JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 56, No. 7, Nov. 2021, pp. 2584–2604

doi:10.1017/S0022109021000466

Natural Disaster Effects on Popular Sentiment Toward Finance

Manish Jha
Georgia State University Robinson College of Business
mjha@gsu.edu (corresponding author)

Hongyi Liu
Washington University in St. Louis Arts and Science
hongyi.liu@wustl.edu

Asaf Manela
Washington University in St. Louis Olin Business School and IDC Herzliya
amanela@wustl.edu

Abstract

We use a text-based measure of popular sentiment toward finance to study how finance sentiment responds to rare historical disasters and to the ongoing COVID-19 pandemic. Finance sentiment declines after epidemics and earthquakes but rises following severe droughts, floods, and landslides. These heterogeneous effects suggest finance sentiment responds differently to the realization of insured versus uninsured risks. Finance sentiment declines at the start of the COVID-19 pandemic, but recovers in countries that experienced high stock markets returns and that responded with large fiscal spending. Finance sentiment seems to depend on the insurance provided by private markets and by public finance.

I. Introduction

When disaster strikes, finance can play both savior and oppressor. Insurance policies, for example, are designed to facilitate risk sharing and would likely be perceived as helpful to those adversely affected by a natural disaster. Debt contracts, by contrast, are often designed to prevent renegotiation and could be perceived as onerous after the fact. The prevalence and enforcement of financial contracts in the aftermath of natural catastrophes can therefore improve or worsen popular sentiment toward finance. We use a recently developed panel of popular sentiment toward finance spanning hundreds of years and 8 large economies to study how finance sentiment responds to rare disasters and how it affects economic and financial outcomes.

As Zingales (2015) forcefully argues, as finance researchers, we should care deeply about how finance is perceived, especially if financial services benefit society. Positive popular sentiment toward finance can spread its benefits widely,

We thank Ran Duchin and Jarrad Harford for detailed comments. We also thank Yves-Paul Auffray, Joseph Kloecker, David Lindequist, Rodrigo Moser, Andrea Paloschi, Rita Podledneva, Tatiana Vdovina, Juan Ignacio Vizcaino, and seminar participants at the University of Connecticut, Virtual Finance Seminar, and Washington University in St. Louis for helpful comments. Computations used the Washington University Center for High Performance Computing, which is partially funded by NIH grant S10 OD018091.

while suspicion toward financial services can restrict credit, risk-sharing, and competition. Empirical work on the matter is largely based on survey evidence, which reveals that trust in bankers fell sharply following the 2007–2008 financial crisis (Sapienza and Zingales (2012)) that such public perceptions often diverge from those of economists (Sapienza and Zingales (2013)), and that low trust can hinder insurance market efficiency (Gennaioli, La Porta, Lopez-de-Silanes, and Shleifer (2020)). But the relatively short time series of survey data limits our understanding of how finance sentiment responds to rare disasters like COVID-19, and how such changes relate to economic and financial outcomes. While we cannot survey those who lived through the devastating wars and natural disasters of the 20th century, books provide an avenue to fill this gap.

We rely on an annual panel of popular sentiment toward finance covering 8 large economies from 1870 to 2009, which we develop in Jha, Liu, and Manela (2021). There we describe the methodology, validate and contrast it with alternatives, and document persistent differences in finance sentiment across countries. This finance sentiment measure uses a computational linguistics approach applied to the text of millions of books. Intuitively, we rely on a recently developed language model (BERT, or Bidirectional Encoder Representations from Transformers) (Devlin, Chang, Lee, and Toutanova (2018)) to measure whether references to finance are, on average, semantically closer to positive versus negative sentences. BERT and its offspring have shattered records on multiple natural language processing tasks, surpassing human ability on many. Specifically, we use BERT to embed sentences into a relatively low dimensional numerical vector. Following Kozlowski, Taddy, and Evans (2019), we measure the angle between the embedding of sentences mentioning "finance" and the "positive" minus "negative" dimension, and aggregate this positivity angle for all finance-mentioning sentences in each language and in each year to form a finance sentiment panel.

How does finance sentiment respond to natural disasters? To answer this question, we combine the finance sentiment panel with natural disaster data from the Centre for Research on the Epidemiology of Disasters (CRED) and focus on severe disasters that kill at least 20 people per million population. We find that finance sentiment declines by about 1%, 1 year after a country suffers a severe natural disaster. This average treatment effect, however, hides ample heterogeneity across disaster types. In particular, epidemics and earthquakes reduce finance sentiment by about 4%, whereas droughts, floods, and landslides increase it by 3%, 2%, and 5%, respectively. The effects of extreme temperature, storms, and smog are statistically no different from zero. These results hold controlling for wars, fatalities, and for country and year fixed effects. Thus, our panel allows us to overcome a common concern about cross-country comparisons that other sources of heterogeneity may be omitted (Guiso, Sapienza, and Zingales (2004)). The inclusion of year fixed effects also means these estimates are not driven by a single common shock such as the 1918 flu pandemic.

What explains these disparate effects? Disaster insurance data, available over the later part of our sample, suggest that epidemic and earthquake risks are largely uninsured by insurance companies, whereas extreme temperatures, floods, wildfires, and storms are relatively well covered by insurance. Thus, one potential answer is that finance facilitates risk sharing of some types of risks through insurance, securitization or derivatives, but financial contracts and intermediaries are often designed to prevent ex post renegotiation (Diamond and Rajan (2001), Agarwal, Amromin, Ben-David, Chomsisengphet, Piskorski, and Seru (2017)). When insured disasters hit, economic costs are shared broadly across households and generations. But as the COVID-19 pandemic illustrates, when uninsured disasters strike (Walsh (2020)), their damage can be concentrated in parts of the population (Mongey, Pilossoph, and Weinberg (2020)), destroy fragile businesses (Chetty, Friedman, Hendren, and Stepner (2020)), and generate resentment against financial intermediaries (Scism (2020)). Another explanation is that insurance claim disputes affect finance sentiment. Gennaioli et al. (2020) show that insurance claims are frequently disputed and result in rejections or lower payments. Sentiment toward insurers may worsen if households learn they are uninsured only after disaster strikes.

What do these results imply about the currently spreading COVID-19 pandemic? Jha et al. (2021) use local projections to estimate that the average effect over the 5 years following a –1-percentage-point shock to finance sentiment growth is a 0.2-percentage-point reduction in annual GDP growth and a 0.25-percentage-point reduction in credit growth. These estimates are based on historical data from 1870 to 2009. Assuming the COVID-19 death toll is no greater than the 1918–1920 flu pandemic, our estimates predict a 4% contraction in finance sentiment after 1 year. For comparison, U.S. English finance sentiment declines by 2% on average 1 year after banking crises (1907 Panic, Great Depression, Savings and Loan Crisis, and Global Financial Crisis). Such a shock would exacerbate the direct negative effect of the health crisis on economic growth and further reduce cumulative GDP and credit growth by 4 and 5 percentage points, respectively, over the next 5 years.

To better understand the ongoing COVID-19 pandemic, we augment the books corpus with a news corpus containing the text of 11 million articles published online between 2016 and 2020. This more recent and higher frequency data set reveals that finance sentiment plummets at the start of the COVID-19 pandemic in Mar. 2020. However, finance sentiment largely recovers in countries that responded with large government spending and guarantees. Comparing across countries, we find that the change in finance sentiment experienced from Jan. to Sept. 2020 correlates positively with the fiscal response over the same period. Governments and central bank interventions up to this point appear to have alleviated the pandemic's physical and financial damage and to reduce any damage to public sentiment toward finance.

Another reason for the recovery in finance sentiment is that financial market volatility, which skyrockets during the first wave of the pandemic, largely calms down even as the second and deadlier wave of the disease arrives. Investors disappointed with the performance of their "rainy-day" funds during times of high marginal utility of wealth, may find this covariance risk unanticipated and perhaps not sufficiently advertised by the financial industry. But when stock markets boom, as they have in most countries during the second wave of the pandemic, they provide a form of private insurance against pandemic-related job losses and elevated health expenses.

Our article relates to recent work on the measurement of public attitude toward the financial sector. Stulz and Williamson (2003) find that a country's language and religion predict its creditor rights. Guiso, Sapienza, and Zingales (2008) find that a general lack of trust reduces stock market participation.

