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When the markets get CO.V.I.D: COntagion, Viruses, and Information Diffusion☆

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ABSTRACT

We quantify the exposure of major financial markets to news shocks about global contagion risk while accounting for local epidemic conditions. For a wide cross section of countries, we construct a novel dataset comprising (i) announcements related to COVID19 and (ii) high-frequency data on epidemic news diffused through Twitter (Hassan et al., 2019's methodology). We provide novel empirical evidence about financial dynamics both around epidemic announcements and at daily/intra-daily frequencies. Analysis of contagion data and social media activity about COVID19 suggest that the market price of contagion risk is significant.

1. Introduction

COVID19 has manifested itself as a very aggressive and fast epidemic that – at the time of the first draft of this paper – brought major economic countries to their knees.[1] Given the fast-increasing contagion curve of COVID19 and its global scale, this epidemic event is challenging common economic policy interventions and depressing the global value of our assets, *i.e.*, the financial wealth of millions of households all over the world.

Given that severe virus-related crises are expected to become more frequent, we find it relevant to use COVID-19-related data to ask the following broad questions about financial market reactions to viral contagion risk. First, what is the average impact of medical announcements on financial returns? Equivalently, is the diffusion of this information enhancing wealth or adding risk? Second, what is the market price of news risk related to global contagion dynamics? Third, can local contagion conditions help us predict expected returns?

Last but not least, can we use social media activity to measure the production and diffusion of information about epidemic risk? This question is important for at least two reasons. First, fast epidemic outbreaks catch investors off guard; hence, real-time indexes based on

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[1] Our first draft is dated 3/23/2020. To assess the severity of COVID19, see the March 11, 2020 WHO Director-General's opening remarks (https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020).

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social media news may function as a useful predictive tool. Second, estimating multidimensional models requires many observations that we may gather by using high-frequency data instead of waiting for daily medical bulletins.

In this study, we address these questions by quantifying the exposure of major financial markets to news shocks about global contagion risk accounting for local epidemic conditions. For a broad cross-section of countries, we construct a novel data set comprising (i) medical announcements related to COVID-19; and (ii) high-frequency data on epidemic news diffused through Twitter (among others, see Hassan et al., 2019; van Binsbergen et al., 2022). Across several classes of financial assets and currencies, we provide novel empirical evidence about financial dynamics (i) around epidemic announcements, (ii) at a daily frequency, and (iii) at an intra-daily frequency. Formal estimations based on contagion data and social media activity about COVID-19 confirm that the market price of epidemic risk is very significant. Hence prudential policies that mitigate global contagion or local diffusion may be extremely valuable for financial wealth. More broadly, we offer a methodology for constructing a rich framework of information diffusion and information attention that future empiricists can adapt to examine future sources of global crises.

Interpretation of our findings. Before describing our findings in more detail, we must clarify how to interpret them. There is no doubt that the COVID pandemic was unprecedented in many dimensions (Baker et al., 2020). Nevertheless, our high-frequency social-media-based approach can also be informative when adapted to future pandemic events. Tracking pandemic-related sentiment and contagion dynamics can be fundamental to portfolio managers in future pandemic events. In this sense, our analysis is not simply a case study of a unique, rare event. Rather, it is very flexible as it shows how to gather a rich-and-reliable dataset for formal statistical tests even after a few weeks from the beginning of a 'brand new' pandemic. Given our high-frequency approach, we can track the full evolution of the pandemic across multiple different contagion waves. Furthermore, our methodology is broad as it allows financial economists to study many relevant dimensions of financial markets (see, for example, Hassan et al., 2020).

In addition, after having collected more than 15,800 medical announcements across many countries, our results on the positive *average* appreciation of equity markets can be reasonably interpreted as a statement on *expected* appreciation. Our novel and sizeable dataset should minimize concerns about 'peso problems'.

Even though we aim to provide a flexible set of tools for future pandemic-related studies, we acknowledge that future crises may differ from the COVID one. In this case, future research should adopt our seminal approach as already done, for example, in the financial intermediation literature, to analyze rare-but-severe global financial crises.

Current results in detail. An important contribution of our work is the collection of a novel dataset on the COVID-19 pandemic that includes (i) an extensive set of official announcements on medical conditions (more than 16,000 announcements) and (ii) news diffused on Twitter in real-time by major newspapers (based on more than 823,000 tweets). We identify major newspapers for a large cross-section of countries in the spirit of Baker et al. (2016). We do not analyze articles; instead, we track news published on Twitter in real-time to produce high-frequency data when needed.

More specifically, we track tweets posted by major newspapers with keywords such as 'coronavirus' and 'covid19'. For each newspaper, we use the location of its headquarters to identify its specific time zone. As a result, we gather thousands of tweets for a large cross-section of countries that we can aggregate at different frequencies and across regions.

Given this data set, we document several important facts about news diffusion. First, both Twitter-based news diffusion (measured by the number of tweets) and attention (measured by the number of retweets) spike upon contagion-related announcements. Second and more broadly, the diffusion of information increases substantially in each country in our data set as soon as that country goes into an epidemic state.[2] Third, our measured increase in information diffusion is particularly pronounced precisely during the hours in which financial markets are open. All of these empirical facts suggest that tracking Twitter-diffused news is a reliable way to capture the information set of investors at a high frequency.

Turning our attention to financial dynamics, we look at equity returns around announcements, that is, in a ± 60 minute window. We find that cumulative equity returns jump upward in the post-announcement time window. This result is robust across several different specifications. In addition, we conduct the same analysis by looking at the government bond market and find a small decline in advanced economies (henceforth AEs) and no adjustment in emerging economies (henceforth EEs). We show that these results are consistent with a simple model in which the (i) demand of assets (see, for example, Koijen and Yogo, 2019) is driven by agents who care about the timing of resolution of cash-flow uncertainty; and (ii) the supply of bonds is less upward sloping than the supply of equities. Our high-frequency result is also consistent with the results documented by Gormsen and Koijen (2020) looking at dividend futures.

According to an LDA model applied to our tweets (in the spirit of Bybee et al., 2020a), cases are one of the main drivers of the topics that received attention during the pandemic. Accordingly, in the last step of our analysis, we group countries into three portfolios daily according to their relative number of COVID-19 cases. We do this separately for AEs and EEs. The H (L) portfolio comprises the equity returns of the top (bottom) countries in terms of COVID-19 contagion cases. We then estimate a no-arbitrage based model in which we allow for time-varying betas ($\beta_{i,t}$) with respect to global contagion risk. Specifically, we allow equity returns to respond to global viral contagion news according to each portfolio's relative share of official COVID-19 cases. Global contagion risk is measured either by innovations in the growth rate of global COVID-19 contagion cases or by innovations in the tone of our COVID-19-related tweets.

This model can capture many of the features of equity returns that we document in our descriptive analysis. First, this model captures predictability through contagion-based time-varying betas. Second, this specification has the potential to capture higher negative skewness for countries that go through more severe contagion paths.[3] Third, this model accounts for heterogeneous exposure to global contagion news, enabling us to identify the market price of risk of this global contagion component.

Across all of our specifications, the market price of contagion risk is both statistically significant and extremely high. Equities are more exposed to risk than bonds. Both within AEs and EEs, heterogeneous exposure to contagion risk is substantial, and as a result, an equity-based HML-COVID strategy bears a high risk premium. An HML-COVID strategy that goes long in bonds of countries with a larger share of cases and short in those with a smaller share of cases, instead, provides an insurance premium. This suggests that bonds tend to become safer in countries exposed to heightened contagion risk. We find that this result is particularly sizable among EEs.

[2] We identify the beginning of the epidemic state with the day on which the number of confirmed COVID-19 cases becomes greater than or equal to 100.

[3] Consider the case of portfolio H comprising countries receiving a sequence of relatively more severe contagion news. This portfolio will have greater exposure to adverse news ($|\beta_{H,t}|$ increases) as the relative contagion share of the portfolio grows. As the relative contagion share starts to flatten out and eventually decline, the sensitivity of this portfolio to good news is reduced ($|\beta_{H,t}|$ shrinks), meaning that returns will be less sensitive to positive news and hence the right tail of their distribution will not be very long.

These results conform well with the data on weekly international investment flows. Countries with lower (higher) contagion levels are expected to experience equity inflows (outflows). Expected inflows are stronger in AEs than in EEs. In contrast, when looking at bonds, these findings are almost absent in AEs and reversed in EEs, meaning that in high-covid emerging economies, the flows going toward government bonds increase. This is consistent with the idea that bonds are perceived as safer assets in EEs.

In order to further exploit our rich framework, we consider a more granular cross section by looking at industry-level equity indices in Europe. This task is relevant for at least two reasons: (i) industries are well known to be difficult to price; and (ii) our industries comprise firms based in different countries and hence their riskiness is based on an interesting mix of country-level contagion conditions. Our estimation confirms that the market price of contagion risk is significant. In addition, we find relevant heterogeneity in risk exposure across industries.

In the last step of our analysis, we run intra-day regressions taking advantage of our high-frequency Twitter-based risk measure. We focus on European countries whose markets are open simultaneously, namely, ITA, ESP, UK, FRA, DEU, CHE, and SWE. Every day, we group them into three portfolios according to their relative number of COVID-19 cases measured in the previous 24 h. The H (L) portfolio comprises the equity returns of the top-2 (bottom-2) countries for COVID-19 contagion cases.

Our novel high-frequency estimation confirms our main findings: contagion risk carries a significant market price of risk. Hence policies related to the prevention and containment of contagion could be valuable not only in terms of lives saved but also in terms of global financial wealth. These results also hold after controlling for the market and changes in equity volatility. Our results have been very stable over time and can be explored at https://sites.google.com/view/when-markets-get-covid/, a website that we use for the visualization of our data.

Related literature. Due to its relevance, the COVID-19 crisis has spurred a lot of contemporaneous research (Goldstein et al., 2021). An important strand of the literature focuses on the measurement of both COVID-19-induced uncertainty and firm-level risk exposure by utilizing textual analysis and surveys (see, for example, Hassan et al., 2020; Giglio et al., 2020). We focus on high-frequency data, Twitter-based news diffusion, epidemic announcements, and country-level asset price dynamics.

Within the literature that studies news coverage and reaction to news, our manuscript is methodologically related to the work of, among others, (van Binsbergen et al., 2022), (Bianchi et al., 2021), (Hassan et al., 2019), (Manela and Moreira, 2017), (Garmaise et al., 2021), (Bybee et al., 2020b), (Schmeling and Wagner, 2023) and (Engle et al., 2020).

Many studies look at the financial implications of COVID-19 (see, among others, Augustin et al., 2021; Bonaccolto et al., 2019; Bretscher et al., 2020a,b; Albuquerque et al., 2020; Ramelli and Wagner, 2020; Pástor and Vorsatz, 2020, Papanikolaou and Schmidt, 2020, Breugem et al., 2022; Kaniel and Wang, 2020). In contrast to us, they do not focus on medical announcements and they do not assess the market price of viral contagion risk.

Several studies focus on firm-level implications (see, among other, Cororaton and Rosen, 2020; Acharya and Steffen, 2020; Carletti et al., 2020). Hartley and Rebucci (2020) and Sinagl (2020) look at monetary policy announcements and cash-flow risk, respectively. We differ in our attention to medical announcements; our social media-based measures of information diffusion and attention; and our high frequency analysis. Our work complements the evidence in Gormsen and Koijen (2020) and Gormsen et al. (2021) who extract relevant information about expectations and risk premia from derivatives.

