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WHEN THE MARKETS GET COVID: CONTAGION, VIRUSES, AND INFORMATION DIFFUSION.

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JEL Classification: G01, G1, I1

Keywords: contagion, Epidemic, asset prices

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When the Markets Get COVID: 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.

*First Draft:*March 23, 2020. *This Draft:* April 28, 2020

Keywords: Contagion, Epidemic, Asset Prices.

JEL Classification: G01, G1, I1.

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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 contagion risk. First, what is the average impact of medical announcements on financial returns? Equivalently, is the diffusion of this information wealth-enhancing 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 3/11/2020 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, and (ii) news diffused on Twitter in real-time by major newspapers. 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, that is, in a ± 90 minute window. We find that cumulative equity returns have no clear pattern

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

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 upon the announcement and then they exhibit a significant downward path for about 60 minutes.

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 $\pm$60-minute window around the announcement, there is no significant adjustment in bonds returns. 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.

In the last step of our analysis we focus 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. The H (L) portfolio comprises the equity returns of the top-2 (bottom-2) countries for 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 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, λ. Across all of our specifications, the market price of contagion risk is both statistically significant and extremely high.

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 (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). Other studies assess policy concerns (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; 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.

Gerding et al. (2020) look at equity market dynamics and link the epidemic risk exposure to country-level fiscal capacity. 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 contagion risk. Ramelli and Wagner (2020) study equity returns across industries accounting for both international supply chains and investor attention. They use Google search volume 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. 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. 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.

2 Data

Twitter-based news. In the spirit of Baker et al. (2016), we identify major newspapers for a large cross section of major 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 viral infection 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 1, 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 indicators is depicted in figure 1. 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.

Figure 2 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

Table 1. Newspapers Dataset

Country	No. News Providers	Tweets	Retweets	Likes	Topics			
					Mortality	Symptoms	Quarant.	Med. Supply
Australia	4	2749	26493	51421	31%	9%	37%	23%
Canada	5	8702	77440	153272	23%	10%	25%	42%
China	3	12223	617172	1638694	26%	9%	26%	39%
France	4	13510	597993	986433	39%	4%	38%	19%
Germany	4	2807	57449	106613	20%	23%	35%	23%
Hong Kong	3	7163	258182	359694	16%	5%	46%	34%
India	4	20561	268873	1412118	28%	5%	45%	21%
Italy	3	11649	141779	393901	54%	7%	22%	17%
Japan	4	3505	53027	69952	22%	9%	32%	38%
Korea	4	3763	40787	54215	29%	6%	24%	41%
New Zealand	4	4849	52529	99205	32%	9%	39%	20%
Spain	4	11624	1050037	1599901	44%	19%	14%	23%
Switzerland	4	2057	20274	25102	36%	9%	33%	22%
UK	4	6188	322973	697886	24%	16%	39%	22%
USA	11	23896	2147624	4377633	25%	15%	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.

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 3 shows the intraday pattern of the diffusion of COVID19 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, 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; (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.

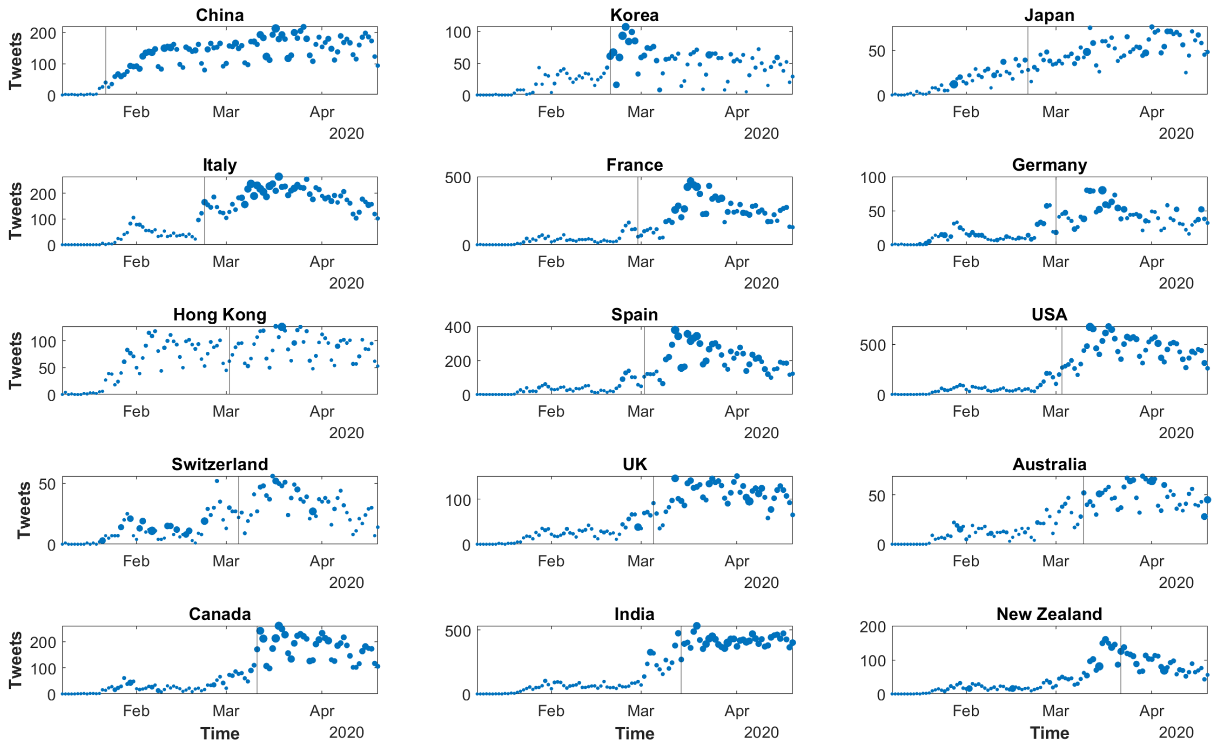


Fig. 1. Information Diffusion and Attention across Countries

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.

