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 accounting for local epidemic conditions. For a wide cross section of countries, we construct a novel data set comprising (i) announcements related to COVID19, and (ii) high-frequency data on epidemic news diffused through Twitter. Across several classes of financial assets, 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 both contagion data and social media activity about COVID19 confirm that the market price of contagion risk is very significant. We conclude that prudential policies aimed at mitigating either global contagion or local diffusion may be extremely valuable.

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1 Introduction

COVID19 has manifested itself as a very aggressive and fast epidemic that—at the time of the first draft of this paper—has 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 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 COVID19-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 risk of news related to global contagion dynamics? Third, can local contagion conditions help us to predict expected returns?

Last but not least, can we use social media activity to measure production and diffusion of information about epidemic risk? This question is important for at least two reasons. First, fast epidemic outbreaks tend to get investors off guard and hence real-time indexes based on social media news may function as a useful predictive tool. Second, the estimation of multidimensional models requires many observations that we may gather by using high-frequency data, as opposed to 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 wide cross section of countries, we construct a novel data set comprising (i) medical announcements related to COVID19; 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 (i) around epidemic announcements, (ii) at a daily frequency, and (iii) at an

[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`).

intra-daily frequency. Formal estimations based on both contagion data and social media activity about COVID19 confirm that the market price of epidemic risk is very significant. We conclude that prudential policies aimed at mitigating either global contagion or local diffusion may be extremely valuable.

Current results in detail. An important contribution of our work is the collection of a novel dataset on the COVID19 pandemic that includes both (i) a very large set of official announcements on medical conditions (more than 7,500 announcements), and (ii) news diffused on Twitter in real-time by major newspapers (based on more than 450,000 tweets). We identify major newspapers for a large cross section of major countries in the spirit of Baker et al. (2016). In contrast to Baker et al. (2016), we do not analyze articles, rather we track news published on Twitter in real time, so that we can produce high frequency data when needed.

More specifically, we track tweets posted by major newspapers with key words such as 'coronavirus' and 'covid19'. For each newspaper, we identify the location of its headquarters so that we can 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 number of tweets) and attention (measured by 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 can be a reliable way to characterize the information set of investors at high frequency.

Turning our attention to financial dynamics, we look at equity returns around announcements,

[2] We identify the beginning of the epidemic state with the day in which the number of confirmed COVID19 cases becomes greater than or equal to 100.

that is, in a ± 60 minute window. We find that cumulative equity returns have no clear pattern before the announcement, as they tend to be relatively flat and indistinguishable from zero. In the post-announcement time window, instead, cumulated returns jump upward.

We note that this time behavior of returns is not present in the pre-epidemic state and is quite different from that documented in Lucca and Moench (2015). Lucca and Moench (2015) shows a slow and persistent accumulation of positive returns before monetary policy announcements. In our case, instead, the increase in the cumulative returns at the announcement is consistent with the Ai and Bansal (2018) model. When the representative investor cares about the timing of resolution of uncertainty, prices jump upward when uncertainty is resolved along the information cycle and then they start to decline.

Furthermore, we conduct the same analysis looking at the government bond market. The response of bonds is less severe than that observed in equities. In a ± 60-minute window around the announcement, there is no significant adjustment in bonds returns among advanced economies. Among emerging economies, there is a positive sudden increase, but it is less relevant than that for equities. This observation is important as, by no-arbitrage, it suggests that cash-flow uncertainty is an important determinant of the market fluctuations observed during the COVID19 crisis. This high-frequency result is consistent with the results documented by Gormsen and Koijen (2020) looking at dividend futures.

We look also at equity market trading volume around announcement times and document that it exhibits a downward drop upon the announcement time and then a slow reversal. We show that this pattern is not as severe for advanced economies. When we look at bid-ask spread for sovereign bonds, we find a reduction around announcements for advanced economies and an increase for emerging economies. Taken together, these patters suggest that investors continue to be relatively more active with safer assets in advanced economies.

In the last step of our analysis, we group on a daily basis our countries into three portfolios according to their relative number of COVID19 cases. We do this separately for advanced and emerging economies. The H (L) portfolio comprises the equity returns of the top (bottom) countries in terms of COVID19 contagion cases. We then estimate a no-arbitrage based model in which we allow for time-varying betas with respect to global contagion risk. Specifically we allow equity returns to respond to global viral contagion news according to the relative share of official COVID19 cases associated to each portfolio. Global contagion risk is measured either by innovations in the growth rate of global COVID19 contagion cases or by innovations in the tone of our COVID19-related tweets.

This model can potentially 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. 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 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.

Third, this model accounts for heterogeneous exposure to global contagion news and hence it enables 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 advanced and emerging economies, 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 a smaller share of cases, instead, provides an insurance premium. This means that in countries very exposed to contagion risk, bonds tend to become safer. We find that this result is particularly sizable among emerging economies.

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 COVID19 cases measured in the previous 24 hours. The H (L) portfolio comprises the equity returns of the top-2 (bottom-2) countries for COVID19 contagion cases. Our novel high-frequency estimation confirms our main findings: policies related to prevention and containment of contagion could be very valuable not only in terms of lives saved but also in terms of global wealth.

Related literature. Due to its relevance, the COVID19 crisis has spurred a lot of contemporaneous research. Macroeconomic studies are focusing on both the aggregate and distributional dynamic implications of the epidemic crisis (Hagedorn and Mitman 2020; Coibion et al. 2020; Eichenbaum et al. 2020; Fornaro and Wolf 2020; Chiou and Tucker 2020; Barrot et al. 2020; Alon et al. 2020; Glover et al. 2020; Corsetti et al. 2020; Caballero and Simsek 2020; Coven and Gupta 2020; Hensvik et al. 2020).

Other analyses assess policy concerns (Acemoglu et al. 2020; Alvarez et al. 2020; Jones et al. 2020; Bahaj and Reis 2020; Elgin et al. 2020; Faria-e Castro and Louis 2020; Krueger et al. 2020; Farboodi et al. 2020). Correia et al. (2020) and Barro et al. (2020) provide evidence using data from the 1918-Flu epidemic. We differ from these studies for our strong attention to asset prices and COVID19-driven risk.

Other studies at the intersection of macroeconomics and econometrics focus on forecasting the diffusion of both contagion cases and COVID19-implied economic activity disruptions (Favero 2020; Ichino et al. 2020; Atkeson 2020; Atkeson 2020; Ma et al. 2020; Ludvigson et al. 2020). We focus on both the cross sectional and time series implications for asset prices across different asset classes.

An important strand of the literature focuses on the measurement of both COVID19-induced uncertainty and firm-level risk exposure by utilizing textual analysis and surveys (Baker et al. 2020; Hassan et al. 2020; Bartik et al. 2020). Giglio et al. (2020) use a survey to study investor expectations over different horizons. Lewis et al. (2020) provide a novel weekly measure of economic activity using several labor market-based timeseries. We focus on high-frequency data, Twitter-based news diffusion, epidemic announcements, and country-level asset price dynamics. Our study adds viral contagion risk considerations to the findings of Pelger (2020).

Gerding et al. (2020) look at equity market dynamics and link the epidemic risk exposure to country-level fiscal capacity. Augustin et al. (2020) looks at CDS. Bonaccolto et al. (2019) focus on currency union break up risk due to COVID19. Papanikolaou and Schmidt (2020) look at the financial implications of industry-level job disruption due to COVID. Albuquerque et al. (2020) focus on the performance of firms with high environmental and social ratings during the COVID19 outbreak. They do not study announcements and they do not assess the market price of viral contagion risk. Ramelli and Wagner (2020) study equity returns across firms accounting for international trade, financial strength, and investor attention. They use both Google search volume and conference calls as a measure of attention, whereas we use high-frequency data on retweets of tweets issued by news provider. We provide novel evidence about both (i) market reactions around contagion-related announcement times, and (ii) the market price of contagion risk at high frequency.

Schoenfeld (2020) examines buy-and-hold returns for many assets and finds that managers systematically underestimate their exposure to COVID19. Cororaton and Rosen (2020) look at the characteristics of firms participating to the US Paycheck Protection Program. Acharya and Steffen (2020) study firm-loan-level data to study the implications for liquidity. Carletti et al. (2020) look at Italian firms. Alfaro et al. (2020) focus on the link between aggregate equity market returns and unanticipated changes in predicted infections during the SARS and COVID19 pandemics. Bretscher et al. (2020) look at the supply channel of uncertainty shocks. Hartley and Rebucci (2020) and Sinagl (2020) look at monetary policy announcements and cash-flow risk, respectively. Cox et al. (2020) confirm the relevance of monetary policy estimating a dynamic asset pricing model. 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) who extract relevant information about expectations and risk premia from dividend futures.

More broadly, our manuscript is methodologically related to the work of, among others, Tetlock (2007), Manela and Moreira (2017), and Calomiris and Mamaysky (2019).

2 Medical Announcements

In this section, we illustrate key features of our novel data set comprising thousands of COVID19-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 returns are insensitive to announcements in AEs, but appreciate to some extent in EEs; (iii) in AEs, bond (equity) markets become more (less) liquid after announcements, whereas in EEs both bonds and equity markets become less active.

2.1 Data Collection

We treat the release of each medical bulletin as an announcement. The same applies to travel limitations and lock down policies related to COVID19. We note that we have manually tracked these policy interventions on a daily basis and hence we have constructed a novel dataset important to study real-time high frequency reactions of financial markets to epidemic risk.