Darmouni et al. (2023) studies the US corporate bond market fragility and assess policy interventions in times of COVID-19. The authors show that the weakness of mutual funds targeting corporate bonds has significantly exacerbated the drop in corporate bond prices. Our model is silent on the role played by risky bonds. We leave the analysis of the link between medical announcements and international corporate bond risk premia to future research.

2. Medical announcements

In this section, we propose a simple model to think of asset demand around announcements. The model suggests that, on average, announcements should produce a reallocation from bonds to equities. As a result, equities should appreciate upon announcement, whereas bond prices should stay stable (decline) if their supply is flat (upward sloping). We test these predictions in our novel data set comprising thousands of COVID-19-related announcements across twenty-one countries. We then show our main results. Specifically, we document that: (i) equity markets, on average, appreciate upon announcements, and especially so in EEs; (ii) bond prices decline slightly in AEs, but stay stable in EEs; (iii) across both AEs and EEs, trade becomes more active upon medical announcements.

2.1. A simple model of assets demand and announcements

Consider an agent with Epstein and Zin (1989) recursive preferences over two times in a period, $t = 0, 1$:

$$U_0 = \left[(1-\delta)C_0^{1-1/\psi} + \delta E_0\left[C_1^{1-\gamma}\right]^{\frac{1-1/\psi}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}}.$$

For the sake of simplicity, consider the case in which the intertemporal elasticity of substitution is one, $\psi = 1$, and consumption at time 0 is equal to one, $C_0 = 1$. Without loss of generality, impose a subjective discount rate $\delta = 1$. If consumption is log-normal, the following applies:

$$U_0 = E_0[C_1^{1-\gamma}]^{\frac{1}{1-\gamma}} \approx E_0[C_1] - \frac{1}{2}(\gamma-1)V_0[C_1], \tag{1}$$

meaning that when $\gamma = 1$, the agent cares only about expected utility, $E_0[C_1]$, whereas when $\gamma > 1$ the agent dislikes uncertainty, $V_0[C_1]$. At time $t = 0$, the agent chooses how many bonds, B, and stocks, S, to buy taking as given prices along their supply curves. Think of B and S as the face value and the book value of bonds and stocks, respectively. The agent faces the following problem:

$$\begin{aligned} U_0(W_0) &= \max_{B,S} E_0[B+\theta S] - \frac{1}{2}(\gamma-1)V_0[B+\theta S], \\ W_0 &\geq p(B)B + p(S)S, \end{aligned} \tag{2}$$

where θ is a random variable that captures the riskiness of equity payouts. Since $V_0[B+\theta S] = S^2 V_0[\theta]$, the implied demand curves for bonds and equities are:

$$\begin{aligned} \frac{p(S)}{p(B)} &= E_0[\theta] - (\gamma-1)V_0[\theta]\cdot S \\ p(B) &= \frac{W_0 - Sp(S)}{B}. \end{aligned} \tag{3}$$

Assume that the supply of bonds is perfectly controlled by the central bank so that $p(B) = \overline{P}$. Without loss of generality, assume that $\overline{P} = 1$. Assume that the supply of equity is linear and upward sloping,

$$p^s(S) = a + \underbrace{b}_{>0} S, \tag{4}$$

where we impose $a < E_0[\theta]$. Under these conditions, at the equilibrium,

$$S = \frac{E_0[\theta] - a}{(\gamma-1)\sigma^2 + b} > 0. \tag{5}$$

We think of an announcement as an unbiased signal about θ that arrives at time $t \in (0, 1)$ and that reduces the posterior uncertainty

Table 1
Summary statistics for announcements. This table shows summary statistics for COVID19-related announcements that we collect for a large cross section of countries. Our real-time data range from 01/01/2020 to 02/22/2022. For each country, we report the total number of announcements, the fraction of announcements that report the number of positive COVID cases, that are live streamed, and that are announced by the country's President or Prime Minister. In the last column, we report the fraction of announcements that took place at a daily regular time.

Country	Total no. announcements	Case reports	Live streamed	President/ Prime minister	Regularly scheduled
AR	605	33%	64%	3%	90%
AU	678	78%	4%	1%	34%
BR	975	64%	26%	2%	54%
CA	791	58%	21%	18%	31%
CH	627	78%	9%	13%	73%
CL	896	59%	29%	3%	45%
CN	721	82%	3%	1%	75%
CN-HK	1,376	55%	2%	1%	100%
CO	1,006	58%	34%	8%	79%
DE	283	87%	1%	7%	61%
ES	570	83%	1%	17%	63%
FR	567	77%	16%	6%	84%
IN	759	89%	1%	1%	63%
IT	654	74%	17%	8%	81%
JA	332	59%	5%	5%	32%
KR	642	80%	1%	4%	72%
MX	1,803	10%	45%	21%	51%
NZ	457	61%	29%	7%	72%
UK	711	82%	11%	7%	68%
US	1,386	17%	54%	7%	33%
Total	15,839	64%	18%	7%	62%

about equities, σ^2 (Ai and Bansal, 2018). The agent can freely revise her portfolio composition upon the arrival of the announcement. Since we can prove that,

$$\frac{\partial p(S)}{\partial \sigma^2} < 0 \quad \text{if} \quad \gamma > 1 \text{ and } \frac{\partial p(S)}{\partial \sigma^2} = 0 \quad \text{if} \quad \gamma = 1, \tag{6}$$

if the investor cares about the timing of information ($\gamma > 1$), *on average* announcements should be associated to equity appreciation as the investors shift their allocation toward equities. In what follows, we work with a novel dataset of covid-related announcements to test this hypothesis. In addition, we point out that if the supply curve of bonds is slightly upward sloping instead of being flat, we should expect to see both an average appreciation for equities and a depreciation for bonds, respectively.

2.2. Data collection

We treat the release of each medical bulletin as an announcement. The same applies to travel limitations and lockdown policies related to COVID-19. We note that we have manually tracked these policy interventions on a daily basis and have constructed a novel dataset important to study real-time high frequency reactions of financial markets to epidemic risk.

At the beginning of our sample, we also witnessed important announcements related to both monetary and fiscal policy interventions. These announcements are not included in our study and, in addition, we also run our analysis excluding days with major monetary and fiscal policy announcements.[4] Hence we are confident that our results are not contaminated by other announcements.

Our data collection is very comprehensive, as documented in Table 1, and it comprises more than 15,000 medical announcements. An example of a COVID-19-related announcement follows:

> **2020-03-14 15:35:00 CET; Vice President @Mike_Pence and members of the Coronavirus Task Force will hold a press briefing at 12:00 p.m. ET. Watch LIVE:** http://45.wh.gov/RtVRmD

We 'hand-collect' these announcements in several ways. First, for each country, we look for official press statements publicly available on the local Ministry of Health (MoH) webpage. Suppose the press statement does not have an official time stamp. In that case, we look for it on the official Twitter account of the MoH or other related government entities (for example, the Twitter account of the Prime Minister). If this second attempt fails, we also look at the Twitter accounts of major local newspapers and focus on news about medical reports. These steps, which we repeat multiple times each week, are sufficient to identify the effective time of each announcement in our data set relevant for financial investors.

Our dataset comprises mostly regularly scheduled announcements, that is, daily releases at a pre-established well-known time. We also collected irregularly pre-scheduled announcements. As an example of an irregularly pre-scheduled announcement, in Fig. 1, we report our record of the first scheduled Coronavirus Task Force Press briefing. In contrast to the subsequent White House press meetings, this briefing occurred earlier, at 3:40 p.m. EST. Note that this meeting was announced to the public 2.5 h before it took place, hence it must be considered a pre-scheduled announcement. The country-level fraction of regularly scheduled announcements is reported in the last column of Table 1. We run our tests with and without irregularly pre-scheduled announcements and show that our main results hold in both cases.

More broadly, our dataset comprises an extensive set of purely COVID-19-related announcements, and it enables researchers to easily identify each specific announcement. In Table 1, we provide some interesting dimensions of our data set by detailing the share of announcements related to reports about Covid cases, live-streamed press conferences, and announcements by the President or the Prime Minister.

2.3. Announcements and financial markets

Pre- and post-epidemic samples. In what follows, we study the financial dynamics around medical announcement times. In order to isolate the dynamics related solely to medical announcements, we plot the differential behavior of our variable of interest with respect to normal times, *i.e.*, pre-epidemic times. In each country, we define the beginning of the epidemic period as the day in which the country experienced an official number of contagion cases greater than or equal to 100. Given this threshold, China is the first country in our sample to go into the epidemic phase, whereas New Zealand is last. The appendix shows that our main results remain unchanged when we start the epidemic sample for all countries when China reached 100 cases, *i.e.*, at a common date (see Internet Appendix A).

The pre-epidemic sample starts for all countries on October 1st, 2019, so the pre-epidemic period comprises at least four months of data. This subsample is long enough to run meaningful comparisons with the post-pandemic subsample. Consider, for example, an announcement on a Friday at 3:40 p.m. EST. We compare the reaction of our financial variables around this announcement to their behavior at the same time in our pre-epidemic sample.

[4] As an example, here is an announcement related to a monetary policy intervention in response to COVID-19:

> **2020-03-18 23:05:00 CET; FT Breaking News; ECB to launch €750bn bond-buying programme.**

Announcements: January 31, 15:41 EST (21:41 CET)

- 9,700 cases in China, and 200 deaths
- 132 cases in 23 countries outside of China
- 6 cases in the United States
- Report from Germany affirms that asymptomatic carriers can transmit the virus
- Following the WHO the USA declared coronavirus a public health emergency
- Mandatory 14 days quarantine any U.S. citizen who has been in Hubei Province in the previous 14 days
- Temporary suspension of entry into the USA of foreign nationals who pose a risk of transmitting the 2019 novel coronavirus

Fig. 1. Announcement Time from Twitter. This figure shows a tweet about one of the first COVID-related announcements in the US. The tweet time stamp enables us to identify the effective timing of the announcement. On the right hand side of this figure, we summarize the topics discussed during the briefing.

Pre- and post-announcement behavior. We run a high-frequency analysis around announcement times. In what follows, we estimate the following regression at the minute-level:

$$Z_t = (c_{pre} + c_{t>t^*}) + (\alpha_{pre} + \alpha_{t>t^*}) \cdot t + (\beta_{pre} + \beta_{t>t^*}) \cdot t^2, \quad t \in [t^* \pm K] \quad (7)$$

where t^* is the time of the announcement, K is equal to 60 min; and Z_t is the differential behavior of our variable of interest across the pre- and post-epidemic sample. By doing so, we remove the need of introducing country and day fixed effects. This specification is a quadratic function of time that includes dummy variables to account for post-announcement jumps in both the level ($c_{t>t^*}$) and the slope ($\alpha_{t>t^*}$, $\beta_{t>t^*}$). We test the null assumption that there is no difference post-announcement, $H_0 : c_{t>t^*} = \alpha_{t>t^*} = \beta_{t>t^*} = 0$, and if we fail to reject the null we depict the resulting smooth quadratic fit. Standard errors are always HAC-adjusted.

Financial data sources. All data are from Thomson Reuters and Bloomberg. Equity, bond, and currency data are obtained at the minute frequency and then aggregated at lower frequencies when necessary. For each country, we collect data on its major equity index and 10-year maturity treasury bond index. We measure the risk-free rate by focusing on the yield of 3-month government bills. Due to data availability, CDS data are collected at the daily frequency. All details about our data can be found in table A.3 (see Internet Appendix A).

