When the Markets Get CO.V.I.D.: COntagion, Viruses, and Information Diffusion

M. J. Arteaga-Garavito [1] M. M. Croce [1] P. Farroni [1] [2] I. Wolfskeil [3]

[1]Bocconi University

[2]Banca d'Italia

[3]Federal Reserve Board of Governors

Why we care about pandemic risk: starting observation (I)

Rare event in the past ...

Pre-1980: once every 2 decades (3-4x in a lifetime) ...

Name	**Period**	**Deaths**
3rd Bubonic Plague	1855-1960	12+ Mil.
Russian Flu	1889-1890	1 Mil.
Encephalitis	1915-1926	1.5 Mil.
Spanish Flu	1918-1920	50 Mil.
Asian Flu	1957-1958	1-4 Mil
Hong Kong Flu	1968 - 1970	1-4 Mil.

Starting observation (I)

... more frequent now.

Post-1980: once every 5 years (15x in a lifetime).

Name	Period	Deaths
SARS	2002-04	774
Avian Flu	2003-2019	455
Swine Flu	2009-2010	285K
Ebola	2013-2016	11K
Zika	2015-2016	53
COVID-19	2019-2023	$\approx$ 6.9 Mil

$\hookrightarrow$ Given that virus-related crises are expected to become more frequent, we find it relevant to use COVID-related data to ask broad questions about financial market reactions to viral contagion risk

Starting observation (II)

Unique feature of COVID: New information environment

- Unprecedented wave of official news announcements by leaders across the world

(Fauci, USA)

(Johnson, UK)

- Official reports from many country's departments of health
- Information about this pandemic was rich and diffused rapidly $\rightarrow$ *we wanted to understand how this information was being priced in financial markets*

Questions of this study

1. What is the impact of official medical announcements on financial returns?
   ↪ Equivalently, is the diffusion of official information enhancing wealth or adding risk?

2. What is the market price of news risk related to global contagion dynamics?
   ↪ Can local contagion conditions help us predict expected returns?

3. Can we *systematically* measure the production and diffusion of information about pandemic risk?
   ↪ In particular, can we use social media to provide a flexible set of tools to gather rich-and-reliable data (can be adapted to examine future sources of global crises)

This paper

1. Can we *systematically* measure the production and diffusion of information about pandemic risk?
   - ↪ Use Twitter to construct two novel data sets (i) official medical announcements, related to COVID; and (ii) country-specific COVID news diffusion (and tone)
     - ⋆ *Pandemics unfold quickly: real-time indexes may function as a useful predictive tool*
     - ⋆ *High-frequency data: sharper inferences early on when estimating multidimensional models*

2. What is the impact of official medical announcements on financial returns?
   - ↪ Across several classes of financial assets, we provide novel event study about high-frequency financial dynamics around official COVID announcements

3. What is the market price of news risk related to global contagion dynamics?
   - ↪ Using contagion data and social media news tone, we estimate a no-arbitrage model with time-varying betas with respect to global contagion risk
   - ↪ We confirm that contagion risk carries a significant market price of risk

Data

Our analysis is based on two data collection dimensions:

1. Comprehensive dataset of official COVID-related announcements
2. COVID news production, diffusion, and tone

Data

Our analysis is based on two data collection dimensions:

1. Comprehensive dataset of official COVID-related announcements
2. COVID news production, diffusion, and tone

Announcements: what we do

High-frequency event study: estimate the effect of announcements in equity and bond markets

- Define the precise timing of 'events' for 20 countries

'Automatically-collected' official announcements for each country, publicly available on:

1. Twitter accounts of relevant government agencies US
2. Web-page of the MoH / other government agencies, with time stamps Japan
3. Major newspapers breaking news about official announcements (via Twitter)

Announcements: what we do

High-frequency event study: estimate the effect of announcements in equity and bond markets

- Define the precise timing of 'events' for 20 countries

'Automatically-collected' official announcements for each country, publicly available on:

1. Twitter accounts of relevant government agencies US
2. Web-page of the MoH / other government agencies, with time stamps Japan
3. Major newspapers breaking news about official announcements (via Twitter)

Announcements: what we do

High-frequency event study: estimate the effect of announcements in equity and bond markets

- Define the precise timing of 'events' for 20 countries

'Automatically-collected' official announcements for each country, publicly available on:

1. Twitter accounts of relevant government agencies US
2. Web-page of the MoH / other government agencies, with time stamps Japan
3. Major newspapers breaking news about official announcements (via Twitter)