Since in our sample we have also witnessed important announcements related to both monetary and fiscal policy interventions, we complement the medical announcements with major policy-related announcements as well. We note that medical announcements in our sample period are much more prominent than policy-related announcements as they represent nearly 99% of all of the announcements collected. Our data collection is very comprehensive, as documented in table 1, and it comprises more than 7500 observations. An example of a COVID19-related announcement follows:

Table 1. Summary Statistics for Announcements

Country	No. Announcements	Governments & Central Banks	Med. Bulletins & Lockdowns
Argentina	363	0.00%	100.00%
Australia	272	0.00%	100.00%
Brazil	663	0.15%	99.85%
Canada	149	0.00%	100.00%
Chile	541	0.00%	100.00%
China	263	0.00%	100.00%
Colombia	648	0.00%	100.00%
France	176	4.55%	95.45%
Germany	195	4.10%	95.90%
Hong Kong	506	0.00%	100.00%
India	202	1.98%	98.02%
Italy	242	9.50%	90.50%
Japan	59	37.29%	62.71%
Korea	296	0.34%	99.66%
Mexico	1366	0.00%	100.00%
New Zealand	189	0.00%	100.00%
Spain	319	2.82%	97.18%
Sweden	168	0.00%	100.00%
Switzerland	243	0.82%	99.18%
UK	216	4.63%	95.37%
USA	503	3.38%	96.62%
Total	7579	1.39%	98.61%

Notes: 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 1/1/2020 to the date of this manuscript. For each country, we report the total number of announcements, the fraction related to either medical bulletins or lock-down measures, as well as the fraction of other announcements issued by governments and central banks about fiscal and monetary policy, respectively.

> **2020-03-14 15:35:00; 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`

In this case, we set the time of the announcement at 12:00 p.m. ET. To clarify further our methodology, we also give an example of an announcement related to a monetary policy intervention in response to COVID19:

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

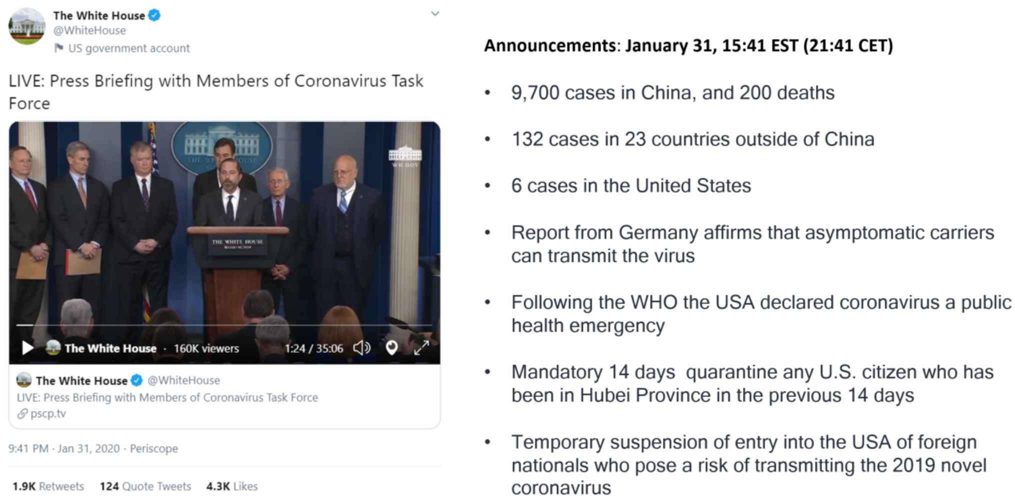


Fig. 1. Announcement Time from Twitter.

Notes: 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.

In this case, the time of the announcement is 11:05 p.m. CET.

We 'hand-collect' these announcements in several ways. First of all, for each country we look for official press statements publicly available on the webpage of the local Ministry of Health (MoH). If the press statement does not have an official time stamp, 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 as well, we look at the Twitter accounts of major local newspapers and focus on news about medical reports. These steps, which we repeat multiple times during each week, are sufficient to identify the effective time of each announcements in our data set relevant for financial investors.

As an example, in figure 1 we report our record of the first scheduled Coronavirus Task Force Press briefing. In contrast to the following White House press meetings, this briefing took place earlier, at 3:40 p.m. EST. This example demonstrates two important aspects of our dataset construction: (i) it accounts for meetings scheduled at not-recurrent times; and (ii) it captures purely COVID-related news.[3]

2.2 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 in the epidemic phase, whereas New Zealand is last.

The pre-epidemic sample starts for all countries on October 1st 2019 so that 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. More specifically, 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 across all of the Fridays comprised in our pre-epidemic sample.

Per- 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:

$$Z_t = (c_{pre} + c_{t>t^*}) + (\alpha_{pre} + \alpha_{t>t^*}) \cdot t + (\beta_{pre} + \beta_{t>t^*}) \cdot t^2, \quad t \in [t^* \pm K] \tag{1}$$

where t^* is the time of the announcement, K is equal to 60 minutes; and Z_t is the differential behavior of our variable of interest across the pre- and post-epidemic sample. This specification is a quadratic function of time that includes dummy variables to account for post-announcement

[3] Our dataset enables researchers to easily identify each specifc announcement and hence look for the content discussed in each one of the events that we detect.

jumps in both the level and the slope. 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.

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-related tweets issued in a $\pm$60-minute window around announcement time by major newspapers in each country. We provide a detailed description of our data collection procedure in the next section. For the sake of statistical power, we aggregate all of these tweets across all of our countries and we call the resulting aggregate 'World'.

In the left panel of figure 2, we show per-country per-minute average number of tweets around announcement times during epidemic periods in excess of the same average measured in the pre-epidemic samples (dots). This procedure enables us to capture news diffusion patterns specific to the epidemic period. The right panel refers to retweets, that is, our measure of attention to the news.

Formal tests reject the null assumption of a common time-behavior before and after the announcement for information diffusion. In figure 2, the solid line denotes our estimate whereas the shaded area refers to our confidence intervals. Importantly, both information diffusion and attention to the news increase significantly in the hour after announcements.

Since we focus solely on announcements related to medical bulletins and policy measures to fight the epidemic our results refer to both sources and topics distinct from those studied in the previous papers about economic announcements. Our results confirm that medical announcements gather special attention and hence it is important to understand whether they have a significant impact on financial markets.

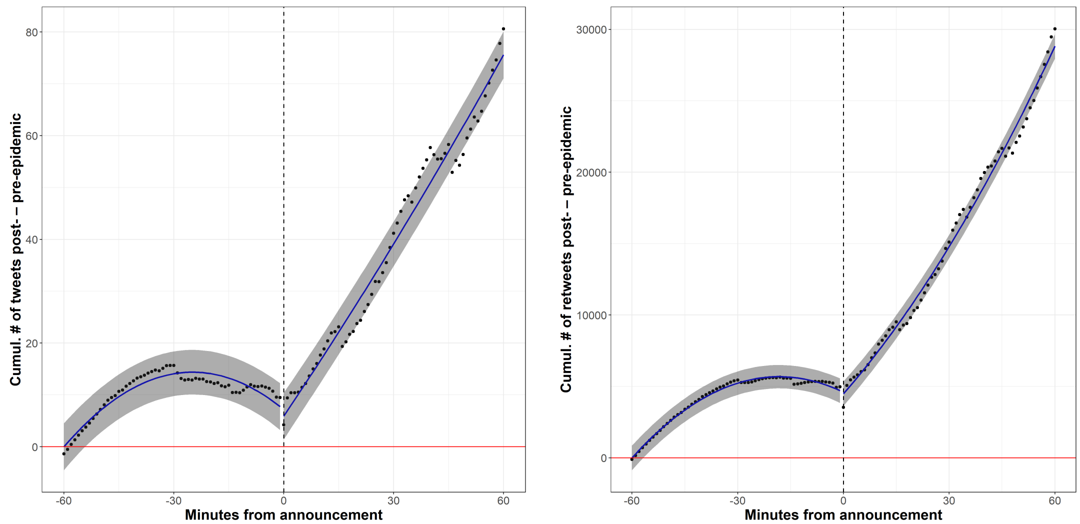


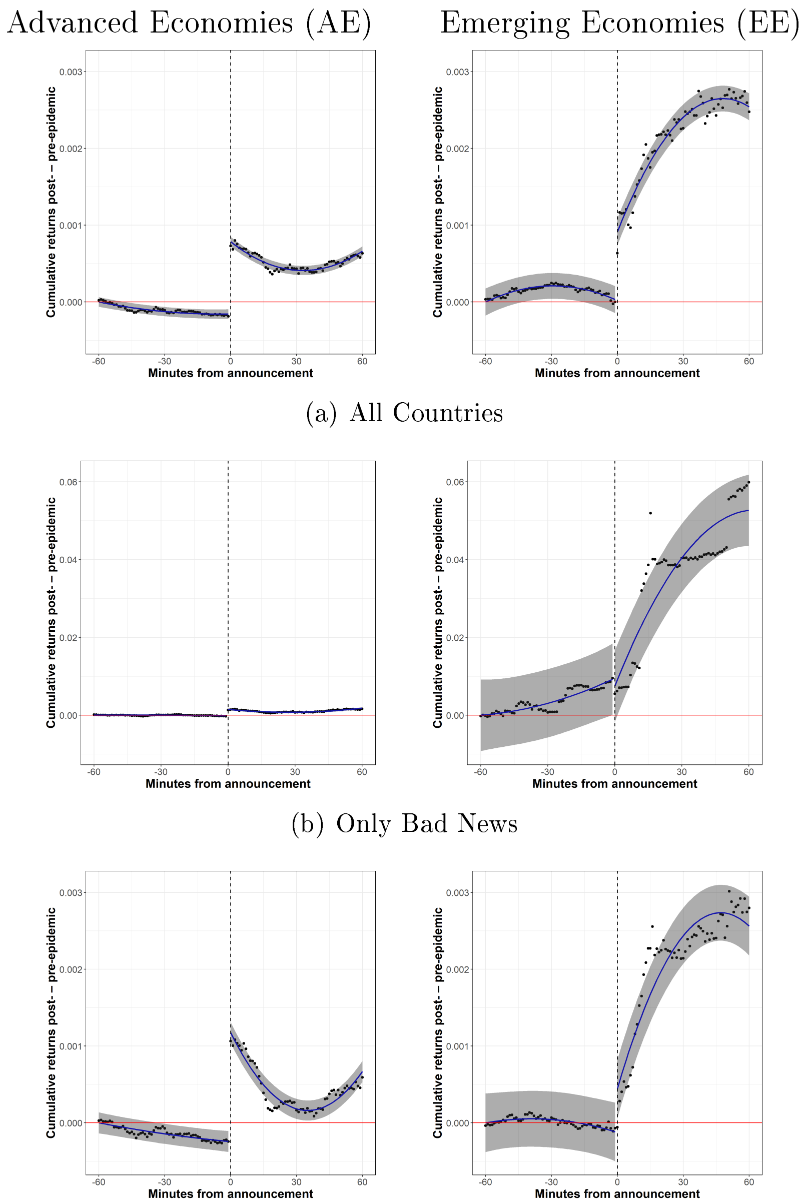
Fig. 2. Information Diffusion and Attention around Announcements

Notes: The left (right) panel of this figure shows the average per-minute and per-country number of tweets (retweets) around announcement times in excess of the same average in the pre-epidemic period. 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 equation (1). The sample starts on October 1st 2019 and ends on the date of this draft.