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).

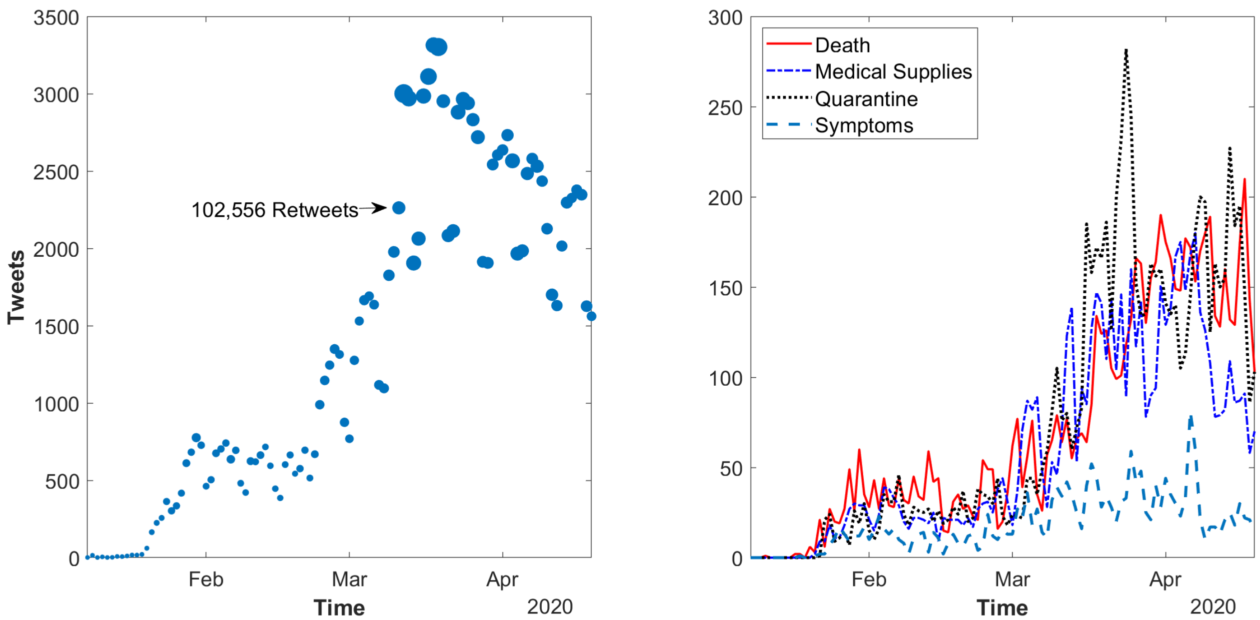


FIG. 2. GLOBAL INFORMATION DIFFUSION

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.

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 4, 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

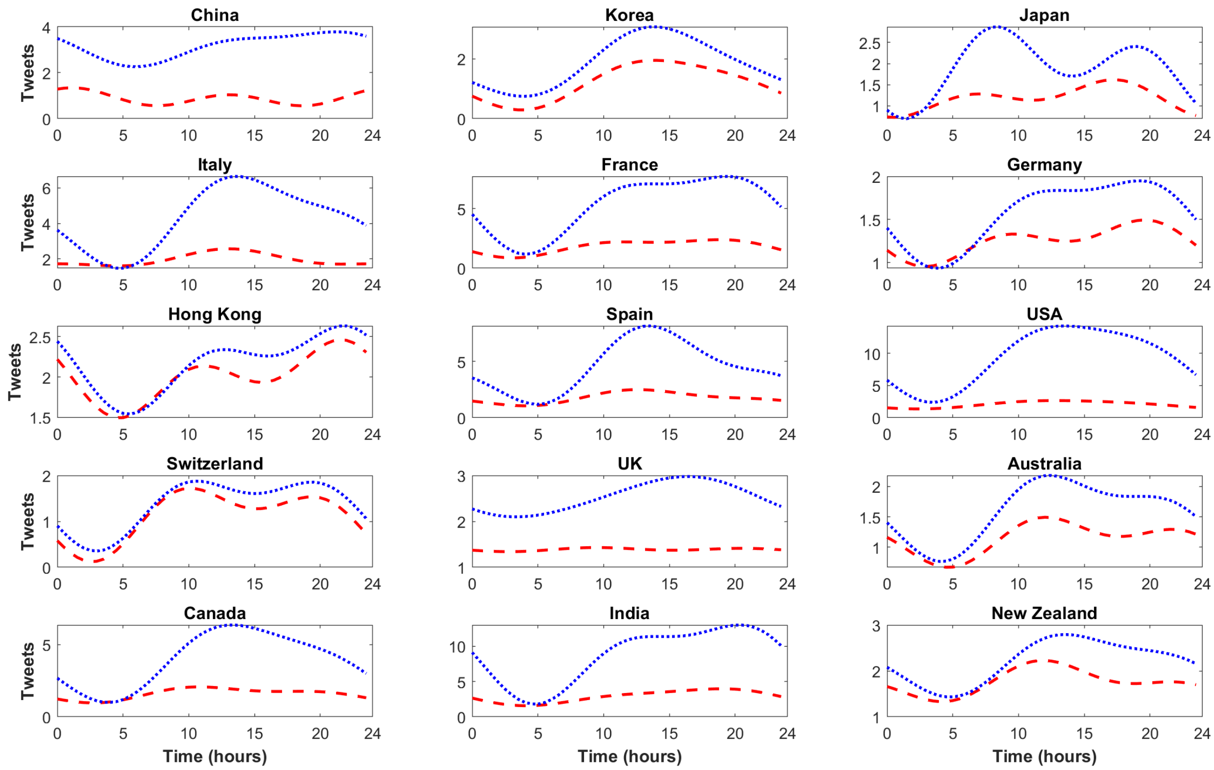


FIG. 3. INTRADAY INFORMATION DIFFUSION

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.

