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

(In Progress)

M Max Croce

Bocconi

IGIER

CEPR Centre for Economic Policy Research

Maria Jose Arteaga-Garavito
PhD Student, year 1

Bocconi

Previously at

BANCO DE MÉXICO

Isabella Wolfskeil
PhD Candidate

Bocconi

Previously at

UF UNIVERSITY of FLORIDA

Paolo Farroni
PhD Student, year 3

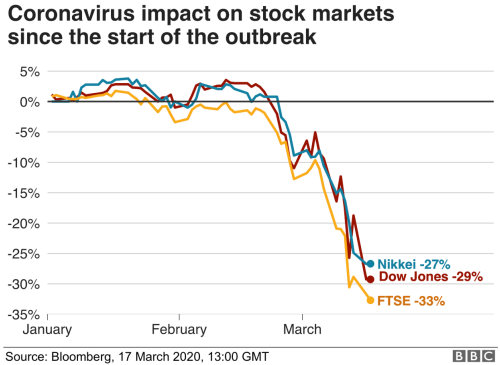
Bocconi

and

BANCA D'ITALIA

Starting Observations (I)

COVID19: atomic bomb for the wealth of millions of people



Starting Observations (II)

Rare event in the past ...

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Rare event in the past ...
Pre-1980: once every 2 decades for $\approx$ 2 years ...

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 Observations (II)

... more frequent now.

Post-1980: once every 5 years for $\approx$ 2 years.

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–	$\approx$ 1 Mil

Starting Observations and Considerations (III)

Novel set of daily news

Questions of this study

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2. Can local contagion conditions predict excess returns?
3. What is the market price of global/local contagion news?

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Need of new datasets to provide:

1. a comprehensive dataset of announcements
2. High frequency data on contagion news
   - Newspapers Tweets (BIG data);
   - Early Warnings.

Data

Two dimensions:

1. Collect health-related announcements dates
2. Collect news production, diffusion, and tone

Announcements: what we do (I)

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1. the webpage of the Ministry of Health (MoH) with time stamp.
2. the twitter accounts of MoHs & major newspapers releasing news about reports.

↪ select the effective date and time of release of the news.

↪ for each country, remove 'redundant' announcements.

Announcements: Twitter Example 1

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

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

Takeaway: we account for sudden releases and changes of time

Announcements: Twitter Example 2

Included in sample

*Live announcement
*Official Source
*Daily press conference or additional announcement

Not-included in sample

*Not live announcement

Takeaway: we discard redundant tweets: a lot of work (21 countries)!

Announcements: RSS Example

GERMAN MEDICAL BULLETIN

- Parse RSS (Really Simple Syndication) feeds from Robert Koch Institute (RKI) *at least* twice a week before RKI discards old feeds
- Sample announcement: “06/09/2020 14:45 Situationsbericht des Robert Koch-Instituts vom 6.9.2020 zu COVID-19“

Takeaway: Country-specific official sources.

Announcements: where we stand

Table 2. 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.

Information: sources

- High frequency and large span: Twitter (Why? Google's limitations)

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- High frequency and large span: Twitter (Why? Google's limitations)
- Course of dimensionality: only major newspapers accounts
- Some numbers: 21 countries; 85 news papers; 12 languages...
  ... 460K COVID19-related tweets so far!

Information: data in a table

Table 1. 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.

A Global Perspective

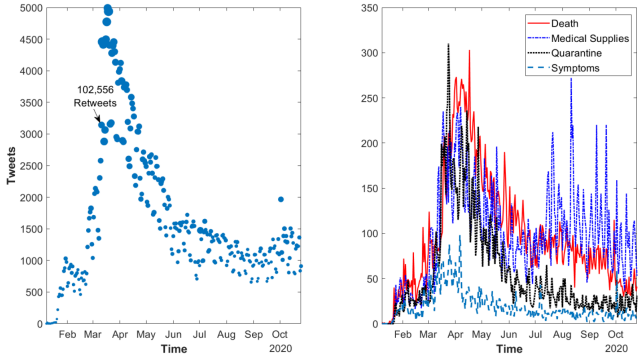

Fig. 2. Global Information Diffusion

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.