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 appendix).

Equity markets. In figure 3, we show the average cumulative returns obtained from buying country-specific equities 60 minutes before a country-specific announcement and holding them for 120 minutes. Our results are averaged across both countries and announcements. Countries are divided in two groups, advanced and emerging economies, according to the IMF classification.[4]

[4] If a country-specific announcement happens when the exchange of the country is closed, we consider the 60 minutes prior to the closing time of the previous day and the first 60 minutes after the opening of the exchange in the next day. This is, for example, what we do with the ECB announcement made at 11:05 p.m. on 3/18/2020.



(a) All Countries

(b) Only Bad News

(c) High-COVID Countries

FIG. 3. EQUITY RETURNS AROUND ANNOUNCEMENTS

Notes: In each panel, dots denote the difference across subsamples of the cross-country-cross-announcement average cumulative returns obtained from buying equities 60 minutes before an announcement and holding them for 120 minutes. Panel a (b) comprises announcements from all countries (top-50% countries in terms of contagion cases) in each group. Panel c excludes announcements conveying good news. Returns are in raw log units. Solid line and shaded areas are based on the estimation of equation (1). Our sample starts on October 1st 2019 and ends on the date of this draft.

The top panels show what happens when we consider all countries and all announcements. Namely, in AEs (EEs) equity values tend to slightly decline (stay flat) before the announcement and then appreciate substantially upon the announcement. This appreciation is persistent, as it remains almost constant during the next hour in AEs and it gets amplified in EEs. This observation suggests that the release of covid-related news helps equities. Since we are considering both announcements conveying positive news and announcements conveying negative news, we think of this jump in equity valuation as a measure of the value of the pure release of information about epidemic risk.

More specifically, we note that this figure shows a time varying behavior of returns **that is** quite different from that documented in Lucca and Moench (2015). Lucca and Moench (2015) show a slow and persistent accumulation of positive returns before monetary policy announcements. In our case, instead, the increase in the cumulative returns at the announcement is consistent with the Ai and Bansal (2018) model. When the representative investor cares about the timing of a resolution of uncertainty, prices jump upward when uncertainty is resolved along the information cycle, and then they eventually start to decline.

In figure 3(b), we show that the same phenomenon is present to a similar extent when we focus on the subset of announcements associated to bad news within the the group of AEs.[5] 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.

Turning our attention to EEs, we note that there still exists a positive jump in equity valuations, but it happens with about a 15 minutes delay with respect to our announcement time stamps. Given our quadratic specification, this phenomenon is captured through a significant increase in the slope of our cumulative returns time series. We also point out that in this case the jump is one order of magnitude greater than under the case in which we consider all announcements, implying that in these countries the value of a resolution of uncertainty may be extremely high even when

[5]Note that the scale for this panel is one order of magnitude grater than that in figure 3(a).

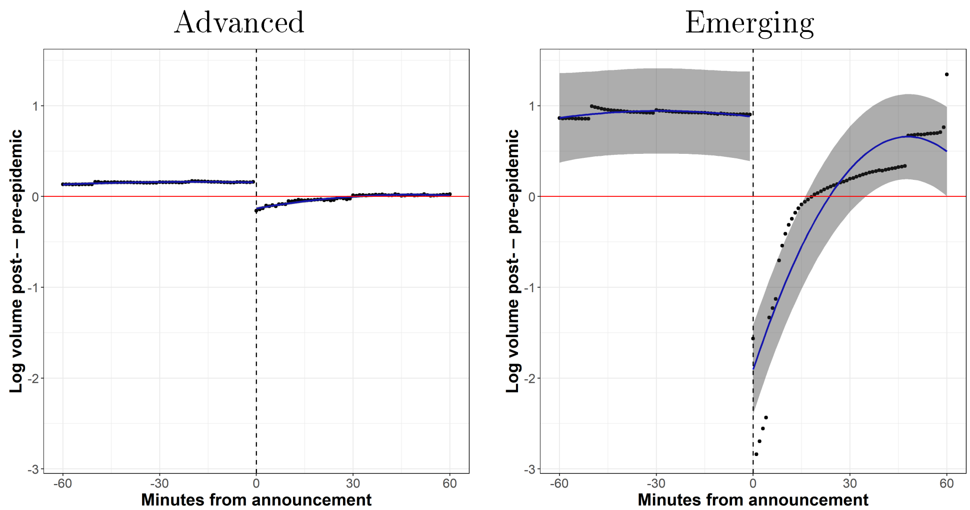


Fig. 4. Equity Volume around Announcements

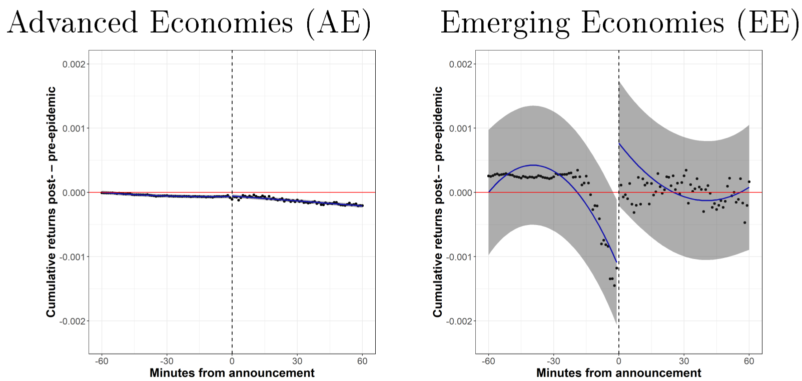
Notes: The left (right) panel shows the average equity log-volume for all (above median of contagion cases) countries around announcement times. We depict the difference across per- and post-epidemic samples. In each country, the epidemic period starts when there are more than 100 cases of COVID19. Solid line and shaded areas are based on the estimation of equation (1). Our sample starts on October 1st 2019 and ends on the date of this draft.

we condition on bad news.

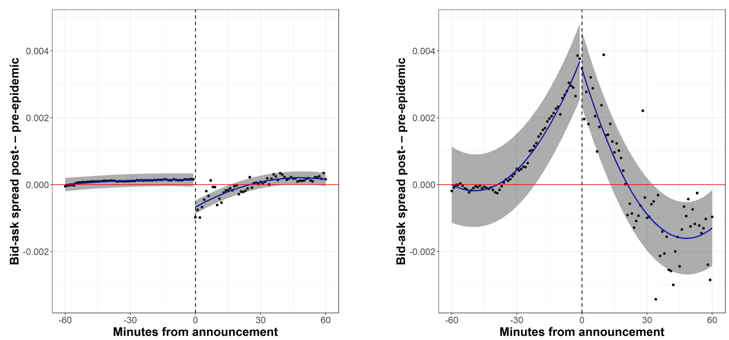
In figure 3(c), we consider all of our announcements but we limit our attention to countries that are above median in terms of total contagion cases. The scale in these panels is identical to that used in figure 3(a). Not surprisingly, the smaller sample that we use produces estimates surrounded by higher 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 volume. In figure 4, we directly depict the difference in log volume across



(a) Bond Returns



(b) Bonds Bid-Ask Spread

Fig. 5. Sovereign Bonds around Announcements

Notes: 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 minutes before an announcement and holding them for 120 minutes. 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 raw log units. Solid line and shaded areas are based on the estimation of equation (1). Our sample starts on October 1st 2019 and ends on the date of this draft.

normal and epidemic subsamples. We find that both in AEs and in EEs trade volume is higher than in the pre-epidemic sample before the announcements. Furthermore, trade volume increases ahead of the announcements and suddenly declines right afterward. This downward adjustment is more pronounced in EEs. In the next part of this study, we focus on sovereign bonds and document that liquidity seems to increase in the bond markets of AEs. This suggests a reallocation of trade toward these kind of assets.

Bond markets. Figure 5(a) shows our results for bonds returns. The construction of the depicted data is identical to that used for equities. We note that the dynamics in the bond markets are less severe than those observed from equities. In a ± 60-minute window around the announcement, there is no significant adjustment in bonds returns for AEs. This observation is important as, by no-arbitrage, it suggests that cash-flow uncertainty is an important determinant of the market fluctuations observed during the COVID19 crisis. This high-frequency result is consistent with the results documented by Gormsen and Koijen (2020) looking at dividend futures.

Focusing on EEs, however, we note that sovereign bonds loose value ahead of announcements and then appreciate at the time of announcement like equities. over, our $\pm 60-$minute window, however, the cumulative return is nearly zero both across AEs and EEs, suggesting that bonds are an important hedge against contagion risk announcements.

In order to further investigate the role of sovereign bonds, we also look at the behavior of their bid-ask spread. Absent high-frequency data on bonds trading volume, we think of this spread as a measure of liquidity in the market. We note very different patterns across AEs and EEs. Specifically, in AEs liquidity tends to improve right after announcements. This observation, paired with the decline in equity volume depicted in figure 4, suggests that investors may tilt their trade toward bonds of AEs right after announcements. In this countries, we should not be surprised that such a reallocation of investment flows comes with almost no adjustment in bond prices since it may be the result of their monetary policy.[6]

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 21^2

[6]An alternative explanation for this muted response is that bond markets are subject to two offsetting forces. Specifically, flight to safety may promote bond appreciation but, simultaneously, sovereign default risk may increase and push bond prices downward. We are working on this issue by collecting country-level data on CDS spreads. Given that different countries entered this crisis with different levels of fiscal capacity, exploring country-level heterogeneity is important.