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 4 and note that (i) it has become progressively less volatile; and (ii) it is basically serially uncorrelated.

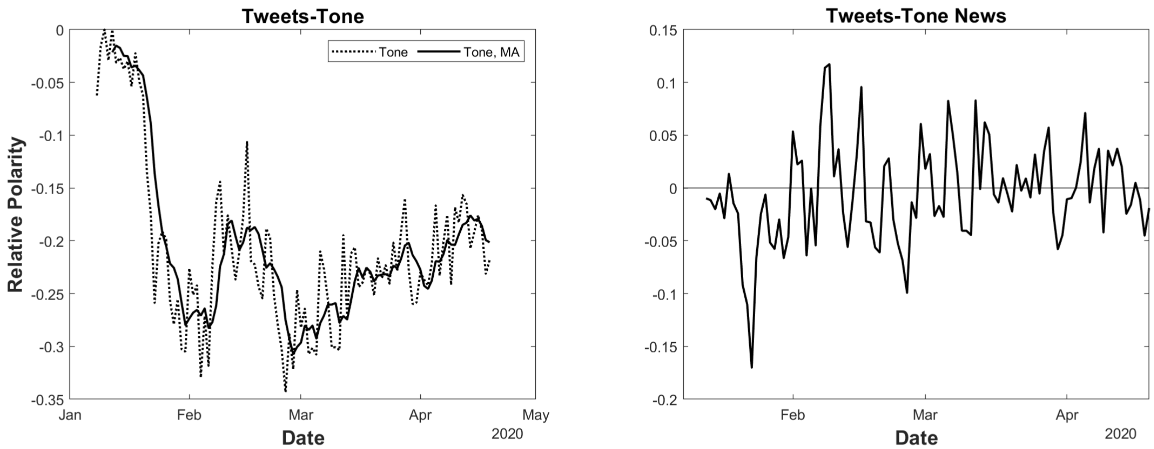


Fig. 4. Twitter-Based COVID19 Factor

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.

Contagion data. Contagion data are from official medical bulletins. Our primary source is CSSE at Johns Hopkins University.[3] Since we are interested in the timing of the announcements, we complement this information with hand-collected official press statements publicly available on the webpage of the Ministry of Health (or, equivalently, Health Department) of each country in our data set. When the time stamp of the announcement is not reported on the official report, for each country we investigate the twitter accounts of both the Ministry of Health and major newspapers releasing news with the content of the reports. Hence in our data collection we select the effective date and time of release of the news.

Announcements. For the sake of our intraday analysis, 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

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

Table 2. Summary Statistics for Announcements

Country	No. Announcements	Governments & Central Banks	Med. Bulletins & Lockdowns
Australia	82	0.00%	100.00%
Canada	28	0.00%	100.00%
China	76	0.00%	100.00%
France	55	7.27%	92.73%
Germany	27	14.81%	85.19%
Hong Kong	59	0.00%	100.00%
India	33	12.12%	87.88%
Italy	66	27.27%	72.73%
Japan	14	7.14%	92.86%
Korea	131	0.00%	100.00%
New Zealand	37	0.00%	100.00%
Spain	70	5.71%	94.29%
Sweden	20	0.00%	100.00%
Switzerland	47	2.13%	97.87%
UK	96	3.12%	96.88%
USA	70	7.14%	92.86%

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.

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. Our data collection is very comprehensive, as documented in table 2. An example of COVID19-related announcement follows:

> **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.

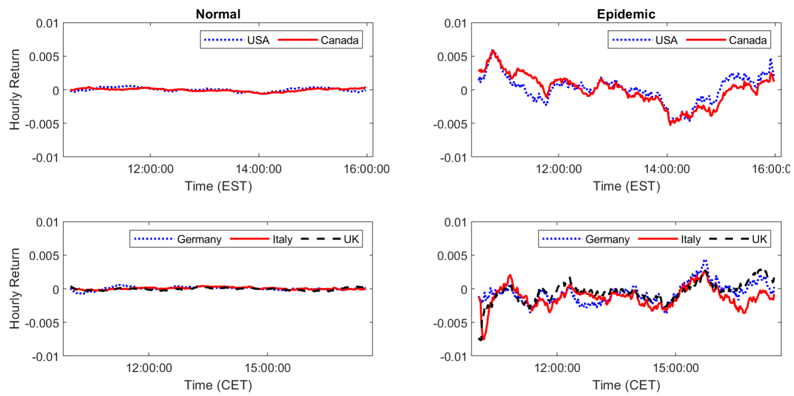
In this case, the time of the announcement is 11:05p.m. CET.

Sometimes, we may have two consecutive related announcements in the same country (for example, an official medical bulletin released by the Health Department immediately followed by a press conference of the Prime Minister). To avoid redundant information, we only consider announcements non-overlapping over a 60 minute window. In table 2, we report our effective number of announcements that we use for each country.

