-19 pandemic is considered the most adverse peacetime shock to the global economy in a century (World Bank, 2020, p. 136). According to Baker et al. (2020), its effects on the volatility of financial markets has been the largest in the history of pandemics (see also Costa Junior et al., 2021), while Altig et al. (2020) identify significant jumps in uncertainty as a reaction to the pandemic and its economic fallout. Such increases may have profound adverse effects on resource allocation (Bloom, 2014) and financial stability (Bekaert and Hoerova, 2014), so the pandemic has naturally boosted academic debate on its effect on the financial markets worldwide.

Most of the debate focuses on stock markets. Bai et al. (2021) draw from the work of Baker et al. (2020) and show that the spread of infectious diseases with international repercussions, including COVID-19 but also predecessors such as SARS or Ebola, occurring within the last 24 months has increased volatility in international stock markets permanently. Due to different actions by governments in response to the pandemics, its effects have been heterogeneous. Likewise, David et al. (2021) find that stock markets tend to recover fast and sustainably after pandemics, except for the COVID-19 where they have experienced a much slower recovery together with historically high levels of volatility. Focusing exclusively on COVID-19, Onali (2020) is an early contribution that shows how changes in the number of cases and deaths in the US and other countries affected by the coronavirus have an effect on the US stock market returns and on the CBOE Volatility Index (VIX).

Similarly, Ashraf (2020) identifies a strong market reaction early in the pandemic and then 40–60 days afterwards. Stock markets responded to the COVID-19 pandemic quickly but then the responses have varied over time depending on the stage of the pandemic. This conclusion is in line with Lyócsa and Molnár (2020) who find that the persistence of stock market returns increased as market uncertainty and attention to COVID-19 increased.

On the other hand, Topcu and Gulal (2020) discuss the early negative effect of COVID-19 on emerging stock markets. Its effect depended on whether governments took timely measures and announced larger stimulus packages. The findings are consistent with Zaremba et al. (2020) who show that government non-pharmaceutical interventions to significantly and robustly increased the volatility in international stock markets, and Zhang et al. (2020) and Narayan et al. (2021) who conclude that global risks in financial markets increased substantially in response to the pandemic, with individual reactions depending on the severity of the pandemic in each country. Studies such as Topcu and Gulal (2020), Corbet et al. (2021b), Díaz and Henríquez (2021) and Pandey and Kumari (2021) reach similar conclusions.

Apart from stock markets, Mirza et al. (2020) investigate the responses of European investment funds to COVID-19, while Rizwan et al. (2020) study how the pandemic affected the systemic risk in banking sectors around the globe. A common pattern is an initial significant increase in risk, followed by stagnancy at an elevated level that may be reduced with appropriate policy responses to containing systemic risk. On the other hand, Aslam et al. (2020) study foreign exchange markets and report a decline in their efficiency during the pandemic. Bazán-Palomino and Winkelried (2021) find that the response of foreign exchange markets to the pandemic was large but, contrary to what is found in other markets, the increase in risk was not as significant as in previous stressful events, such as the Global Financial Crisis of 2008.

Several studies have examined the influence of the pandemic on the prices of cryptocurrencies. Corbet et al. (2020) show that the
volatility in main Chinese stock markets and Bitcoin evolved jointly during the beginning of the pandemic. Along with gold, cryptocurrencies temporarily displayed some of the characteristics of a safe haven during this period of enormous financial stress. Goodell and Goutte (2021) reach a similar conclusion with a different method. Mnif et al. (2020) investigate the herding biases in cryptocurrency markets, which are complex systems based on speculation, and conclude that COVID-19 has a positive effect on the efficiency of these markets. Iqbal et al. (2021) explore asymmetric responses to good and bad news and show that COVID-19 news had effects of different intensities on the bearish and the bullish scenarios of cryptocurrencies.

Regarding commodity markets, Salisu et al. (2020) find a positive relationship between commodity price returns and a global fear index that confirms the idea that commodity returns increased as pandemic-related fear rose and that some commodity markets were better safe havens than stock markets. Corbet et al. (2020) and Ji et al. (2020) also find the same result. Mensi et al. (2020) show that during the pandemic, the efficiency of gold and oil markets has depended on scales and market trends that highlights the effect of investor sentiment. Further, Yoshino et al. (2021) explore the effects of the pandemic on the competitiveness of renewable energy projects.

The excess volatility in financial markets, especially when the shock is large, responds to irrational herd behavior. For instance, Corbet et al. (2021a) find negative knock-on effects from the pandemic on some companies with related names (such as Corona beer) that exceeded the actual economic effects. But the response is often to bad news about current and expected fundamentals. In the case of the COVID-19 pandemic, Haroon and Rizvi (2020) highlight that the pandemic resulted in unprecedented news coverage and outpouring of opinions in this age of swift propagation of information that made market participants particularly sensitive to coronavirus related news. Indeed, Baek et al. (2020) show that volatility is sensitive to COVID-19 news such as the number of confirmed cases, deaths, and recoveries. Moreover, while negative and positive COVID-19 figures are both significant, the negative news is more impactful. All these findings are confirmed in Salisu and Vinh Vo (2020).