Giannetti and Wang (2016) document that after the revelation of corporate fraud in a state, household participation and trust in the stock market decreases. D'Acunto, Prokopczuk, and Weber (2019) find that present-day demand for finance is lower in German counties where historical antisemitism (and therefore distrust in finance) was higher. Gurun, Stoffman, and Yonker (2018) find that communities indirectly exposed to a Ponzi scheme withdraw assets from investment advisers. Levine, Lin, and Xie (2019) link the African slave trade to household demand and trust of financial services. We contribute to this work by documenting how finance sentiment is shaped by natural disasters, and that insured (uninsured) disasters affect finance sentiment positively (negatively).

Natural disasters and their effects on the economy are of great interest since the onset of the COVID-19 pandemic. Eisensee and Stromberg (2007) study disaster relief and news coverage. Baker, Bloom, and Terry (2020) use natural disasters as instruments for stock market uncertainty. Jordà, Singh, and Taylor (2020) document persistent declines in real rates of return and increases in wages after pandemics. Closely related is Aksoy, Eichengreen, and Saka (2020), who find that epidemic exposure in an individual's impressionable years negatively affects their confidence in political institutions and leaders. Our evidence suggests that financial insurance, be it private by financial markets, or public by governments, can ameliorate the effects of natural disasters on sentiment toward finance.

A broader related literature considers the measurement of culture and its effects on economic outcomes (Guiso, Sapienza, and Zingales (2006)). Cultural differences can persist for generations (Spolaore and Wacziarg (2013)). Changes in culture, ideas, and, in particular, language have been tied to the dramatic enrichment the world experienced starting in the 19th century (McCloskey (2016), Mokyr (2016)). It remains unclear, however, exactly why cultural changes occur (Guiso, Sapienza, and Zingales (2015). Our results about natural disasters provide one plausibly exogenous cause for such cultural differences.

We proceed as follows: Section II describes how we measure finance sentiment using books and our data on natural disasters. Section III studies how previous natural disasters affect finance sentiment. Section IV uses online news to study changes in finance sentiment around the COVID-19 pandemic. Section V concludes.

II. Methods

In this section, we describe our approach to measuring finance sentiment, introduce our natural disasters sample and define severe natural disasters. We then provide descriptive statistics for these data sets.

A. Finance Sentiment Data

Following the methodology of Jha et al. (2021), each language and year, we start with a sample of finance-mentioning sentences published in the language and year according to the Google Books 5-gram data set. Next, we measure the degree to which each sentence places finance in a positive context. We then aggregate these scores to an average finance sentiment that reflects the mean sentiment toward finance of books written in the language in that year.

Finance sentiment $f_{i,t}$ is available for every year t from 1870 to 2009 for 8 languages i. American English, British English, French, German, Italian, Russian, and Spanish are available for the entire sample. We have a shorter 95-year sample for Chinese because prior to 1922, its corpus is more sparse, and most years feature no mentions of finance. Each language can be traced to a major geographical area, centered around a distinct country, throughout most of our sample. For example, the concentration of Russian speakers is highest in Russia. Therefore, in what follows, we refer to the finance sentiment of these languages and countries interchangeably but note that this requires a modest leap of faith.

Given the positive trend in finance sentiment documented by Jha et al. (2021), also evident from Table 1, our analysis below focuses on finance sentiment growth $\Delta f_{i,t}$. The finance sentiment growth characterizes the relative change of finance sentiment toward either positive or negative change direction given the absolute value of the previous year's sentiment for country i and year t:

$$(1) \qquad \Delta f_{i,t} = \frac{f_{i,t} - f_{i,t-1}}{|f_{i,t-1}|} \times 100.$$

TABLE 1

Finance Sentiment Summary Statistics

The sample in Table 1 spans from 1870 to 2009 for 8 country-language pairs. The corpus of sentences for each language is gathered from the Google Book Ngram Corpus. The connotation for each finance-mentioning sentence is measured based on its cosine similarity with respect to the positive minus negative vector. Finance sentiment for each year is the weighted average of the cosine similarity, weighted by the frequency of sentences in the language corpus for the year.

Language	Finance Sentiment (%)	Mean	Volatility	No. of Obs.
Chinese	Level	7.5	0.5	95
	Growth	0.1	7.9	88
French	Level	7.6	0.7	140
	Growth	0.2	1.3	139
German	Level	−4.9	0.5	140
	Growth	0.0	4.4	139
Italian	Level	4.4	0.4	140
	Growth	0.4	5.2	139
Russian	Level	−11.9	0.8	140
	Growth	0.1	1.5	139
Spanish	Level	8.3	0.7	140
	Growth	0.2	3.4	139
U.K. English	Level	14.2	0.3	140
	Growth	0.0	1.5	139
U.S. English	Level	14.5	0.6	140
	Growth	0.1	1.3	139
Total	Level	4.8	8.7	1,075
	Growth	0.2	3.7	1,061

Figure 1 plots finance sentiment growth for each country in our panel. It shows that China exhibits the highest volatility (7.9), followed by Italy (5.2) and Germany (4.4).

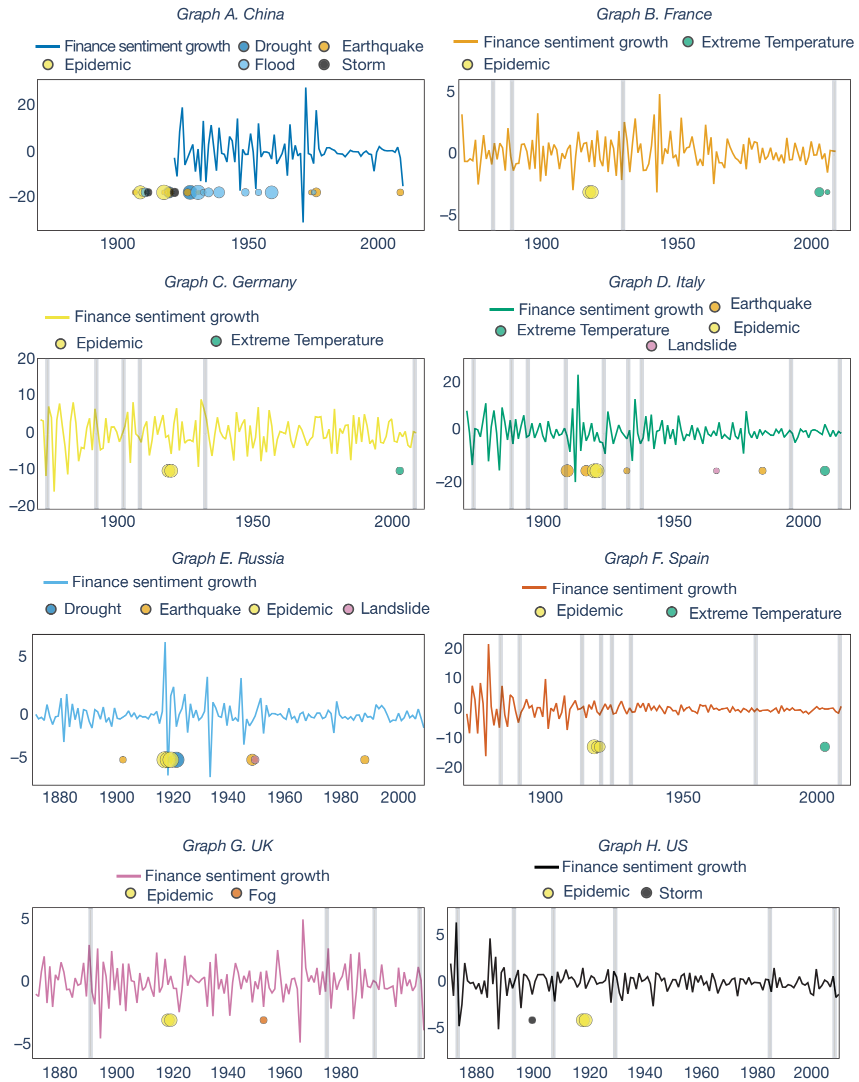
B. Disaster Data

Natural disasters data are from the Emergency Events Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disasters (CRED).