Equity markets. In Fig. 2, we show the average cumulative returns obtained from buying country-specific equities 60 min before a country-specific announcement and holding them for 120 min. Our results are averaged across both countries and announcements. Countries are divided into two groups, AEs and EEs, according to the IMF classification.[5]

The top panels show what happens when considering all countries and all announcements. Both in AEs and EEs, equity values appreciate substantially upon the announcement, consistent with our simple model presented in Section 2.1. This appreciation is persistent, as it remains almost constant during the next hour in AEs and gets amplified in EEs. This observation suggests that the release of COVID-19-related news helps equities. Since we are considering a large number of announcements conveying both positive and negative news, we think of this jump in equity valuation as a measure of expected appreciation due to the reduction of uncertainty on epidemic risk (in our simple model, think of a reduction of the posterior variance, σ^2).[6]

One potential concern related to our results is that they may be driven by a peso problem. In order to address this problem, we do two things. First, we work with a very large cross section of announcements. Second, we repeat our analysis by focusing only on announcements conveying bad news. We measure bad news as an unexpected increase in the growth rate of contagion cases on the day of the announcement. We explain in detail our construction of the news in the next section when we price them using the cross section of equity and bond returns. In Fig. 2(b), left panel, we show that the same phenomenon is present to a similar extent when we focus on the subset of announcements associated with bad news within the group of AEs. Note that the scale for this panel is one order of magnitude greater than that in Fig. 2(a). Hence our average results for AEs are not driven by a few extreme realizations.

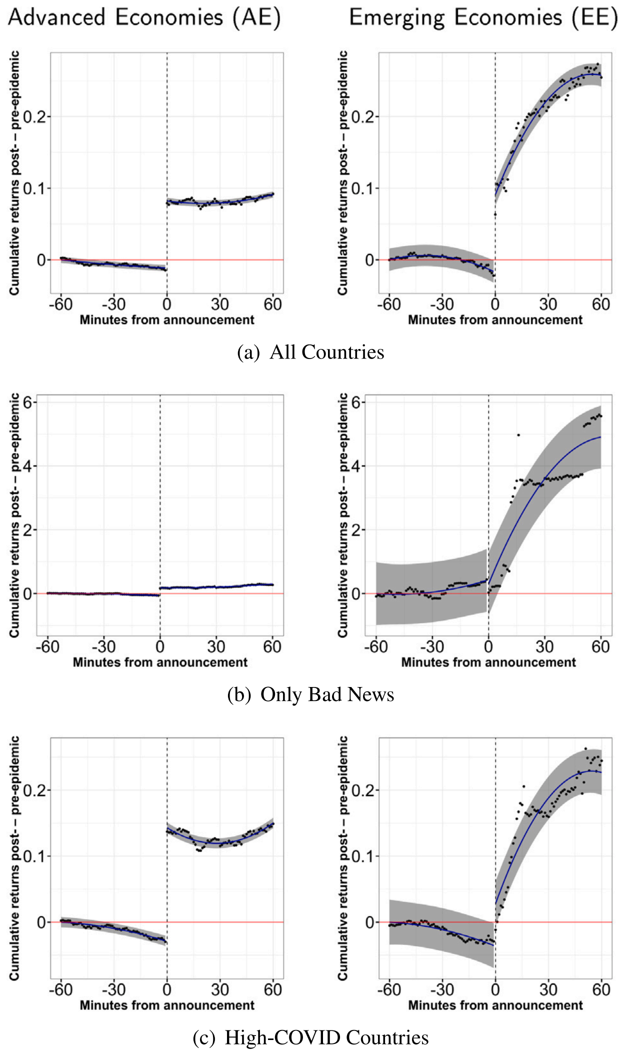
We further support this point by replicating our analysis on a subsample in which we remove days with news in either the top- or bottom-1% of our distribution (see figure A.1 in the Internet Appendix). Our results are unchanged (see figure A.2, panel a). In addition, our results are qualitatively unchanged if we focus on a subsample ending in December 2020, *i.e.*, at the peak of the second COVID wave (figure A.2, panel b).

Turning our attention to EEs, we point out that in this case, the jump is one order of magnitude greater than under the case in which we consider all announcements. In EEs, it is clear that the average appreciation that we see in the hour after the announcements is not driven by the arrival of positive news.[7] In general, one could be concerned that our results are driven by an in-sample predominance of good news, resulting in more equity appreciations than depreciations upon announcement. In order to address this concern, we estimate the average of our news across countries and days. According to standard t-test, we cannot reject the null assumption that our news are on average zero. Equivalently, our novel and extensive data set comprises a similar

[5] If a country-specific announcement happens when the exchange of the country is closed, we consider the 60 min prior to the closing time of the previous day and the first 60 min after the opening of the exchange in the next day.

[6] Lucca and Moench (2015) show a slow and persistent accumulation of positive returns before monetary policy announcements. This drift may be explained by information leakage. In our case, instead, the sudden increase in the cumulative returns at the announcement is consistent with no information leakage.

[7] In the first ten minutes after the announcement, negative news on average dominate the announcement premium. We depict our results for announcements associated to good news in figure A.2, panel c.



(a) All Countries

(b) Only Bad News

(c) High-COVID Countries

Fig. 2. Equity Returns around Announcements. In each panel, dots denote the difference across subsamples of the cross-country-cross-announcement average cumulative returns obtained from buying equities 60 min before an announcement and holding them for 120 min. Panel a (c) comprises announcements from all countries (top-50% countries in terms of contagion cases) in each group. Panel b excludes announcements conveying good news. Returns are in log units and multiplied by 100. Solid line and shaded areas are based on the estimation of Eq. (7). Our sample starts on 10/01/2019 and ends on 02/22/2022.

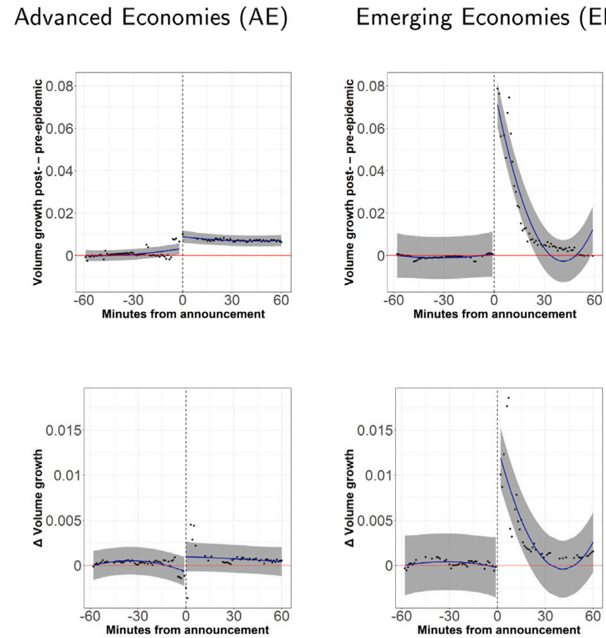


Fig. 3. Equity Trade Volume around Announcements. The figure shows the average equity log-volume growth for all countries around announcement times. In the top panel we depict the difference across pre- and post-epidemic samples. In the bottom panel we plot the difference in volume growth for the post-epidemic sample between days when the absolute value of contagion news is above median and days when it is below median. In each country, the epidemic period starts when there are more than 100 cases of COVID19. Solid line and shaded areas are based on the estimation of Eq. (7). Our sample starts on 10/01/2019 and ends on 02/22/2022.

number of good and bad news across a large cross section of countries and a long daily time series.

In Fig. 2(c), we consider all of our announcements, but we limit our attention to countries above the median in total contagion cases. The scale in these panels is identical to that used in Fig. 2(a). Not surprisingly, the smaller sample we use produces estimates surrounded by higher estimation uncertainty. Taking this into account, the value of the information disclosed during these announcements is higher among high-COVID AEs and remains almost unchanged among high-COVID EEs. More broadly, when we look at the entire cross section of our 21 countries, low-COVID countries appear to be less sensitive to contagion-risk news. This is consistent with the results of the no-arbitrage factor model that we estimate in the second part of our study.

The equity returns patterns that we document may also be consistent with models featuring behavioral attributes and micro-frictions. In order to provide more data to distinguish across theories, we also look at equity trade volume. In Fig. 3, we directly depict the difference in the log-growth of trade volume across normal and epidemic subsamples. We find that both in AEs and in EEs trade volume features no change before the announcements. Consistent with previous studies (see, among others, Han, 2020), trade volume increases right after the announcement. This upward adjustment is more pronounced in EEs. We interpret these results as strongly supporting the relevance of information arrival in markets where investors care about the timing of uncertainty resolution (see, for example, Ai and Bansal, 2018, Ai et al., 2022a and Ai et al., 2022b).

In addition, these models predict that volume should be more pronounced when the announcements carry stronger news. In theory, this should apply to both positive and negative news. In order to examine this prediction, we look at the absolute value of the surprise in the number of cases across different days. In the bottom panels of Fig. 3, we show that volume increases relatively more on days with more extreme (unexpected) cases news. In the next part of this study, we focus on sovereign bonds and document that liquidity seems to increase in the bond markets as well.

Bond markets. Fig. 4(a) shows our results for bond returns. The construction of the depicted data is identical to that used for equities. In a ±60-minute window around the announcement, there is no significant adjustment in bond returns for EEs, consistent with our model in Section 2.1. In AEs, the adjustment is modest and negative, consistent with our simple portfolio allocation model if we assume that the supply curve of bonds is slightly upward sloping.

Through the lens of our model, these results suggest two important lessons. First, during the COVID-19 crisis, cash-flow uncertainty was an important determinant of the equity market. This high-frequency result is consistent with the results documented by Gormsen and Koijen (2020) looking at dividend futures. Second, given that their cumulative return is nearly zero across AEs and EEs, bonds are an important hedge against contagion risk announcements.

According to our model, announcements should prompt a trade away from bonds. Absent high-frequency data on bonds trading volume, we test this hypothesis by looking at their bid–ask spread which

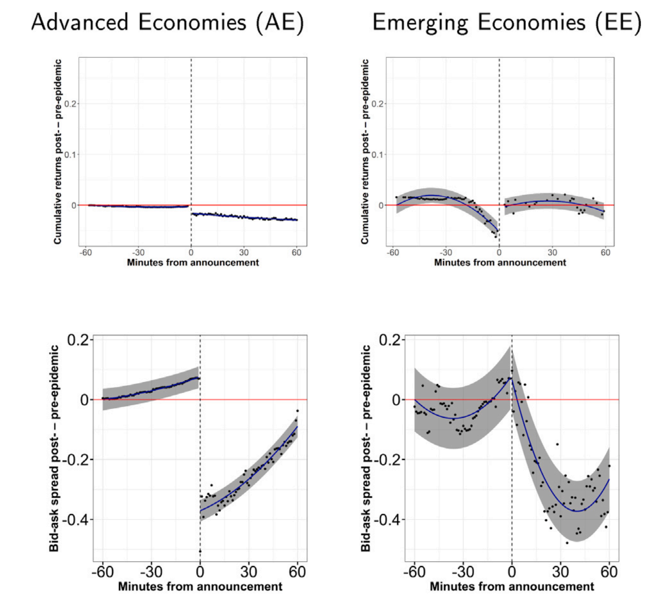


Fig. 4. Sovereign Bonds around Announcements. In the top panels, dots denote the difference across subsamples of the cross-country-cross-announcement average cumulative returns obtained from buying 10-year sovereign bonds 60 min before an announcement and holding them for 120 min. In the bottom panels, dots refer to the difference across subsamples of the cross-country-cross-announcement average of the bid–ask spread of the bonds. Returns are in log units. All series are multiplied by 100. Solid line and shaded areas are based on the estimation of Eq. (7). Our sample starts on 10/01/2019 and ends on 02/22/2022.

we interpret as a measure of inaction in the market. On average, after an announcement, there is an immediate decline in the bid–ask spread in AEs and a delayed one in EEs. This is consistent with the idea that covid announcements have been an important source of trade.