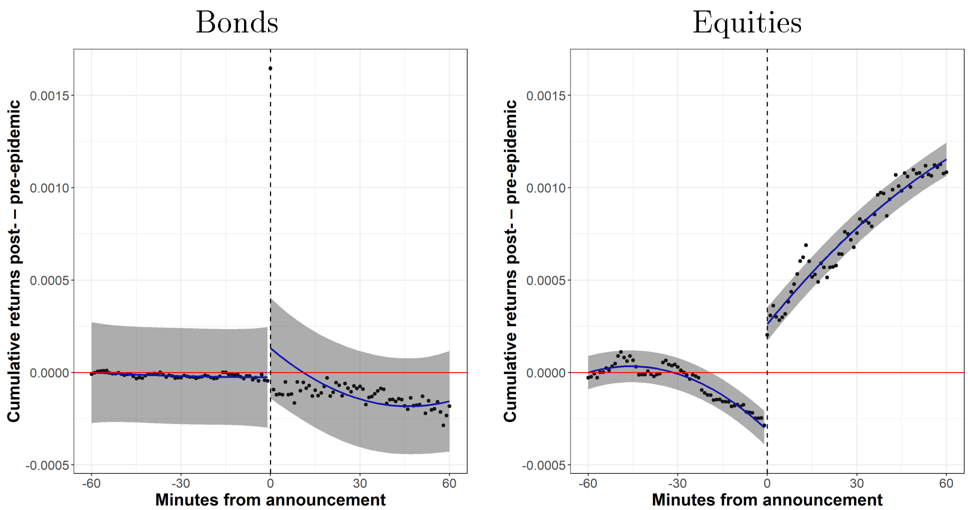


FIG. 6. LOCAL RETURNS AROUND DOMESTIC ANNOUNCEMENTS

Notes: In each panel, dots denote the difference across subsamples of the cross-country average cumulative returns obtained from buying domestic equities 60 minutes before a domestic announcement and holding for 120 minutes. Returns are in raw log units. Solid line and shaded areas are based on the estimation of equation (1). Our sample starts on October 1st 2019 and ends on the date of this draft.

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 6, we focus on the average cumulative returns across 21 trade strategies that involve neither foreign news nor foreign assets.

Our data confirms that bonds have a muted response to announcements. Equities, in contrast, tend to depreciate ahead of the announcement and then suddenly appreciate afterward. This pattern resembles that derived by Ai and Bansal (2018) in a model in which the timing of information matters.

3 Contagion News

In this section, we attempt to price news about pandemic risk. We do it using two fundamental measures, namely, unexpected change in number of contagion cases and unexpected change in the tone of the news about contagion. The first measure is based on an objective count of COVID19 positive cases. Yet, across different months or contagion waves, the same variation in the number of cases may be associated to different assessments of risk. For this reason, we find it important to study also a media-based measure of news tone.

Our analysis confirms that global epidemic news have a significant market price of risk. In April 2020, at the peak of the first COVID contagion wave, daily equity risk premia may have increased by 0.4% in AEs and by 2% in EEs.

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 appendix). In contrast to Baker et al. (2016), we do not analyze articles, rather we track news published on Twitter in real time, so that we can produce high frequency data when needed. More specifically, we track the news related to the COVID19 pandemic posted by major newspapers on Twitter. We do so by searching for key words such as 'coronavirus' and 'covid19'. For each newspaper, we identify the location of its headquarter so that we can identify its specific time-zone.

In table 2, 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

Table 2. Newspapers Dataset

Country	No. News Providers	Tweets	Retweets	Likes	Topics			
					Mortality	Symptoms	Quarant.	Med. Supply
Argentina	4	44,776	818,962	2,041,108	21%	16%	13%	50%
Australia	4	7,568	80,515	162,524	31%	5%	36%	28%
Brazil	4	20,834	1,024,299	6,139,727	57%	7%	2%	35%
Canada	5	20,619	180,409	342,711	41%	5%	15%	39%
Chile	4	16,333	244,458	340,125	63%	12%	3%	23%
China	3	23,390	827,363	2,271,595	49%	4%	16%	30%
Colombia	4	17,870	294,462	809,446	19%	10%	15%	56%
France	4	26,923	972,378	1,591,329	27%	5%	33%	35%
Germany	4	5,908	93,784	185,910	11%	12%	23%	54%
Hong Kong	3	12,999	359,772	506,445	21%	4%	36%	39%
India	4	56,138	613,132	3,561,373	39%	3%	30%	28%
Italy	3	21,679	207,879	554,601	16%	8%	30%	46%
Japan	4	9,079	93,931	142,366	25%	6%	19%	50%
Korea	4	7,190	56,698	84,114	35%	4%	18%	42%
Mexico	4	44,130	1,040,326	2,509,879	22%	16%	8%	54%
New Zealand	4	11,796	108,143	232,385	34%	5%	37%	24%
Spain	4	24,454	1,876,127	2,968,189	44%	18%	5%	33%
Switzerland	4	4,202	26,892	33,916	18%	7%	26%	48%
UK	4	15,471	755,302	1,666,327	34%	7%	34%	25%
USA	11	58,108	4,645,014	9,654,077	42%	8%	12%	38%
Total	85	449,467	14,319,846	35,798,147	32%	8%	21%	39%

Notes: 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 January 1st 2020 to the date of this manuscript. 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, symptoms, quarantine measures, and medical supply, respectively.

capital market reactions.

The time series behavior of our news indicator is depicted in figure 7. For each country, we also depict the beginning of the epidemic period which we identify on the day in which the number of confirmed cases of COVID19 becomes greater than 100. We note several interesting patterns. First of all, there is significant heterogeneity across countries in the timing of the 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, number of tweets, and the attention to the news, that is, number of retweets, increase rapidly after the beginning of the local epidemic period.

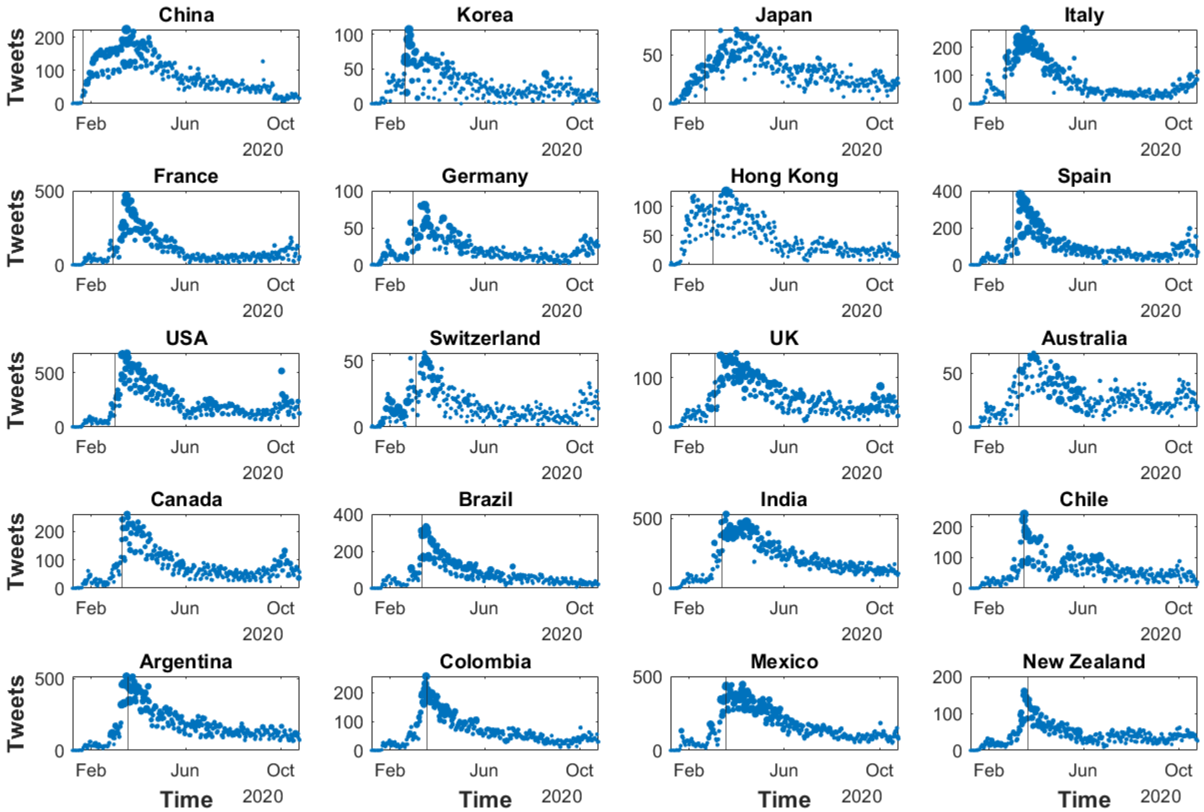


Fig. 7. Information Diffusion and Attention across Countries

Notes: 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 January 8th 2020 and ends on the date of this draft. 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 Appendix.

Figure 8 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. The right panel of this figure provides a breakdown of the most prominent topics addressed in the COVID19 tweets, namely, symptoms, death risk, quarantine measures, and availability of medical supply. The attention to all of them increased substantially, except for the number of tweets devoted to the discussion of the symptoms of COVID19 which has increased only slightly.