Announcements: what we do

High-frequency event study: estimate the effect of announcements in equity and bond markets

- Define the precise timing of 'events' for 20 countries

'Automatically-collected' official announcements for each country, publicly available on:

1. Twitter accounts of relevant government agencies US
2. Web-page of the MoH / other government agencies, with time stamps Japan
3. Major newspapers breaking news about official announcements (via Twitter)

Announcements: what we do

High-frequency event study: estimate the effect of announcements in equity and bond markets

- Define the precise timing of 'events' for 20 countries

'Automatically-collected' official announcements for each country, publicly available on:

1. Twitter accounts of relevant government agencies US
2. Web-page of the MoH / other government agencies, with time stamps Japan
3. Major newspapers breaking news about official announcements (via Twitter)

Announcements: where we stand

TABLE 1. SUMMARY STATISTICS FOR ANNOUNCEMENTS

Country	No. Announcements	Case Reports	Live Streamed	President/ Prime Minister
AR	605	33%	64%	3%
AU	678	78%	4%	1%
BR	975	64%	26%	2%
CA	791	58%	21%	18%
CH	627	78%	9%	13%
CL	896	59%	29%	3%
CN	721	82%	3%	1%
CN-HK	1,376	55%	2%	1%
CO	1,006	58%	34%	8%
DE	283	87%	1%	7%
ES	570	83%	1%	17%
FR	567	77%	16%	6%
IN	759	89%	1%	1%
IT	654	74%	17%	8%
JA	332	59%	5%	5%
KR	642	80%	1%	4%
MX	1,803	10%	45%	21%
NZ	457	61%	29%	7%
UK	711	82%	11%	7%
US	1,386	17%	54%	7%
Total	15,839	64%	18%	7%

Highlights

- 20 countries
- Jan 2020 – now
- $\approx$ 16k announcements

Examples

- US
- Japan

Model: Quick Intuition

- We propose a simple model to think of asset demand around announcements
  - $\hookrightarrow$ We test these predictions using our novel data set of thousands of COVID-related announcements across twenty countries

Intuition

- If announcements reduce uncertainty about expected equity prices, then *on average*, they should produce a reallocation from bonds to equities

- As a result, equities should appreciate upon announcements, whereas bond prices should stay stable (decline) if their supply is flat (upward sloping)

A Simple Model of Assets Demand and Announcements

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

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

Without loss of generality, impose $\psi = 1$, $C_0 = 1$, and $\delta = 1$. If consumption is log-normal, the following applies:

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

- when $\gamma > 1$ the agent dislikes uncertainty
- γ is the intertemporal elasticity of substitution

A Simple Model of Assets Demand and Announcements (continued)

The agent faces the following problem:

$$\begin{aligned} U_0(W_0) &= \max_{B,S} E_0[B+\theta S] - \frac{1}{2}(\gamma-1)V_0[B+\theta S]. \\ W_0 &\geq p(B)B + p(S)S. \end{aligned} \tag{3}$$

We think of an announcement as an unbiased signal about θ that arrives at time $t \in (0,1)$ and reduces the posterior uncertainty about equities, σ^2 (Ai and Bansal 2018). At the equilibrium we prove that:

$$\frac{\partial p(S)}{\partial \sigma^2} < 0 \quad \text{if} \quad \gamma > 1 \text{ and } \frac{\partial p(S)}{\partial \sigma^2} = 0 \quad \text{if} \quad \gamma = 1. \tag{4}$$

Hence, if the investor cares about the timing of information ($\gamma > 1$), *on average* announcements should be associated to equity appreciation as the investors shift their allocation toward equities.

(Intro to) Econometrics

Next slides: lots of graphs based on

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

Quadratic function of t: where t^* is the time of the announcement and Z_t is a cumulative return

Test for post-announcement difference, then depict the final results graphically.

Note: final result is the difference between
– *Epidemic period: (country specific) cases > 100*
– *Normal period: from Oct 1st 2019 to epidemic period*

(Intro to) Econometrics

Next slides: lots of graphs based on

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

Quadratic function of t: where t^* is the time of the announcement and Z_t is a cumulative return

Test for post-announcement difference, then depict the final results graphically.

