Using Disasters to Estimate
the Impact of Uncertainty[*]

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Abstract

Uncertainty rises in recessions and falls in booms. But what is the causal relationship? We construct cross-country panel data on stock market levels and volatility and use natural disasters, terrorist attacks, and political shocks as instruments in regressions and VAR estimations. We find that increased volatility robustly lowers growth. We also structurally estimate a heterogeneous firms business cycle model with uncertainty and disasters and use this to analyze our empirical results. Finally, we used our VAR results in early 2020 to produce and circulate a real-time forecast, based on the initial stock market returns and volatility response to COVID-19, which accurately predicted the magnitude of the initial drop in US GDP.

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1 Introduction

A rapidly growing literature investigates the relationship between uncertainty and growth. One unifying fact emerges. Both macro and micro uncertainty move countercyclically, rising steeply in recessions and falling in booms.[1]

However, the extent to which this relationship is casual remains far from clear. Does uncertainty drive recessions, do recessions drive uncertainty, or does another factor drive both? Since theoretical models of uncertainty and economic activity predict effects in both directions, identifying the direction of causation ultimately requires an empirical approach.[2]

Identifying the causal direction of this relationship proves difficult because most macro variables move together over the business cycle. Such challenges should appear familiar because, as Kocherlakota (2009) aptly noted, *"The difficulty in macroeconomics is that virtually every variable is endogenous."* As a result, prior work on uncertainty typically either assumes the direction of causation or relies on timing for identification within a VAR framework. Because of the contemporaneous movement of macro variables and the forward-looking nature of investment and hiring, such approaches face formidable identification challenges.[3]

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[1]See, for example, evidence of counter-cyclical volatility in: macro stock returns in the US in Schwert (1989), in firm-level stock asset prices in Campbell et al. (2001) and Gilchrist, Sim, and Zakrajsek (2012); in plant, firm, industry and aggregate output and productivity in Bloom et al. (2018), Kehrig (2015) and Bachmann and Bayer (2013) Bachmann and Bayer (2014); in price changes in Berger and Vavra (2018); and in consumption and income in Storesletten, Telmer, and Yaron (2004), Meghir and Pistaferri (2004) and Guvenen, Ozkan, and Song (2014). Other papers find that GDP and prices forecasts have a higher within-forecaster dispersion and cross-forecaster disagreement in recessions, for example, Bachmann, Elstner, and Sims (2013), Popescu and Smets (2009) and Arslan et al. (2015); that the frequency of the word "uncertainty" close to the word "economy" rises steeply in recessions (e.g. Alexopoulos and Cohen (2009)), and that a broad uncertainty factor indicator is counter-cyclical (Jurado, Ludvigson, and Ng 2015).

[2]Models predicting impacts of uncertainty on economic activity include effects via: (a) risk aversion; (b) via the concavity of the production function (for example Oi (1961), Hartman (1972) and Abel (1983)); (c) real-options effects (for example Bernanke (1983), Bertola and Caballero (1994), Dixit and Pindyck (1994), Hassler (1996), Gilchrist and Williams (2005), Sim (2006)); (d) via financial contracting frictions (for example, Arellano, Bai, and Kehoe (2019), and Narita (2011)), and (e) via search frictions Leduc and Liu (2016) and Schaal (2017). There are also models predicting effects of economic activity on uncertainty, for example on information collection in Van Nieuwerburgh and Veldkamp (2006) and Fajgelbaum, Schaal, and Taschereau-Dumouchel (2017), on noise-trading in Albagli (2011), on R&D in Decker, D'Erasmo, and Moscoso Boedo (2016), on experimentation in Bachmann and Moscarini (2011) and on policy in Bianchi and Melosi (2014).

[3]For example, Bloom (2009), Christiano, Motto, and Rostagno (2014), Arslan et al. (2015), Basu and Bundick (2017), Fernández-Villaverde et al. (2011) and Alexopoulos and Cohen (2009) report a large impact of uncertainty on recessions in their VARs, while Bachmann and Bayer (2013) report

In this paper we take a different approach involving two steps. First, we combine measures of aggregated/macro stock-market volatility (i.e. the volatility of the market as a whole) with measures of micro stock-returns volatility (i.e. the dispersion across individual firm returns). Given the emphasis in the literature on the importance of both macro and micro uncertainty, we take a standardized index of our macro and micro proxies as our baseline measure of uncertainty.