An alternative explanation for the muted response of bonds is that they are subject to two offsetting forces. Specifically, flight to safety may promote bond appreciation, but sovereign default risk may increase and push bond prices downward simultaneously. In order to study the plausibility of this hypothesis, we collect daily country-level data on CDS spreads and link their daily variation to the daily news on contagion cases. We explain in detail how we measure news in the next section. Since different countries entered this crisis with different levels of fiscal capacity, exploring country-level heterogeneity is essential. For this reason, in our empirical analysis, we include both country-level fixed effects and week-level time fixed effects.

In Table 2, we show that adverse contagion news tends to increase CDS spreads in a statistically significant way. This effect is three times stronger in EEs. Simultaneously, we document that this news produces a very modest increase in the adjusted R-squared of our regression, implying that for AEs, default concerns have been a second-order issue.

2.4. Additional results

This section summarizes a list of additional results reported in detail in Internet Appendix A. Since our benchmark analysis is based on several methodological choices, we show the role played by each of them in what follows. More broadly, we show that our results are robust to several methodological changes.

The role of country-specific epidemic dates. In our benchmark analysis, we have country-specific dates defining the beginning of the pandemic. As an alternative, we can pick a common date, namely the day on which China reported 100 official cases. Our results are unchanged when we adopt this strategy. As an example, see our results for equity in figure A.3.

Table 2
CDS spreads and contagion news. This table reports the results of the following regression:

$$\Delta S^i_t = d^i_0 + d^i_t \cdot D^{Week}_t + \beta^g \cdot news_{t-1} + \epsilon^i_t, \quad \forall i \in g$$

where ΔS^i_t refers to the daily change of the CDS spread in country i; g refers to either the group of Advanced Economies (AEs) or that of Emerging Economies (EEs); d^i_0 is a country-level fixed effect and D^{Week}_t is a weekly time fixed effect. 'Contagion cases - news' refers to the innovation in the growth of the global number of contagion cases as measured in Section 3. 'Adj. R2 w/o' refers to the adjusted R squared from the same regression in which we omit the contagion news. Standard Errors are clustered at the country-level. Our sample starts on 02/01/2020 and ends on 02/22/2022.

	A.E.		E.E.	
Contagion cases - news	6.133***	7.735**	27.897***	27.290***
	(1.988)	(3.782)	(8.298)	(8.364)
Adj. R2	0.02%	4.64%	0.20%	14.24%
Adj. R2 w/o	0.02%	4.64%	0.20%	14.24%
Country FE	Yes	Yes	Yes	Yes
Week FE	No	Yes	No	Yes

Post-epidemic dynamics. In our analysis, we plot the differential behavior of equity markets around announcement times across our pre- and post-epidemic samples. We also report our results for equities in the post-epidemic sample (see figure A.4) and confirm that medical announcements, on average, are associated with an appreciation of equities. In addition, our model suggests that the realized jump in cumulative returns should decrease with bad news, *i.e.*, it should be low (high) when the number of cases announced is above (below) expectations. In figure A.5 in the Internet Appendix, we depict the difference in cumulative returns across days in which countries experienced an unexpectedly high number of cases (bad news) and days in which they experienced an unexpectedly low number of cases (good news). The model suggests that this difference should be negative around the announcement time, and our figure confirms this result.

The role of domestic announcements. Recall that our cross section comprises 21 countries. We can think about the previous results about equity (bond) returns as the equal-weighted cumulative returns that an investor could obtain by trading ahead of each announcement across 21 sources of announcements (one per country) and in 21 equity (bond) markets, for a total of 21 × 21 possible trade combinations.

In order to disentangle the effects of local announcements on local markets, we also consider the average cumulative return of an investor that trades only in the domestic market ahead of domestic announcements. In figure A.6, we focus on the average cumulative returns across 21 trade strategies that involve neither foreign news nor foreign assets. Our data confirm that bonds have a muted response to announcements, whereas equities appreciate afterward.

Covid vs. macroeconomic announcements. In order to further isolate the role of medical announcements, we have created a dataset comprising the dates on which either inflation, industrial production, or GDP data are released in each country in our cross section. Our results continue to hold when we exclude these days from our dataset (see, for example, figure A.7). In other words, our announcement results are unrelated to other announcements already explored in the literature in terms of content (we focus on medical announcements) and timing (our results also hold on days when there are no major macroeconomic announcements).

Regularly pre-scheduled announcements. At high frequency, all of the announcements that we have utilized so far are pre-scheduled. This means that investors are aware that an announcement is going to be made within a few hours. Still, some of our announcements are not regularly scheduled, in contrast to macroeconomic announcements. In order to be consistent with previous studies, for each country, we identify regularly scheduled announcements by ensuring that (i) they are about case reports or live-streamed events and (ii) they are released at a recurrent country-specific time of the day. Our results also hold if we focus on regularly pre-scheduled announcements (see figure A.8). In addition, when focusing on regularly pre-scheduled announcements, our sample excludes almost entirely observations from the first six weeks of pandemic diffusion. Therefore, our results are not driven by early announcements of expansionary fiscal and monetary interventions or those discussing the spread of the pandemic in early-affected foreign countries like China and Italy. This subset of announcements primarily centers on the domestic number of cases.

Information diffusion. Our novel social media-based data set enables us to measure the diffusion of information at a very high frequency. For each announcement in our data set, we compile all COVID-19-related tweets issued in a ±60-minute window around announcement time by major newspapers in each country. In the next section, we provide a detailed description of our data collection procedure. For the sake of statistical power, we aggregate all of these tweets across all of our countries and call the resulting aggregate 'World'.

In the left panel of figure A.9, we show the per-country per-minute average cumulative number of tweets around announcement times during the post-epidemic sample. The right panel refers to retweets, that is, our measure of attention to the news. Both information diffusion and attention to the news increase significantly in the hour after announcements. In order to interpret the magnitude of the diffusion, we must clarify that we collect only tweets from major newspapers and their respective number of retweets. Because of API limitations, it is impossible for to us measure how many users read an individual tweet. Hence our figures represent a lower bound on the overall diffusion.

In addition, it is evident that most of the twitting activity takes place in the time window [−90 −30] ('preview' tweets about the announcement) and [0 +90] ('rehash' tweets). These results are reassuring as they provide additional support to our covid-related data set, as the time of our announcements nicely aligns with that of the news media cycle.

3. Contagion news

In this section, we attempt to price news about pandemic risk. We do it using two fundamental measures, namely, unexpected changes in the number of contagion cases and unexpected changes in the tone of the news about contagion. The first measure is based on an objective count of COVID-19 positive cases. Nevertheless, across different months or contagion waves, the same variation in the number of cases may be associated with different assessments of risk. For this reason, we find it necessary also to study a media-based measure of news tone.

Our analysis confirms that global epidemic news has a significant market price of risk. In April 2020, at the peak of the first COVID contagion wave in AE, daily equity risk premia may have increased by 28% in AEs and by 13% in EEs compared to the median risk premia in our sample. This disruption is comparable to that measured during the global financial crisis.[8]

3.1. Data collection

Twitter-based news. In the spirit of Baker et al. (2016), we identify major newspapers for a large cross section of countries (see table A.1 in the Internet Appendix). In contrast to Baker et al. (2016), we do not analyze articles; rather, we track news published on Twitter in real-time to produce high-frequency data when needed. More specifically, we track the news related to the COVID-19 pandemic posted by major newspapers on Twitter. We do so by searching for keywords such as 'coronavirus' and 'covid19'. For each newspaper, we identify its headquarters location so we can determine its specific time zone.

In Table 3, we report a summary of our social media-based dataset. It is very comprehensive and it features several dimensions that enable us to study both information production and diffusion. Specifically, our ability to track retweets and likes gives us a high-frequency measure of attention. Google searches are often used to measure attention (Da et al., 2011; Ramelli and Wagner, 2020), but to the best of our knowledge, they are not provided minute-by-minute, and they do not account for the timing of initial production of the news, an aspect that is very important when analyzing capital market reactions.

The time series behavior of our news indicator is depicted in Fig. 5. For each country, we also depict the beginning of the epidemic period, which we identify as the day the number of confirmed cases of COVID-19 exceeds 100. We note several interesting patterns. First, there is significant heterogeneity across countries in the timing of information diffusion. Across several countries, information diffusion becomes more intense after the beginning of the local epidemic period. We note that both the diffusion of news, that is, the number of tweets, and the attention to the news, that is, the number of retweets, increase rapidly after the beginning of the local epidemic period.

Fig. 6 shows both diffusion and attention to the news at the global level, that is, when we aggregate all of our tweets and retweets across countries. In Fig. 6(a), the right panel of this figure provides a breakdown of the most prominent topics addressed in the COVID-19 tweets, namely, vaccines, death risk, quarantine measures, and availability of medical supplies. The attention to all of them increased substantially, with vaccines becoming prominent in the fall of 2020. In Fig. 6(b), we document similar results for high-attention tweets, *i.e.*, tweets ranked top-1% by the number of retweets within each one of our countries. For this subset of tweets, we also collected their retweets with a 'quote', *i.e.*, with text written by the "retweeters" in order to study their tone. We find a high correlation between the tone of the original newspaper tweets and that of the quoted retweets, meaning that our methodology captures a relevant-and-consistent partition of tweets. We provide detailed results in the Internet Appendix (see table B.1).

Fig. 7 shows the intraday pattern of the diffusion of COVID-19 news for each country. This figure is not based on universal time, rather it accounts for country-specific time. In each country, we consider two country-specific subsamples: the pre-epidemic period and the first wave of the epidemic. The first wave spans from the time a country records its 100th COVID-19 case to the peak of global daily deaths, on 01/18/2021. The pre-epidemic sample starts on 01/01/2020 and it ends on the time a country records its 100th COVID-19 case. There are two main takeaways from this picture: (i) the diffusion of COVID-19-related news increases significantly with local epidemic conditions, and (ii) a significant share of the diffusion occurs while the local capital markets are open. Hence monitoring media activity can be a valuable tool for tracking the real-time information set of financial market participants.

Tweet tone. Since we use Twitter activity to form a high-frequency risk factor, we need to identify the tone of the tweets, that is, we need to know whether they relate to either good or bad news. Given (i) the high volume of tweets that we collect and (ii) the fact that our tweets are written in different languages, we use Polyglot (available at https://pypi.org/project/polyglot/), *i.e.*, a natural language pipeline that supports multilingual applications with polarity lexicons for 136 languages. This computer-based mapping algorithm reads our text and classifies the words into three degrees of polarity: +1 for positive words, −1 for negative words, and 0 for neutral words. We provide two examples in table A.2 (see our Internet Appendix).

Our measure of the tone of tweets is based on the count of positive words minus the count of negative words, divided by the sum of positive and negative word counts (Twedt and Rees, 2012). We compute this measure at the country level at both the hourly and the daily frequency, focusing solely on initial tweets and excluding any retweets. We then aggregate this measure across countries to obtain a global measure.

[8] These numbers are annualized according to the number of annual trading days and are net of the median risk premium in our full sample.