Figure 9 shows the intraday pattern of the diffusion of COVID19 news for each country. This

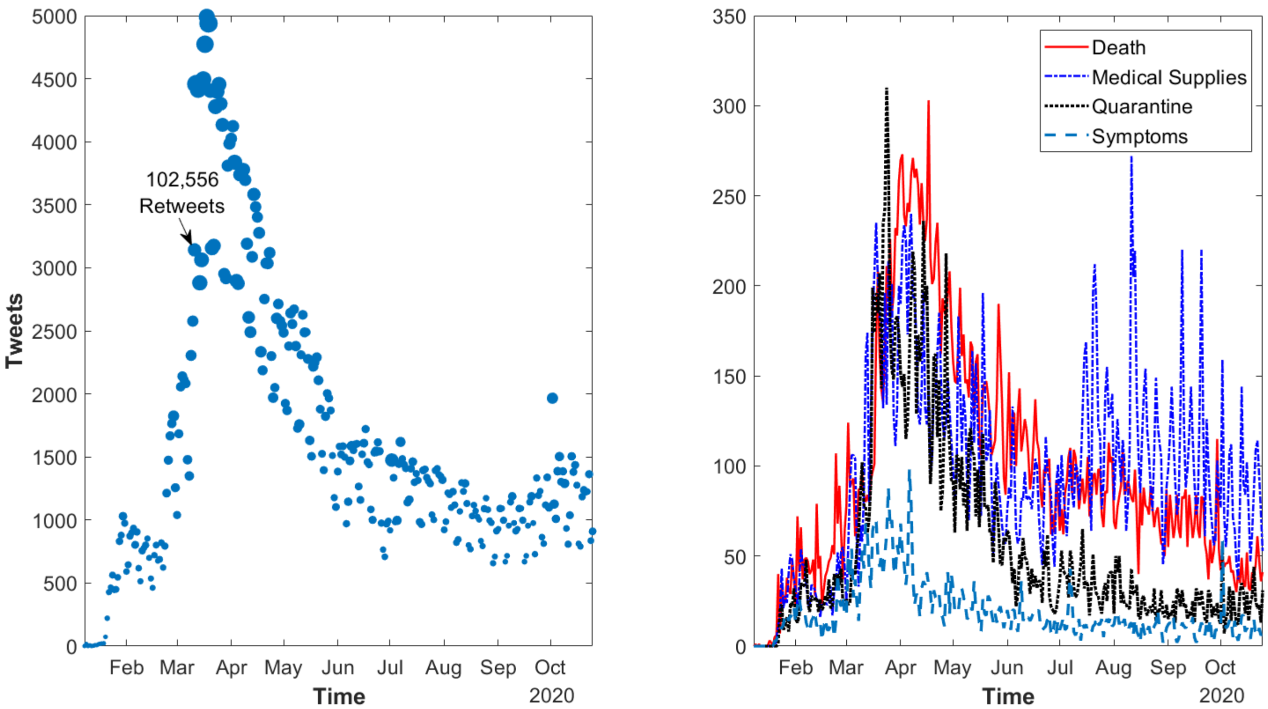


Fig. 8. Global Information Diffusion

Notes: 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 symptoms. The tweets were identified using a multilingual bag-of-words approach. The sample starts on January 8th 2020 and ends on the date of this draft. More details on the data collection are reported in the Appendix.

figure is not based on universal time, rather it accounts for country-specific time. In each country, we consider two country-specific subsamples, that is, the pre-epidemic and epidemic period. There are two main takeaways from this picture: (i) the diffusion of COVID19-related news increases significantly with local epidemic conditions; and (ii) a significant share of the diffusion takes place while the local capital markets are open. This observation is important because it suggests that monitoring media activity can be a very useful tool to track in real-time the information set of financial market participants.

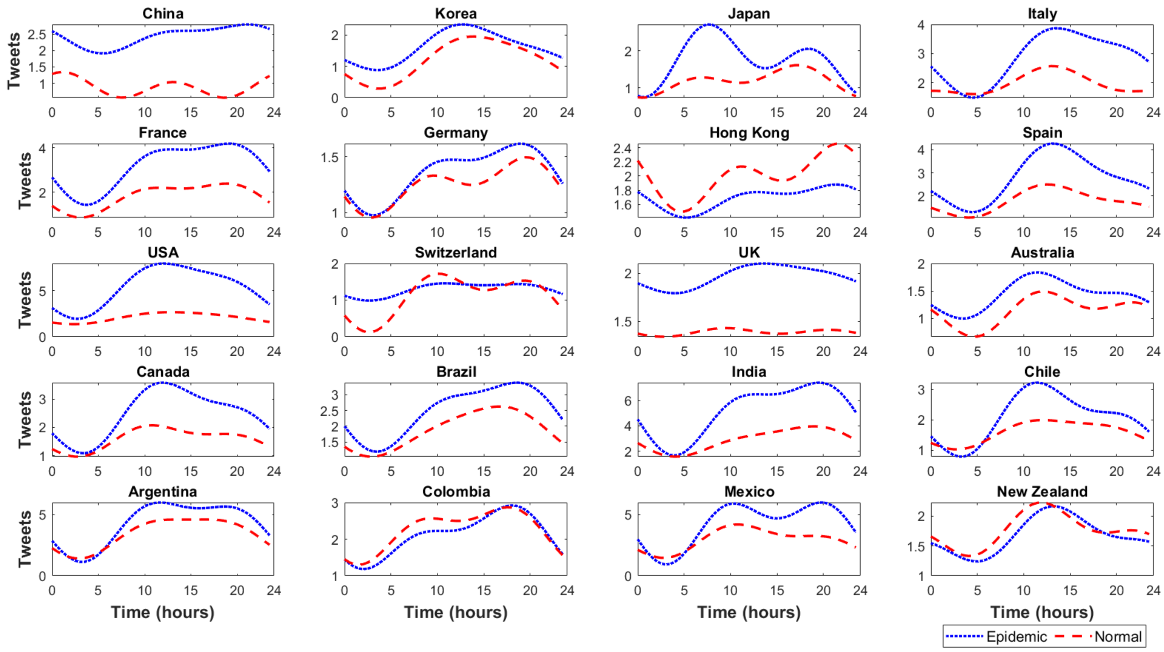


Fig. 9. Intraday Information Diffusion

Notes: This figure shows the intra-day trend of the number of tweets posted every 30 minutes across several countries in our dataset. The dotted line represents the intra-day trend in the epidemic period, identified when a country has more than 100 cases of COVID19. The dashed line represents the intra-day trend in the pre-epidemic period. The sample starts on January 8th 2020 and ends on the date of this draft. Time refers to local time zone of each newspaper. More details on the data collection are reported in the Appendix.

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 negatives words and 0 for neutral words. We provide two examples in table A.2 (see our appendix).

Our measure of the tone of the 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. We then aggregate this measure across countries in order to obtain a global measure.

We depict our global tone factor in figure 10, 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.

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 figure 10 and note that it is nearly serially uncorrelated.

Contagion and financial data. Contagion data are from official medical bulletins. Our primary source is CSSE at Johns Hopkins University.[7] News to the contagion factor are 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.[8] Our financial data sources are detailed in table A.3 (see appendix).

In order to show the relevance of local epidemic conditions, in figure 11 we show the intra-day

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

[8] For the Easter Holiday, we assign to Thr 4/9/2020 the average daily growth rate of global cases from Thr 4/9/2020 to Mon 4/13/2020.

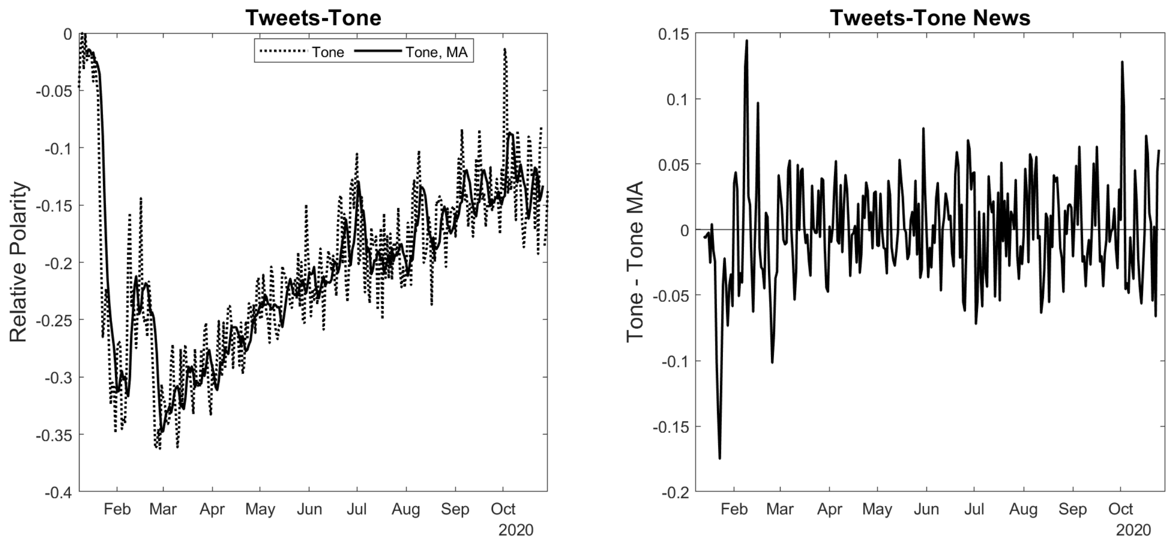
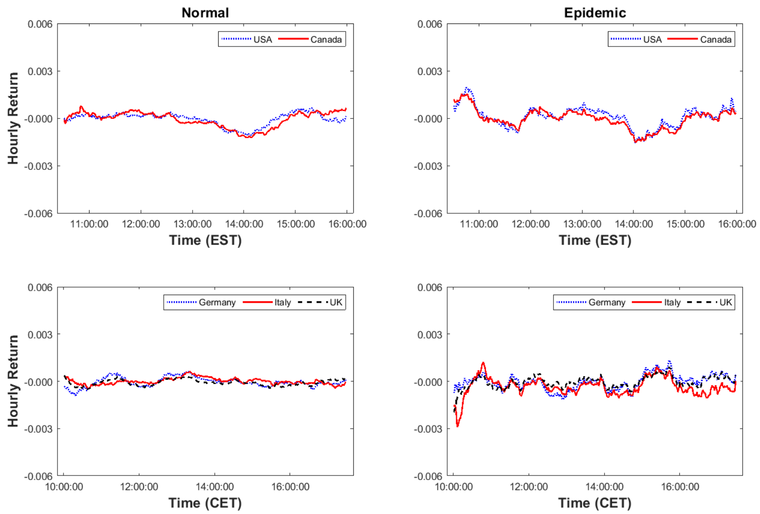


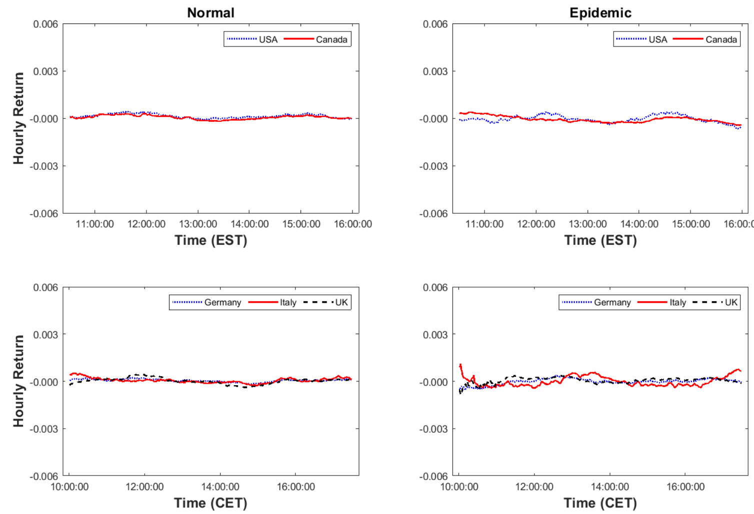
Fig. 10. Twitter-Based COVID19 Factor

Notes: 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 in early January 2020 and ends on the date of this draft.