Note: final result is the difference between

– *Epidemic period: (country specific) cases > 100*

– *Normal period: from Oct 1st 2019 to epidemic period*

(Intro to) Econometrics

Next slides: lots of graphs based on

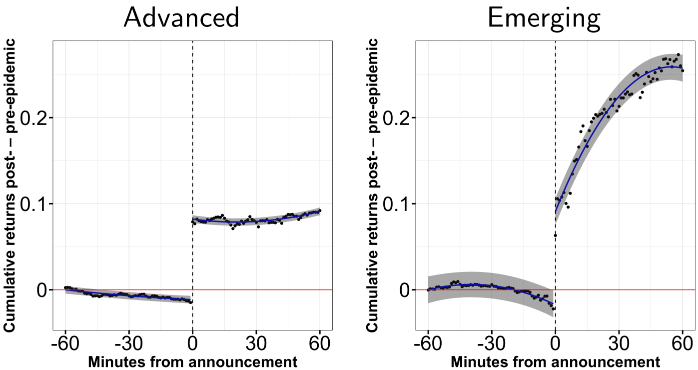
$$Z_t = (c_{pre} + c_{t>t^*}) + (\alpha_{pre} + \alpha_{t>t^*}) \cdot t + (\beta_{pre} + \beta_{t>t^*}) \cdot t^2, \quad t \in [t^* \pm K]$$

Quadratic function of t: where t^* is the time of the announcement and Z_t is a cumulative return

Test for post-announcement difference, then depict the final results graphically.

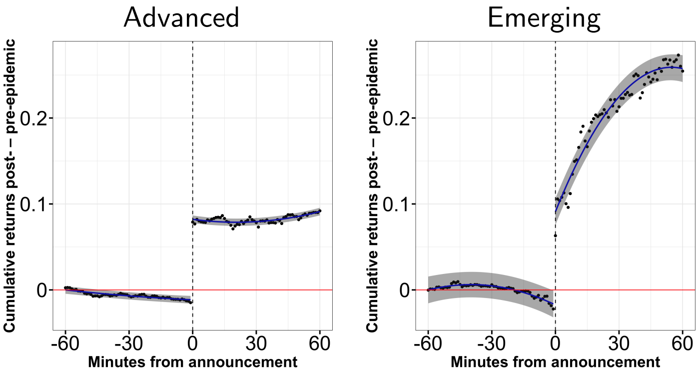
Note: final result is the difference between
– *Epidemic period: (country specific) cases* > 100
– *Normal period: from Oct 1st 2019 to epidemic period*

Equity Returns Around Announcements: AE vs EE



Strategy: Cumulative abnormal return of investing one dollar in each country one hour before every announcement, and holding the position until one hour after the announcement ▸ Local Only

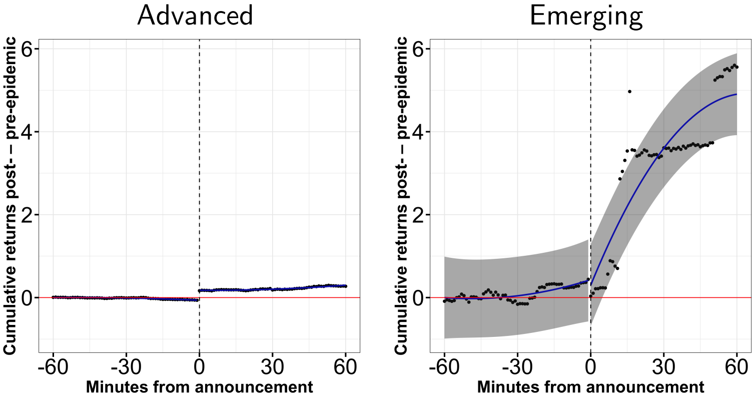
Equity Returns Around Announcements: AE vs EE



Takeaway: We consider a large number of announcements conveying both positive and negative news

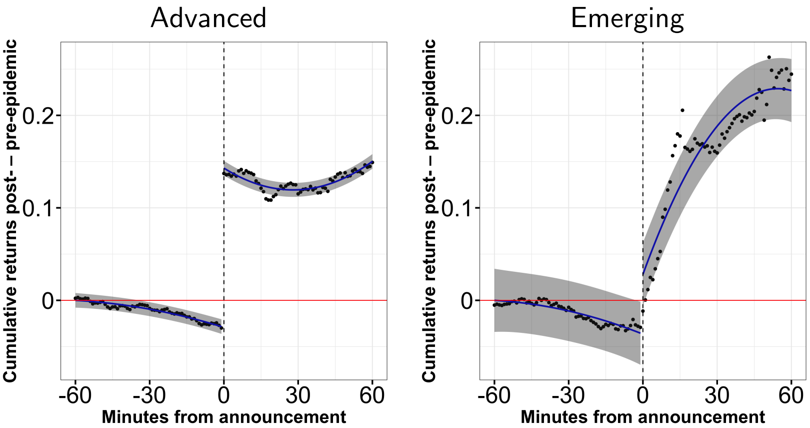
↪ Jump in equity valuation captures the expected appreciation due to the reduction of uncertainty on epidemic risk *(consistent with our model)*