Table 3
Newspapers dataset. This table shows summary statistics of COVID19-related news data that we collect for a large cross section of countries. Our real-time data range from 01/01/2020 to 02/22/2022. For each country, we report number of news providers and number of tweets collected. We also report the total number of retweets and likes as measures of attention. The last four columns report the share of tweets mentioning number of deaths, quarantine measures, medical supply, and vaccines, respectively.

Country	No. news providers	Tweets	Retweets	Likes	Topics			
					Mortality	Quarant.	Med. supply	Vaccines
Argentina	4	77,338	1,205,269	3,154,158	13%	10%	14%	63%
Australia	4	17,641	144,685	348,074	19%	39%	12%	29%
Brazil	4	32,552	1,331,641	8,705,983	45%	8%	15%	32%
Canada	5	48,545	442,675	861,102	33%	10%	17%	40%
Chile	4	33,954	408,095	630,825	56%	6%	10%	28%
China	3	32,791	947,706	2,580,177	39%	14%	19%	28%
Colombia	4	32,877	474,795	1,450,808	17%	12%	25%	45%
France	4	47,059	1,424,717	2,384,879	25%	26%	27%	22%
Germany	4	12,213	147,977	331,434	20%	24%	20%	35%
Hong Kong	3	21,204	419,964	606,520	17%	32%	21%	31%
India	4	103,907	937,468	5,611,874	32%	23%	16%	29%
Italy	3	33,696	265,658	715,064	10%	32%	29%	28%
Japan	4	18,984	156,845	277,461	18%	13%	30%	39%
Korea	4	13,459	82,445	143,649	44%	10%	26%	20%
Mexico	4	79,244	1,625,687	4,262,382	14%	11%	25%	50%
New Zealand	3	9,520	45,474	169,920	10%	40%	15%	35%
Spain	4	38,865	2,668,188	4,792,047	30%	20%	14%	36%
Switzerland	4	8,390	37,173	47,191	22%	20%	25%	33%
UK	4	25,356	1,145,404	2,286,491	27%	30%	15%	29%
USA	11	116,365	7,264,225	17,259,747	29%	7%	23%	41%
Total	84	803,960	21,176,091	56,619,786	26%	19%	20%	35%

We depict our global tone factor in Fig. 8, left panel. Its time pattern is consistent with the observed contagion dynamics. Specifically, the tone became very negative by the end of January as the conditions in China started to precipitate. It improved in early February when there was still no sign of massive contagion in Europe, and it declined again when the epidemic started in Italy. The slow improvement of the tone of our tweets observed after the beginning of March pairs well with the observed flattening of the contagion curves in many of the countries in our dataset. We find these results reassuring as they confirm that our text analysis algorithm tracks the contagion dynamics in a reliable manner.

In addition, we note that collecting all original tweets and their retweets is computationally impossible for us. In table B.1 (see Internet Appendix B), we show that there is a positive and significant correlation between the tone of the original tweets and that of the top-1% quote (re)tweets, meaning that our methodology captures a relevant-and-consistent partition of tweets.

For the sake of our asset pricing analysis, we focus on the innovations to the tone of our tweets. One simple way to extract these innovations is to consider the difference in the tone at day t and its 5-day backward-looking moving average assessed at time $t-1$. We depict this time series in the right panel of Fig. 8 and note that it is nearly serially uncorrelated.

Cases and financial data. Cases data are from official medical bulletins. Our primary source is CSSE at Johns Hopkins University.[9] News to the contagion factor is obtained by computing the difference between the daily growth rate of contagion cases at time t and its backward-looking time $t-1$ moving average computed over the previous 5 days. We choose a 5-day window because it matches the number of days of a typical trading week.

Since our contagion-based factor spans a 7-day week, we assign to Friday the average growth rate of global contagion cases that occurred on Friday, Saturday, and Sunday.[10] Our financial data sources are detailed in table A.3 (see Internet Appendix A). Our empirical asset pricing analysis takes into consideration the hypothesis that our countries may feature heterogeneous exposure to global contagion risk.

Cases as a driver of time-varying exposure. One additional reason to focus on the number of cases as a relevant determinant of risk-premia is that many tweets in our sample focus on this topic. Specifically, we apply the Sievert and Shirley (2014) Latent Dirichlet Allocation (LDA) topic model to our covid-related tweets from English-written newspapers. Tweets are preprocessed, *i.e.*, we remove stopwords and symbols such as #, we 'stem' our words, and account for both unigrams and bigrams. We apply the unsupervised machine learning model to our data at the country-level.[11] When λ is set to the canonical value of 0.5, in most of our English-speaking countries, the top unigrams and bigrams from the main topics include 'covid cases' or related terms. We report an example in figure B.1 (see Internet Appendix B). Our data visualization webpage lets the interested reader choose different values of λ.

3.2. The market price of viral contagion news

Daily news. Every day, we group countries into three portfolios according to their relative number of COVID-19 cases measured the previous day. We do this separately for AEs and EEs. In Internet Appendix B, we demonstrate that these results remain robust even when the share of COVID-19 cases is weighted by population (table B.2), indicating that our results are not driven by countries with larger populations. The H (L) portfolio comprises the top (bottom) countries in terms of COVID-19 cases. We also consider an investment strategy long in the H portfolio and short in the L portfolio. We refer to the returns of this portfolio as HML-COVID19.

We report common summary statistics for these portfolios in Table 4. The turnover in each portfolio is moderate. The in-sample average of the returns in all portfolios is not different from zero, which is not surprising given our short sample, which comprises multiple

[9] https://github.com/CSSEGISandData/COVID19/tree/master/csse_covid_19_data/csse_covid_19_time_series

[10] For the Easter Holiday, we assign to Thursday the average daily growth rate of global cases from Thursday to the following Monday.

[11] Topics are indexed by $k = 1, \ldots, 5$. λ determines the weight given to the probability of term w under topic k relative to its lift (measuring both on the log scale). Setting $\lambda = 1$ results in the familiar ranking of terms in decreasing order of their topic-specific probability, and setting $\lambda = 0$ ranks terms solely by their lift.

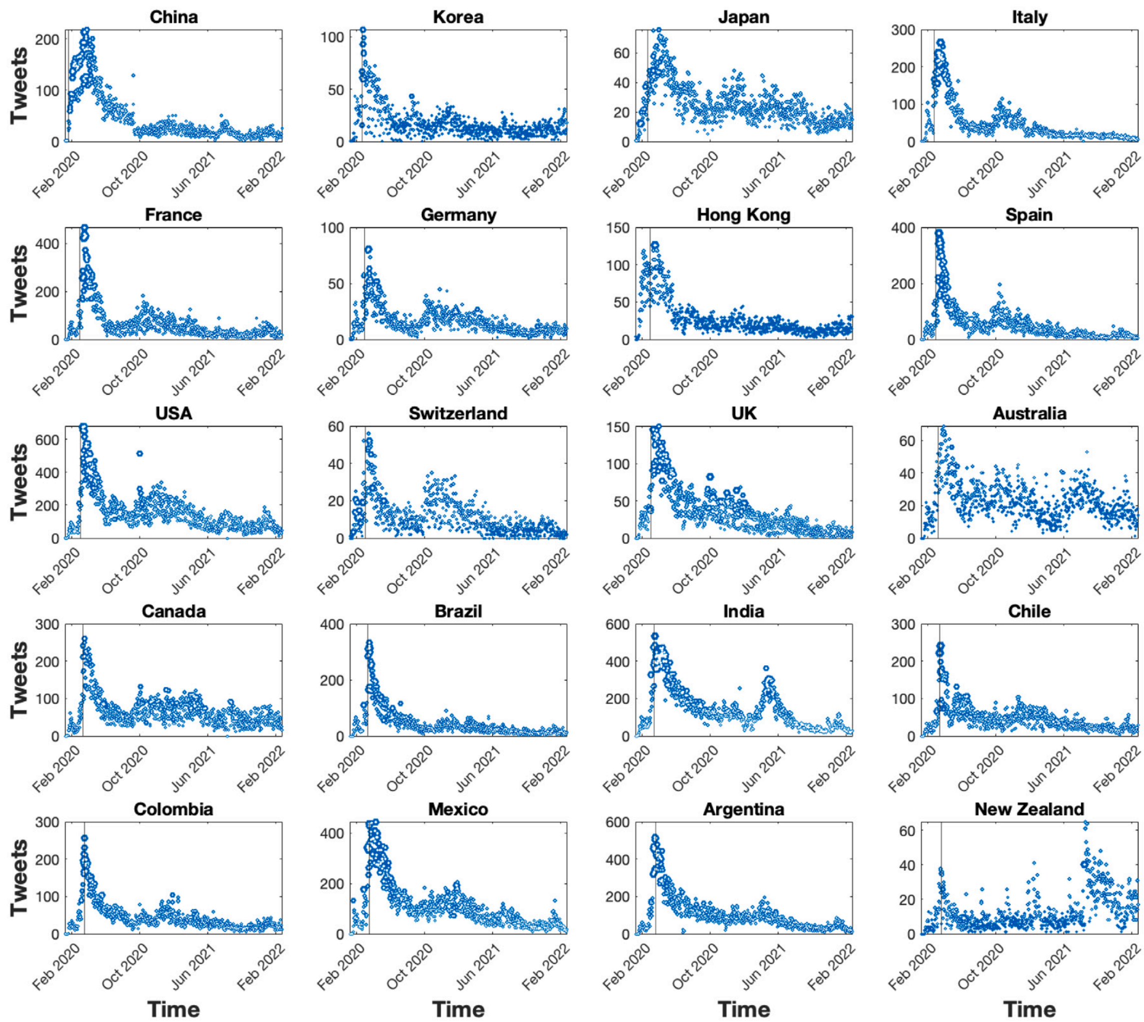


Fig. 5. Information Diffusion and Attention across Countries. This figure shows the daily number of tweets posted in each country by major newspapers. The vertical axis shows the daily number of tweets. The size of each data point represents the number of retweets scaled by the maximum daily number of retweets for each country. The sample starts on 01/01/2020 and ends on 02/22/2022. The vertical line depicts the date that each country had more than 100 confirmed cases of COVID19. More details on the data collection are reported in the Internet Appendix.

contagion waves with natural peaks and valleys. All portfolio returns have substantial volatility and negative skewness. Focusing on the first quartile of the distribution of returns, we see that the portfolio comprising the more exposed countries tends to have more severe negative downside risk. This is an aspect that we capture in our conditional no-arbitrage model.

Model and estimation. Given these preliminary observations, we consider the following conditional asset pricing model,

$$r^{ex}_{f,t+1} = \bar{r}^{ex}_{f,t} + \beta_{f,t} \cdot news^{glob}_{t+1}, \quad f \in \{H, M, L\}, \tag{8}$$

$$\beta_{f,t} = \beta_0 + \beta_{f,1} X_{f,t}, \tag{9}$$

$$\frac{\partial \bar{r}^{ex}_{f,t}}{\partial X_{f,t}} = \lambda \beta_{f,1}, \tag{10}$$

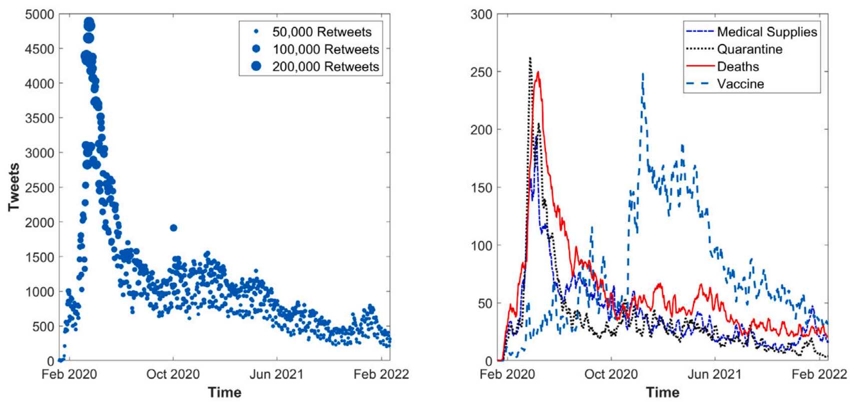
where $X_{f,t}$ is the share of contagion cases associated to portfolio f at time t, and λ is the market price of risk (MPR) of the global news factor $news^{glob}_{t+1}$.