Local Heterogeneity (Across Days)

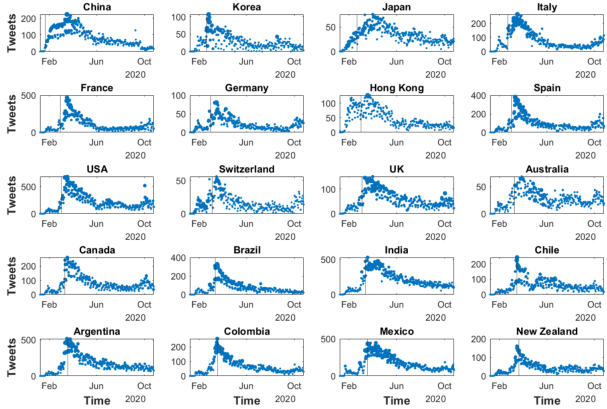

Fig. 1. Information Diffusion and Attention across Countries

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.

Local Heterogeneity (Intra-Day)

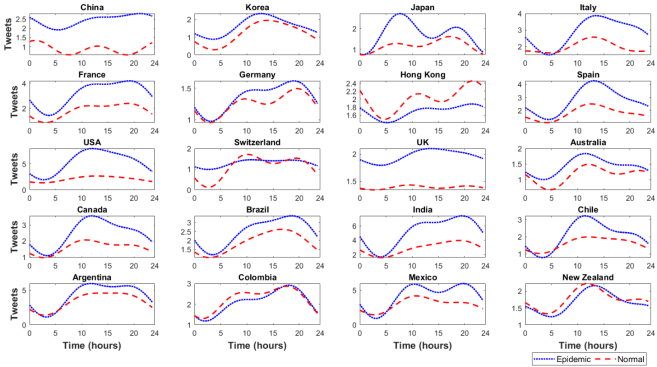

Fig. 3. Intraday Information Diffusion

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.

Good News, Bad News

Capital markets respond differently to good/bad news.
Measurements:

- Number of confirmed cases: 'objective' count (daily, JHopkins)
- Tweets tone: text analysis applied to news paper' tweets (intraday, novel, it uses multi-language routines)

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Notes:

- Trading week (5 days): consolidate Fr-Sat-Sun evening data
- Expected component: backward looking 5-day MA

(Intro to) Econometrics

Next slides: lots of graphs based on

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

t^*: the time of the announcement.

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

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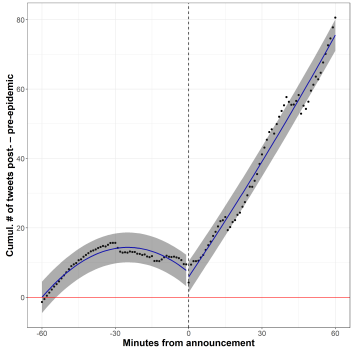
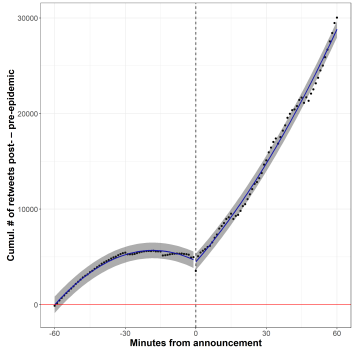
Test for post-announcement difference, then depict the final result.
Note:
– Epidemic period: (country specific) cases$>$ 100.
– Normal period: from Oct 1st 2019 to epidemic period.