Equity Returns Around Announcements: Only Bad News



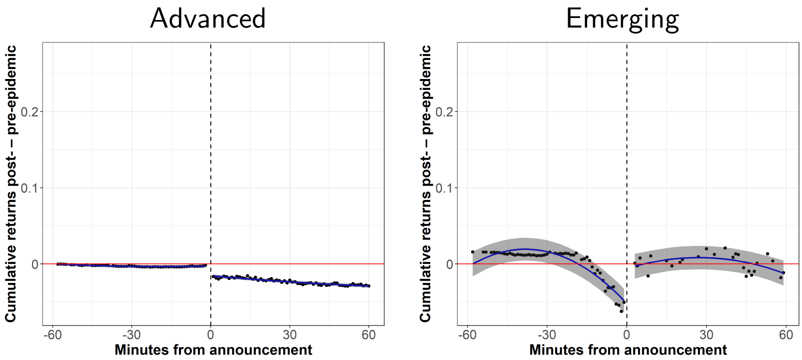
AEs: phenomenon still present after bad news (+ unexpected variation in # of cases)
EEs: positive jump, but it happens with about a 15-minute delay

Equity Returns Around Announcements: High COVID



Takeaway: stronger effects in H-COVID AEs (sorted daily)

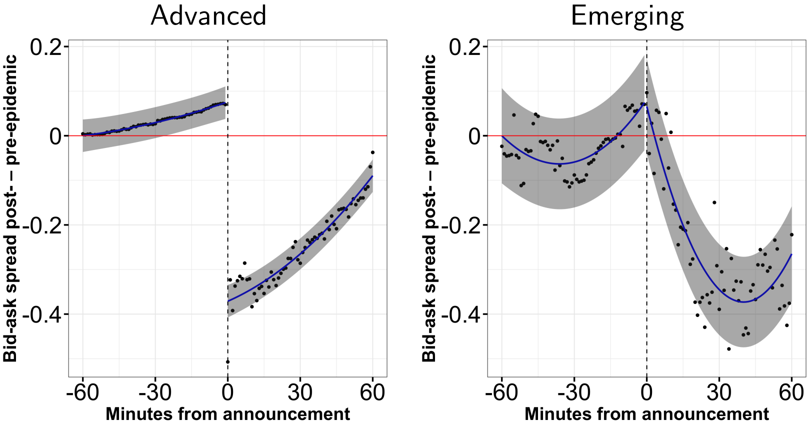
Bond Returns Around Announcements: AE vs EE



Bond returns are relatively insensitive to announcements

↪ Takeaway: Bonds are an important hedge against contagion risk announcements

Bonds Bid-Ask Spread: AE vs EE



'Liquidity' increases in bonds' markets of AEs and EEs

↪ Takeaway: Consistent with the idea that COVID announcements have been an important source of trade

Additional results: highlights

- **Local returns and domestic announcements:** domestic announcements are as important as foreign ones (for equities) Contents page
- **Trading volume:** trade activity shows no change before the announcements, but increases right after the announcement Contents page

Data

Our analysis is based on two data collection dimensions:

1. Comprehensive dataset of official COVID-related announcements
2. COVID news production, diffusion, and tone

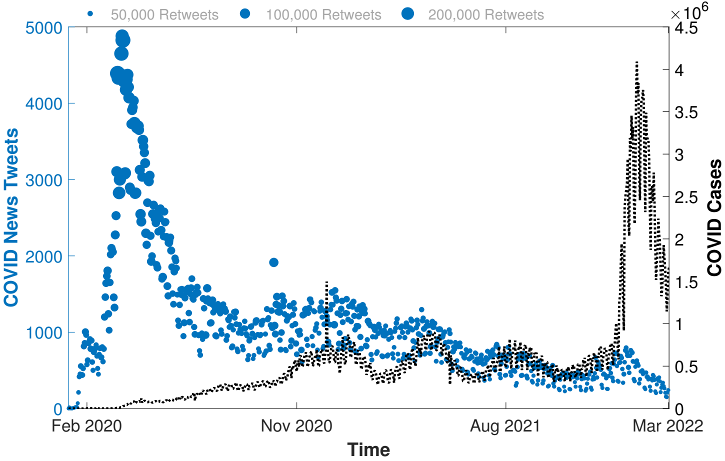
Information Diffusion and Attention: what we do