This model can potentially capture many of the features of returns seen so far. First, it captures predictability through contagion-based time-varying betas. Second, it has the potential to capture higher negative skewness for countries that go through more severe contagion paths. Consider the case of portfolio H comprising countries receiving a sequence of relatively more severe adverse contagion news. This portfolio will have severe exposure to adverse news as the relative contagion share of the portfolio grows. When the relative contagion share starts to flatten out and decline, the sensitivity of this portfolio to good news is reduced ($|\beta_{H,t}|$ shrinks). This means that returns become less sensitive to positive news, and hence the right tail of the returns distribution is shortened.

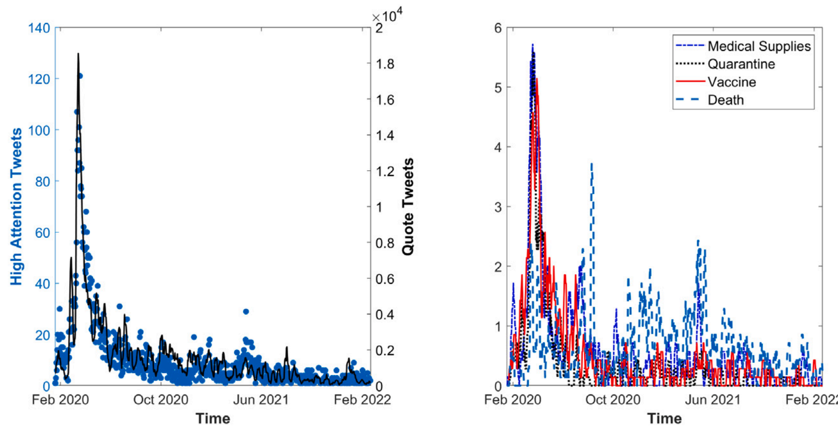
Third, consistent with our previous descriptive returns, it accounts for heterogeneous exposure to global contagion news. Last but not least, it enables us to identify the market price of risk of this global contagion component, λ. By no-arbitrage, the extent of time-series predictability of our excess returns must equal $\lambda\beta_{f,1}$, and $\beta_{f,1}$ can be easily estimated in the time-series by considering the multiplicative factor $X_{f,t} \cdot news^{glob}_{t+1}$.

We report our main results obtained from daily data in Table 5. The first two columns are based on unexpected changes in the growth of global contagion cases. The right-most columns are based on unexpected changes in the global tone of tweets. Note that the countries we consider provide daily updates about contagion cases at the end of the day. In order to properly represent the information set of investors, in our asset pricing model we lag the news by one day, *i.e.*, we assume that day-t returns respond to news released in the evening of day $t-1$.

We estimate our asset pricing model through GMM and notice that all portfolios have an untabulated significant exposure to our



(a) Full Sample



(b) High-Attention Tweets

Fig. 6. Global Information Diffusion. In panel a, the left panel of this figure shows the daily total number of tweets posted across countries by major newspapers. The vertical axis shows the daily number of tweets. The size of each data point represents the number of retweets scaled by the maximum daily number of retweets. The right panel shows the daily number of tweets related to death-risk, (scarcity of) medical supplies, quarantine, and vaccines. The tweets were identified using a multilingual bag-of-words approach. In panel b, we focus on high-attention tweets, *i.e.*, top-1% by number of quote (re)tweets. The sample starts on 01/01/2020 and ends on 02/22/2022. More details on the data collection are reported in the Internet Appendix.

Table 4
Summary statistics for portfolios. This table shows summary statistics for the equity excess returns of portfolios formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation. Hourly excess returns are in log units and multiplied by 100. Portfolios are obtained from equity indexes. Our real-time data range from 02/01/2020 to 02/22/2022. Turnover measures the number of countries entering or exiting a portfolio relative to the total number of countries in a specific portfolio × number of days in our sample. Numbers in parenthesis are HAC-adjusted standard errors.

	Low	Medium	High	$HML_{COVID19}$
Panel A: Advanced economies				
Mean	0.014	0.039	0.020	0.006
	(0.060)	(0.060)	(0.072)	(0.031)
StDev	1.159	1.331	1.433	1.044
Skewness	−1.222	−0.762	−1.648	−0.108
First Quartile	−0.471	−0.496	−0.497	−0.545
Avg. N. Countries	5	4	5	–
Turnover (%)	0.5	1.3	0.6	–
Panel B: Emerging economies				
Mean	0.009	0.044	0.096**	0.086
	(0.087)	(0.094)	(0.049)	(0.063)
StDev	1.69	1.855	1.75	1.605
Skewness	−2.106	−1.255	−0.752	0.316
First Quartile	−0.662	−0.862	−0.774	−0.942
Avg. N. Countries	3	2	2	–
Turnover (%)	0.4	0.8	0.5	–

Table 5
Summary of MPR estimation. This table shows the results of the conditional linear factor model described in Eqs. (8)–(10). Portfolios are formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation (X_t). On the left (right), the COVID19 factor is measured as the news to global COVID cases growth (tone of COVID-related tweets). When we measure the COVID19 news as unexpected number of contagion cases (unexpected improvement in COVID19-related tweets), we expect a negative (positive) market price of risk (MPR). Both daily excess returns and market prices of risk are in log units. Our cross section of test assets comprises both equity and bond portfolios. Our real-time data range from 02/01/2020 to 02/22/2022. Estimates and HAC-adjusted standard errors are obtained through GMM.

	Covid cases		Twitter news	
	A.E.	E.E.	A.E.	E.E.
Local units				
coef	−0.003***	−0.006***	0.013***	0.007***
se	(0.001)	(0.001)	(0.003)	(0.001)
USD units				
coef	−0.005***	−0.005***	0.011***	0.006***
se	(0.001)	(0.002)	(0.003)	(0.001)
Controlling for MKT				
coef	−0.002***	−0.007***	0.008***	0.008***
se	(0.001)	(0.001)	(0.002)	(0.001)

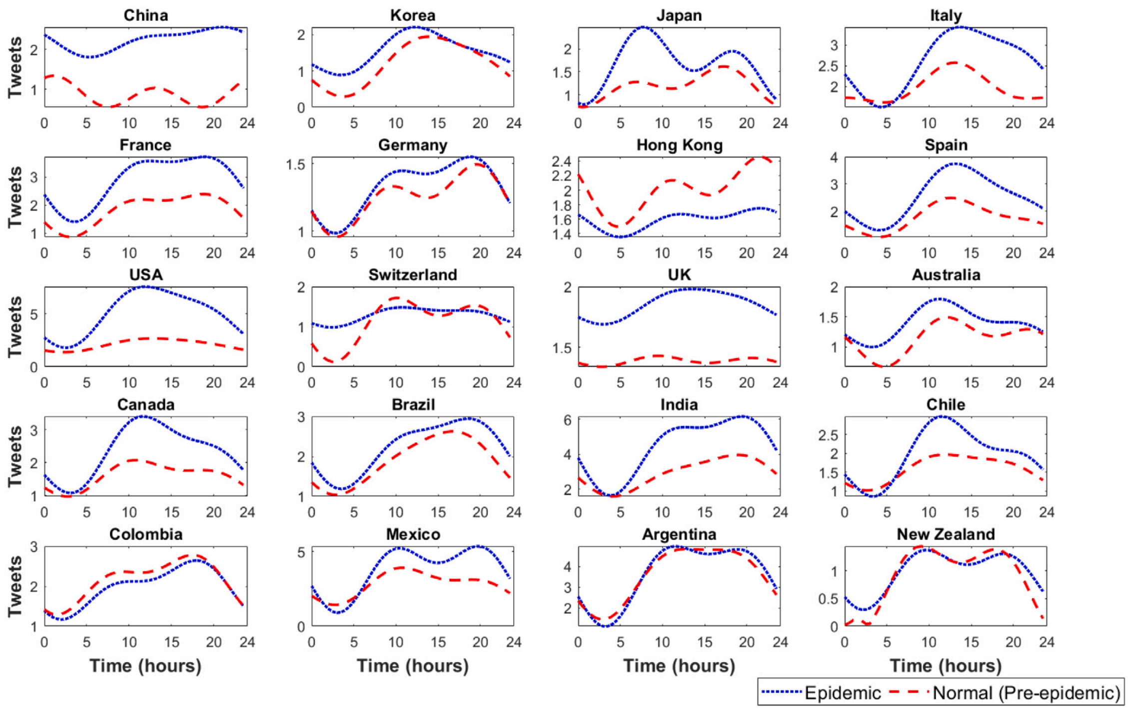


Fig. 7. Intraday Information Diffusion. This figure shows the intra-day trend of the number of tweets posted every 30 min across several countries in our dataset. The dotted line depicts the trend during the first wave of the epidemic, while the dashed line shows the pre-epidemic trend. The first wave spans from the time a country records its 100th COVID-19 case to the peak of global daily deaths, on 01/18/2021. The pre-epidemic sample starts on 01/01/2020 and it ends on the time a country records its 100th COVID-19 case. The time reflects the local time zone of each newspaper. More details on the data collection are reported in the Internet Appendix.

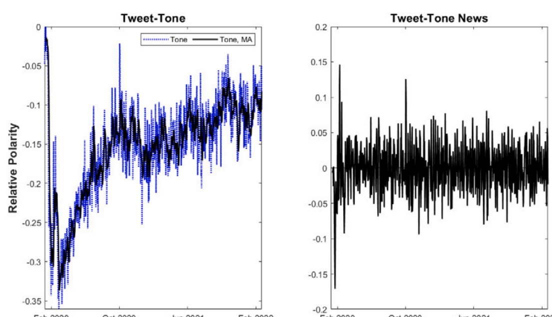


Fig. 8. Twitter-Based COVID19 Factor. This figure shows our daily global Twitter-based COVID19 factor. We use Polygot to measure the polarity of our tweets and compute the tone of each tweet according to Twedt and Rees (2012). We aggregate the tones at a daily frequency and across countries. MA refers to a backward looking 5-day moving average. The news at time t is computed as the difference between the tweets-tone at time t and their MA at time $t-1$. The sample starts on 01/01/2020 and ends on 02/22/2022.

contagion-based news, $\beta_{f,t}$.[12] In our sample, the portfolio of countries with the highest share of COVID-19 cases tends to be more exposed to contagion news. This sign is consistent with our expectations since positive (negative) news about global contagion growth (tone of tweets) refers to an adverse shock to equity returns. Most importantly, the implied daily market price of risk is negative (positive) and significant with respect to contagion (tone of tweets) news. This means that the relative share of contagion cases forecasts an increase in expected future returns across all portfolios ($\lambda\beta_{f,1} > 0$). Equivalently, the share of contagion cases is a relevant positive predictor of the future cost of capital.