Information Around Announcements

Tweets

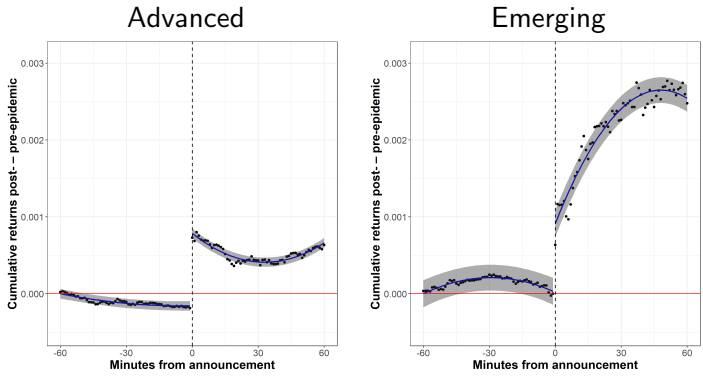


Retweets



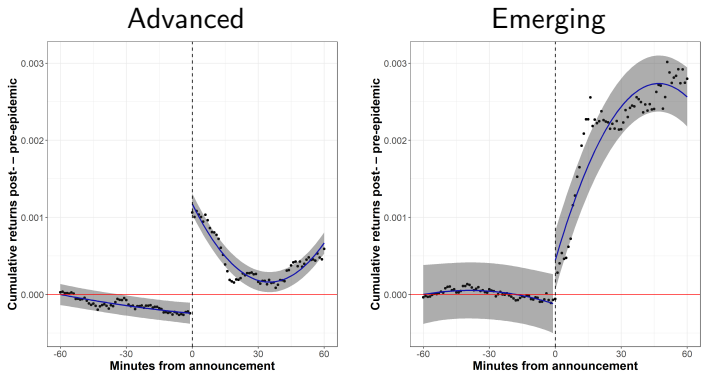
Takeaway: announcements gather 'special' attention

Equity Returns Around Announcements: AE vs EE



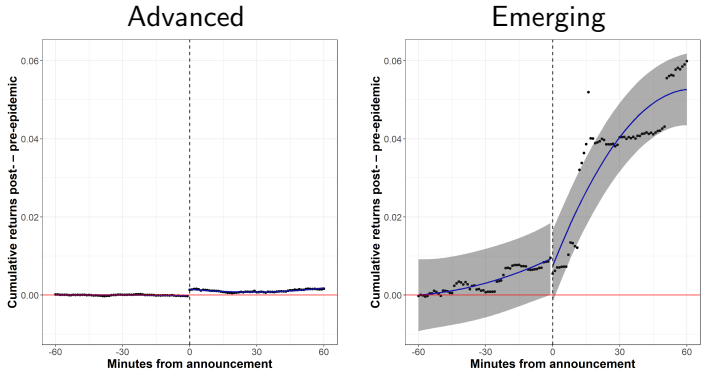
Takeaway: announcements 'help' equities in epidemic periods

Equity Returns Around Announcements: High COVID



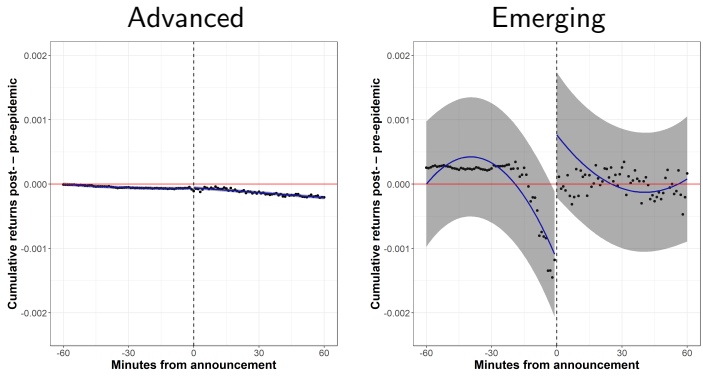
Takeaway: stronger effects in H-COVID Adv. countries (sorted daily)

Equity Returns Around Announcements: Only Bad News



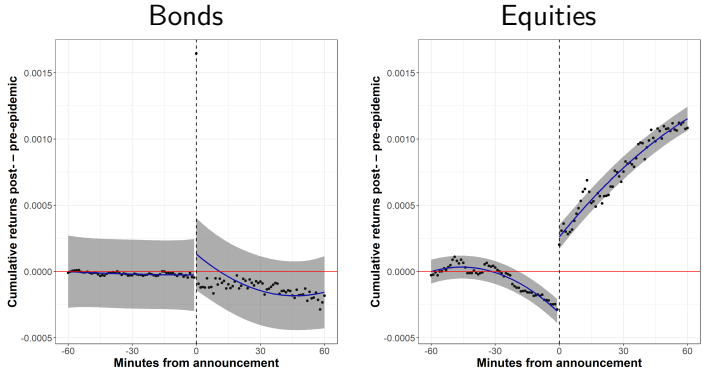
Takeaway: stronger effects after bad news (positive unexpected variation in # of cases)