Second, we exploit the large number of exogenous shocks that occur in a quarterly panel of up to sixty countries since 1970. These exogenous shocks are natural disasters, terrorist attacks, political coups, and revolutions. We use these shocks to instrument for changes in the level and volatility of stock market returns as a way to separate the effects of our exogenous shocks into first- and second-moment components. The identifying assumption is that some shocks – like natural disasters – lead primarily to a change in stock market levels and more closely map to first-moment shocks, while other events like coups lead more to changes in stock market volatility, implying they are more of a second-moment shock. A series of instrumental variables estimators exploits these differences to separate the impact of first- vs second-moment shocks on the economy.

To refine this analysis, we weight each event by the increase in daily count of articles mentioning the affected country in Access World News in the fifteen days after the event compared to the fifteen days before the event. For example, we would use the 322% increase in the count of the word "Japan" in fifteen days after the March 11th 2011 earthquake compared to the fifteen days before to weight this shock. This ensures that only events that are unanticipated are included, since anticipated events like elections and major sports events do not generate jumps in coverage on the day they occur. Moreover, the largest and most newsworthy shocks will get the largest weight, which should be correlated with their economic impact.

To highlight how our identification strategy focuses on surprise events, Figure 1 shows the average increase in newspaper coverage of the countries in which the shocks occurred for fifteen days before and after they occurred. This shows these events lead to a jump in newspaper coverage on the day of the event, with an average increase of 39% over the fifteen days after the event. For comparison Figure 2 shows the media coverage around general elections, showing no jump in the days after compared to

the reverse (a large effect of recessions on uncertainty).

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the days before the event.[4]

Using this strategy of weighting events by their increase in media coverage, we find a significant causal impact of both first- and second-moment effects on economic activity. In the year following a shock, we estimate a one standard deviation increase in our first moment proxy and a one standard deviation increase in our second moment proxy lead to an approximately 2% increase and a 7% decrease in GDP growth, respectively. That is, first- and second-moment effects are both significant drivers of growth.

There are clearly some potential issues with this identification strategy. One of these is whether our particular stock market uncertainty measure is a good indicator of second-moment shocks to business conditions. As alternative estimation approaches, we also try using solely cross-firm stock returns dispersion or solely broad stock index volatility, finding similar results. In addition, we construct alternative versions of our main instruments where we include shocks to geographically neighboring economies and trade partners, finding that these also tend to drive similar effects. Finally, we compare the combined stock volatility measure to two indicators of economic uncertainty, the World Uncertainty Index and country-level Economic Policy Uncertainty Indexes. We find a strong correlation between the different measures at a country-quarter level, suggesting that stock market volatility can indeed represent a useful indicator of broader second-moment shocks.[5]

A second concern is whether these events are really shocks or are endogenous events. For example, maybe some revolutions were predicted in advance or natural disasters arising from human actions (like deforestation) could be foreseen. To address this, we test our shock instruments directly and find while these have extremely high predictive power for future economic outcomes like stock returns and GDP growth, we cannot find any predictive power for these shocks using lagged stock returns and GDP growth. Moreover, as shown in Figure 1, there is no increase in newspaper mentions of these countries in the days leading up to the day of the event, suggesting they were not anticipated in the short run, either. We also run various over-identification tests

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[4]We also did similar analysis for other predictable but media-important events like the World Cup and Super Bowl, also finding no significant jump in coverage around the event.

[5]We display the correlation between the WUI index and EPU index against our combined micro and macro volatility index in Figure A1 across an overlapping sample of countries back to 1987 (34 for the WUI and 20 for EPU). Similar levels of correlation are seen for either of the constituent stock market volatility metrics (ie. solely cross-firm or solely aggregate volatility).

in our regressions and find no evidence to reject the instruments. Hence, while some of the shocks may be predictable in the very long run (for example, global warming may increase large hurricanes), over the short time horizon of our analysis they appear to be unpredictable.