Our results hold regardless of whether we run our model using local currency returns or returns in USD. Furthermore, our results remain significant when we estimate a two-factor version of our model which controls for global market risk as measured by the MSCI Global Index.[13] Looking at the output of our specifications and accounting for estimation uncertainty, we conclude that 0.3% is a reasonable lower bound on the daily market price of risk of daily contagion news. We consider this estimate very significant, consistent with the great contraction experienced in equity markets during the first wave of the epidemic period.

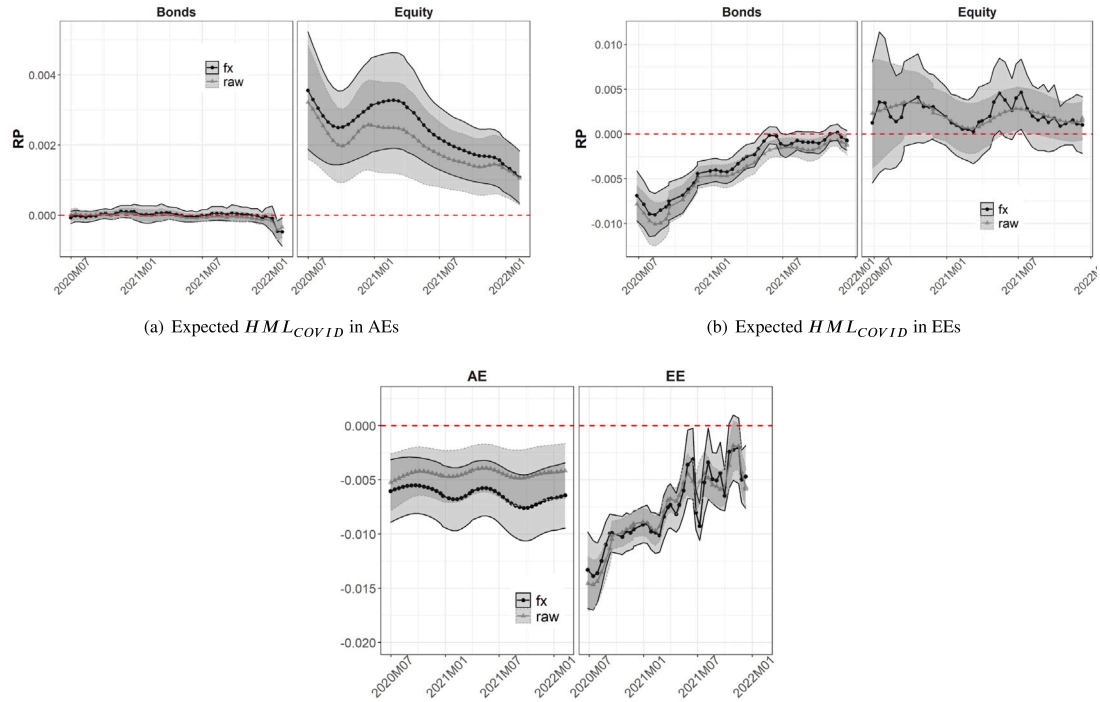
Simultaneously, we note that this value is very plausible once we account for two observations. First, this is not the MPR of a financial factor and the associated estimated betas are very small. Second, contagion risk follows waves with a relatively short half-life. Equivalently, the exposure of our assets to this risk is small and relatively quick in reverting to zero.

Real-time estimation results. We visualize our results in Fig. 9. In contrast to what has been done so far, we estimate our model sequentially on samples of increasing length. Specifically, we start by estimating our model on a sample ending in June 2020, and then we re-estimate it by adding two weeks of data at the time. The very last estimation iteration delivers results identical to those reported in Table 5. This exercise clarifies to which extent investors can identify exposures to contagion risk in real-time with our methodology.

In Fig. 9(c), we show that our estimates of the MPR are statistically significant in almost the entire sample for both AEs and EEs. Since the figures are based on Covid cases, the MPR is negative. In Figs. 9(a) and 9(b), we show the estimated risk premium on an HML-COVID19 strategy on either bond or equity portfolios across AEs and

[12] The share of contagion cases across our three portfolios have very different scales and variability. As a result, the coefficients $\beta_{f,1}$ are not revealing of the sorting of $\beta_{f,t}$ across portfolios. For this reason, we report only estimated MPRs.

[13] Throughout our study when considering the MSCI index to control for the market, we use returns in USD. For EEs (EAs), we use the EE (EAs) MSCI.



(a) Expected HML_{COVID} in AEs

(b) Expected HML_{COVID} in EEs

(c) Estimated MPR

Fig. 9. Sequentially Estimated MPRs and Risk Premia. The top panels refer to the HML-COVID strategy in AEs (EEs) estimated sequentially on samples of increasing size. The first sample ends in June 2020, we then add 2 weeks of data at the time. The bottom panels show the market price of risk of covid cases from the same sequence of estimations. 'fx' ('raw') refers to returns expressed in USD (local currency). Shaded area show 90% confidence intervals.

EEs. An HML-COVID19 strategy on bonds delivers a zero (negative) risk premium in AEs (EEs). Equities, instead, deliver a positive risk premium both in AEs and EEs. The estimated premium is smaller but better identified in AEs than in EEs. This result is important because it implies that containment policies that keep contagion cases relatively low may be very valuable in terms of saving lives and preventing severe financial wealth losses. The companion estimates of the exposure of these strategies can be found in figure B.2, Internet Appendix B.

Additional results with daily data. In table B.3 (see Internet Appendix B), we show that replacing covid-related news with market returns in our conditional model delivers no positive and statistically significant market price of risk. This result confirms that (i) a conditional CAPM model fails in capturing viral contagion risk, and (ii) our measures are informative about viral risk.

K. French provides the FF5 factors at a daily frequency for developed countries (Fama and French, 2017). Given our limited cross section, estimating our model with time-varying betas for both our covid factor and the FF3/FF5 factors is not feasible. We take a hybrid approach and estimate a model in which the betas of our covid factor are time-varying, whereas the betas of the additional FF3/FF5 factors are constant. We report our estimated MPRs in table B.4 and confirm our main results.

So far, we have estimated a model with heterogeneous and time-varying exposure to a common risk factor related to global contagion news. Our dataset also enables us to construct AE- and EE-specific measures of COVID-19 case growth and Twitter tone. See, for example, figure B.3 in the Internet Appendix.

We identify purely AE- and EE-specific components by regressing these fundamental measures on their global counterpart. The residuals of these two separate regressions represent AE- and EE-specific news for us. We show mixed results in Internet Appendix B, table B.5. Specifically, when we use only equity-based test assets, local contagion news (panel A) is priced negatively in AEs and positively in EEs. Twitter-based local news (panel B) has a market price of risk statistically not different from zero. Local news is priced only when we use both bond and equity indices as test assets.[14] Given these considerations, we consider our specification with heterogeneous and time-varying exposure to global contagion risk news as more robust.

Controlling for jumps. Baker et al. (2020) point out that the COVID-19 epidemic period is characterized by a high frequency of extreme realizations of the US equity market returns. In order to check whether jump risk is driving our results, we repeat our analysis by using returns orthogonalized with respect to measures of jump risk. Specifically, we regress the equity returns of each one of the countries in our sample (indexed by i) on a country-specific daily dummy variable equal to $\texttt{sign}\, ret_{i,t}$ when $\texttt{abs}\, ret_{i,t} > 2.5\%$.

Since we work with a broad cross section of countries which includes also EEs, we consider an additional relative definition of jump risk. Namely, we construct a daily country-specific dummy variable equal to $\texttt{sign}\, ret_{i,t}$ when $\texttt{abs}\, ret_{i,t}$ is above the 99th percentile of its pre-epidemic country-specific distribution. We report our country-level percentiles in the Internet Appendix (table B.6).

In Table 6, we show our estimates of the market price of risk after controlling for realized jumps. Our main results continue to hold. In addition, we also consider a specification in which we orthogonalize our global factors with respect to a dummy variable that takes value $\texttt{sign}\, MSCI_t$ when the return of the MSCI global index is greater (smaller) than 2.5% (−2.5%). Our results confirm that pandemic risk carries a relevant market price.

Industry-level results. In order to further exploit our rich framework, we consider a more granular cross section by looking at industry-level equity indices in Europe. This task is relevant for at least two

[14] By "local news" we mean a variation in tone that is not spanned by a common global component. The content of the news may refer to either domestic or foreign events.

Table 6
MPR estimation - controlling for jump risk. This table shows the estimates of the MPR for Twitter news controlling for jump risk. We pre-clean excess returns/factors by orthogonalize them with respect to an indicator variable equal to 1 when markets experienced a "jump". Except for this preliminary step, the portfolio formation, sample selection, and estimation procedure are the same as in Table 5. In column (1) we orthogonalize the excess returns of our test assets with respect to a country-level daily dummy variable that takes the value $\texttt{sign}\, ret_{i,t}$ if $\texttt{abs}\, ret_{i,t} > 2.5\%$. In column (2), we repeat the same procedure but the dummy variable is equal to $\texttt{sign}\, ret_{i,t}$ if $\texttt{abs}\, ret_{i,t}$ is above the 99th percentile of its pre-epidemic country-specific distribution. In columns (1b) and (2b), we also orthogonalize our global risk factors using a global dummy variable that takes value $\texttt{sign}\, MSCI_t$ when the return of the MSCI global index is greater (smaller) than 2.5% (−2.5%).

	(1)		(2)		(1b)		(2b)	
	A.E.	E.E.	A.E.	E.E.	A.E.	E.E.	A.E.	E.E.
Local units								
coef	0.014***	0.007***	0.012***	0.006***	0.015***	0.004***	0.013***	0.003***
se	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)
USD units								
coef	0.017**	0.006***	0.011***	0.006***	0.011**	0.003***	0.007	0.002**
se	(0.007)	(0.001)	(0.003)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
Controlling for MKT								
coef	0.012***	0.007***	0.006***	0.007***	0.012***	0.006***	0.007***	0.004***
se	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)

reasons: (i) industries are well known to be difficult to price; and (ii) our industries comprise firms based in different countries and hence their riskiness is based on an interesting mix of country-level contagion conditions.

Specifically, we utilize daily firm-level data for the entirety of the STOXX Europe 600, extracted from Bloomberg. The STOXX Europe 600 is a comprehensive index encompassing 600 constituents that span large, mid, and small capitalization companies across 17 European nations; we account for the quarterly compositional changes of the index. This selection represents nearly 90% of the free-float market capitalization in the European stock market. For our analysis, we only focus on firms headquartered in one of the European countries in our sample (CH, DE, ES, FR, IT, SE, UK). We aggregate their equity returns at the industry level using the 2-digit Global Industry Classification Standard (GICS) code and obtain 11 distinct portfolios whose composition is detailed in table B.7. As shown in Table 7, the market prices of risk estimated in our cross section of industries are comparable to those reported in Table 5. This result supports our methodology as it shows that it can deliver significant results even at the industry-level, not just when pricing managed portfolio with country-level returns. In addition, in panel B and C we show the average exposure of each industry to our covid factors. Industries are ranked according to their average betas. We note two important points. First, the ranking of our industries when we define news as unexpected covid case growth is the perfect mirror image of the ranking when we use innovations to the tone of our Twitter news. Equivalently, once we account the fact that the MPRs have opposite signs, the ranking is the same. We find this result reassuring.

Our estimation confirms that Energy, Utilities and Consumption Discretionary have been the most exposed to covid risk.[15] Health, Materials and IT, instead, have been relatively safer. This cross sectional average ranking is preserved in the time series through our sample.