Bond Returns Around Announcements: AE vs EE



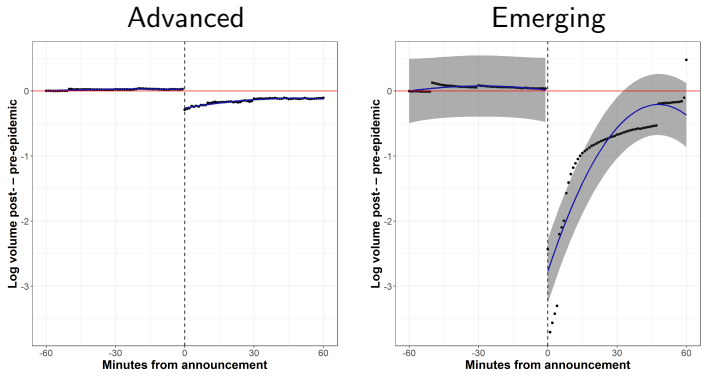
Takeaway: Good hedge, some movement in EE bonds

Global Returns Around *Domestic* Announcements: Bonds vs Equities



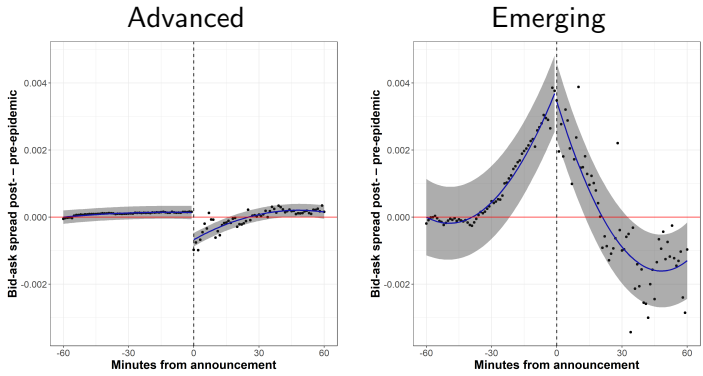
Takeaway: domestic announcements as important as foreign ones.

Equity Volume Around Announcements: AE vs EE



Takeaway: Trade activity in equities slows

Bonds Bid-Ask Spread: AE vs EE



Takeaway: 'Liquidity' increases in bonds' market of AEs

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Twitter-Based News: Global

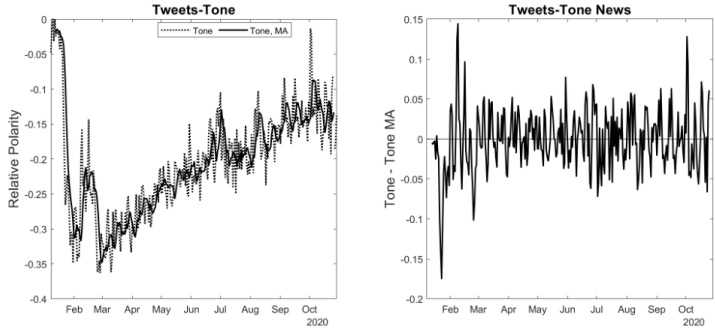
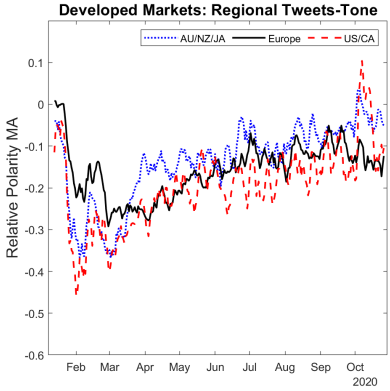
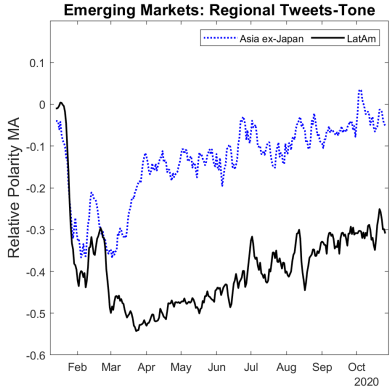


Fig. 4. Twitter-Based COVID19 Factor

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.