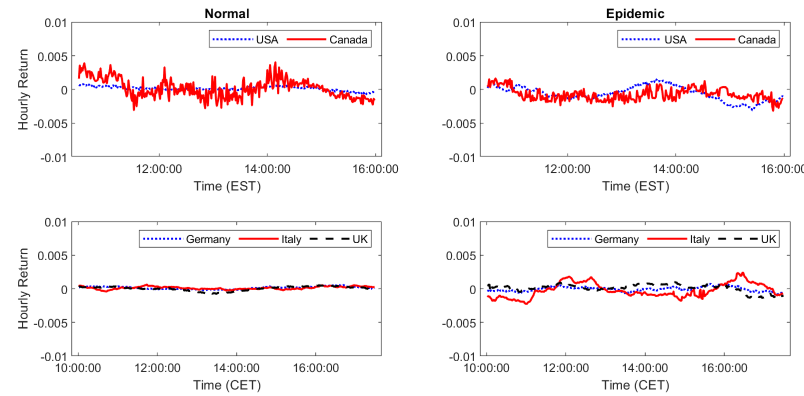
Most importantly, we show that the vast majority of the announcements that we gather are solely related to medical bulletins and policy measures to fight the epidemic. This is an important point, as the returns reaction in our study is different from that observed with respect to other economic announcements.

Financial Data. All data are from Eikon, Thomson Reuter. Equity and currency data are obtained at the minute frequency and then aggregated at lower frequency when necessary. We measure the risk-free rate by focusing on the yield of 3-month government bills. We also focus on treasury bonds with a 10-year maturity. All details about our data can be found in table A.3 (see appendix).

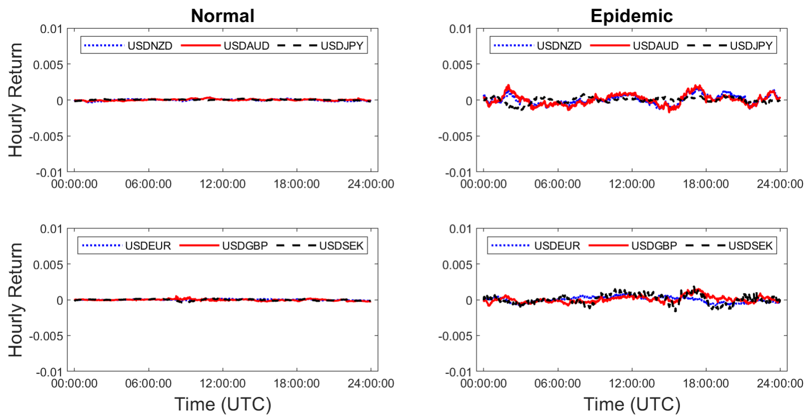
In order to show the relevance of local epidemic conditions, in figure 5 we show the intra-day behavior of returns pre- and post-epidemic for equities, bonds, and currencies. We focus on two groups of countries with similar stock exchange timing, namely US and Canada (EST timezone), and Italy, UK, and 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 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



Currecies

Fig. 5. 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. **Sentence deleted**

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 global 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.

3 Empirical Findings

In this section, we report our major empirical findings. We first look at the behavior of asset prices around announcement time. We then turn our attention to the study of a conditional linear factor model which accounts for heterogeneous exposure to COVID19. The latter approach produces interesting results both when we use daily medical bulletins and when we use higher frequency data based on our social media measures. The last subsection highlights our next research steps.

3.1 Announcements

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 collect all tweets issued in a $\pm$90-minute window around announcement time. 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 6, we show per-country per-minute average number of tweets around announcement time during epidemic periods in excess of the same average measured in the pre-epidemic samples (dots). As before, the start of the epidemic period is country-specific and is identified with the day when the number of COVID19 cases becomes greater than 100. 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.

We interpolate our data with a quadratic function of time and include dummy variables to account for post-announcement jumps in both the level and the slope. Formal tests reject the null of a common time-behavior before and after the announcement. In figure 6, the solid line denotes our estimate whereas the shaded area refers to our confidence intervals. Importantly, both information diffusion and attention to the news jump and increase significantly in the aftermath of the announcements.

Note that we assign to retweets the time of the original tweet they refer to. This means that we match attention level with the original time of the news diffusion. As a result, the jump in attention is likely underestimated with respect to the timing of the retweets since many retweets refer to pre-announcement tweets but happen post-announcement.

This pattern pairs nicely with that of equity returns depicted in figure 7. Specifically, the panel on the left shows the average cumulative returns obtained from buying country-specific equities 90 minutes before a country-specific announcement and holding them over an increasing horizon of 180 minutes. Our results are averaged across both countries and announcements.[4]

In this picture, we plot the behavior of the returns in both the normal and the epidemic states or, equivalently, subsamples. In both cases, cumulative 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, the dynamics become quite different across the normal and the epidemic state. Specifically, in the epidemic state, cumulated returns jump upward upon the

[4] If a country-specific announcement happens when the exchange of the country is closed, we consider the 90 minutes prior to the closing time of the previous day and the first 90 minutes after the opening of the exchange in the next day. This is, for example, what we do with the ECB announcement made at 11:05pm on 3/18/2020.