FIGURE 1

Finance Sentiment Growth

Figure 1 shows finance sentiment growth during the period 1870–2009 for each country. Vertical shaded areas indicate financial crises, as defined by Jordà, Schularick, and Taylor (2017) (not available for China and Russia). Severe natural disasters are indicated by circles whose size is proportional to log of deaths.



EM-DAT records an event as a disaster if it kills 10 or more people, if it affects 100 or more people, or if it leads to a formal declaration of a state of emergency or an appeal for international assistance.

To match with our text data, we extract an 8-country subsample from EM-DAT data set, including mainland China, France, Germany, Italy, Russia, Spain, the United Kingdom, and the United States. Following Eisensee and Stromberg

(2007), we focus on natural disasters and omit complex disasters (e.g., famine) and technological disasters (e.g., coal mine collapse), which are likely human-made. We manually add the death tolls caused by the 1918 flu pandemic when missing. The number of estimated deaths from the 1918 flu pandemic for each country is from Johnson and Mueller (2002), Guénel (2004), de la Rosa (2008), Trilla, Trilla, and Daer (2008), Buchholz, Buda, Reuß, Haas, and Uphoff (2016), Fornasin, Breschi, and Manfredini (2018), and Barro, Ursúa, and Weng (2020). Due to the difficulty of accurately determining the actual timing of deaths during the 1918–1920 flu pandemic, we distribute the estimated death number equally to each year for those countries where EM-DAT does not specify the death toll.

The EM-DAT data set classifies disasters by (sub) group and type. Our sample includes 11 distinct natural disaster types, belonging to 5 broader groups. Some countries encounter more than one natural disaster in the same year while other countries experience none. We thus sum the death toll by disaster type within the same year for each country.

Table 2 reports summary statistics for the matched sample of disasters, which includes 825 naturals disasters from 1900 to 2009, 733 of which caused fatalities. While some of these events are clearly salient disasters, some are of a more local nature, and unlikely to change popular sentiment. We, therefore, classify a disaster as severe if it kills at least 20 per million population, and focus on severe disasters for the most part. As we show below, the exact choice of cutoff is not as important as having a cutoff. The cutoff filters out disasters that affected many people but killed few.

Our analysis thus focuses on 60 severe disasters, of which 32% are epidemics, 30% are earthquakes, and 15% are floods. Table 2 shows that droughts and epidemics were most lethal, killing on average 783,000 and 378,000 people. EM-DAT includes an estimate of total damage in current U.S. dollars for some disasters. For a subset of disasters with damage information, EM-DAT reports how much of that damage is covered by insurance companies. Insurance is

TABLE 2

Natural Disasters Summary Statistics

Table 2 presents natural disasters by group and type that affect countries in our sample, 1900–2009. For each disaster type, we report the number of disasters, the number of severe disasters, the mean number of people killed, the mean damage (in current USD millions), and the mean percentage of damage that is insured. Severe disasters are those that killed at least 20 people per million population. Damage, when available, is the total estimated value of damages and economic losses directly or indirectly related to the disaster in USD millions. Insured losses, when available, are the percentage of total damage covered by insurance companies, which sometimes exceed the damage. Publication Lag is the number of years from severe disaster occurrence to its first mention in the corpus.

Disaster Group	Type	No. of Obs.	Severe	Mean Killed	Damage ($M)	Insured (%)	Pub. Lag
Biological	EPIDEMIC	46	19	388,333			0.58
Climatological	DROUGHT	20	3	783,922	1,830		0.00
	WILDFIRE	53	0	41	504	37.22	
Geophysical	EARTHQUAKE	150	18	7,534	1,744	21.23	0.28
	VOLCANO	5	0	206	431		
	MASS_MOVE	8	0	79			
Hydrological	FLOOD	189	9	38,949	859	42.97	0.00
	LANDSLIDE	66	2	321	224		3.50
Meteorological	STORM	217	3	951	1,132	101.20	0.00
	EXTREME_TEMP	70	5	1,068	2,233	36.26	0.00
	FOG (Smog)	1	1	4,000			0.00
All				35,662	1,116	83	0.38

available for wildfires, earthquakes, floods, storms, and extreme temperature disasters with sample coverage increasing over time. Floods and storms are well covered by insurance, with storms having higher than 100% coverage. However, earthquakes and especially epidemics are rarely covered by insurance. Since 2017, Munich Re, a large reinsurance company, has tried to start underwriting business insurance for epidemics. This effort was primarily unsuccessful until the COVID-19 pandemic hit in late 2019 (Walsh (2020)).

The last column of Table 2 shows that the average severe disaster first appears in the Google Books corpus in the same year that it occurs. This short publication lag is partly the result of books' prominence over most of our sample period as a source of timely information. For example, after a severe hurricane hit the city of Galveston, Texas, on Sept. 8, 1900, a book describing the disaster was published in the same year as a fundraising device for the area's devastated public schools (Ousley (1900)). Another reason for this modest average lag is that the Google Books corpus includes many library-stored serial publications. For example, the 1930 Irpinia earthquake is first mentioned in an information bulletin of the Italian National Research Council (Consiglio nazionale delle ricerche (1930)). Based on this average lag, below we regress finance sentiment growth on 1-year lagged disaster indicators.

War is another type of disaster, although arguably more human-made. Our interest in wars and their casualties is mostly as regression controls, because some of the natural disasters in our sample overlap with major armed conflicts. For example, the 1918 "Spanish Flu" overlaps with World War I. We rely on war death tolls from http://necrometrics.com, and concentrate on severe ones as well, which killed a similar fraction of a country's population as severe natural disasters.

Figure 2 visualizes the distribution of disasters across time and countries. It provides a simple explanation for the lack of insurance coverage for epidemics; when the 1918 flu hit, it spread across the globe within a year and affected all major countries in our sample. Such systematic sources of risk may not provide enough opportunities for risk sharing, and therefore feature high insurance premia and low take up. The figure also shows that severe disasters occur more frequently in developing countries such as China and Russia. The U.K. and the U.S., on the other hand, experienced the 1918 flu and one additional disaster. The dearth of disasters for the more developed economies means that estimates of the effects of natural disasters largely originate in developing counties. Because of the clustering of disasters in time and across countries shown by the figure, we include country and year fixed effects in our analysis below.

III. Natural Disasters Affect Finance Sentiment

How do natural disasters and wars affect sentiment toward finance? Column 1 of Table 3 shows that the mean severe natural disaster hitting a country i in year t decreases next year's finance sentiment growth $\Delta f_{i,t+1}$ by about 1 percentage point. Column 2 considers war as another source of variation in finance sentiment but shows that wars do not have a material effect on finance sentiment. Unlike natural disasters, war and, in particular, its timing, is endogenous, as it is under the control of the aggressor and partially under the control of the retaliating country, and

FIGURE 2

Severe Natural Disasters and Mortality Rates

In Figure 2, circles indicate severe natural disasters with size proportional to the logarithm of the number of deaths. We classify a disaster as severe if the death toll is above 20 per million population.