Our research is related to the strand of the literature on how the overwhelming panic that the news outlets generate is associated with increasing volatility in the stock markets. From a policy point of view, it is also related to Baek et al. (2020), Ashraf (2020), Topcu and Gulal (2020), Zaremba et al. (2020), and Zhang et al. (2020); but to the best of our knowledge, this is the first time that R has been treated explicitly as an explanatory factor of volatility.

3. Data and preliminary evidence

3.1. Data and measurements

We construct a panel with data information from various public sources. The panel is unbalanced and covers, at most, 27 countries that jointly account for 97 percent of the global market capitalization and 57 percent of the world population. The sample covers the period from February 2 to August 4, 2020, which amounts to an average of 94 trading days per country. Thus, it includes the outbreaks of COVID-19 in most of Asia, and all of Europe, the US, and the Americas.

We denote the stock market volatility as y, and entertain two measures for it. The first (RV henceforth) is the standard deviation derived from the 5-min sub-sampled realized variance that is advanced by Barndorff-Nielsen and Shephard (2002), surveyed by McAleer and Medeiros (2008), and made available for 24 countries by Heber et al. (2009). The second measure (HL henceforth) is a range estimator for the daily standard deviation in returns based on the high and low indices recorded in intraday trading. The data for all 27 countries are obtained from the webpage investing.com. Following Chou et al. (2015), the corresponding volatility estimator is given by $y = \ln(\text{High}/\text{Low})/\sqrt{4\ln(2)}$.

We also use two alternatives for the time-varying reproductive number $R$. For the first measure, we simulate the epidemiological model developed in Fernández-Villaverde and Jones (2020) and were able to obtain a smooth series of $R$ for 19 countries. The approach is designed to infer the historical $R$ from the data and dynamics (higher-order differences) on the number of deaths, which we obtain from Roser et al. (2020). We refer to this measure as FVJ.

For the second measure of $R$, we resort directly to the predictions of Arroyo-Marioli et al. (2021) for all 27 countries. These authors use signal extraction techniques to infer a slowly varying $R$ from the noisy data of the number of infected (rather than the number of deaths). We refer to this measure as ABKR.

Moreover, the sample correlation between both measures of $R$ is 0.77 that is statistically significant at any level of confidence. In the appendix, we provide a brief discussion of the epidemiological models used to compute our FVJ measure and its main differences with the reproductive number ABKR computed by Arroyo-Marioli et al. (2021).³

Next, we control for policy responses to the pandemic, by using the so-called “stringency index” developed by Hale et al. (2020). The index records the strictness of lockdown style policies that governments around the globe implemented and is available from Roser et al. (2020). The original index ranges from 1 to 100, but we compute a re-scaled version S such that the standard deviation in the whole sample of S equals that of $R$.

³ Further methodological details and several additional results of Fernández-Villaverde and Jones (2020) are available at https://web.stanford.edu/~chadj/Covid/Dashboard.html, and of Arroyo-Marioli et al. (2021) are available at http://trackingr-env.eba-9muars8y.us-east-2.elasticbeanstalk.com.
3.2. Univariate analysis

Table 1 shows the descriptive statistics and prima facie evidence on the significance of some of the effects in our sample, when y is RV volatility. In particular, the correlation coefficient between volatility and the reproductive number is positive and statistically significant in a vast majority of countries, regardless of the measures used for R. The table also gives a comparison of the average volatility between low-contagion (yL, when R ≤ 1) and high-contagion (yH, when R > 1) periods that enable us to examine whether the state of the pandemic is associated with different levels of volatility. The table presents standard t-tests for the null hypothesis that volatility is equal between different states. As expected, the average volatility is higher during the high-contagion state than during the low-contagion state. In most cases, these differences produce very high t-statistics that are statistically significant regardless of the measure of R used in the comparison. The few exceptions are Brazil, China, India, and South Korea.

Table 2 repeats the previous analysis but for HL volatility. The results are remarkably robust and the conclusions remain unaltered.

Although indicative, these results are not necessarily conclusive. The t-tests do allow for heteroscedasticity but fail to account for other distorting factors such as serial correlation and the influence of other conditioning variables. We focus on these factors next.

4. Econometric specification and results

4.1. Methods

To further investigate the relationship between volatility y and R we estimate a piece-wise linear function using panel data for i = 1, 2, ..., n countries and t = 1, 2, ..., T time periods. The regressions control for policy responses measured by the stringency index $S_i$ and for country-specific fixed effects $a_i$. If $1(A)$ denotes the step function such that $1(A) = 1$ if A is true and $1(A) = 0$ otherwise, we define $D_t = 1(R_t > 1)$ as the dummy variable that indicates whether country i is in a high-contagion state in period t. Then:

$$ y_{it} = (\beta^{RL}_0 + \beta^{RL}_1 R_L) (1 - D_t) + (\beta^{RH}_0 + \beta^{RH}_1 R_H) D_t + \beta^{1} S_i + a_i + u_{it}. $$ (1)

This equation enables a nonlinear relationship between $y_{it}$ and $R_{it}$. Not only does (1) capture the heterogeneity displayed in Tables 1 and 2 that corresponds to state-dependent intercepts $\beta_0^{RL} \neq \beta_0^{RH}$, but it also allows $R_{it}$ to affect $y_{it}$ continuously and differently ($\beta^{RL}_{1} \neq \beta^{RH}_{1}$) within each state: $\partial y_{it} / \partial R_{it} = \beta^{RL}_1 (1 - D_t) + \beta^{RH}_1 D_t$.