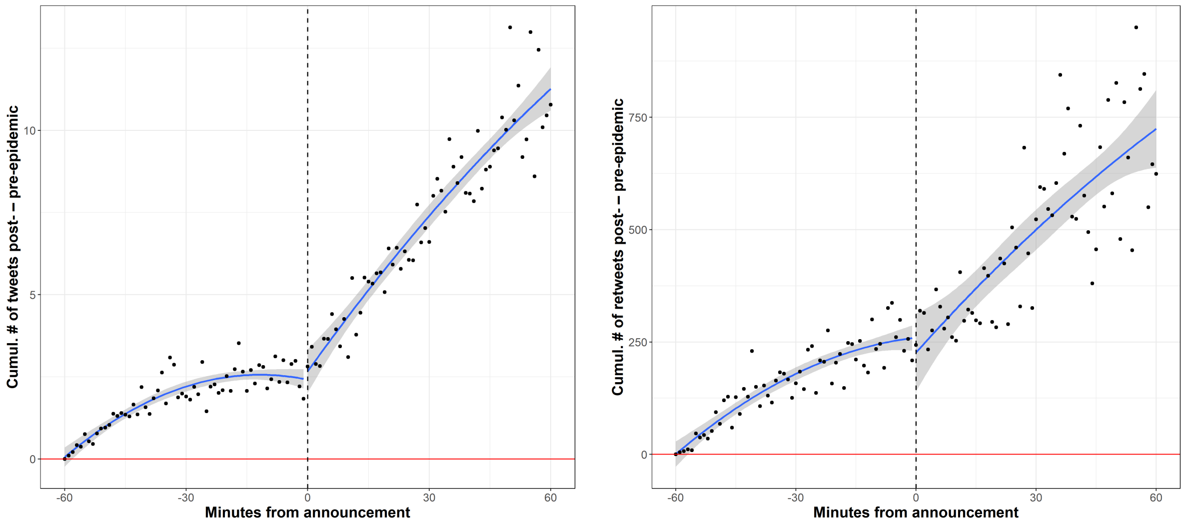


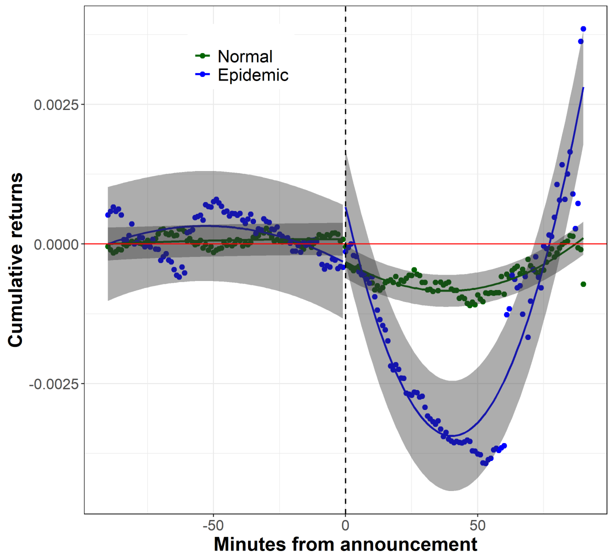
Fig. 6. Information Diffusion and Attention around Announcements

Notes: The left (right) panel of this figure shows the average per-minute and per-country number of tweets (retweets) around announcement time 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. The solid line comes from a quadratic interpolation estimated before and after the announcement. Shaded areas refer to HAC-adjusted confidence intervals. The sample starts on January 8th 2020 and ends on the date of this draft.

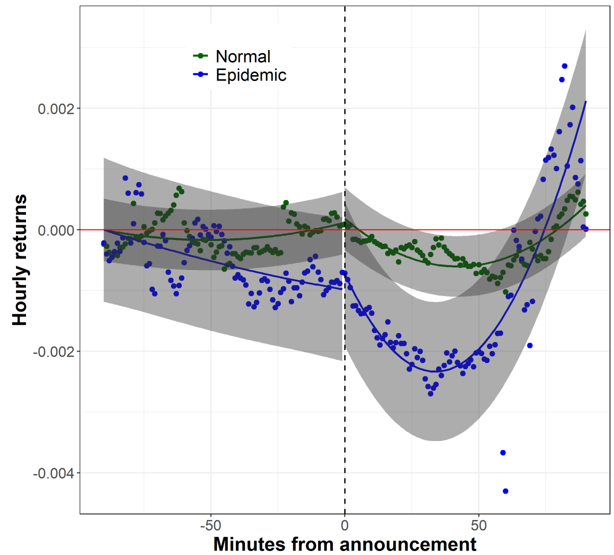
announcement and then they exhibit a significant downward path for about 60 minutes.

We note that this figure shows a time varying behavior of returns 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 resolution of uncertainty, prices jump upward when uncertainty is resolved along the information cycle, and then they start to decline.

To further validate this point, in the right panel we plot hourly returns computed on a backward looking rolling window. For example, a data point reported at the time of the announcement refers to the returns from an investment strategy started 60 minutes before the announcement time and liquidated at the announcement time. Given this construction, we can also think of these values as a measure of 60-minute ahead expected returns.



Cumulative Returns



Hourly Returns

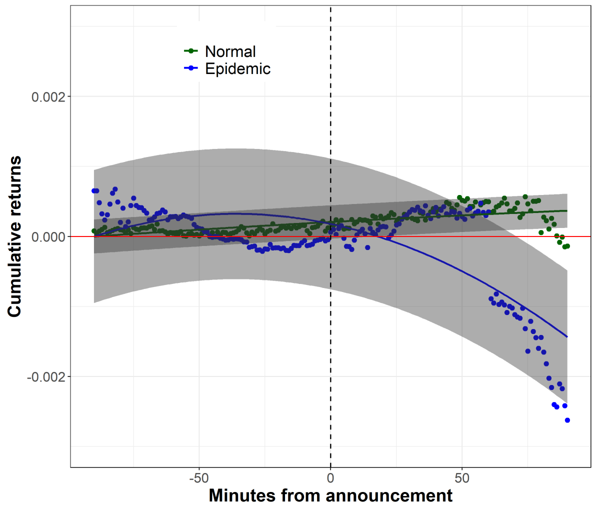
Fig. 7. Equity Returns around Announcements

Notes: The panel on the left shows the average cumulative returns obtained from buying equities 90 minutes before an announcement and holding them over an increasing horizon of 180 minutes. The panel on the right shows the average realized returns from holding equities for 60 minutes at the end of the investment strategy, that is, the value reported at +30 minutes refers to an investment started 30 minutes before the announcement. Returns are in raw log units. In each country, the epidemic period starts when there are more than 100 cases of COVID19. The solid line comes from a quadratic OLS augmented with post-announcement dummies. Shaded areas refer to HAC-adjusted confidence intervals. The sample starts on January 8th 2020 and ends on the date of this draft.