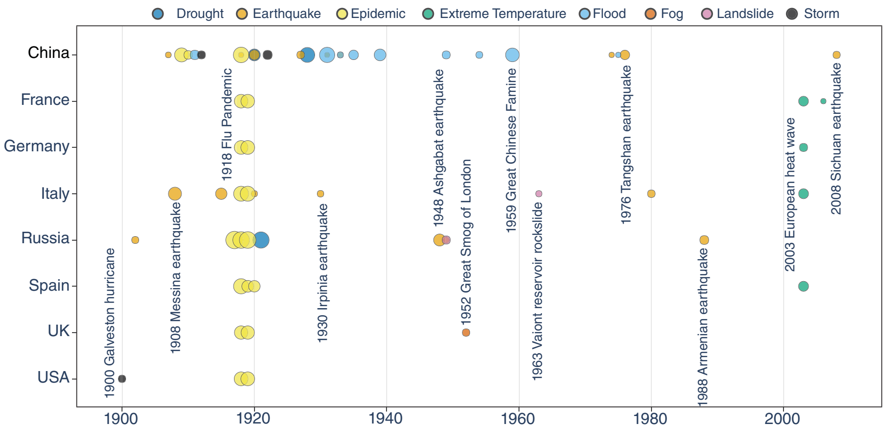


TABLE 3

Natural Disasters Affect Financial Sentiment

The dependent variable in Table 3 is FINANCE_SENTIMENT_GROWTH, which is the percentage growth from year t to $t+1$. NATURAL_DISASTER and WAR indicate that a country suffers a severe natural disaster or war in year t, killing at least 20 people per million population. Type-specific indicators for severe disasters are similarly defined. LOW_INSURED indicates that no more than one third of the damage caused by the disaster is covered by insurance. log(KILLED) is the logarithm of the number of deaths plus 1. Standard errors clustered by country are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	FINANCE_SENTIMENT_GROWTH$_{t+1}$					
	1	2	3	4	5	6
NATURAL_DISASTER$_t$	−0.88**	−0.88**	−0.89**			2.01**
	(0.32)	(0.33)	(0.33)			(0.70)
WAR$_t$		0.10	0.08			
		(0.40)	(0.42)			
NATURAL_DISASTER$_t$ × LOW_INSURED$_t$						−4.44**
						(1.70)
log(KILLED)$_t$			0.10		0.12	
			(0.09)		(0.09)	
DROUGHT$_t$				3.27*	3.60*	
				(1.39)	(1.55)	
EARTHQUAKE$_t$				−4.57**	−4.64**	
				(1.88)	(1.92)	
EPIDEMIC$_t$				−4.13**	−4.17**	
				(1.64)	(1.69)	
EXTREME_TEMP$_t$				−0.07	−0.05	
				(0.35)	(0.37)	
FLOOD$_t$				2.39**	2.42***	
				(0.68)	(0.68)	
LANDSLIDE$_t$				5.20***	5.41***	
				(1.08)	(1.26)	
STORM$_t$				−5.87	−5.93	
				(4.90)	(5.19)	
FOG$_t$				3.31	3.37	
				(2.57)	(2.50)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.13	0.13	0.13	0.16	0.17	0.14
No. of obs.	851	851	851	851	851	851

therefore likely shaped by other economic and political considerations. It is also possible that our war severity indicator is based on realized casualties, but a country's citizens respond more to war news and to expectations of damage (Verdickt (2020)). One may expect the number of fatalities caused by a disaster to be more important than the mere occurrence of a natural disaster. However, column 3 shows that controlling for the number of people killed hardly changes the natural disaster indicator's coefficient or the R^2. These panel regressions control for country and year fixed effects. Thus unobserved sources of heterogeneity across countries or time do not confound this result.

The average treatment effect of a severe natural disaster, however, masks considerable heterogeneity. In column 4 of Table 3, we replace the single disaster indicator with type-specific disaster indicators that turn on if a disaster of the listed type hits a country in year t. We find that droughts, floods, and landslides tend to increase future finance sentiment, while epidemics and earthquakes decrease it significantly. Storms and fog (smog) disasters have large economic effects as well, but cannot be statistically distinguished from zero. Column 5 shows that this result is robust to controlling for disaster fatalities.

The differential effect of a low insurance disaster is considerably negative. As column 6 of Table 3 shows, the considerable heterogeneity in effects across disaster types can be explained by the variation in insurance coverage mentioned previously. To investigate this hypothesis more formally, we define an indicator for low insurance taking the value of 1, if insurance companies cover less than one third of the damage caused by the disaster. Because data on insurance is sparse and concentrated in the latter part of our sample, we impute missing insured percentages for each disaster type, assuming no coverage for missing droughts, epidemics, landslides, volcano eruptions, and fogs.[1]

A potential explanation is the dual roles of finance. Finance facilitates risk sharing through insurance, securitization, or derivatives, so that when insured disasters hit, their economic costs are shared broadly across households and generations. But financial contracts and intermediaries are often designed to prevent ex post renegotiation (Diamond and Rajan (2001), Agarwal et al. (2017)). As a result, damage caused by uninsured disasters can be concentrated in parts of the population and generate resentment against financial intermediaries.

A related explanation is that sentiment toward financial intermediaries and insurers, in particular, may worsen if households and businesses learn they are uninsured only after the fact. Consistent with this channel, Gennaioli et al. (2020) document that insurance claims are frequently disputed, and in countries where this is the norm, insurance policies are more expensive and purchased less.

Although the effect heterogeneity between insured and uninsured disasters is intriguing, we note that unlike the disasters themselves, which are plausibly exogenous, unobservable omitted variables may confound the differential effect of insurance. For example, insurance markets may be more sophisticated in developed economies or in recent periods due to other technological changes we do not observe. Identifying the exact mechanism is, as usual, more complex than identifying the reduced form effect without an instrument for insurance coverage.

[1] Section II.B shows that our conclusions are robust to increasing or decreasing the cutoff by 20%.

A. Common Shocks

Our main results in Table 3 control for global shocks by including year fixed effects. It is equally interesting, however, to study how finance sentiment responds to common shocks across countries. The major common shock in our data set is the 1918 flu pandemic, which resembles COVID-19 in many ways. It is interesting to investigate how the same shock affects different countries and to explore the variation in their response to it.

Figure 3 focuses on the 1918 pandemic. To facilitate comparison across countries, we report standard deviation changes relative to 1917 for each country. The figure shows that Italian and U.K. English language books gradually place finance in worse and worse context, as their finance sentiment drops by 1.5 standard deviations over the subsequent 5 years. The effect on Russian and German sentiment is negative as well, although more temporary. By contrast, French, Spanish, and United States finance sentiment does not decline and even rise moderately. As Benmelech and Frydman (2020) explain, a large expansion in the U.S. government spending on World War I and the fact that the United States had recently suffered a financial crisis can explain why its economy or its sentiment toward finance did not shrink when the 1918 flu hit.

Table 4 provides a regression analysis of the effect of the common shock of the 1918 flu pandemic on finance sentiment growth. The first column shows that the average country hit with the virus suffers a decline in finance sentiment of 0.7% in the subsequent year. The second column shows that much of the decline can be explained by the number of flu-related fatalities. Specifically, countries that suffered more flu-related deaths show a steeper decline in finance sentiment. These results are consistent with the findings of Correia, Luck, and Verner (2020) that the

FIGURE 3

Changes in Finance Sentiment During the 1918 Flu Pandemic

Figure 3 shows changes in finance sentiment following the 1918 flu pandemic. We highlight each country's shift in sentiment since 1917, scaled by standard deviation.

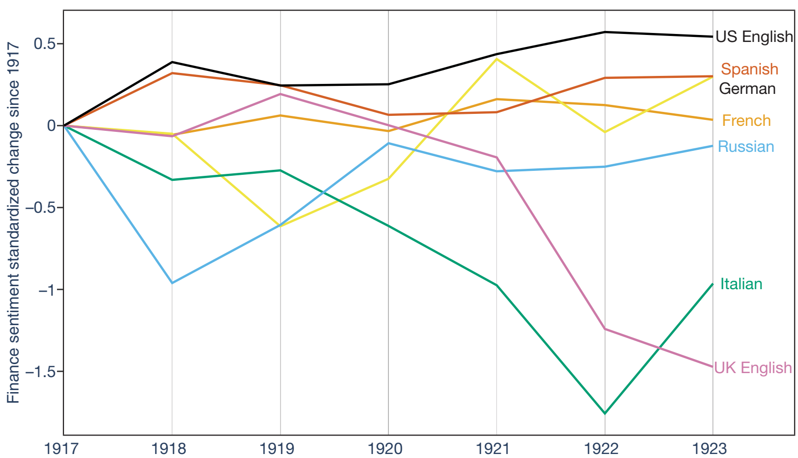


TABLE 4

The Effect of the 1918–1920 Flu Pandemic on Finance Sentiment

The dependent variable in Table 4 is finance sentiment percentage growth from year t to $t+1$. FLU_PANDEMIC is an indicator for the year the virus is identified in each country, and log(FLU_PANDEMIC_DEATHS$_t$) is the logarithm of the number of deaths caused by the pandemic plus 1. Standard errors clustered by country are in parentheses.

	FINANCE_SENTIMENT_GROWTH$_{t+1}$	
	1	2
FLU_PANDEMIC$_t$	–0.70**	–0.23
	(0.23)	(0.42)
log(FLU_PANDEMIC_DEATHS$_t$)		–1.08**
		(0.39)
Country FE	Yes	Yes
Year FE	No	No
R^2	0.0	0.0
No. of obs.	851	851

health gains from nonpharmaceutical interventions like social distancing in reducing disease transmission outweighed the economic costs during this episode.