The regression error $u_{it}$ has zero mean for every i and t. Since in financial markets volatility tends to cluster and persist after innovations, we expect $u_{it}$ to be serially correlated, and such correlation may be modeled as an AR(1) process. Then, Eq. (1) can be written in regression format as:

$$ y_{it} = \beta^1 x_{it} + \alpha_i + u_{it}, \quad \text{and} \quad u_{it} = \rho u_{i,t-1} + \varepsilon_{it}, $$ (2)

where $x_{it} = (1 - D_t, (1 - D_t)R_L, R_H, D_t R_L, S_i)'$ and $\beta = (\beta_{RL0}, \beta_{RL1}, \beta_{RH0}, \beta_{RH1})'$. It seems uncontroversial to assume that $x_{it}$ contains exogenous variables, that is, that $R$ and $S$ are not determined contemporaneously by the behavior of the stock markets. Thus, $E(x_{it}u_{it}) = 0$, and the vector $\beta$ collects the effects of interest, that is:

$$ \frac{\partial E(y_{it})}{\partial E(x_{it})} = \beta^1, $$ (3)

and can be consistently estimated by least squares methods, after controlling for the country-specific fixed effects. Correct inferences about $\beta$ require suitable estimators for the standard errors of the coefficient’s estimator.

To this end, we follow two approaches. The first leaves the serial correlation in $u_{it}$ unmodeled but corrects the standard errors of the fixed-effects estimator either by clustering errors by country (FEC) as described by Hansen (2007), or by using a nonparametric estimator (DK) as advanced by Driscoll and Kraay (1998). Both options allow for an arbitrary serial correlation, and DK is also robust to general forms of spatial dependence. The second approach, advocated by Beck and Katz (1995), is to estimate $\rho$ to compute “panel-corrected standard errors”. Often $\rho$ is assumed to be common across countries (ARc), but the large time dimension in our study allows us to estimate a specific $\rho$ for each country (ARI).

An alternative way to deal with serial correlation is to augment the regression model with the lag of $y_{it}$:

$$ y_{it} = \rho y_{i,t-1} + \delta x_{it} + \alpha_i + \varepsilon_{it}. $$ (4)

In this dynamic equation, the error terms are not serially correlated. However, the effects of interest, comparable to (3), are no longer on $\delta$ but on the transformation:

$$ \frac{\partial E(y_{it})}{\partial E(x_{it})} - \delta \frac{1}{1 - \rho} = \beta^1. $$ (5)

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Both equations in (2) show that $y_{it} = \rho y_{i,t-1} + (1 - \rho) \delta x_{it} + \rho \varepsilon_{it} + (1 - \rho) \alpha_i + \varepsilon_{it}$. Thus, (4) can be regarded as an approximation of (2) with $\rho \delta > 0$ or when $\Delta x_{it}$ is small compared to $x_{it}$, which are conditions that are satisfied in our sample.
4.2. Results

Table 3 presents the estimates of the coefficients $\beta$ in (1) and, when applicable, of the autoregressive parameter $\rho$, for both ways to measure $R$ and for several estimation methods as well as when $y_r$ is RV volatility. The policy variable $S_r$ is the stringency index re-scaled such that the standard deviation of $S_r$ equals that of $R$, so that $\beta_{RL}, \beta_{RL}^*, \gamma_R$, and $\gamma_S$ are measured in the same units.

The estimations have a good fit as reflected by the adjusted $R^2$ statistics above 0.3. More importantly, even though we do not explicitly report the test statistics of the null hypothesis $\beta_{RL} = \beta_{RL}^*$ and $\gamma_R = \gamma_S$, it is strongly rejected in all instances. The non-linearity of the relationship between volatility and $R$ is quite apparent from the point estimates and their significance.

The coefficients of the high-contagion state $\beta_{HL}$ and $\beta_{RL}$ are precisely estimated and always statistically significant. The estimations of the low-contagion state coefficients $\beta_{LU}$ and $\beta_{RL}$ are not as robust, because whether they are statistically significant depends on the data used to measure $R$ and the estimation method. In all cases, $\beta_{LU} \neq \beta_{RL}$ confirms that the average volatility increases as the pandemic evolves from $R \leq 1$ to $R > 1$, while $\beta_{RL} > 0$ indicates that once in the high-contagion state market volatility becomes particularly sensitive and responsive to the dynamics of $R$. This is true even when the estimate of $\beta_{RL}$, the slope in the low-contagion state, happens