Intra-day news. An important advantage of our Twitter-based risk-factor is that we can measure it at very high frequencies, in contrast to daily contagion cases. Using higher frequency data may help sharpen the estimate of the market price of risk because it provides an increased number of observations.

This section focuses only on European countries whose markets are open simultaneously. Specifically, we focus on CH, DE, ES, FR, IT, SE and UK. Every day, we group them into three portfolios according to their relative number of COVID-19 cases. In Table 8, we show our estimation results when we link hourly equity and bond excess returns to hourly Twitter-based news.

As for daily data, we consider multiple specifications of our no-arbitrage model. In this case, we also report our estimated beta coefficients. The implied market price of risk is positive, well-identified, and sizable. Our implied betas continue to be positive, *i.e.*, viral contagion is priced as a source of risk. Consistent with the failure of the international-CAPM documented in table B.3, our the implied market price of risk is still positive and sizable when we control for the market and use a broader cross section of test assets.

There may be several country-specific characteristics (*e.g.*, fiscal conditions, competition, etc.) that could make our portfolios differently exposed to pandemic risk—in order to address this concern, we replace β_0 in Eq. (9) with β_0^f, *i.e.*, a country-specific fixed effect to its exposure. Thanks to the hourly frequency, we have enough observations to estimate this richer model. Our results continue to hold and are reported in table B.8.

Controlling for volatility. In this last step of our research, we project our Twitter-based COVID factor on realized market volatility and use the implied residual to redo our analysis. Equivalently, we look at COVID news that are orthogonal to pure volatility shocks. We measure realized volatility as the standard deviation of the MSCI Global Index at the daily (hourly) frequency using minute-level data. We report our results in Table 9. Both daily data and intra-day data confirm that contagion news has an extremely high MPR, even after controlling for volatility.

International flows. To further validate our results, we study international investment flows related to the countries in our cross section. Weekly net flows are from EPFR and they are rescaled by country-level GDP so that our results are not driven by country size. In this step, we exclude the US, given its unique role in international markets (among others, see Maggiori, 2017). Over such a long span of time, capital flows toward/from the US were driven by many other factors above and beyond COVID. After forming portfolios according to relative contagion levels, we forecast one-week ahead flows using the (lagged) weekly share of portfolio-level COVID-19 cases.

As reported in Table 10, countries that start the week with a higher level of relative contagion are expected to receive lower net inflows ($\beta_1 < 0$). This effect is reversed ($\beta_1 > 0$) when we focus on net bond flows in EE, consistent with the idea that they may be perceived as safer assets and hence their demand may actually increase due to flight to safety.[16] We visualize these findings in figure B.4, Internet Appendix B.

4. Conclusion

In this study, we quantify the exposure of major financial markets to news shocks about global contagion risk, taking into account local

[15] Consumption discretionary comprises segments that have been seriously armed during the pandemic such as Automobiles, Hotels, Restaurants and Leisure. A minority of segments, instead, have grown (for example, households durables and homefurnishing Retail)

[16] Recall that in EEs, bonds provide insurance against bad covid news (see Fig. 9(b)).

Table 7
Industry-level MPR estimation. This table shows the results of the conditional linear factor model described in Eqs. (8)–(10) applied to the industries detailed in table B.7. For each day t and industry i, we compute its exposure coefficient $\beta_{i,t}$ using the following industry-level share of contagion cases:

$$X_{i,t} = \sum_{f\in i} \omega_{f,t} X_{f,t},$$

where f denotes the firms in industry i, $X_{f,t}$ is the share of contagion cases in the country in which firm f is located, and $\omega_{f,t}$ is a value weight equal to the relative value of firm f with respect to the total value of the firms in industry i at time t. In panel A, the first (last) two columns refer to the results obtained when the COVID19 factor is measured as the news to global COVID cases growth (tone of COVID-related tweets). In all cases, we control for the market factor. Both daily excess returns and market prices of risk are in log units and expressed in EUR. In panel B (C), we report the average exposure coefficient for each industry when the factor is based on Covid cases (Twitter news). Our sample starts on 02/01/2020 and ends on 2/22/2022. Estimates and HAC-adjusted standard errors are obtained through GMM.

	Covid cases		Twitter news		
	MPR Covid	MPR Kkt	MPR Covid	MPR Mkt	Obs
Panel A: Market price of risk.					
coef	-0.001^{**}	0.001^{***}	0.006^{***}	0.001^{**}	491
se	(0.000)	(0.000)	(0.000)	(0.000)	491
Panel B: Average Covid Betas - Covid Cases					
Industry (i)	10 Energy	55 Utilities	25 Cons. Discr.	50 Commn.	
$\text{Avg}_t \beta_{i,t}$	−2.092	−1.869	−1.684	−1.625	
Industry (i)	40 Financials	30 Cons. Staples	60 Real Estate	20 Industrials	
$\text{Avg}_t \beta_{i,t}$	−1.387	−1.375	−1.204	−1.189	
Industry (i)	45 IT	15 Materials	35 Health		
$\text{Avg}_t \beta_{i,t}$	−1.103	−1.023	−0.926		
Panel C: Average Twitter Betas - Twitter News					
Industry (i)	35 Health	15 Materials	45 IT	20 Industrials	
$\text{Avg}_t \beta_{i,t}$	−0.126	−0.032	−0.002	0.034	
Industry (i)	60 Real Estate	30 Cons. Staples	40 Financials	50 Commn.	
$\text{Avg}_t \beta_{i,t}$	0.04	0.077	0.08	0.197	
Industry (i)	25 Cons. Discr.	55 Utilities	10 Energy		
$\text{Avg}_t \beta_{i,t}$	0.251	0.34	0.443		

Table 8
Hourly Conditional Linear Factor Model. This table shows the results of the conditional linear factor model described in Eqs. (8)–(10). Portfolios are formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation (X_t). The coefficient $\beta_{f,t} = \beta_0 + \beta_f X_{f,t}$ refers to the exposure of the equity portfolio $f \in \{H, M, L\}$ to the COVID19 factor. We measure hourly COVID19 news as unexpected improvement in the hourly tone of COVID19-related tweets. Both hourly excess returns and market prices of risk are in log units. When we control for the market, returns are in USD, the market is measured by the MSCI Global Index and our factor model comprises a total of two factors. Our real-time data range from 02/01/2020 to 02/22/2022. Estimates and HAC-adjusted standard errors are obtained through GMM.

	β_0	$\beta_{L,1}$	$\beta_{M,1}$	$\beta_{H,1}$	MPR	N.Obs	N. Assets
Panel A: equities and bonds, equities betas							
Hourly log returns							
coef	-0.090^{***}	9.879^{***}	4.043^{***}	2.853^{***}	0.014^{***}	4190	6
se	(0.007)	(0.712)	(0.294)	(0.207)	(0.003)	4190	6
Hourly log EUR returns (adjusting for FX)							
coef	-0.083^{***}	9.164^{***}	3.773^{***}	2.673^{***}	0.017^{***}	4190	6
se	(0.006)	(0.598)	(0.249)	(0.177)	(0.003)	4190	6
Hourly log returns controlling for the Market							
coef	-0.158^{***}	16.892^{***}	6.980^{***}	4.968^{***}	0.009^{***}	3951	6
se	(0.014)	(1.549)	(0.643)	(0.457)	(0.003)	3951	6
Panel B: equities and bonds, bond betas							
Hourly log returns							
coef	-0.062^{***}	6.872^{***}	2.780^{***}	1.966^{***}	0.014^{***}	4190	6
se	(0.005)	(0.496)	(0.201)	(0.144)	(0.003)	4190	6
Hourly log EUR returns (adjusting for FX)							
coef	-0.058^{***}	6.385^{***}	2.609^{***}	1.851^{***}	0.017^{***}	4190	6
se	(0.004)	(0.421)	(0.174)	(0.124)	(0.003)	4190	6
Hourly log returns controlling for the Market							
coef	-0.109^{***}	11.743^{***}	4.831^{***}	3.439^{***}	0.009^{***}	3951	6
se	(0.010)	(1.072)	(0.442)	(0.315)	(0.003)	3951	6

epidemic conditions. We construct a novel data set that includes (i) medical announcements related to COVID-19 for a broad cross section of countries; and (ii) high-frequency data on epidemic news diffused through Twitter. Across several classes of financial assets and currencies, we provide novel empirical evidence about financial dynamics surrounding epidemic announcements, both at a daily frequency and an intra-daily frequency. Formal estimations based on both contagion data and social media activity about COVID-19 confirm the significant market price of epidemic risk. We conclude that policies related to the prevention and containment of contagion could be precious not only in terms of lives saved but also in terms of preserving global financial wealth. Future research should study the interplay of our analysis and the methodology in Diercks et al. (2023).

CRediT authorship contribution statement

Maria Jose Arteaga-Garavito: Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mariano M. Croce:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal

Table 9
Vol-Adjusted Conditional Linear Factor Model. This table shows the results of the conditional linear factor model described in Eqs. (8)–(10). Portfolios are formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation (X_t). The coefficient $\beta_{f,t} = \beta_0 + \beta_f X_{f,t}$ refers to the exposure of the equity portfolio $f \in \{H, M, L\}$ to the COVID19 factor. We measure hourly (daily) COVID19 news as unexpected improvement in the hourly (daily) tone of COVID19-related tweets. We project this factor on realized market volatility and use the implied residual in our estimation. Both excess returns and market prices of risk are in log units and are expressed in USD. The market is measured by the MSCI Global Index. Our real-time data range from 02/01/2020 to 02/22/2022. Estimates and HAC-adjusted standard errors are obtained through GMM.

	β_0	$\beta_{L,1}$	$\beta_{M,1}$	$\beta_{H,1}$	MPR	N.Obs	N. Assets
Panel A: equities, news from Twitter							
Daily log returns							
coef	−0.312***	41.132***	19.797***	6.102***	0.006**	499	3
se	(0.053)	(5.775)	(2.585)	(1.468)	(0.003)	499	3
Panel B: equities, news from Twitter							
Hourly log returns							
coef	−0.005***	0.453***	0.174***	0.134***	0.054**	4301	6
se	(0.001)	(0.131)	(0.055)	(0.040)	(0.028)	4301	6

Table 10
International Flows and News. This table reports the results of the following linear system:

$$FL_t^f = \beta_0 + \beta_1 X_{t-1}^f + \epsilon_t^f$$

where FL_t^f is the flow to funds that invest in portfolio $f \in \{H, M, L\}$ during week t rescaled by portfolio−f 2019 GDP; X_{t-1}^f refers to the weekly share of portfolio-specific COVID19 cases. Portfolios are formed on a weekly basis according to the relative share of country-specific COVID19 cases measured the week before formation. Fund flows-to-GDP is expressed in basis points (bps). Our data range from 02/01/2020 to 07/14/2021 at a weekly frequency. Estimates and HAC-adjusted standard errors are obtained through GMM.

	Bonds		Equities	
	AE	EE	AE	EE
β_0	0.247***	−0.171***	0.589***	0.135***
	(0.026)	(0.032)	(0.051)	(0.036)
β_1	−0.921***	0.311***	−4.500***	−0.996***
	(0.073)	(0.070)	(0.274)	(0.123)
J-stat	11.234	11.825	7.069	11.676
N	75	71	75	71

analysis, Data curation, Conceptualization. **Paolo Farroni:** Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Isabella Wolfskeil:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

when the markets get covid (Reference data) (Mendeley Data)
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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2024.103850.

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