B. Robustness

We have thus far focused only on disasters that we deem severe enough to affect attitudes toward finance at the country level. We next investigate the robustness of our conclusions to the particular choice of disaster classification criteria.

Figures 4 and 5 show that our baseline estimates of the effect of natural disasters are fairly robust to varying the cutoff for the fraction of the population killed by the disaster. Lower cutoffs include more benign natural disasters, whereas higher cutoffs concentrate the treatment effect estimates on fewer but more fatal disasters. As a result, the point estimates for more fatal disasters are generally larger in magnitude, but also feature greater parameter uncertainty.

Figure 5 also shows what happens when we aggregate the disasters into fewer groups. It shows that biological and geophysical natural disasters adversely affect finance sentiment, whereas climatological and hydrological disasters tend to improve public perceptions of the financial sector.

IV. The COVID-19 Pandemic

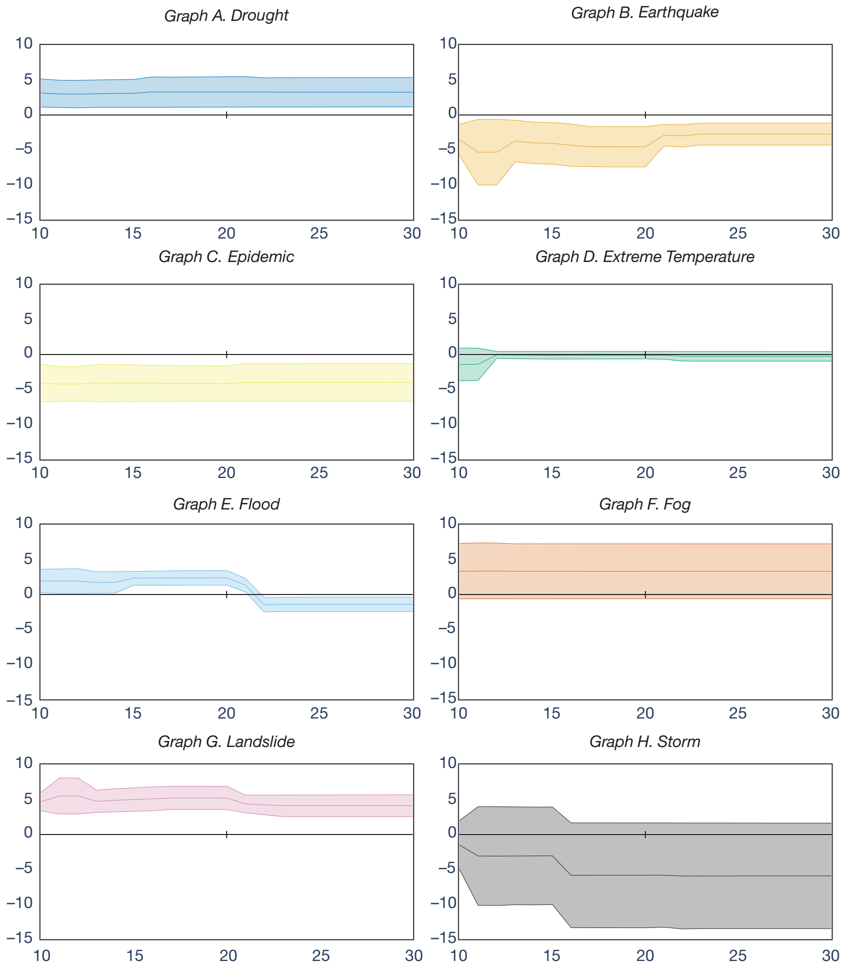
What do these estimates imply about the effects of the COVID-19 pandemic on economic growth? Jha et al. (2021) use local projections to estimate that the average effect over the 5 years following a –1-percentage-point shock to finance sentiment growth is a 0.2-percentage-point reduction in annual GDP growth and a 0.25-percentage-point reduction in credit growth. These estimates control for 3 lags of GDP, credit, and finance sentiment growth.

Table 3 shows that the effect of a severe epidemic is a 4-percentage-point reduction in finance sentiment growth. Therefore, the expected cumulative effect of such a decline in finance sentiment on GDP growth over the subsequent 5 years is about 4 percentage points $((1.002^5-1)\times 4$. The corresponding effect on credit growth is about 5 percentage points $\left(1.0025^5-1\right)\times 4)$. These economically

FIGURE 4

Robustness to the Severe Disaster Cutoff for Natural Disaster Types

Figure 4 shows how the estimated treatment effects of severe natural disaster types change as we vary the minimum number of deaths per million for a disaster to be considered severe, thus filtering out less devastating disasters. Bands indicate 90% confidence intervals.



substantial estimates are for the economic effects of the pandemic through the finance sentiment channel, over and above any direct effects of the pandemic on GDP and credit growth, for example, through a decline in the labor force.

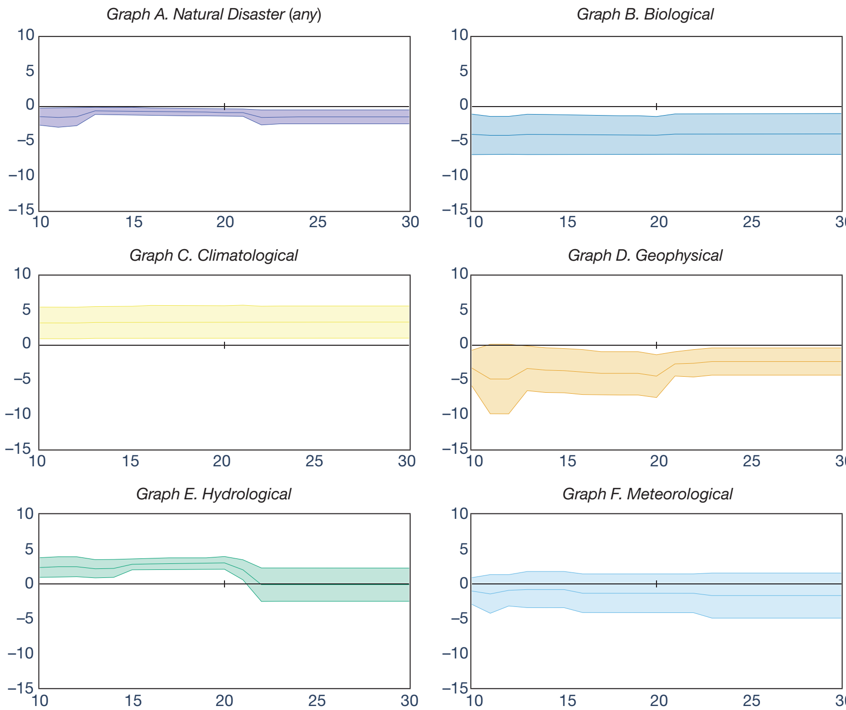
Finance Sentiment Around the COVID-19 Pandemic

Although it is still too early to assess whether these projections about economic growth following the COVID-19 pandemic materialize (we hope they do not), writing 1 year since the pandemic started, we can begin to study the response of finance sentiment to this disaster.

FIGURE 5

Robustness to the Severe Disaster Cutoff for Natural Disaster Groups

Figure 5 shows how the estimated treatment effects of severe natural disaster groups change as we vary the minimum number of deaths per million for a disaster to be considered severe, thus filtering out less devastating disasters. Bands indicate 90% confidence intervals.



The Google Books corpus that we rely on is not particularly useful for this purpose because it ends in 2009, and even if it was updated to the present, its annual frequency is not ideal. Instead, we collect online newspaper articles from the most popular newspapers of 7 of the 8 countries in our sample and apply the same methodology. Our data come from the News subset of the Common Crawl data set and contains 11.4 million articles published between 2016 and 2020. The Appendix lists the newspapers we use for each country. We rely on the news-please python package to extract the relevant articles (Hamborg, Meuschke, Breitinger, and Gipp (2017)).

Although similar in the information they include, the news corpus and the Google Books differ in three ways. First, our earlier caveat about potential confusion between countries and languages in the Google Books corpus does not apply to the news corpus because we rely on national newspapers (e.g., El Pais in Spain). Second, the news corpus contains complete sentences as opposed to 5-grams in the Google Books corpus. The availability of complete sentences allows us to better understand and extract finance sentiment because BERT embeddings are context-dependent. Third, the newspaper corpus has a daily frequency, as opposed to the

TABLE 5

Finance Mentions in Newspaper Articles Across Countries

Table 5 reports the number of mentions of the word "finance," translated and stemmed, in newspaper articles for each country. Our data set covers the period 2016–2020, at the daily frequency.