Table 1

| Country       | Mean | $T$ | $R$ from deceased (PVJ) | $R$ from infected (ABKR) |
|---------------|------|-----|-------------------------|--------------------------|
|               |      |     | $T$ | $y_H$ | $y_L$ | $t$ | $T$ | $y_H$ | $y_L$ | $t$ |
| Argentina     | –    | –    | 101 | 1.73  | 1.17  | 0.88 | 2.27 | 97  | 1.62  | –    | –    |
| Australia     | 97   | 1.62 | –   | –     | –     | –   | –   | 0.39*** | 1.12 | 0.83 | 2.15** |
| Belgium       | 101  | 1.73 | 0.53*** | 1.17 | 0.88  | 2.27** | 0.65*** | 1.09 | 0.88 | 2.12** |
| Brazil        | 94   | 1.55 | 0.89*** | –   | –     | –   | 0.86*** | –   | –   | –   |
| Canada        | 94   | 1.15 | 0.88*** | 1.78 | 0.71  | 6.91*** | 0.88*** | 1.26 | 0.74 | 4.21*** |
| Chile         | 109  | 0.93 | –   | –     | –     | –   | –   | 0.08 | 1.04 | 0.93 | 1.07 |
| China         | 109  | 0.93 | –   | –     | –     | –   | –   | –   | –   | –   | –   |
| Colombia      | –    | –    | –   | –     | –     | –   | –   | –   | –   | –   | –   |
| Denmark       | 91   | 1.15 | 0.47*** | 1.24 | 0.86  | 2.37** | 0.2’ | –   | –   | –   |
| Finland       | 86   | 1.1  | –   | –     | –     | –   | –   | 0.31*** | 1.06 | 0.93 | 1.61 |
| France        | 107  | 1.77 | 0.49*** | 1.76 | 0.76  | 5.95*** | 0.68*** | 1.09 | 0.78 | 3.51*** |
| Germany       | 100  | 1.58 | 0.67*** | 1.34 | 0.79  | 3.79*** | 0.82*** | 1.25 | 0.77 | 3.96*** |
| India         | 96   | 1.54 | 0.82*** | 1.01 | 0.89  | 0.96 | 0.81*** | –   | –   | –   |
| Italy         | 111  | 1.54 | 0.35*** | 1.76 | 0.81  | 5.79*** | 0.47*** | 1.22 | 0.82 | 3.48*** |
| Japan         | 109  | 1.24 | 0.29*** | 1.19 | 0.72  | 4.19*** | 0.22** | 1.11 | 0.72 | 3.89*** |
| Mexico        | 93   | 1.07 | 0.59*** | 1.02 | 0.69  | 3.79*** | 0.61*** | 1.01 | 0.57 | 11.28*** |
| Netherlands   | 103  | 1.6  | 0.36*** | 1.48 | 0.74  | 4.02*** | 0.75*** | 1.38 | 0.71 | 4.28*** |
| Norway        | 77   | 1.65 | –   | –     | –     | –   | –   | 0.42*** | 1.2  | 0.8  | 2.69*** |
| Pakistan      | 87   | 1.19 | –   | –     | –     | –   | –   | 0.63*** | 1.18 | 0.6  | 5.28*** |
| Portugal      | 94   | 0.99 | 0.52*** | 1.36 | 0.85  | 3.09*** | 0.87*** | 1.1  | 0.83 | 2.92*** |
| Singapore     | 83   | 0.95 | –   | –     | –     | –   | –   | 0.45*** | 1.24 | 0.8  | 4.29*** |
| South Korea   | 114  | 1.25 | –0.03 | 0.94 | 1.04  | –0.83 | –0.24*** | 0.78 | 1.18 | –3.82*** |
| Spain         | 90   | 1.87 | –   | –     | –     | –   | –   | 0.5*** | 1.11 | 0.8  | 3.44*** |
| Sweden        | 97   | 1.18 | 0.86*** | 1.94 | 0.74  | 6.18*** | 0.84*** | 1.08 | 0.59 | 6.22*** |
| Switzerland   | 96   | 1.58 | –   | –     | –     | –   | –   | 0.7*** | 1.14 | 0.73 | 2.78*** |
| United Kingdom| 103  | 1.86 | 0.79*** | 1.55 | 0.74  | 4.76*** | 0.69*** | 1.24 | 0.73 | 4.23*** |
| United States | 100  | 1.72 | 0.73*** | 1.17 | 0.7  | 3.9***  | 0.89*** | 1.21 | 0.61 | 5.21*** |

Notes: $T$ is the number of time periods. Mean is the sample average of $y_t$, times 100. Corr is the Pearson correlation. $y_H$ and $y_L$ are sample averages in the high or low-contagion states (respectively, $R > 1$ and $R < 1$), and $t$ is the $t$-statistic of the null hypothesis that $y_H = y_L$. Some cells may be blank due to data unavailability or because there was an insufficient number of observations in either the low or high-contagion states. The symbol ‘’ (‘‘) (‘***’) denotes statistical significance at the 10% [5%] [1%] confidence level.

Once $\beta$ and $\rho$ are estimated, the standard errors of $\beta$ can be computed using the delta method. It is well known that the bias of the fixed-effects estimator of this dynamic equation (DFE) is $O(T^{-1})$ (see, inter alia, Kiviet, 1995), so it is expected to be negligible for the large $T$ in our application. Alternatively, Eq. (4) can be estimated country by country and the estimators averaged to render the mean group estimator (MG) of Pesaran and Smith (1995), which is consistent under mild conditions.