Twitter-Based News: Regional





Takeaway: Rich data and pronounced heterogeneity

Pricing News

Simple conditional NA model:

$$
\begin{aligned}
r^{ex}_{f,t+1} &= \overline{r}^{ex}_{f,t} + \beta_{f,t} \cdot news_{t+1}, \quad f = \text{`country'} && (1)\\
\beta_{f,t} &= \beta_0 + \beta_{f,1} X_{f,t}, && (2)\\
\frac{\partial \overline{r}^{ex}_{f,t}}{\partial X_{f,t}} &= \lambda \beta_{f,1}, && (3)
\end{aligned}
$$

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- We do add (control for) the market (MSCI Global)...
- At intra-day freq. (Twitter), we must look at similar time-zones.

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We look at global/local contagion news:

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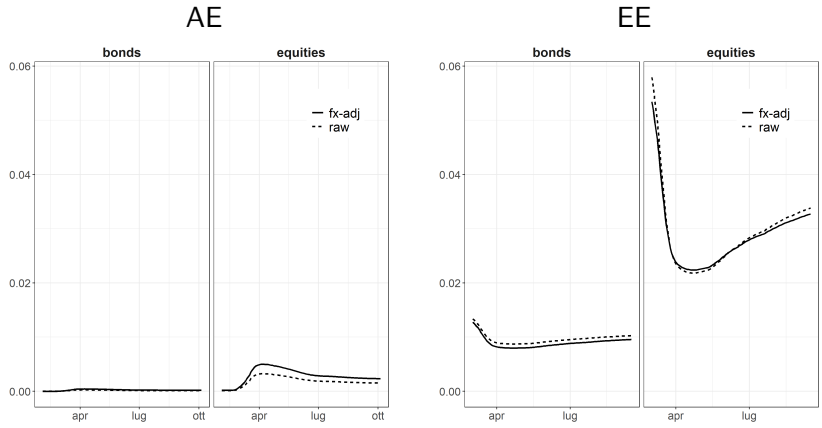
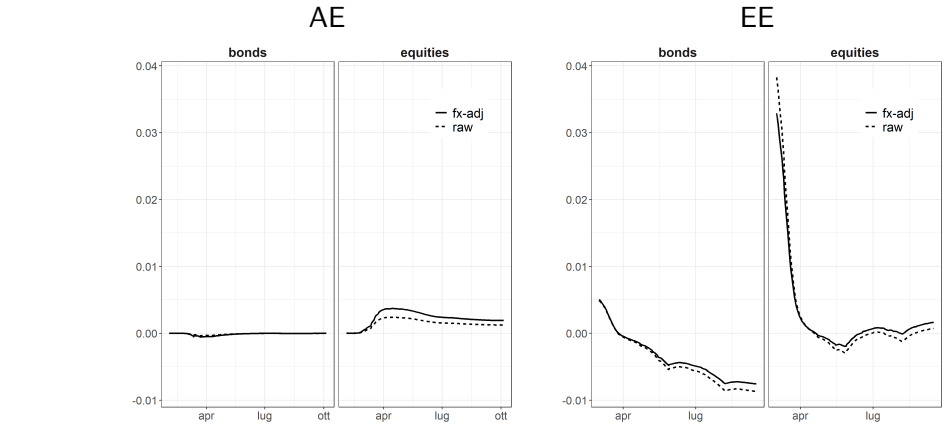
Next: implied estimates for risk premia on H_{COVID} and HML_{COVID}

Estimation of Expected Excess Return for H_{COVID}



Takeaway: EE more exposed, bonds less sensitive

Estimation of Expected Excess Return for HML_{COVID}



Takeaway: H-Covid bonds are good hedge, equities are risky

Daily MPRs

Table: **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)

Conclusions

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THANK YOU!