Third, our stock market levels and volatility indicators proxy for a range of channels of economic impact, e.g. the destruction of capital (e.g. buildings and equipment) after a natural disaster and the closure of the banking system after a revolution. We see these as all part of the first- and second-moment impacts of these shocks. But it is worth noting that in obtaining causal identification of the impact of first and second moment effects of exogenous shocks on the economy, we are conflating all these channels together.

Finally, our results are only valid to the extent that they identify the first and second moment impact of our shocks in the countries and years that they occur. This is a classic local average treatment effect (LATE) issue (Imbens and Angrist 1994), in that our identification is driven by the variation in our instrument which comes mainly in developing or less developed countries, which experience many more shocks than developed countries. As robustness, we also re-estimate our results using a variety of sample splits and specifications. We find very similar results for countries above and below median income levels and for different time periods.

Moving on from our univariate IV regressions, we also we use the disaster shocks as external instruments in a vector autoregression (VAR) following the approach of Mertens and Ravn (2013) and Stock and Watson (2018). This approach is, essentially, a multivariate dynamic generalization of our baseline univariate strategy. We uncover a negative impact of volatility shocks on growth which proves robust across a range of alternative VAR specifications and subsamples.

To validate our empirical identification strategy, we build a rich quantitative business cycle model with firm heterogeneity and incorporate disaster shocks. In the model, an uncertainty shock causes a drop in GDP growth because individual firms pause their hiring and investment activity, freezing in the face of increased volatility and adjustment costs. Disaster shocks in the model lead to flexibly parameterized shifts in the levels and the volatility of the exogenous productivity processes at the micro and macro levels. We structurally estimate this model, which must be numerically solved and simulated, by choosing the disaster mappings in an indirect inference procedure which targets our baseline IV regressions. In our simulated data, both the

IV regressions and our IV-VAR based on disaster instruments correctly uncover the negative impact of uncertainty on GDP growth.

Finally, armed with our validated empirical estimates, we then turn to the disruptions in the stock market occurring with the COVID-19 pandemic in early 2020. The stock market experienced both a sharp drop in average returns together with a spike in volatility.[6] Our empirical strategy exploits historical events which bundle together first- and second-moment innovations. In a real-time forecasting exercise, the results of which we initially circulated in a working paper in May 2020 (Baker, Bloom, and Terry 2020), we fed both the early 2020 levels drop in the US stock market, over two standard deviations by our measure, as well as the concurrent volatility jump of over one standard deviation, into our IV-VAR. Based on this forward-looking asset pricing information up through only 2020Q1, we forecasted a drop of about 7% in US GDP growth in 2020Q2. Ex-post, this initial forecasted decline proved to be similar to the observed decline of about 9%. We conclude that our IV-VAR framework may provide useful insight into the impact of large, disruptive events on the macroeconomy.

This paper links closely to the broader literature on volatility and growth. Ramey and Ramey (1995)'s paper looked at a cross-country panel data and found a strong negative relationship between growth and volatility. Other related growth papers include Barro (1991) who finds a negative relationship between growth and political instability, Koren and Tenreyro (2007) who find strongly negative correlations between growth and the volatility of country-level macro shocks, and Engel and Rangel (2008) who show a negative correlation between GARCH measures of heteroskedasticity and growth in cross-country panels. Carrière-Swallow and Céspedes (2013) demonstrate that this relationship appears much stronger for emerging countries with less developed financial systems relative to the United States. The challenge with this literature is identifying the nature of causality underlying these relationships between growth and volatility.

Our use of disaster instruments also clearly relates to a rich literature in economics and finance. Early work by Rietz (1988) and Barro (2006) emphasizing the implications of disasters for financial markets has been followed by wide investigation of their broader impact (Barro and Ursúa 2012; Gabaix 2012; Gourio 2012; Nakamura

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[6]While the stock market recovered somewhat subsequently, we did not include this rebound as it reflects the response of fiscal and monetary policy, including for example the stimulus in the CARES Act.

et al. 2013). We view our work as complementary to the disaster literature, although our focus is not on the impact of disasters per se. We instead exploit them as a useful source of variation in levels and volatility, variation which proves key to our identification strategy.