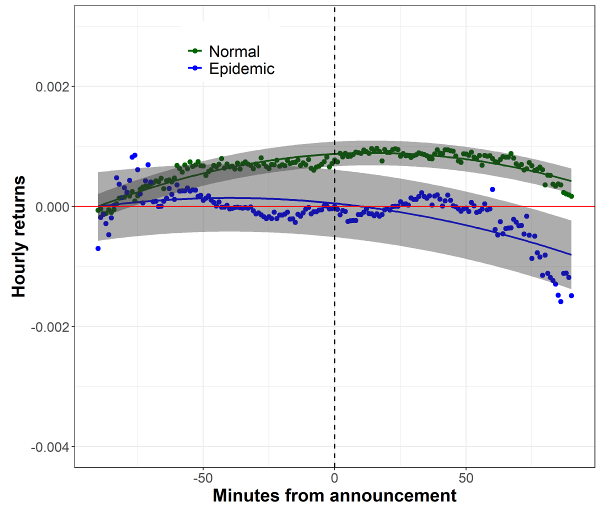
Our results indicate that there is no significant pattern in the pre-epidemic period. Most importantly, in the epidemic subsample, expected returns are stable up to an hour prior to the announcement, they jump upward when the hour ahead includes the announcement time, and then they decline and start to revert half an hour prior to the announcement. In our graph, this means to look at at $t = +30$ minutes from announcement.

Figure A.3 (see Appendix) shows the difference in cumulative returns and hourly returns across normal and epidemic subsamples. Formal tests confirm substantial differences in the time behavior of returns pre- and post-announcement across the normal and the epidemic samples, consistent with our discussion of figure 7.

Figure 8 shows our results for bonds returns. The construction of the depicted data is identical



Cumulative Returns



Hourly Returns

FIG. 8. BOND RETURNS AROUND ANNOUNCEMENTS

Notes: The panel on the left shows the average cumulative returns obtained from buying 10y government bonds 90 minutes before an announcement and holding them over an increasing horizon of 180 minutes. The panel on the right shows the average realized returns from holding bonds for 60 minutes at the end of the investment strategy, that is, the value reported at +30 minutes refers to an investment started 30 minutes before the announcement. Returns are in raw log units. In each country, the epidemic period starts when there are more than 100 cases of COVID19. The solid line comes from a quadratic OLS augmented with post-announcement dummies. Shaded areas refer to HAC-adjusted confidence intervals. The sample starts on January 8th 2020 and ends on the date of this draft.

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. 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.

3.2 Cross Sectional Results: HML$_{COVID19}$

Daily News. We start by focusing 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. The H (L) port-

Table 3. Summary Statistics for Portfolios

	Low	**Medium**	**High**	**HML$_{COVID19}$**
Mean	-0.032	-0.035	-0.074	-0.042^{**}
	(0.048)	(0.043)	(0.050)	(0.017)
StDev	0.97	0.88	0.99	0.49
First Quartile	-0.28	-0.32	-0.3	-0.17
Median	-0.01	-0.01	-0.02	-0.01
Third Quartile	0.26	0.24	0.23	0.13
Avg. N. Countries	2	3	2	-
Turnover (%)	2	6	5	-
International-CAPM α	0.001	-0.007	-0.043^{***}	-0.044^{***}
	(0.008)	(0.012)	(0.016)	(0.016)

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 for ITA, ESP, UK, FRA, DEU, CHE, and SWE. 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. International-CAPM α is the intercept obtained by regressing the portfolio returns on the average equity return across the above mentioned countries. Numbers in parenthesis are HAC-adjusted standard errors.

folio comprises the top-2 (bottom-2) 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 in-sample average of the returns in all portfolios is negative. Given our sample, this not surprising. Focusing on the quartiles of the returns distribution, we see that the portfolio comprising the more exposed countries tends to have more severe negative skewness. This is an aspect that we capture in our conditional no-arbitrage model.

The turnover in each portfolio is not excessive and, most importantly, our HML-COVID19 returns are not explained by an international CAPM model. Specifically, when we regress our HML returns on the excess returns of an equity index including all of our countries, the alpha estimated from the timeseries is statistically significant.

We consider the following conditional asset pricing model,

$$
\begin{aligned}
r^{ex}_{f,t+1} &= \overline{r}^{ex}_{f,t} + \beta_{f,t} \cdot news^{glob}_{t+1}, \quad f \in \{H, M, L\}, && (1)\\
\beta_{f,t} &= \beta_0 + \beta_{f,1} X_{f,t}, && (2)\\
\frac{\partial \overline{r}^{ex}_{f,t}}{\partial X_{f,t}} &= \lambda \beta_{f,1}, && (3)
\end{aligned}
$$

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 heterogenous 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. In the first two specifications, the 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.

Table 4. Conditional Linear Factor Model

	β_0	$\beta_{L,1}$	$\beta_{M,1}$	$\beta_{H,1}$	MPR	N.Obs	N. Assets
News about Covid Cases							
coef	-0.207^{***}	-39.079^{***}	-9.111^{***}	-3.121^{***}	-0.008^{*}	52	3
se	(0.067)	(6.268)	(2.784)	(0.633)	(0.004)	52	3
News about Covid Cases, controlling for MKT							
coef	0.004	0.398	-0.177	0.625^{**}	-0.048^{**}	52	3
se	(0.005)	(0.649)	(0.372)	(0.266)	(0.023)	52	3
News from Twitter							
coef	-0.006	28.467^{***}	12.236^{***}	2.834^{***}	0.025^{***}	52	3
se	(0.064)	(4.070)	(0.940)	(0.279)	(0.005)	52	3
News from Twitter, controlling for MKT							
coef	-0.011^{**}	2.078^{***}	1.679^{***}	-0.686^{***}	0.019^{***}	52	3
se	(0.005)	(0.712)	(0.435)	(0.175)	(0.004)	52	3

Notes: This table shows the results of the conditional linear factor model described in equations (1)–(3). 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. 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 real-time data range from February 2020 to the date of this manuscript. Estimates and HAC-adjusted standard errors are obtained through GMM.