4.2. Results
Correlations and population as the pandemic develops. However, it is always orders of magnitude smaller than that of $\beta$. On the other hand, the estimate of $\beta$, which is the effect of the policy responses, is statistically significant and positive most of the time, which is in line with findings in Zaremba et al. (2020). However, it is always orders of magnitude smaller than that of $R$. An interpretation is that $R$ conveys relevant information about the pandemic dynamics not signaled by the policy interventions. Alternatively, Li et al. (2021) and Arroyo-Marioli et al. (2021) show that policy responses precede $R$, so another reading is that participants are more responsive to news on the current $R$ than to news on the forecasts of $R$ that represents the policy interventions in a context of high uncertainty.

Table 4 is similar to Table 3 but with HL volatility. The main conclusions of our exploration remain almost unaltered: for all estimation methods and both ways to measure $R$, the parameters of the high-contagion state can be precisely estimated, are statistically different from those of the low-contagion state, and $\beta_{HL}$ is much larger than $\beta$. An important difference is that the coefficients of the low-contagion state are precisely estimated when $R$ is measured as in Arroyo-Marioli et al. (2021). The finding that the magnitude of $\beta_{HL}$ is half as large as that of $\beta_{HL}$ remains.

### Table 2
Correlations and t-tests for high-low range volatility.

| Country       | $T$ | Mean | Corr | $y_1$ | $y_2$ | $t$ | $R$ from deceased (PVJ) | Corr | $y_1$ | $y_2$ | $t$ | $R$ from infected (ABKR) | Corr | $y_1$ | $y_2$ | $t$ |
|---------------|-----|------|------|-------|-------|----|-------------------------|------|-------|-------|----|--------------------------|------|-------|-------|----|
| Argentina     | 87  | 2.8  | 0.97 |       |       |    | 0.27        |      |       |       |    |                          |      |       |       |    |
| Australia     | 97  | 1.66 |       |       |       |    | 0.38        |      |       |       |    |                          |      |       |       |    |
| Belgium       | 101 | 1.6  | 0.49  | 1.16  | 0.89  | 1.78 | 0.57        |      |       |       |    |                          |      |       |       |    |
| Brazil        | 94  | 2.1  | 0.86  |       |       |    | 0.82        |      |       |       |    |                          |      |       |       |    |
| Canada        | 94  | 1.16 | 0.82  | 1.88  | 0.66  | 4.83 | 0.82        |      |       |       |    |                          |      |       |       |    |
| Chile         | 92  | 1.46 | 0.34  | 1.16  | 0.74  | 4.42 | 0.62        |      |       |       |    |                          |      |       |       |    |
| China         | 109 | 0.93 |       |       |       |    | 0.09        |      |       |       |    |                          |      |       |       |    |
| Colombia      | 88  | 1.38 | 0.53  |       |       |    | 0.67        |      |       |       |    |                          |      |       |       |    |
| Denmark       | 91  | 1.07 | 0.45  | 1.23  | 0.87  | 2.3  | 0.19        |      |       |       |    |                          |      |       |       |    |
| Finland       | 86  | 1.06 |       |       |       |    | 0.21        |      |       |       |    |                          |      |       |       |    |
| France        | 107 | 1.57 | 0.47  | 1.73  | 0.76  | 5.69 | 0.65        |      |       |       |    |                          |      |       |       |    |
| Germany       | 100 | 1.56 | 0.61  | 1.32  | 0.8   | 3.2  | 0.74        |      |       |       |    |                          |      |       |       |    |
| India         | 96  | 1.59 | 0.8   | 1     | 0.93  | 0.49 | 0.8         |      |       |       |    |                          |      |       |       |    |
| Italy         | 111 | 1.96 | 0.36  | 1.95  | 0.77  | 4.13 | 0.46        |      |       |       |    |                          |      |       |       |    |
| Japan         | 109 | 1.2  | 0.31  | 1.19  | 0.7   | 4.27 | 0.23        |      |       |       |    |                          |      |       |       |    |
| Mexico        | 93  | 1.14 | 0.73  | 1.03  | 0.58  | 4.59 | 0.6         |      |       |       |    |                          |      |       |       |    |
| Netherlands   | 103 | 1.42 | 0.35  | 1.46  | 0.75  | 3.98 | 0.73        |      |       |       |    |                          |      |       |       |    |
| Norway        | 77  | 1.41 |       |       |       |    | 0.36        |      |       |       |    |                          |      |       |       |    |
| Pakistan      | 87  | 1.08 |       |       |       |    | 0.61        |      |       |       |    |                          |      |       |       |    |
| Portugal      | 94  | 1.27 | 0.44  | 1.39  | 0.84  | 2.77 | 0.75        |      |       |       |    |                          |      |       |       |    |
| Singapore     | 83  | 1.06 |       |       |       |    | 0.41        |      |       |       |    |                          |      |       |       |    |
| South Korea   | 114 | 1.28 | 0.01  | 0.91  | 1.05  | −1.02| −0.21       |      |       |       |    |                          |      |       |       |    |
| Spain         | 90  | 1.8  |       |       |       |    | 0.53        |      |       |       |    |                          |      |       |       |    |
| Sweden        | 97  | 1.19 | 0.82  | 1.98  | 0.73  | 5.24 | 0.79        |      |       |       |    |                          |      |       |       |    |
| Switzerland   | 96  | 1.37 |       |       |       |    | 0.71        |      |       |       |    |                          |      |       |       |    |
| United Kingdom| 103 | 1.6  | 0.77  | 1.49  | 0.76  | 3.99 | 0.7         |      |       |       |    |                          |      |       |       |    |
| United States | 100 | 1.53 | 0.7   | 1.2   | 0.66  | 4.56 | 0.8         |      |       |       |    |                          |      |       |       |    |

Notes: See notes to Table 1.