COVID Tweets (dimensionality reduction)

- In the spirit of Baker, Bloom & Davis (2016) we identify major newspapers for our cross section of countries
  - $\hookrightarrow$ Rather then analyze full-length articles, we track COVID-related news on Twitter
- High frequency dataset: captures the real-time information set of financial market participants
- Some numbers: 20 countries; 85 news papers; 12 languages...
  ... 823K COVID19-related tweets so far!

Table

A global perspective of COVID-news

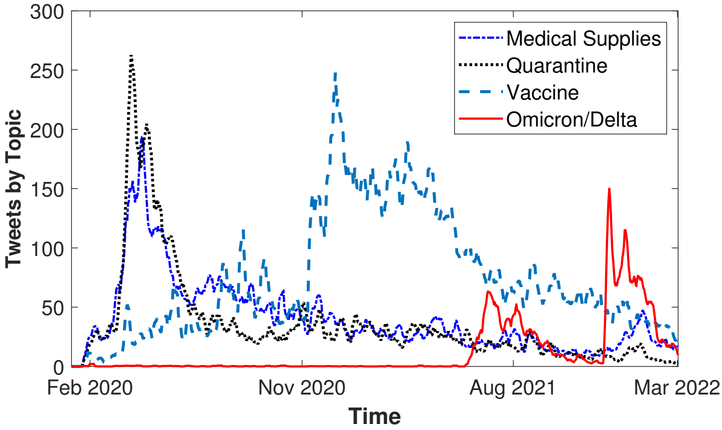


Information diffusion becomes more intense at the beginning of the global pandemic.

Information diffusion continues to display local peaks that reflect various waves of the virus.

Advantage of news:
Can capture the perceived risk.

A global perspective of COVID-news



Information content changes over time.

Pricing News

Conditional linear factor model:

$$\begin{aligned} r^{ex}_{f,t+1} &= \bar{r}^{ex}_{f,t} + \beta_{f,t} \cdot news^{glob}_{t+1}, \quad f \in \{H, M, L\} && (5) \\ \beta_{f,t} &= \beta_0 + \beta_{f,1} X_{f,t}, && (6) \\ \frac{\partial \bar{r}^{ex}_{f,t}}{\partial X_{f,t}} &= \lambda \beta_{f,1}, && (7) \end{aligned}$$

- COVID-news factor: $news^{glob}$
  - $\hookrightarrow$ The unexpected change in global tone of tweets (or global contagion cases)

How do we measure news?

We need a way to quantify the global COVID news.

Measurements:

1. Innovations to tone of tweets: apply standard multi-lingual text analysis to newspaper tweets (polarity lexicons from polyglot)
2. Unexpected growth in confirmed COVID cases: ‘objective’ measure (daily, JHopkins)

- Advantages of tone
  - Perceived risk $\longrightarrow$ across different waves, the same variation in the number of cases may be associated with different risk
  - High frequency $\longrightarrow$ sharper estimates

How do we measure news?

We need a way to quantify the global COVID news.

Measurements:

1. Innovations to tone of tweets: apply standard multi-lingual text analysis to newspaper tweets (polarity lexicons from polyglot)
2. Unexpected growth in confirmed COVID cases: ‘objective’ measure (daily, JHopkins)

- Advantages of tone
  - Perceived risk $\longrightarrow$ across different waves, the same variation in the number of cases may be associated with different risk
  - High frequency $\longrightarrow$ sharper estimates

How do we measure news?

We need a way to quantify the global COVID news.