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.[5] 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 a significant negative exposure to our contagion-based news, $\beta_{f,t}$. This sign is consistent with our expectations since positive news about global contagion growth refers to an adverse shock. Most importantly, the implied daily market price of risk is negative and significant. This means that the

[5]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.

relative share of contagion cases forecasts an increase in expected future returns across all portfolios.

We note that 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. In our sample, the portfolio of countries with the highest share of COVID19 cases tends to be more exposed to contagion news.

Consistent with the failure of the international-CAPM, our result remains unchanged if we control for the market. Specifically, we regress our portfolio returns on the excess returns of an equity index including all of our countries and use the residuals of this regression in our conditional one-factor model. Our second specification in table 4 shows that the implied daily market price of risk is still negative, significant, and six times greater than in our first specification.

Next, we replicate our estimation procedure using our daily measure of innovations in the global factor derived from our tweets' tone. In this case, positive news should be interpreted as good news. As a result, both our estimated beta and the market price of risk are positive. Equivalently, the share of contagion cases is a relevant positive predictor of future expected returns.

Looking at the results of our four specifications and accounting for estimation uncertainty, we conclude that 1% 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.

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 helps sharpen the estimate of the market price of risk because it provides an increased number of observations and hence it gives us enough degrees of freedom to control for other relevant factors, i.e, to estimate a multi-factor conditional model.

In table 5, we show our results when we link hourly equity excess returns to hourly Twitter-based news. Our implied betas continue to be positive, but our inference is less precise as hourly returns

Table 5. Conditional Linear Factor Model

	β_0	$\beta_{L,1}$	$\beta_{M,1}$	$\beta_{H,1}$	MPR	N.Obs	N. Assets
News from Twitter, hourly							
coef	0.003	0.195*	0.059**	0.006	0.317***	468	3
se	(0.002)	(0.100)	(0.030)	(0.006)	(0.098)	468	3

Notes: This table shows the results of the conditional linear factor model described in equations (1)–(3). 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. 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 hourly excess returns and market prices of risk are in log units. Our real-time data range from February 2020 to the date of this manuscript. Estimates and HAC-adjusted standard errors are obtained through GMM.

are much noisier than daily returns. The implied market price of risk is positive, well identified, and enormous. We interpret this preliminary result as suggesting that our factor may remain very relevant even after controlling for other relevant sources of risk highlighted in the literature.

3.3 Next steps

We are working on addressing the following questions:

1. What happens to the estimate of the market price of contagion risk if we include information from bond returns?

2. Is the $HML_{COVID19}$ factor spanned by currencies? If so, we can use currencies to track this factor across time zones (UTC time), as currencies are traded all day long.

3. Is the $HML_{COVID19}$ factor that we can construct from either America or Asia equity markets similar to the one constructed using European data? If not, why?

4. How would our portfolio results change if we focused on winners and losers in terms of daily contagion changes, as opposed to the share of the total 'stock' of cases?

5. Do different news shocks (mortality, contagion, ...) have a different impact on the MPR of our COVID19 factor?
6. Given the heterogeneous response of equity and bonds to the same factor, what are the resulting prescriptions for the construction of a high-performance portfolio?
7. As the contagion risk tapers off in Europe, will announcements have a different impact on equity returns?

4 Conclusion

In this study, we quantify the exposure of major financial markets to news shocks about global contagion risk 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 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 first-order, that is, extremely valuable, for global wealth.

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Appendix A. Data Sources

Table A.1: News Papers

Country	Newspaper	Twitter Account	BBD	Language
USA	LA Times	@latimes	Yes	English
USA	USA Today	@USATODAY	Yes	English
USA	Chicago Tribune	@chicagotribune	Yes	English
USA	Washington 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 Francisco Chronicle	@sfchronicle	Yes	English
USA	New York Times	@nytimes	Yes	English
Italy	Corriere Della Sera	@Corriere	Yes	Italian
Italy	La Repubblica	@repubblica	Yes	Italian
Italy	Il Sole 24 ORE	@sole24ore		Italian
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
China	People's Daily, China	@PDChina		English
China	China Xinhua News	@XHNews		English
China	China Daily	@ChinaDaily		English

(To be continued)

Country	Newspaper	Twitter Account	BBD	Language
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
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
Japan	Asahi Shimbun AJW	@AJWasahi	Yes	English
Japan	The Japan News by Yomiuri	@The_Japan_News	Yes	English
Japan	The Japan Times	@japantimes		English
Japan	Japan Today News	@JapanToday		English
Korea	Yonhap News Agency	@YonhapNews		Korean
Korea	The Korea Times	@koreatimescokr		Korean
Korea	Korea JoongAng Daily	@JoongAngDaily		English
Korea	The Korea Herald	@TheKoreaHerald		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
UK	The Times	@thetimes	Yes	English

(To be continued)