5. Conclusions

This study is a first attempt to examine the influence of the COVID-19 reproductive number $R$ on the dynamics of volatility in international stock markets. We show that volatility is more (less) sensitive to $R$ when the pandemic is in a high-contagion (low-contagion) state. Furthermore, since we control not only for fixed effects but also for the stringency of policy interventions, the $R$ conveys information to financial market participants regarding the future development of the pandemic that is not signaled by policy interventions. This is so because the spread of the virus not only depends on those policies, but also on the changing behavior of the population as the pandemic develops.

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5 Another robust finding is that the hypothesis $H_0: \beta_{HL} = \beta_{HL} + \beta_{HL}$ cannot be rejected that indicates the piece-wise linear function is continuous at $R = 1$. Although, the finding is not of direct relevance to our analysis, it may be useful for future explorations on the relation between volatility and $R$. 

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Table 3
Estimation results for realized volatility.

|                | $R$ from deceased (FVJ) |                | $R$ from infected (ABKR) |
|----------------|-------------------------|----------------|--------------------------|
|                | (1) FEC                | (2) DK         | (3) ARc                  | (4) ARi                  | (5) DFE                  | (6) MG                  | (1) FEC                | (2) DK         | (3) ARc                  | (4) ARi                  | (5) DFE                  | (6) MG                  |
| $\beta_{uc}$  | -0.002                  | -0.002         | 0.001                   | 0.002                    | 0.003                    | 0.065                   | 0.012***                | 0.012***                | 0.001                   | 0.007***                | 0.017***                | 0.005                   |
|                | (0.45)                  | (0.43)         | (1.43)                  | (0.60)                   | (1.38)                   | (1.34)                  | (2.20)                  | (2.27)                   | (1.43)                  | (2.28)                   | (2.44)                  | (0.57)                   |
| $\rho$        | 0.004                   | 0.004          | 0.003                   | 0.003                    | 0.001                    | -0.065                  | 0.008**                 | 0.008**                 | 0.003                   | -0.005**                | -0.009**                | 0.002                   |
|                | (1.1)                   | (1.37)         | (1.29)                  | (0.94)                   | (0.74)                   | (1.34)                  | (1.68)                  | (1.98)                   | (1.29)                  | (1.76)                   | (1.70)                  | (0.28)                   |
| $\beta_{ul}$  | 0.023***                | 0.023***       | 0.028***                | 0.024***                 | 0.021***                 | 0.023***                | 0.015***                | 0.015***                | 0.028***                | 0.019***                | 0.010***                | 0.013***                |
|                | (3.52)                  | (3.08)         | (8.03)                  | (6.72)                   | (2.66)                   | (2.60)                  | (2.86)                  | (2.67)                   | (8.03)                  | (8.48)                   | (2.18)                  | (2.00)                   |
| $\beta_{ht}$  | 0.026***                | 0.026***       | 0.030***                | 0.029***                 | 0.025***                 | 0.026***                | 0.020***                | 0.020***                | 0.030***                | 0.021***                | 0.017***                | 0.022***                |
|                | (5.32)                  | (5.09)         | (13.06)                 | (18.12)                  | (4.18)                   | (4.22)                  | (5.64)                  | (4.76)                   | (13.06)                 | (21.83)                 | (5.60)                  | (6.05)                   |
| $\beta_{ht}$  | 0.009***                | 0.009***       | 0.008***                | 0.006***                 | 0.007***                 | 0.008***                | 0.004**                 | 0.004*                  | 0.003**                 | 0.002                  | -0                      | 0.002                   |
|                | (4.22)                  | (2.53)         | (5.76)                  | (2.80)                   | (6.03)                   | (2.03)                  | (2.32)                  | (1.88)                   | (5.76)                  | (2.57)                   | (1.23)                  | (0.01)                   |
| $\beta_{h}$   | 0.649                   | 0.610          | 0.653***                | 0.467***                 | 0.649                    | 0.552                   | 0.619***                | 0.396***                | 0.396***                | 0.739                   | 0.665                   |
|                | (.5)                    | (.5)           | (.5)                    | (.5)                     | (.5)                     | (.5)                    | (.5)                    | (.5)                     | (.5)                     | (.5)                     | (.5)                     | (.5)                     |
| $\rho$        |                        |                |                        |                          |                          |                          | 0.649                   | 0.552                   | 0.619***                | 0.396***                |
|                |                        |                |                        |                          |                          |                          | (.5)                    | (.5)                     | (.5)                     | (.5)                     | (.5)                     | (.5)                     |
| $N$           | 1566                    | 1566           | 1550                    | 1566                     | 1213                     | 1213                    | 2277                    | 2277                     | 1550                    | 2277                     | 1754                    | 1754                    |
| $n$           | 16                      | 16             | 16                      | 16                       | 16                       | 16                      | 24                      | 24                       | 24                      | 24                       | 24                       | 24                       |
| $T$           | 98                      | 98             | 97                      | 98                       | 76                       | 76                      | 95                      | 95                       | 97                      | 97                       | 73                       | 73                       |
| Adj $R^2$     | 0.368                   | 0.368          | 0.312                   | 0.445                    | 0.660                    | 0.678                   | 0.370                   | 0.370                    | 0.312                   | 0.489                    | 0.642                    | 0.665                    |