Country	Finance Word Stem	Unique Sentences	Total Sentences
France	Financ	153K	166K
Germany	Finanz	90K	116K
Italy	Finanz	79K	86K
Russia	Финан	49K	52K
Spain	Finan	170K	175K
U.K.	Financ	291K	431K
U.S.	Financ	209K	300K

Google Books yearly frequency. The higher frequency allows us to analyze event-specific sentiment changes.

For each newspaper article, we combine its title and body to a joined article text. We preprocess the article text by stripping case, punctuation, and symbols. Next, we split the article into sentences and keep only sentences mentioning the stem of the word "finance." The finance stem word is different across languages, as listed in Table 5. We use the word stem "financ" for English to include sentences that contain either "finance" or "financial." Similarly for other languages, we use a word stem common to the different verb and noun forms of "finance." The filtering yields a set of unique sentences mentioning finance for each country. In our data set, the United Kingdom has the highest number of unique sentences that mention finance, followed by the United States and Spain. The data set does not include Chinese newspapers, and its coverage of Russian-language news is somewhat sparse, but it covers the other 6 languages adequately. The news corpus contains the publication date of each article and the associated finance-mentioning sentences.

To avoid day-of-the-week effects from both newspaper coverage and viral testing patterns, we aggregate these data to the weekly frequency. Following the methodology of Jha et al. (2021), for each country and each Saturday, we start with a sample of finance-mentioning sentences published in the newspaper on the date and 6 days prior. To reduce noise, we filter out weeks that have fewer than 1,000 finance-mentioning sentences during the 7-day period. Next, we measure the degree to which each sentence places finance in a positive context. We then aggregate the sentence-level sentiment to an average finance sentiment that reflects the mean sentiment toward finance of news articles written in the language in that week.

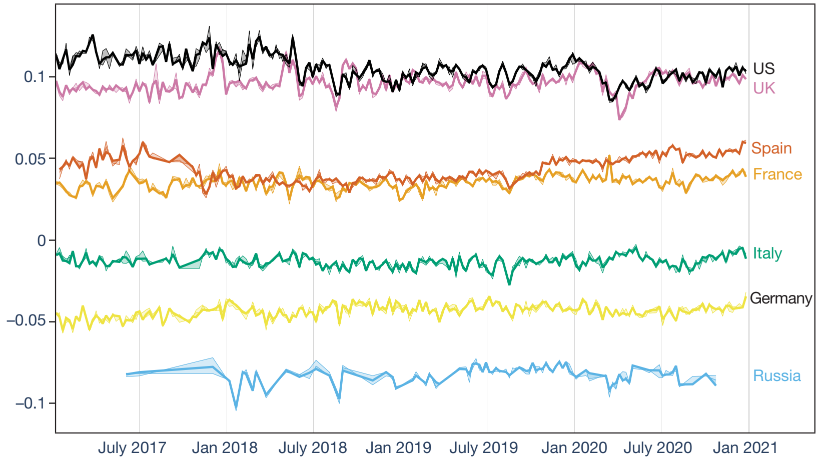
Figure 6 reports this higher frequency finance sentiment for the recent period. The band around the sentiment measure represents 95% confidence interval produced by subsampling. The ordering across countries is similar to the one reported in Jha et al. (2021) for the Google Books corpus over a much longer period, and confirms its finding that more capitalist countries exhibit more favorable attitudes toward finance. That the ordering is similar across corpora is partly because the language model used to embed each sentence is held constant, and partly because the frequency of positive versus negative finance-mentioning sentences does not drastically change over time.

In Figure 7, we zoom in on the COVID-19 pandemic. We find that newspapers in most countries feature a sharp decline in finance sentiment in Mar. and

FIGURE 6

News-Based Finance Sentiment (2017–2021)

In Figure 6, finance sentiment is based on the 7-day average projection of finance-mentioning sentences' embeddings onto the positive minus negative finance sentiment dimension. Sentences are gathered from web crawling the top 6 news sources for each country (listed in the Appendix), and embedded using BERT. For each Saturday, we look for sentences mentioning "finance," and its translations, across all the news sources over the past 7 days. We exclude country-week observations with fewer than 1,000 finance-mentioning sentences. Bands represent 95% confidence intervals produced by subsampling.



Apr. 2020, when it becomes evident that the virus has started spreading beyond China. Encouragingly, however, we can see that finance sentiment largely recovers by July 2020. As Graph B shows, around that time, the first wave of the virus ends in most of the countries in our sample, as measured by COVID-19 deaths gathered from COVID-19 Data Repository by the Center for Systems Science and Engineering at Johns Hopkins University.

Graph C of Figure 7 reports the stock market response measured by the returns on the most popular market index for each country gathered from Yahoo Finance. Returns are highly correlated across countries, and show a large drop in the early days of the pandemic followed by a gradual recovery. The highest returns are in early Nov. 2020 when the first COVID-19 vaccines were found to be safe and effective.

Table 6 separately reports the response during the first and second waves of COVID-19 across countries. We define the 2 waves based on the dates where the number of COVID-19 deaths in the country is on an increasing trend (shown in Figure 7). For the first wave, we start on Feb. 15, 2020 for each country and go till the date the number of COVID-19 deaths in the country is increasing. For the second wave, we start from the date when the number of COVID-19 deaths in the country starts increasing after the summer 2020 drop. The second wave ends when the number of COVID-19 deaths peaks or Dec. 31, 2020, when our news sample ends, whichever is earlier.[2]

During the first wave, an average of 145 people died of COVID-19 per million population. As people sheltered at home and economic activity contracted sharply,

[2] For example, Italy's first wave is Feb. 15, 2020 to Apr. 2, 2020 and its second wave is Sept. 1, 2020 to Dec. 7, 2020.

FIGURE 7

Finance Sentiment and COVID-19 Deaths

Graph A of Figure 7 shows changes in finance sentiment following the COVID-19 pandemic. We calculate weekly finance sentiment on each Saturday based on the news articles published during the preceding week. From the news articles, we filter out sentences containing the word "financ," and its translations for each language. Subsequently, we measure the degree to which each sentence places finance in a positive context, and aggregate the sentiments for the week. The change in sentiment is scaled by the standard deviation. Graph B shows rolling 7-day averages of confirmed COVID-19 deaths. Graph C shows the weekly change (based on Friday closing prices) in each country's most popular stock market index.