Country	Newspaper	Twitter Account	BBD	Language
UK	Financial Times	@FinancialTimes	Yes	English
UK	BBC News (UK)	@BBCNews		English
UK	Guardian news	@guardiannews		English
Switzerland	Neue Zurcher Zeitung	@NZZ		German
Switzerland	20 Minuten	@20min		German
Switzerland	24 Heures	@24heuresch		French
Switzerland	Le Temps	@LeTemps		French
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
Australia	The Age	@theage		English
Australia	The Australian	@australian		English
Australia	The Daily Telegraph	@dailytelegraph		English
Australia	Financial Review	@FinancialReview		English
New Zeland	The New Zealand Herald	@nzherald		English
New Zeland	The Sydney Morning Herald	@smh		English
New Zeland	Herald Sun	@theheraldsun		English
New Zeland	Guardian Australia	@GuardianAus		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 Tweets' Tone: Two Examples

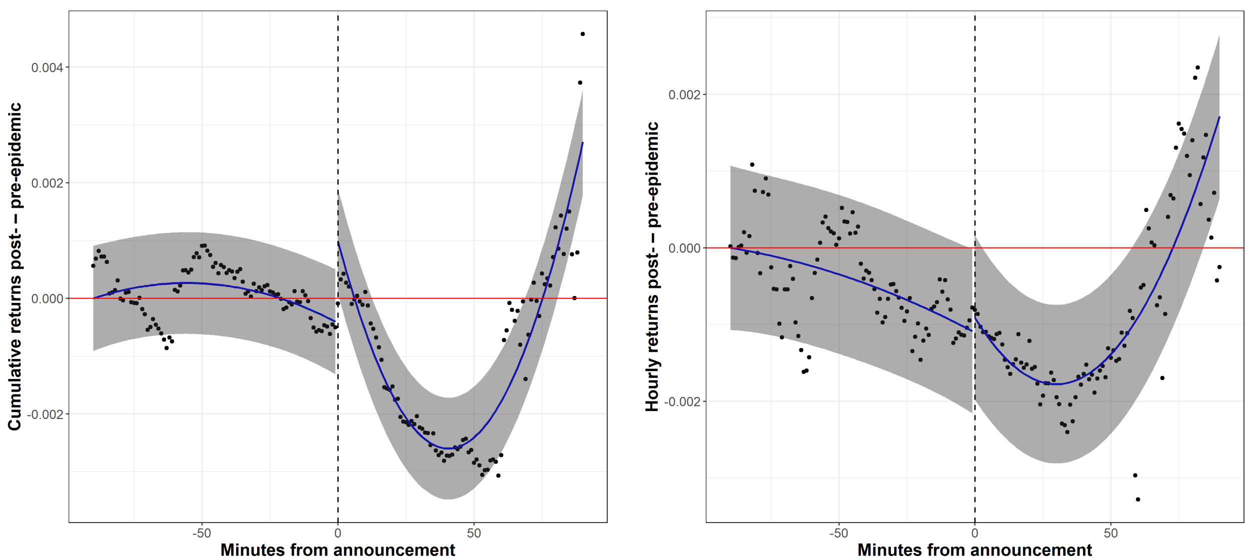
Tweet Text	Positive Words	Negative Words	Tone
The coronavirus pandemic has been particularly devastating to the United States's biggest cities. It comes as the country's major urban centers were already losing their appeal for many Americans.	"devastating", "losing"	"appeal"	$\frac{-2+1}{3} = -0.33$
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	Long Term Bond Index	Short Term Bond Index	Currency
Australia	ASX Index	AU 10y benchmark	AU 1Y benchmark rate	AUDUSD
Canada	SPTSX Composite Index	CA 10y benchmark	CA 3M benchmark rate	USDCAD
China	Shanghai Shenzen Composite Index	CN 10y benchmark	CN 1Y benchmark rate	USDCNY
France	CAC Index	FR 10y benchmark	FR 3M benchmark rate	EURUSD
Germany	DAX Index	DE 10y benchmark	DE 3M benchmark rate	EURUSD
Hong Kong	Hong Kong Hang Seng Index	CN-HK 10y benchmark	HK 3M benchmark rate	USDHKD
Italy	FTSE MIB Index	IT 10y benchmark	IT 3M benchmark rate	EURUSD
India	BSE Senex Index	IN 10y benchmark	ES 3M benchmark rate	USDINR
Japan	Nikkei 225 Index	JA 10y benchmark	JP 3M benchmark rate	USDJPY
Korea	KOSPI Index	KR 10y benchmark	KR 1Y benchmark rate	USDKRW
New Zealand	NZX 50 Gross Index	NZ 10y benchmark	NZ 3M benchmark rate	NZDUSD
Spain	IBEX 35	ES 10y benchmark	ES 3M benchmark rate	EURUSD
Switzerland	SMI Index	CH 10y benchmark	CH 3M benchmark rate	USDCHF
Sweden	OMX Stockholm 30 Index	SE 10y benchmark	SE 3M benchmark rate	USDSEK
USA	SPX Index	US 10y benchmark	US 3M benchmark rate	USD
UK	FTSE Index	UK 10y benchmark	GB 3M benchmark rate	GBPUSD

Notes: This table shows our data sources. All data are obtained from Eikon, Thomson Reuter.



Cumulative Returns Hourly Returns

FIG. A.3. EQUITY RETURNS AROUND ANNOUNCEMENTS

Notes: The panel on the left shows the average cumulative returns obtained from buying equities 90 minutes before an announcement and holding them over an increasing horizon of 180 minutes in the epidemic period minus that obtained in the pre-epidemic sample. The panel on the right shows the difference in the average realized returns from holding equities for 60 minutes across the pre-epidemic and the epidemic sample. We report realized returns at the end of the investment strategy, that is, the value reported at +30 minutes refers to an investment started 30 minutes before the announcement. Returns are in raw log units. In each country, the epidemic period starts when there are more than 100 cases of COVID-19. The solid line comes from a quadratic OLS augmented with post-announcement dummies. Shaded areas refer to HAC-adjusted confidence intervals. The sample starts on January 8th 2020 and ends on the date of this draft.