Notes: Estimates of the coefficients in $\beta$, direct in static models, columns (1) to (4), or transformed as in Eq. (5) in columns (5) and (6). $N = nT$ is the number of observations, $n$ is the number of countries and $T$ the average number of periods per country. Absolute t-statistics in parentheses. The symbol ’∗’ ’∗∗’ ’∗∗∗’ denotes statistical significance at the 10% [5%] [1%] confidence level. All regressions include country-specific effects. FEC: fixed-effects estimator of Eq. (2), standard errors clustered by country; DK, fixed-effects estimator with Driscoll-Kraay standard errors; AR1c, GLS fixed-effects estimator assuming a common $\rho$ across countries; AR1i, GLS fixed-effects estimator with country-specific $\rho$, the average $\rho$ is reported. DFE, fixed-effects estimator of Eq. (4). MG, mean group estimator (average estimates and adjusted $R^2$ reported).
|              | $R$ from deceased (FVJ) |                |              | $R$ from infected (ABKR) |                |              |
|--------------|-------------------------|----------------|--------------|--------------------------|----------------|--------------|
|              | (1) FEC                | (2) DK         | (3) ArC      | (4) ArI                  | (5) DFE        | (6) MG       | (7) FEC    | (8) DK    | (9) ArC | (10) ArI | (11) DFE | (12) MG   |
| $\beta_{L}$ | 0.002                  | -0.002         | -0.002***    | 0.001                    | 0.004          | 0.004        | 0.015***   | 0.015***   | -0.002***   | 0.010***   | 0.020***   | -0.001     |
|              | (0.59)                 | (0.48)         | (3.19)       | (0.19)                   | (1.25)         | (0.20)       | (2.69)     | (2.69)     | (3.19)   | (3.43)   | (3.03) | (0.05)     |
| $\beta_{H}$ | 0.005                  | 0.005          | 0.004*       | 0.003                    | 0.002          | 0.013        | -0.009**   | -0.009**   | 0.004*     | -0.003     | -0.011**   | 0.006      |
|              | (1.49)                 | (1.61)         | (1.72)       | (1.21)                   | (0.76)         | (0.73)       | (2.06)     | (2.27)     | (1.72)   | (1.29)   | (2.05) | (0.51)     |
| $\beta_{ML}$| -0.026***              | -0.026***      | -0.029***    | -0.026***                | -0.025***      | -0.013       | -0.015***   | -0.015***   | -0.029***   | -0.015***   | -0.013***   | -0.027**   |
|              | (3.24)                 | (2.85)         | (7.45)       | (6.62)                   | (3.43)         | (0.80)       | (2.93)     | (2.65)     | (7.45)   | (6.45)   | (3.39) | (2.19)     |
| $\beta_{ML}$| 0.028***               | 0.028***       | 0.030***     | 0.030***                 | 0.029***       | 0.027**      | 0.021***    | 0.021***    | 0.030***    | 0.021***    | 0.020***    | 0.040***   |
|              | (5.06)                 | (4.36)         | (11.93)      | (16.33)                  | (5.51)         | (2.55)       | (5.95)     | (4.94)     | (11.93)  | (21.76)  | (7.68) | (3.88)     |
| $\beta_{S}$ | 0.009***               | 0.009***       | 0.008***     | 0.006***                 | 0.005***       | 0            | 0.003*     | 0.003      | 0.008***   | 0.003***   | 0.001       | -0.005     |
|              | (4.00)                 | (2.60)         | (5.65)       | (3.20)                   | (2.88)         | (0.01)       | (1.70)     | (1.34)     | (5.65)   | (2.61)   | (0.46) | (1.07)     |
| $\rho$      | 0.592                  | 0.549          | 0.588***     | 0.408***                 | 0.592          | 0.500        | 0.592      | 0.500      | 0.568***   | 0.345***   | 0.345***    | 0.345***   |
|              | (.0)                   | (.0)           | (18.65)      | (9.07)                   | (.0)           | (.0)         | (.0)       | (.0)       | (14.89)  | (9.96)   | (9.96) | (9.96)     |
| N            | 1831                   | 1831           | 1812         | 1831                     | 1416           | 1416         | 2542       | 2542       | 1812     | 2542     | 1957   | 1957       |
| n            | 19                     | 19             | 19           | 19                       | 19             | 19           | 27         | 27         | 19       | 27       | 27     | 27         |
| T            | 96                     | 96             | 95           | 96                       | 75             | 75           | 94         | 94         | 95       | 94       | 72     | 72         |
| Adj $R^2$   | 0.291                  | 0.291          | 0.256        | 0.354                    | 0.534          | 0.567        | 0.302      | 0.302      | 0.256    | 0.380    | 0.533  | 0.545      |

Notes: See notes to Table 3.
We hope our findings help guide research to a better understanding of how pandemic news affects market volatility. A relevant topic is the discovery and subsequent announcements of variants of COVID-19, such as the alpha and the delta. The variants are of concern to public policy because they have been more contagious, so initially they have had a large R that would eventually increase the population-wide R. Our analysis suggests a new hypothesis in which news from very contagious variants will increase stock market volatility through this mechanism.