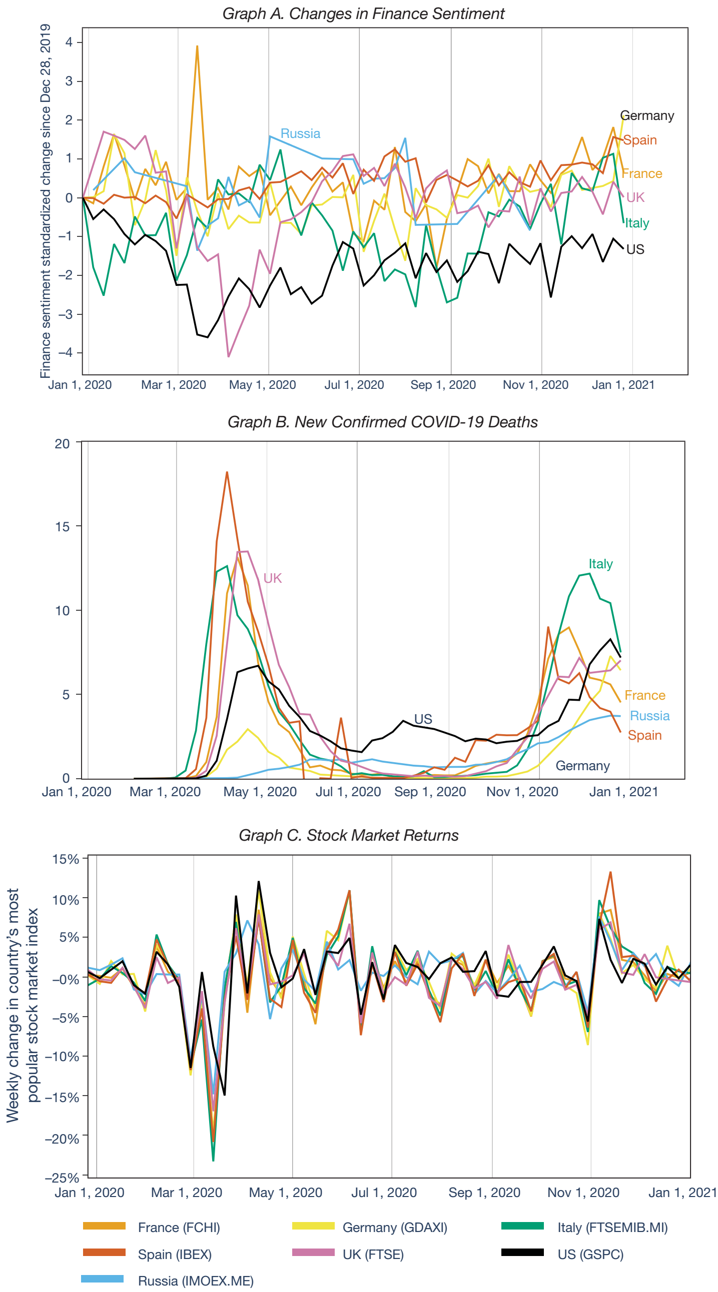


TABLE 6

Finance Sentiment, Deaths, and Market Returns During COVID-19 Waves

In Table 6, for 2 distinct 3-month periods, we report the change in finance sentiment, new COVID-19 deaths per million population, and percentage return on the country's most popular stock market index. Change in finance sentiment is standardized by the corresponding standard deviation.

	First Wave			Second Wave		
Country	Sentiment (std. Δ)	Deaths (per mln.)	Market (% return)	Sentiment (std. Δ)	Deaths (per mln.)	Market (% return)
France	0.1	152	−26.8	0.1	241	9.0
Germany	−1.8	48	−22.7	1.1	284	8.9
Italy	1.0	218	−32.3	3.8	407	12.8
Russia	0.6	34	−8.6	8.5	258	14.4
Spain	−0.2	221	−33.9	−0.5	222	6.9
U.K.	−3.8	182	−21.1	0.2	456	7.1
U.S.	−1.7	159	−16.1	−0.1	391	7.8
Average	−0.8	145	−23.1	1.9	323	9.6

stock markets declined by 23%, and financial volatility became front-page news. For many investors, this may have been the first time since the financial crisis of 2008, or ever, when the covariance risk of their financial holdings became crystal clear; their savings lost value at the same time they lost their jobs and many essential goods and services became expensive or unavailable. Disappointment with the insurance aspect of financial portfolios can partially explain why finance sentiment declines in most countries by an average of 0.8 standard deviations. The second wave of COVID-19 was on average twice as lethal as the first. But, sentiment toward finance increases by about 2 standard deviations during this period.

Why does finance sentiment recover despite an increase in the pandemic's death toll? One explanation is that stock markets, which are forward-looking, largely recovered to pre-pandemic valuations, and volatility declined as the initial flight-to-quality subsided. Table 6 indeed shows that finance sentiment increases the most in Italy and Russia, which experienced the largest stock market returns during the second wave.

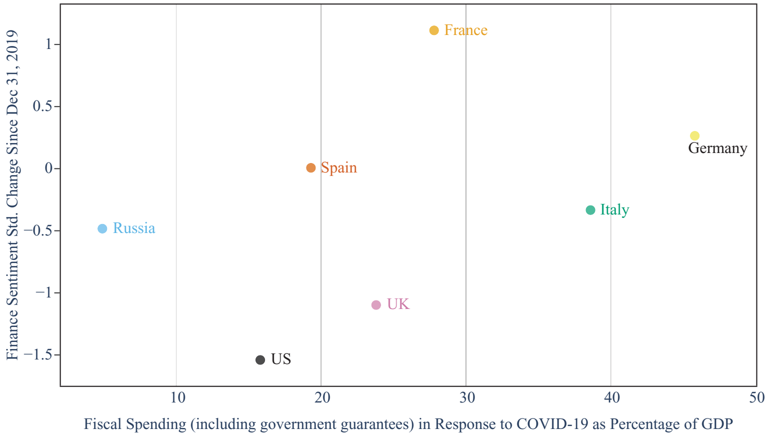
Another explanation for the recovery in finance sentiment is that despite a devastating health crisis, the economic policy response in the advanced economies that we study largely succeeded in preventing a financial crisis. As Benmelech and Tzur-Ilan (2020) document governments and central banks responded to the pandemic using both fiscal and monetary tools at an unprecedented scale. Such government-based insurance payments can reduce the need for private insurance through the financial sector, and therefore prevent a loss of trust in finance.

To analyze how government-provided insurance affects finance sentiment, we correlate finance sentiment changes with fiscal spending (including government guarantees) in response to COVID-19. Figure 8 shows a scatter plot of finance sentiment change with respect to the country's fiscal spending as of Sept. 7, 2020. We see a positive association between a country's support and perceptions of the financial system. Although most countries see a decline in finance sentiment, France and Germany, with high fiscal spending as a percentage of GDP, exhibit improved finance sentiment. Italy and Spain show little change. By contrast, the steepest drop in finance sentiment in Russia, the United States, and the United Kingdom can be explained by their relatively smaller fiscal response. This positive correlation, although based on a small sample of countries, suggests that at least in the short run, fiscal spending can ameliorate the negative effects of the pandemic on finance sentiment.

FIGURE 8

Fiscal Responses to COVID-19 and News-Based Finance Sentiment

In Figure 8, fiscal spending includes deferred and canceled taxes, strengthening the social safety net, direct grants, wage subsidies, money transfers, income support, and government guarantees. Fiscal spending and government guarantees information as of Sept. 7, 2020 is from Benmelech and Tzur-Ilan (2020). The *y*-axis shows the change in finance sentiment from Dec. 31, 2019 to Sept. 7, 2020, standardized by the corresponding standard deviation. Finance sentiment reflects the degree to which newspapers published in the country place finance in a positive context.



What these findings mean for attitudes toward finance going forward is still not obvious. One rosy scenario is that the policy interventions worked, and the negative consequences for economic and credit growth will be avoided. An alternative scenario, however, is that governments can borrow to temporarily smooth the shock, but that eventually higher taxes or the expiration of loose regulatory policies lead to an inevitable slowdown. The data we do have, while limited, suggest that sentiment toward finance depends on the level of insurance provided by private financial markets and by public finance.

V. Conclusion

We use a text-based measure of popular sentiment toward finance to study how finance sentiment responds to rare disasters and its effects on economic and financial outcomes. Finance sentiment declines after epidemics and earthquakes, but rises following severe droughts, floods, and landslides. These heterogeneous effects of natural disasters suggest finance sentiment responds differently to the realization of insured versus uninsured risks.

Our estimates based on historical epidemics imply that beyond its health crisis, the COVID-19 pandemic may reduce GDP growth by 4 percentage points and reduce credit growth by 5 percentage points over the next 5 years by worsening attitudes toward finance. This back-of-the-envelope calculation assumes, of course, that the COVID-19 pandemic affects finance sentiment like previous severe epidemics. Governments and central bank interventions, as well as the recovery in stock markets, however, appear to have alleviated the pandemic's physical and financial damage and reduced any damage to public sentiment toward finance.

Appendix. Newspapers in the News Corpus by Country

The list of newspapers in this Appendix includes the top circulated newspapers in each country. We exclude sports-oriented newspapers. We omit China as the news subset of Common Crawl contains few Chinese news articles.