Measurements:

1. Innovations to tone of tweets: apply standard multi-lingual text analysis to newspaper tweets (polarity lexicons from polyglot)
2. Unexpected growth in confirmed COVID cases: ‘objective’ measure (daily, JHopkins)

- Advantages of tone
  - Perceived risk $\longrightarrow$ across different waves, the same variation in the number of cases may be associated with different risk
  - High frequency $\longrightarrow$ sharper estimates

Pricing News

Conditional linear factor model:

$$
\begin{aligned}
r^{ex}_{f,t+1} &= \bar{r}^{ex}_{f,t} + \beta_{f,t} \cdot news^{glob}_{t+1}, \quad f \in \{H, M, L\} && (8) \\
\beta_{f,t} &= \beta_0 + \beta_{f,1} X_{f,t}, && (9) \\
\frac{\partial \bar{r}^{ex}_{f,t}}{\partial X_{f,t}} &= \lambda \beta_{f,1}, && (10)
\end{aligned}
$$

- We include time-varying betas, linked to the country-specific share of COVID cases
  - $\hookrightarrow$ Portfolios (f) are sorted daily on relative share of country-specific COVID cases
  - $\hookrightarrow$ $X_{f,t}$ is the share of contagion cases for each portfolio at time t

Pricing News

Conditional linear factor model:

$$
\begin{aligned}
r^{ex}_{f,t+1} &= \bar{r}^{ex}_{f,t} + \beta_{f,t} \cdot news^{glob}_{t+1}, \quad f \in \{H, M, L\} && (8)\\
\beta_{f,t} &= \beta_0 + \beta_{f,1} X_{f,t}, && (9)\\
\frac{\partial \bar{r}^{ex}_{f,t}}{\partial X_{f,t}} &= \lambda \beta_{f,1}, && (10)
\end{aligned}
$$

- For countries that go through more severe contagion paths, this model can capture potential higher negative skewness
- Consistent with COVID being a global risk factor that affects countries at different times and with different intensities
- Allows us to estimate the MPR of a global COVID-news factor

GMM Results: Global Contagion News

TABLE 5. SUMMARY OF MPR ESTIMATION

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

- Results: The implied daily market price of risk is negative (positive) and significant with respect to contagion (tone of tweets) news.)

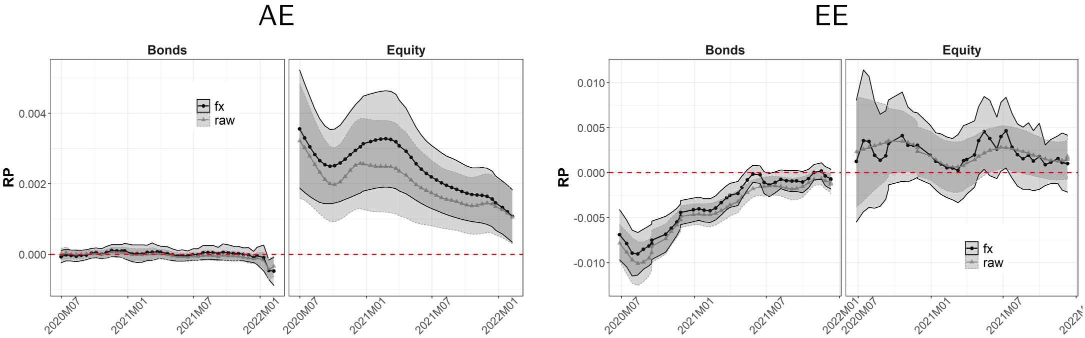
GMM Results: Global Contagion News

Table 5. Summary of MPR estimation

	Covid Cases		Twitter News	
	A.E.	E.E.	A.E.	E.E.
Local units				
coef	-0.003^{***}	-0.006^{***}	0.013^{***}	0.007^{***}
se	(0.001)	(0.001)	(0.003)	(0.001)
USD units				
coef	-0.005^{***}	-0.005^{***}	0.011^{***}	0.006^{***}
se	(0.001)	(0.002)	(0.003)	(0.001)
Controlling for MKT				
coef	-0.002^{***}	-0.007^{***}	0.008^{***}	0.008^{***}
se	(0.001)	(0.001)	(0.002)	(0.001)

- Positive (negative) news about global contagion growth (tone of tweets) refers to an adverse shock to equity returns
  - $\hookrightarrow$ Share of contagion cases is a positive predictor of the future cost of capital ($\lambda\beta_{f,1} > 0$)

Estimation of Expected Excess Return for HML_{COVID}



Takeaways: (1) Equities deliver a positive risk premium both in AEs and EEs (2) Bonds, instead, deliver a zero (negative) risk premium in AEs (EEs)

Additional Results

- **We replace covid-related news with market returns in our APT model**

↪ This model fails: confirms our measures are informative about pandemic risk

- **We look at COVID news that are orthogonal to pure volatility shocks**

↪ Results confirmed: both daily data and intra-day data show that contagion news have an extremely high MPR, even after controlling for volatility