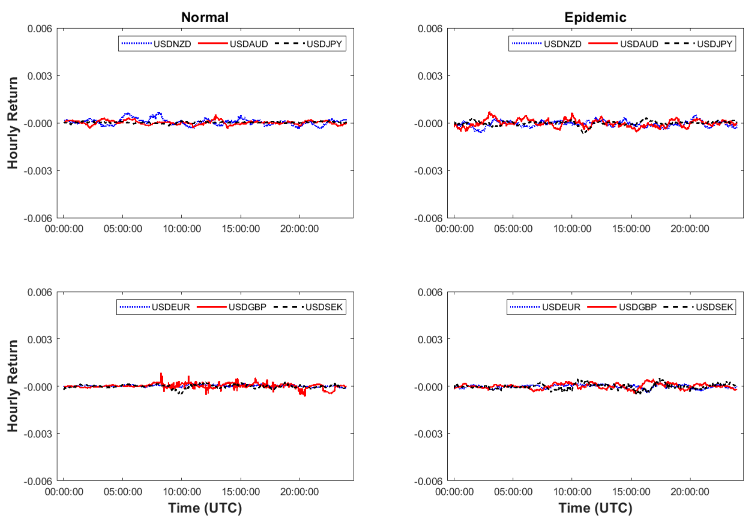
behavior of returns pre- and post-epidemic for equities, bonds, and currencies. We focus on two groups of countries with similar stock exchange timing, namely US and Canada (EST timezone), and Italy, UK, and Germany (CET timezone). The countries in the second group are interesting because they have experienced very different exposures to COVID19. Italy has been affected first and in an intensive way. Germany has been able to mitigate the contagion during the first contagion wave and has seen a pick up in contagion numbers as soon as it lessened the lockdown measures. The UK has changed its strategic response to the crisis in the middle of the epidemic period.



Equity



Bonds



Currencies

Fig. 11. Intra-day Returns Behavior and Epidemic Conditions

Notes: For each asset class, we depict per- and post-pandemic intra-day return patterns. Data are averaged across days. In each country, the epidemic period starts when there are more than 100 cases of COVID19. The sample starts in October 2019 and it ends on the date of this draft. Bond and stock hourly returns start one hour after the opening of the markets. All returns are in raw units.

We note that equity returns have been much more volatile in the epidemic period. Most importunately, the intra-day patterns have become much more correlated once all countries have gone into an epidemic state. This result suggests that we can think of the epidemic as a slowly diffusing common factor. Our empirical asset pricing analysis is based on this observation.

When we turn our attention to bonds in the epidemic period, we see more volatile patterns than in the pre-epidemic period. In contrast to equities, we see no substantial change in their commonalities across countries. Currencies, instead, tend to be more volatile and more correlated in epidemic subsamples, similarly to equities. We see this as consistent with COVID19 being a global risk factor that affects countries at different times and with different intensities. Our empirical asset pricing analysis takes into consideration the hypothesis that our countries may feature heterogeneous exposure to global contagion risk.

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 COVID19 cases measured the previous day. We do this separately for AEs and EEs. The H (L) portfolio comprises the top (bottom) countries in terms of COVID19 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 3. 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 both the first contagion wave and its temporary disappearing. 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.

Table 3. Summary Statistics for Portfolios

	Low	**Medium**	**High**	**HML$_{COVID19}$**
Panel A: Advanced economies				
Mean	-0.001	0.021	-0.073	-0.072
	(0.146)	(0.138)	(0.179)	(0.069)
StDev	1.644	1.96	2.075	1.306
Skewness	-1.132	-0.586	-1.436	-0.169
First Quartile	-0.535	-0.605	-0.758	-0.683
Avg. N. Countries	5.019	4.004	4.977	-
Turnover (%)	1	2.2	1	-
Panel B: Emerging economies				
Mean	-0.082	-0.067	0.114	0.195
	(0.238)	(0.232)	(0.130)	(0.158)
StDev	2.652	2.421	2.275	2.02
Skewness	-1.595	-1.594	-0.912	0.403
First Quartile	-0.848	-0.9	-0.901	-1.007
Avg. N. Countries	3.009	1.991	2	-
Turnover (%)	1.3	2.6	1.5	-

Notes: 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 February 2020 to the date of this manuscript. Turnover measures the number of countries entering or exiting a portfolio relative to the total number of countries in a specific portfolio $\times$ number of days in our sample. Numbers in parenthesis are HAC-adjusted standard errors.

Given these preliminary observations, we consider the following conditional asset pricing model,

$$r^{ex}_{f,t+1} = \overline{r}^{ex}_{f,t} + \beta_{f,t} \cdot news^{glob}_{t+1}, \quad f \in \{H, M, L\}, \tag{2}$$

$$\beta_{f,t} = \beta_0 + \beta_{f,1} X_{f,t}, \tag{3}$$

$$\frac{\partial \overline{r}^{ex}_{f,t}}{\partial X_{f,t}} = \lambda \beta_{f,1}, \tag{4}$$

where X_t is the share of contagion cases associated to portfolio f at time t, and λ is the market price of risk 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 4. Panel A is based on unexpected changes in the growth of global contagion cases. Panel B, instead, is based on unexpected changes in the global Tone of tweets. Note that the set of countries that 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 contagion-based news, $\beta_{f,t}$.[9] In our sample, the portfolio of countries with the highest share of COVID19 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

[9]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.

Table 4. Summary of MPR estimation

	Equity		Bonds & Equity	
	A.E.	E.E.	A.E.	E.E.
Panel A: News about Covid cases				
Local units				
coef	-0.006^{**}	-0.010^{***}	-0.003^{**}	-0.011^{***}
se	(0.003)	(0.002)	(0.001)	(0.001)
USD units				
coef	-0.005^{*}	-0.011^{***}	-0.004^{***}	-0.011^{***}
se	(0.003)	(0.002)	(0.001)	(0.002)
Controlling for MKT				
coef	-0.004^{**}	-0.006^{***}	-0.007^{***}	-0.017^{***}
se	(0.002)	(0.002)	(0.001)	(0.003)
Panel B: News from Twitter				
Local units				
coef	0.022^{***}	0.012^{***}	0.018^{***}	0.006^{***}
se	(0.005)	(0.003)	(0.002)	(0.002)
USD units				
coef	0.025^{***}	0.008^{***}	0.018^{***}	0.007^{***}
se	(0.007)	(0.003)	(0.002)	(0.002)
Controlling for MKT				
coef	0.007^{***}	0.010^{***}	0.012^{***}	0.007^{***}
se	(0.003)	(0.001)	(0.002)	(0.002)

Notes: This table shows the results of the conditional linear factor model described in equations (2)–(4). Portfolios are formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation (X_t). In panel A (panel B), 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. The last two columns are based on a broader cross section of test assets comprising both equity and bond portfolios. 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 2/1/2020 to the date of this manuscript. Estimates and HAC-adjusted standard errors are obtained through GMM.

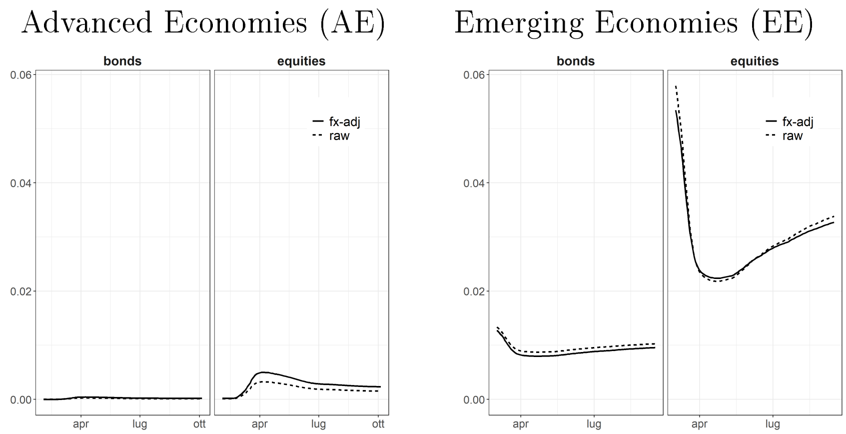
a relevant positive predictor of future cost of capital.

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 by global market risk as measured by the MSCI Global Index.[10] This result holds both when we use only equities as test assets and when we increase our cross section by introducing bonds. 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 as very significant, consistent with the great contraction experienced in equity markets during the epidemic period.