France	Germany	Italy
Le Canard Enchaîné	Der Tagesspiegel	Avvenire
Le Figaro	Die Tageszeitung	Corriere Della Sera
Le Journal du Dimanche	Die Welt	Il Fatto Quotidiano
Le Monde	Frankfurter Allgemeine Zeitung	Il Sole 24 Ore
Le Parisien	Handelsblatt	La Repubblica
Les Echos	Süddeutsche Zeitung	La Stampa
Russia	**Spain**	**U.K.**
Известия	20 Minutos	Daily Mail
Коммерса́нтъ	ABC	Evening Standard
Комсомольская правда	El Confidencial	Financial Times
Московская правда	El Mundo	Metro
Московский комсомолец	El Pais	The Sun
Независимая газета	La Vanguardia	The Times of London
	U.S.	
Boston Globe	Los Angeles Times	USA Today
Chicago Tribune	Miami Herald	Washington Post
Dallas Morning News	San Francisco Chronicle	WSJ
Houston Chronicle		

References

Agarwal, S.; G. Amromin; I. Ben-David; S. Chomsisengphet; T. Piskorski; and A. Seru. "Policy Intervention in Debt Renegotiation: Evidence from the Home Affordable Modification Program." *Journal of Political Economy*, 125 (2017), 654–712.

Aksoy, C. G.; B. Eichengreen; and O. Saka. "The Political Scar of Epidemics." NBER Working Paper No. 27401 (2020).

Baker, S.; N. Bloom; and S. Terry. "Using Disasters to Estimate the Impact of Uncertainty." NBER Working Paper No. 27167 (2020).

Barro, R. J.; J. F. Ursúa; and J. Weng. "The Coronavirus and the Great Influenza Pandemic: Lessons from the 'Spanish Flu' for the Coronavirus's Potential Effects on Mortality and Economic Activity." NBER Working Paper No. 26866 (2020).

Benmelech, E., and C. Frydman, "The 1918 Influenza Did Not Kill the US Economy." Washington, DC: CEPR (Apr. 29, 2020).

Benmelech, E., and N. Tzur-Ilan. "The Determinants of Fiscal and Monetary Policies During the Covid-19 Crisis." NBER Working Paper No. 27461 (2020).

Buchholz, U.; S. Buda; A. Reuß; W. Haas; and H. Uphoff. "Influenza Pandemic Deaths in Germany from 1918 to 2009. Estimates Based on Literature and Own Calculations." *Bundesgesundheitsblatt, Gesundheitsforschung, Gesundheitsschutz*, 59 (2016), 523–536.

Chetty, R.; J. N. Friedman; N. Hendren; and M. Stepner. "Real-Time Economics: A New Platform to Track the Impacts of COVID-19 on People, Businesses, and Communities Using Private Sector Data." Tech. rep., Mimeo (2020).

Consiglio nazionale delle ricerche. *Bollettino d'informazioni* (1930).

Correia, S.; S. Luck; and E. Verner. "Pandemics Depress the Economy, Public Health Interventions Do Not: Evidence from the 1918 Flu." Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3561560 (2020).

D'Acunto, F.; M. Prokopczuk; and M. Weber. "Historical Antisemitism, Ethnic Specialization, and Financial Development." *Review of Economic Studies*, 86 (2019), 1170–1206.

de la Rosa, V. M. "The Persuasive Use of Rhetorical Devices in the Reporting of 'Avian Flu.'" *Vigo International Journal of Applied Linguistics*, (2008), 87–106.

Devlin, J.; M.-W. Chang; K. Lee; and K. Toutanova. "BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding." arXiv:1810.04805 [cs], (2018).

Diamond, D. W., and R. G. Rajan. "Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking." *Journal of Political Economy*, 109 (2001), pp. 287–327.
Eisensee, T., and D. Stromberg. "News Droughts, News Floods, and U. S. Disaster Relief." *Quarterly Journal of Economics*, 122 (2007), 693–728.
Fornasin, A.; M. Breschi; and M. Manfredini. "Spanish Flu in Italy: New Data, New Questions." *Le Infezioni in Medicina*, 26 (2018), 97–106.
Gennaioli, N.; R. La Porta; F. Lopez-de-Silanes; and A. Shleifer. "Trust and Insurance Contracts." NBER Working Paper No. 27189 (2020).
Giannetti, M., and T. Y. Wang. "Corporate Scandals and Household Stock Market Participation." *Journal of Finance*, 71 (2016), 2591–2636.
Guénel, J. "Spanish Influenza in France from 1918–1919." *Histoire Des Sciences Medicales*, 38 (2004), 165–175.
Guiso, L.; P. Sapienza; and L. Zingales. "Does Local Financial Development Matter?" *Quarterly Journal of Economics*, 119 (2004), 929–969.
Guiso, L.; P. Sapienza; and L. Zingales. "Does Culture Affect Economic Outcomes?" *Journal of Economic Perspectives*, 20 (2006), 23–48.
Guiso, L.; P. Sapienza; and L. Zingales. "Trusting the Stock Market." *Journal of Finance*, 63 (2008), 2557–2600.
Guiso, L.; P. Sapienza; and L. Zingales. "Corporate Culture, Societal Culture, and Institutions." *American Economic Review*, 105 (2015), 336–339.
Gurun, U. G.; N. Stoffman; and S. E. Yonker. "Trust Busting: The Effect of Fraud on Investor Behavior." *Review of Financial Studies*, 31 (2018), 1341–1376.
Hamborg, F.; N. Meuschke; C. Breitinger; and B. Gipp. "news-please: A Generic News Crawler and Extractor." 15th International Symposium of Information Science (ISI 2017), 218–223.
Jha, M.; H. Liu; and A. Manela. "Does Finance Benefit Society? A Language Embedding Approach." Working Paper, Washington University in St. Louis (2020).
Johnson, N. P. A. S., and J. Mueller. "Updating the Accounts: Global Mortality of the 1918–1920 'Spanish' Influenza Pandemic." *Bulletin of the History of Medicine*, 76 (2002), 105–115.
Jordà, Ò.; M. Schularick; and A. M. Taylor. "Macrofinancial History and the New Business Cycle Facts." *NBER Macroeconomics Annual*, 31 (2017), 213–263.
Jordà, Ò.; S. R. Singh; and A. M. Taylor. "Longer-Run Economic Consequences of Pandemics." NBER Working Paper No. 26934 (2020).
Kozlowski, A. C.; M. Taddy; and J. A. Evans. "The Geometry of Culture: Analyzing the Meanings of Class Through Word Embeddings." *American Sociological Review*, 84 (2019), 905–949.
Levine, R.; C. Lin; and W. Xie. "The African Slave Trade and Modern Household Finance." SSRN Scholarly Paper ID 3031310, Social Science Research Network, Rochester, NY (2019).
McCloskey, D. N. *Bourgeois Equality: How Ideas, Not Capital or Institutions, Enriched the World*. Chicago, IL: University of Chicago Press (2016).
Mokyr, J. *A Culture of Growth: The Origins of the Modern Economy*, Princeton University Press (2016).
Mongey, S.; L. Pilossoph; and A. Weinberg. "Which Workers Bear the Burden of Social Distancing Policies?" NBER Working Paper No. 27085 (2020).
Ousley, C. *Galveston in Nineteen Hundred: The Authorized and Official Record of the Proud City of the Southwest as It Was Before and After the Hurricane of September 8, and a Logical Forecast of Its Future*. La Crosse, WI: Brookhaven Press (1900).
Sapienza, P., and L. Zingales. "A Trust Crisis." *International Review of Finance*, 12 (2012), 123–131.
Sapienza, P., and L. Zingales. "Economic Experts versus Average Americans." *American Economic Review*, 103 (2013), 636–642.
Scism, L. "Companies Hit by Covid-19 Want Insurance Payouts. Insurers Say No." *Wall Street Journal* (June 30, 2020).
Spolaore, E., and R. Wacziarg. "How Deep Are the Roots of Economic Development?" *Journal of Economic Literature*, 51 (2013), 325–369.
Stulz, R. M., and R. Williamson. "Culture, Openness, and Finance." *Journal of Financial Economics*, 70 (2003), 313–349.
Trilla, A.; G. Trilla; and C. Daer. "The 1918 'Spanish Flu' in Spain." *Clinical Infectious Diseases*, 47 (2008), 668–673.
Verdickt, G. "The Effect of War Risk on Managerial and Investor Behavior: Evidence from the Brussels Stock Exchange in the Pre-1914 Era." *Journal of Economic History*, 80 (2020), 629–669.
Walsh, M. W. "Coronavirus Will Cost Businesses Billions. Insurance May Not Help." *The New York Times* (Mar. 5, 2020).
Zingales, L. "Presidential Address: Does Finance Benefit Society?" *Journal of Finance*, 70 (2015), 1327–1363.