- **We replace global news with ‘local’ AE- and EE-specific news**

↪ Mixed results: local contagion news are priced negatively (positively) in AEs (EEs) and local innovations to our tweets’ tone imply an insignificant MPR

↪ Confirms the importance of global news component

Conclusions

1. We quantify the exposure of major financial markets to news shocks about global contagion risk

2. We construct two novel datasets
   - Official medical announcements related to COVID
   - High-frequency data on epidemic news diffused through Twitter
   - Propose a novel methodology that can be applied to future risk events

3. Financial dynamics surrounding epidemic announcements (daily frequency and an intra-daily frequency)

4. Estimate the market price of pandemic risk based on social media data and contagion data

5. Policies related to the prevention and containment of contagion could be precious in terms of *lives saved*, but also in terms of *preserving global financial wealth*

Conclusions

1. We quantify the exposure of major financial markets to news shocks about global contagion risk

2. We construct two novel datasets
   - Official medical announcements related to COVID
   - High-frequency data on epidemic news diffused through Twitter
   - Propose a novel methodology that can be applied to future risk events

3. Financial dynamics surrounding epidemic announcements (daily frequency and an intra-daily frequency)

4. Estimate the market price of pandemic risk based on social media data and contagion data

5. Policies related to the prevention and containment of contagion could be precious in terms of *lives saved*, but also in terms of *preserving global financial wealth*

Conclusions

1. We quantify the exposure of major financial markets to news shocks about global contagion risk

2. We construct two novel datasets
   - Official medical announcements related to COVID
   - High-frequency data on epidemic news diffused through Twitter
   - Propose a novel methodology that can be applied to future risk events

3. Financial dynamics surrounding epidemic announcements (daily frequency and an intra-daily frequency)

4. Estimate the market price of pandemic risk based on social media data and contagion data

5. Policies related to the prevention and containment of contagion could be precious in terms of *lives saved*, but also in terms of *preserving global financial wealth*

Conclusions

1. We quantify the exposure of major financial markets to news shocks about global contagion risk
2. We construct two novel datasets
   - Official medical announcements related to COVID
   - High-frequency data on epidemic news diffused through Twitter
   - Propose a novel methodology that can be applied to future risk events
3. Financial dynamics surrounding epidemic announcements (daily frequency and an intra-daily frequency)
4. Estimate the market price of pandemic risk based on social media data and contagion data
5. Policies related to the prevention and containment of contagion could be precious in terms of *lives saved*, but also in terms of *preserving global financial wealth*

Conclusions

1. We quantify the exposure of major financial markets to news shocks about global contagion risk
2. We construct two novel datasets
   - Official medical announcements related to COVID
   - High-frequency data on epidemic news diffused through Twitter
   - Propose a novel methodology that can be applied to future risk events
3. Financial dynamics surrounding epidemic announcements (daily frequency and an intra-daily frequency)
4. Estimate the market price of pandemic risk based on social media data and contagion data
5. Policies related to the prevention and containment of contagion could be precious in terms of *lives saved*, but also in terms of *preserving global financial wealth*

Appendix

Next slides ...

Announcements: Twitter Example (USA)

- COVID annoucments are unique
  - ↪ Higher frequency (daily / intra-daily)
  - ↪ Timing evolved over the course of the pandemic
- Twitter allows us to select the effective date and time
- Takeaway: we account for sudden releases and changes of time

Back

Announcements: MoH Example (Japan)

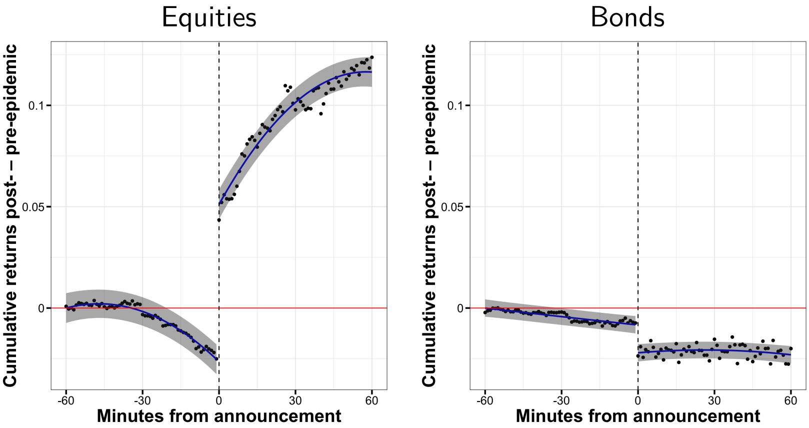
February 25, 2020

Press Conference by Minister of Health, Labour and Welfare, KATO Katsunobu Tuesday, February 25, 2020, 3:30 p.m.
Ministry of Health, Labour and Welfare."Basic Policy for Novel Coronavirus Disease Control" was announced.