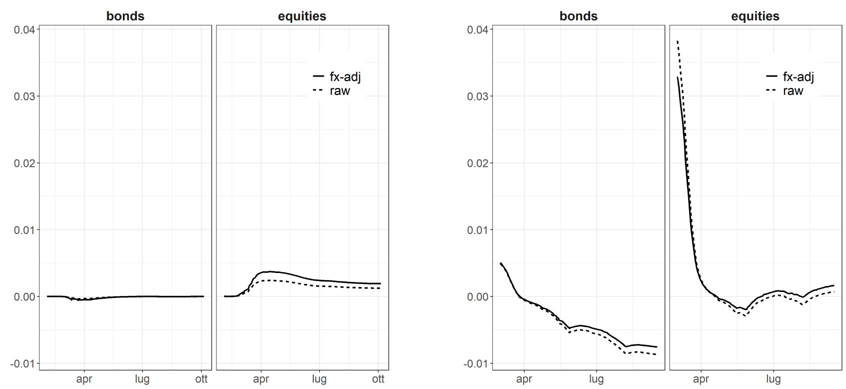
Simultaneously, we note that this value is very plausible once we account for two observations. First, this is not the MPR of a financial factor and the associated estimated beta are very small. Second, contagion risk follows waves with a relatively short half-life. Equivalently, the exposure of our assets to this risk are small and relatively quick in reverting to zero. This phenomenon is depicted in figure 12(a). Our results confirm that sovereign bonds issued by AEs are not sensitive to contagion risk. Equities, instead, experienced a more pronounced increase in their required risk premium among High-COVID countries. In contrast, in EEs both bonds and equities feature a much more pronounced increase in their riskiness. Bonds' exposure, however, has been smaller than that of equities', confirming that also EEs' bonds are safer with respect to contagion risk.

In figure 12(b), we show the estimated risk premium on an HML-COVID19 strategy on either bond or equity portfolios across AEs and EEs. Focusing on this strategy helps us to highlight the role played by heterogeneous exposure to contagion risk. We document several novel empirical results. First of all, we note that the riskiness of bonds has increased less in High-COVID countries than in Low-COVID countries. Equivalently, in High-COVID countries, bonds are relatively safer assets. As a result, an HML-COVID strategy on bonds provides an insurance premium. In AEs, this premium is very moderate, consistent with our prior empirical evidence on the muted response of bonds around medical announcements time. In EEs, instead, the insurance premium is quantitatively relevant both in local units and in USD. Hence this HML strategy may be of interest to international investors seeking a strong hedge against contagion risk.

[10] Throughout our study, when we consider the MSCI index to control for the market we use returns in USD.



(a) Expected returns for H_{COVID} portfolios



(b) Expected HML_{COVID}

Fig. 12. Expected Risk Premia

Notes: The left (right) panels refer to portfolios of countries within the AE (EE) group. The top panels show the estimated risk premium on a portfolio of countries with a share of High-COVID19 cases on bond and equity portfolios. The bottom panels refer to the HML-COVID strategy. These results are based on the specifications reported in the last two columns of table 4. The solid line refers to exchange rate–adjusted returns, i.e., returns expressed in USD.

Second, we notice that the equity-based HML strategy in AEs features a required premium similar to that estimated for the High-COVID portfolio. Equivalently, Low-COVID countries have experienced nearly zero change in their risk premium. This result is important because it implies that containment policies that keep contagion cases relatively low may be very valuable both in terms of lives saved and in terms of preventing severe financial wealth losses.

Turning our attention to equities in the EEs, we notice that the required premium on the associated HML strategy has increased dramatically at the beginning of the pandemic and it is now close to zero. The initial jump should not be surprising as both China and India are in the High-COVID portfolio. It is interesting, however, that the response to global news of High- and Low-COVID EEs quickly became less heterogeneous by the end of April. At the time we are writing this manuscript, our estimation suggests that the HML-COVID is quantitatively very similar across AE and EE equity markets.

Additional results with daily data. In table B.1 (see 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.

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 enables us also to construct AE- and EE-specific measures of both COVID19 case growth and Twitter tone. See, for example, figure B.1 in the 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 for us AE- and EE-specific news. In Appendix Appendix B, we show mixed results. Local contagion news are priced negatively in AEs and positively in EEs. When we use local innovation to our tweets' tone, the implied MPR is often not statistically different from zero. The MPR associated to our Twitter-based measure of risk becomes significantly positive only when we focus on AEs and look at a cross section that includes both equities and bonds.

Taken together, we interpret these additional results as supporting our specification with heterogeneous and time-varying exposure to global contagion risk news.

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.

In this section, we focus only on European countries whose markets are open simultaneously. Specifically, we focus on ITA, ESP, UK, FRA, DEU, CHE, and SWE. Every day, we group them into three portfolios according to their relative number of COVID19 cases. In table 5, 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 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.

4 Conclusion

In this study, we quantify the exposure of major financial markets to news shocks about global contagion risk while accounting for local epidemic conditions. We construct a novel data set comprising (i) medical announcements related to COVID19 for a wide 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 (i) around epidemic announcements, (ii) at a daily frequency, and (iii) at an intra-daily frequency. Formal estimations

Table 5. Hourly Conditional Linear Factor Model

	β_0	$\beta_{L,1}$	$\beta_{M,1}$	$\beta_{H,1}$	MPR	N.Obs	N. Assets
			Panel A: only equities, equity betas				
Hourly log returns							
coef	-0.009^{***}	1.637^{***}	0.850^{***}	0.005	0.064^{***}	1566	3
se	(0.002)	(0.212)	(0.106)	(0.044)	(0.008)	1566	3
Hourly log EUR returns (adjusting for FX)							
coef	-0.014^{***}	0.766^{***}	0.326^{***}	0.336^{***}	0.040^{***}	1566	3
se	(0.002)	(0.147)	(0.063)	(0.049)	(0.012)	1566	3
Hourly log returns controlling for the Market							
coef	-0.003^{*}	0.103	0.030	0.038	0.065	1404	3
se	(0.002)	(0.157)	(0.068)	(0.052)	(0.101)	1404	3
			Panel B: equities and bonds, bond betas				
Hourly log returns							
coef	-0.054^{***}	6.915^{***}	2.444^{***}	1.764^{***}	0.026^{***}	1370	6
se	(0.005)	(0.568)	(0.198)	(0.142)	(0.003)	1370	6
Hourly log EUR returns (adjusting for FX)							
coef	-0.049^{***}	6.655^{***}	2.600^{***}	1.810^{***}	0.033^{***}	1370	6
se	(0.003)	(0.415)	(0.162)	(0.114)	(0.003)	1370	6
Hourly log returns controlling for the Market							
coef	-0.062^{***}	6.707^{***}	2.686^{***}	1.892^{***}	0.019^{***}	1208	6
se	(0.004)	(0.486)	(0.195)	(0.139)	(0.003)	1208	6

Notes: This table shows the results of the conditional linear factor model described in equations (2)–(4). 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 February 2020 to the date of this manuscript. Estimates and HAC-adjusted standard errors are obtained through GMM.

based on both contagion data and social media activity about COVID19 confirm that the market price of epidemic risk is very significant. In the spirit of Mulligan (2020), we conclude that policies related to prevention and containment of contagion could be very valuable not only in terms of lives saved but also in terms of global wealth.

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Appendix A. Data Sources

Table A.1: News Papers

Country	Newspaper	Twitter Account	BBD	Language
Argentina	La Nacion	@LANACION		Spanish
Argentina	Clarin	@clarincom		Spanish
Argentina	Diario Cronica	@cronica		Spanish
Argentina	Infobae	@infobae		Spanish
Australia	The Age	@theage		English
Australia	The Australian	@australian		English
Australia	The Daily Telegraph	@dailytelegraph		English
Australia	Financial Review	@FinancialReview		English
Brazil	O Globo	@JornalOGlobo		Portuguese
Brazil	O Estado de Sao Paulo	@Estadao		Portuguese
Brazil	Folha de S.Paulo	@folha		Portuguese
Brazil	Gaucha ZH	@GauchaZH		Portuguese
Canada	Gazette	@mtlgazette	Yes	English
Canada	Globe and Mail	@globeandmail	Yes	English
Canada	Ottawa Citizen	@OttawaCitizen	Yes	English
Canada	Toronto Star	@TorontoStar	Yes	English
Canada	Vancouver Sun	@VancouverSun	Yes	English
Chile	La Tercera	@latercera		Spanish
Chile	BioBioChile	@biobio		Spanish
Chile	El Mostrador	@elmostrador		Spanish
Chile	The Clinic	@thecliniccl		Spanish
China	People's Daily, China	@PDChina		English

(To be continued)

Country	Newspaper	Twitter Account	BBD	Language
China	China Xinhua News	@XHNews		English
China	China Daily	@ChinaDaily		English
Colombia	El Espectador	@elespectador		Spanish
Colombia	El Colombiano	@elcolombiano		Spanish
Colombia	El Heraldo	@elheraldoco		Spanish
Colombia	El Tiempo	@ELTIEMPO		Spanish
France	Le Monde	@lemondefr	Yes	French
France	Le Figaro	@Le_Figaro		French
France	Liberation	@libe		French
France	Le Parisien	@le_Parisien		French
Germany	Handelsblatt	@handelsblatt	Yes	German
Germany	Frankfurter Allgemeine Zeitun	@faznet	Yes	German
Germany	BILD	@BILD		German
Germany	Zeit Online	@zeitonline		German
Hong Kong	South China Morning Post	@SCMPNews	Yes	English
Hong Kong	Hong Kong Free Press	@HongKongFP		English
Hong Kong	RTHK English News	@rthk_enews		English
India	Economic Times	@EconomicTimes	Yes	English
India	Times of India	@timesofindia	Yes	English
India	Hindustan Times	@htTweets	Yes	English
India	The Hindu	@the_hindu	Yes	English
Italy	Corriere Della Sera	@Corriere	Yes	Italian
Italy	La Repubblica	@repubblica	Yes	Italian
Italy	Il Sole 24 ORE	@sole24ore		Italian
Japan	Asahi Shimbun AJW	@AJWasahi	Yes	English

(To be continued)