Another interesting route is related to vaccination. It is by now well-documented that vaccines alter the dynamics of the virus’s spread (see, inter alia, Levine-Tiefenbrun et al., 2021), thus they have the potential to reduce R. On the other hand, studies such as Yang et al. (2021) suggest that massive inoculation needs to be complemented by other non-pharmaceutical interventions in order to have a sustained reduction in R (see also McCarthy, 2021). Our analysis predicts a reduction in volatility from such interventions.

Appendix A. SIR models

The outbreak of the COVID-19 pandemic immediately renewed the academic interest in epidemiological systems of dynamic equations to describe and predict the spread of the disease in the population. In particular, the so-called SIR models (susceptible-infected-recovered) that follow the tradition of Kermack and McKendrick (1927). Next, we present two approaches, inspired SIR dynamics, to measure the reproductive number from observable data on either the number of deaths, as in Fernández-Villaverde and Jones (2020), or the number of infected people, as in Arroyo-Marioli et al. (2021).

Consider a five-state model, where the members of a population of constant size N are susceptible (S) until they contract the disease by coming into contact with a person who is infectious (I). An infected or resolving individual (B) may die (D) or recover (C) from the disease. Thus, in period t:

\[
S_t + I_t + B_t + D_t + C_t = N. \quad (6)
\]

The model consists of the laws of motion of these interdependent states. Following Fernández-Villaverde and Jones (2020), these are:

\[
S_{t+1} = S_t - \beta_t \left( \frac{I_t}{N} \right) S_t \quad (7)
\]

\[
I_{t+1} = I_t + \beta_t \left( \frac{I_t}{N} \right) S_t - \gamma I_t \quad (8)
\]

\[
B_{t+1} = B_t + \gamma I_t - \theta B_t \quad (9)
\]

\[
D_{t+1} = D_t + \delta \theta B_t \quad (10)
\]

\[
C_{t+1} = C_t + (1 - \delta) \theta B_t \quad (11)
\]

Here a susceptible person comes in contact with a person who is infectious at rate \( \beta_t \). Hence, the rate of spread of the disease is given by \( \beta_t (I_t / N) \), see Eqs. (7) and (8). Interestingly, \( \beta_t \) depends on time-varying factors such as the stringency of government interventions or the sanitary practices of the population. In Eq. (8), the parameter \( \gamma \) is the inverse of the average number of days a person is infectious. Similarly, in Eq. (9) the constant \( \theta \) is the fraction of people that exit the resolving state each period. Finally, in Eqs. (10) and (11), \( \delta \) is the mortality rate of the disease (i.e., the probability that an infected person dies). Note that the model assumes that a recovered individual becomes immune to the disease, which is known to be the case for COVID-19 at least for few months.

The basic reproductive number (the expected number of infections generated by an ill person given the social distancing practices at time t) is defined as \( R_{te} = \beta_t / \gamma \), while the effective reproductive number, the average number of new infections caused by a single infected individual at time t, is given by:

\[
R_t = R_{te} \frac{S_t}{N} = \frac{\beta_t S_t}{\gamma N} \quad (12)
\]

Fernández-Villaverde and Jones (2020) show how to calculate \( R_t \) consistently with the above dynamics and by exclusively using observable data of the number of deaths at time t. In particular, let \( d_t = D_t / N \) and consider the difference operator \( \Delta d_t = d_t - d_{t-1} \). It follows that:

\[
\beta_t = \frac{N}{S_t} \left( \gamma + \frac{\Delta d_{t+2} + \theta \Delta d_{t+1}}{\Delta d_{t+2} + \theta d_{t+1}} \right), \quad (13)
\]

and

\footnote{A variant tracker is www.who.int/en/activities/tracking-SARS-CoV-2-variants.}
Thus, by adding noise to (15), which represents a measurement error, Arroyo-Marioli et al. (2021) obtain the measurement equation of a state space system in which $R_t$ is treated as a hidden state. The transition equation of this system is simply $R_t = R_{t-1} + \text{noise}$, that captures well the idea that $R_t$ varies smoothly through time and that it responds to unpredictable shocks. Thus, given observable data of $I_t$, a real-time prediction of $R_t$ can be inferred by using the Kalman filter and a smoother (see Harvey, 1989, for a textbook treatment). Arroyo-Marioli et al. (2021) show that their predictions on $R$ are quite robust to both potential model misspecification and to measurement errors in the number of new cases.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ribaf.2021.101517.
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