Back

- Unique solution for each country
- Web scraping allows us to automate the process
- Takeaway: we built a novel dataset of **official** announcements for our sample of 20 countries

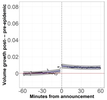
Local Returns Around *Domestic* Announcements: Bonds vs Equities



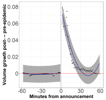
Takeaways: (1) for equities, domestic announcements are as important as foreign ones (2) bonds have a muted response to domestic announcements Back

Equity Volume Around Announcements: AE vs EE

Advanced



Emerging



Takeaway: Trade activity shows no change before the announcements, but increases right after the announcement

Back

CDS Spreads: AE vs EE

Table 2. CDS Spreads and Contagion News

	A.E.		E.E.	
Contagion cases - news	6.138***	7.747**	27.669***	27.223***
	(1.984)	(3.792)	(8.226)	(8.355)
Adj. R2	0.02%	4.58%	0.18%	14.22%
Adj. R2 w/o	0.02%	4.58%	0.18%	14.22%
Country FE	Yes	Yes	Yes	Yes
Week FE	No	Yes	No	Yes

Notes: this table reports the results of the following regression:

$$\Delta S_t^i = d_0^i + d_t^i \cdot D_t^{Week} + \beta^g \cdot news_{t-1} + \epsilon_t^i, \quad \forall i \in g$$

where ΔS_t^i refers to the daily change of the CDS spread in country i; g refers to either the group of Advanced Economies (AEs) or that of Emerging Economies (EEs); d_0^i is a country-level fixed effect and D_t^{Week} is a weekly time fixed effect. 'Contagion cases - news' refers to the innovation in the growth of the global number of contagion cases as measured in section 3. 'Adj. R2 w/o' refers to the adjusted R squred from the same regression in which we omit the contagion news. Standard Errors are clustered at the country-level. Our sample starts on October 1st 2019 and ends on the date of this draft.

- Adverse contagion news tends to increase CDS spreads (especially in EEs)
- The increase in adj. R^2 is **very** modest, implying default concerns have been a second-order issue Back

Information: data in a table

TABLE 3. NEWSPAPERS DATASET

Country	No. News Providers	Tweets	Retweets	Likes	Topics			
					Mortality	Quarant.	Med. Supply	Vaccines
Argentina	4	77,407	1,205,844	3,155,405	13%	10%	14%	63%
Australia	4	17,680	144,940	348,606	20%	39%	12%	29%
Brazil	4	32,596	1,332,180	8,710,524	45%	8%	15%	32%
Canada	5	48,716	443,544	863,678	33%	10%	17%	40%
Chile	4	34,061	408,725	631,767	56%	6%	10%	28%
China	3	32,879	948,862	2,582,197	39%	14%	19%	28%
Colombia	4	32,942	475,007	1,451,463	17%	12%	25%	45%
France	4	47,095	1,426,120	2,388,336	25%	26%	27%	22%
Germany	4	12,240	148,118	332,098	20%	24%	20%	35%
Hong Kong	3	21,339	420,614	607,725	17%	32%	21%	31%
India	4	103,814	937,109	5,610,418	32%	23%	16%	29%
Italy	3	33,721	265,694	715,064	10%	32%	29%	28%
Japan	4	19,051	157,250	278,263	18%	13%	30%	39%
Korea	4	13,550	82,916	144,299	45%	10%	26%	20%
Mexico	4	79,338	1,626,362	4,265,100	14%	11%	25%	50%
New Zealand	3	28,103	73,736	302,778	12%	38%	18%	32%
Spain	4	38,856	2,669,028	4,796,419	30%	20%	14%	36%
Switzerland	4	8,394	37,183	47,194	22%	20%	25%	33%
UK	4	25,366	1,145,886	2,287,563	27%	30%	15%	29%
USA	11	116,644	7,274,708	17,294,236	29%	7%	23%	41%
Total	85	823,792	21,223,826	56,813,133	26%	19%	20%	34%

Highlights

- 85 newspapers
- $\approx$ 823k tweets
- Back

Intraday MPRs

Back

Table 6. Hourly Conditional Linear Factor Model

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

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.

References