Country	Newspaper	Twitter Account	BBD	Language
Japan	The Japan News by Yomiuri	@The_Japan_News	Yes	English
Japan	The Japan Times	@japantimes		English
Japan	Japan Today News	@JapanToday		English
Korea	Korea JoongAng Daily	@JoongAngDaily		English
Korea	The Korea Herald	@TheKoreaHerald		English
Korea	Yonhap News Agency	@YonhapNews		Korean
Korea	The Korea Times	@koreatimescokr		Korean
Mexico	La Jornada	@lajornadaonline		Spanish
Mexico	Reforma	@Reforma		Spanish
Mexico	El Universal	@El_Universal_Mx		Spanish
Mexico	Milenio	@Milenio		Spanish
New Zealand	The New Zealand Herald	@nzherald		English
New Zealand	The Sydney Morning Herald	@smh		English
New Zealand	Herald Sun	@theheraldsun		English
New Zealand	Guardian Australia	@GuardianAus		English
Spain	EL MUNDO	@elmundoes	Yes	Spanish
Spain	EL PAIS	@el_pais	Yes	Spanish
Spain	ABC.es	@abc_es		Spanish
Spain	La Vanguardia	@LaVanguardia		Spanish
Switzerland	Neue Zurcher Zeitung	@NZZ		German
Switzerland	20 Minuten	@20min		German
Switzerland	24heures	@24heuresch		French
Switzerland	Le Temps	@LeTemps		French
USA	LA Times	@latimes	Yes	English
USA	USA Today	@USATODAY	Yes	English

(To be continued)

Country	Newspaper	Twitter Account	BBD	Language
USA	Chicago Tribune	@chicagotribune	Yes	English
USA	Washinton Post	@washingtonpost	Yes	English
USA	Boston Globe	@BostonGlobe	Yes	English
USA	Wall Street Journal	@WSJ	Yes	English
USA	Miami Herald	@MiamiHerald	Yes	English
USA	Dallas Morning News	@dallasnews	Yes	English
USA	Houston Chronicle	@HoustonChron	Yes	English
USA	San Fransisco Chronicle	@sfchronicle	Yes	English
USA	New York Times	@nytimes	Yes	English
UK	The Times	@thetimes	Yes	English
UK	Financial Times	@FinancialTimes	Yes	English
UK	BBC News (UK)	@BBCNews		English
UK	Guardian news	@guardiannews		English

Notes: This table reports our newspaper sources. For each newspaper, we specify headquarter location, original language, and twitter account. A 'Yes' under the column BBD denotes a newspaper used also in Baker et al. (2016).

TABLE A.2. COMPUTING TONE OF TWEETS: TWO EXAMPLES

Tweet Text	**Positive Words**	**Negative Words**	**Tone**
The coronavirus pandemic has been particularly devastating to the United States's biggest cities. It comes as the country's major urban centers were already losing their appeal for many Americans.	"devastating", "losing"	"appeal"	$\frac{-2+1}{3} = -0.33$
A shortage of test kits and technical flaws in the U.S. significantly delayed widespread coronavirus testing. This is how testing has increased since the beginning of March — and how far it still needs to go, according to the Harvard estimates	"shortag", "flaws", "delayed"		$\frac{-3}{3} = -1$

Notes: This table shows two examples of the computation of the tone of a tweet using Polyglot.

Table A.3. Data Sources

Country	Equity Index	Equity Volume Index	Long Term Bond Index	Sovereign CDS	Short Term Bond Index	Currency
Canada	SPTSX Composite Index	TSXVOL Index	GCAN10YR INDEX	CAGV5YUSAC	CA 3M benchmark rate	USDCAD
China	SHSZ300 INDEX	SHSZ300V INDEX	GCNY10YR INDEX	CNGV5YUSAC	CN 1Y benchmark rate	USDCNY
France	CAC Index	CACVOLC Index	GECU10YR INDEX	FRGV5YUSAC	FR 3M benchmark rate	EURUSD
Germany	DAX Index	DAXVOLC Index	GDBR10 INDEX	DEGV5YUSA	DE 3M benchmark rate	EURUSD
Hong Kong	HSI INDEX	HSIVOLC INDEX	HKGG10Y Index	HKGV5YUSAC	HK 3M benchmark rate	USDHKD
Italy	FTSE MIB Index	FTMIBVOL Index	GBTPGR10 INDEX	ITGV5YUSAC	IT 3M benchmark rate	EURUSD
India	SENSEX INDEX	SNSXVOLC INDEX	GIND10YR INDEX	INGV5YUSAC	ES 3M benchmark rate	USDINR
Japan	NKY INDEX	NKYVOLC INDEX	GJGB10 INDEX	JPGV5YUSAC	JP 3M benchmark rate	USDJPY
Korea	KOSPI Index	KOSPIVOLC INDEX	GVSK10YR INDEX	KRGV5YUSAC	KR 1Y benchmark rate	USDKRW
New Zealand	NZSE50FG INDEX	NZ50VOL Index	GNZGB10 INDEX	NZGV5YUSAQ	NZ 3M benchmark rate	NZDUSD
Spain	IBEX 35	IBEXVOLC INDEX	GSPG10YR INDEX	ESGV5YUSAC	ES 3M benchmark rate	EURUSD
Switzerland	SMI Index	SMIVOLC Index	GSWISS10 INDE	CHGV5YUSAC	CH 3M benchmark rate	USDCHF
Sweden	OMXS30 Index	OMXVOLC Index	GSGB10YR INDEX	SEGV5YUSAC	SE 3M benchmark rate	USDSEK
USA	SPX Index	SPXVOLC Index	USGG10YR INDEX	USGV5YEUAC	US 3M benchmark rate	USD
UK	UKX INDEX	UKXVOLC INDEX	GUKG10 INDEX	GBGV5YUSAC	GB 3M benchmark rate	GBPUSD
Source	Bloomberg	Bloomberg	Bloomberg	Thomson Reuters	Bloomberg	Bloomberg
Frequency	Minute	Minute	Minute	Day	Minute	Minute

Notes: This table shows our data sources.

Appendix B. Additional Estimation Results

Table B.1. Summary of MPR Estimation: Conditional CAPM

	Equity		Bonds & Equity	
	A.E.	E.E.	A.E.	E.E.
Local units				
coef	-0.027^{***}	0.004	-0.030^{***}	-0.008^{***}
se	(0.005)	(0.003)	(0.006)	(0.002)
USD units				
coef	-0.032^{***}	0.006	-0.037^{***}	-0.008^{***}
se	(0.007)	(0.004)	(0.006)	(0.002)

Notes: This table shows the results of the conditional linear factor model described in equations (2)–(4) where the risk factor is measured by the news in the MSCI Global Index. Portfolios are formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation (X_t). Both daily excess returns and market prices of risk are in log units and expressed in USD. Our real-time data range from 2/1/2020 to the date of this manuscript. Estimates and HAC-adjusted standard errors are obtained through GMM.

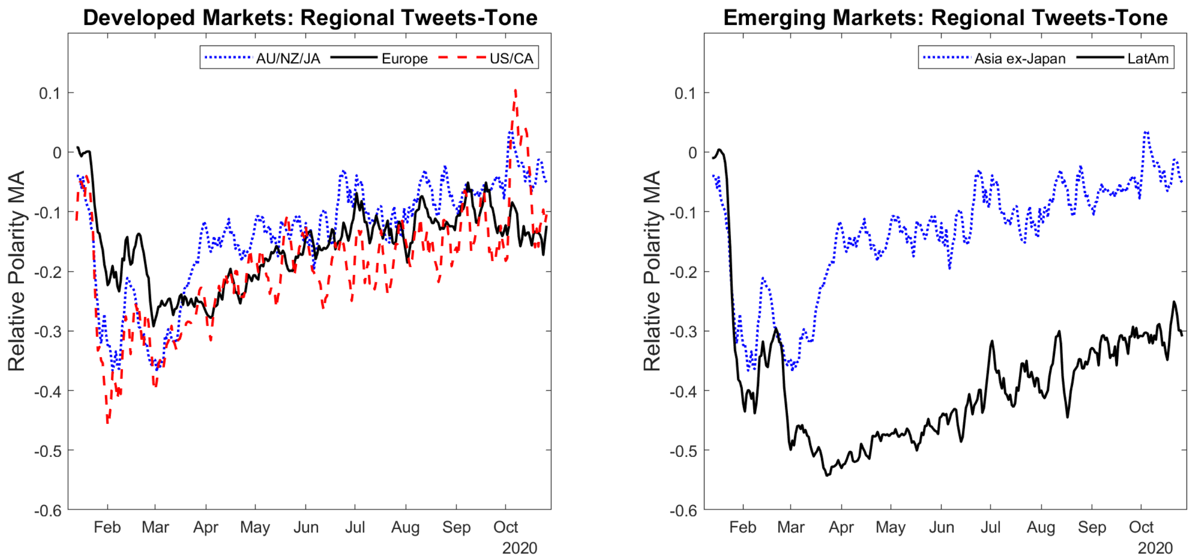

Fig. B.1. Regional Twitter-Based Tone

Notes: This figure shows our daily Twitter-based tone for different countries. 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 regions. MA refers to a backward looking 5-day moving average.

Table B.2. Summary of MPR Estimation: Local News

	Equity		Bonds & Equity	
	A.E.	E.E.	A.E.	E.E.
	Panel A: Local News about Covid cases			
Local units				
coef	−0.007***	0.012***	−0.003**	0.021***
se	(0.003)	(0.001)	(0.001)	(0.002)
USD units				
coef	−0.008**	0.011***	−0.004***	0.021***
se	(0.003)	(0.001)	(0.001)	(0.002)
Controlling for MKT				
coef	−0.001	−0.002	−0.006***	0.013***
se	(0.002)	(0.002)	(0.001)	(0.003)
	Panel B: Local News from Twitter			
Local units				
coef	0.034*	−0.033	0.018***	0.002
se	(0.019)	(0.024)	(0.002)	(0.002)
USD units				
coef	0.032	0.032	0.018***	0.001
se	(0.019)	(0.019)	(0.002)	(0.002)
Controlling for MKT				
coef	0.005**	0.004	−0.001	0.007***
se	(0.002)	(0.004)	(0.001)	(0.002)

Notes: This table shows the results of the conditional linear factor model described in equations (2)–(4) applied to AE- and EE-specific news. Portfolios are formed on a daily basis according to the relative share of country-specific COVID19 cases measured the day before formation (X_t). In panel A (panel B), the COVID19 factor is measured as the news to local 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. The last two columns are based on a broader cross section of test assets comprising both equity and bond portfolios. 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 2/1/2020 to the date of this manuscript. Estimates and HAC-adjusted standard errors are obtained through GMM.