Our analysis of the impact of uncertainty on business cycles links to a rich and rapidly growing set of work in empirical macroeconomics. Ludvigson, Ma, and Ng (2019) use a novel time series identification strategy to examine the impacts of financial and macro uncertainty separately, finding that macro uncertainty is mostly an endogenous response to downturns rather than a driver. Berger, Dew-Becker, and Giglio (2020) use a news-shock empirical approach to conclude that realized volatility, rather than uncertainty per se, plays an important role for driving fluctuations. Dew-Becker and Giglio (2020) use historical options data to analyze cross-sectional versus macro uncertainty, finding a stronger business cycle role for the latter. Carriero, Clark, and Marcellino (2018) estimate a nonlinear model using Bayesian methods and find a limited role for uncertainty in driving cycles. Caldara et al. (2016) uses a penalty function identification strategy and finds an important role for both financial and uncertainty shocks in driving cycles.

The analysis of the COVID-19 shock in our paper also links to a rapidly growing body of work on the economics of the pandemic. Some of that work combines epidemiological structures with economic models (Eichenbaum, Rebelo, and Trabandt 2020; Atkeson 2020). Other papers focus on measuring the asset market and firm-level disruptions associated with the pandemic (Alfaro et al. 2020; Baker et al. 2020b; Hassan et al. 2020). Historical variation from past epidemics informs other papers (Correia, Luck, and Verner 2020). Finally, a group of projects links uncertainty to the pandemic (Baker et al. 2020a; Leduc and Liu 2020; Ludvigson, Ma, and Ng 2020; Carriero et al. 2020). Our approach is complementary to and incorporates many of these streams of work, combining an economic model with historical disaster and asset price variation to inform an uncertainty-based analysis of the pandemic.

In Section 2 we describe our economic and disaster data. In Section 3 we run instrumental variable regressions and estimate our vector autoregression to uncover the impact of uncertainty on GDP growth. In Section 4 we introduce and structurally estimate our business cycle model, validating the disaster instruments identification strategy. Section 5 provides our real-time forecast of US GDP growth from the start of the COVID-19 shock. We conclude in Section 6. Online appendices provide more

detail on our empirical and model analysis.

2   Data

In the data we use up to 60 countries in our analysis, spanning the time period 1970-2019. These nations are selected as countries with more than \$50 billion in nominal GDP in 2008. We require that a country has at least 5 years of daily stock returns data from a national index to be included. While a number of countries have data beginning in the 1940s, most countries have relatively complete data starting only in the 1970s or later. Thus, we construct our sample from 1970 onwards in order to avoid early years that would span only a few countries in our panel. The data can be divided into disaster shock data and economic data, which we now discuss in turn. Each are summarized in Table 1 and discussed further in Appendix A.

2.1   Disaster Shock Data

To obtain the causal impact of first- and second-moment shocks on GDP growth we want to instrument using arguably exogenous shocks. This leads us to focus on natural disasters, terrorist attacks, and political shocks, which are typically exogenous at least in the short run. This approach has some precedent in the literature, such as the paper by Jones and Olken (2005) looking at successful assassinations of national leaders as an instrument for leadership change and Hoover and Perez (1994) who use oil-price shocks as instruments for aggregate productivity shocks. Furthermore, others have found strong effects of political 'shocks' on markets and asset prices (e.g. Zussman, Zussman, and Nielsen (2008)).

   As we discuss below, the exogeneity of many of these shocks is disputable in the long run. For example, faster economic growth may increase the chances of a natural disaster through reduced forest cover but reduce the chances of a revolution by lowering poverty rates. To address this concern, we do three things.

   First, we focus only on short-run impacts of shocks. At these short-run frequencies it is easier to argue shocks are exogenous. For example, while some commentators expected revolutions in the Middle East at some point, the start of the Arab Spring in December 2010 was unexpected.

   Second, we weight shocks by the increase in media coverage 15 days after the event

compared to 15 days before the event. This should remove anticipated shocks in that the media coverage running up to them would be smoothly increasing. Figure 1 shows this media coverage on average for all shocks combined, displaying a large jump after the shocks and no obvious run-up in coverage before the event. In comparison, Figure 2 shows the media coverage in the one month around general elections with no jump in the 15 days after the event.

Third, we confirm econometrically these events appear to be surprises. In Table A1 we report forecasting specifications for these events, and they are not anticipated by the market in advance. This is perhaps not surprising - natural disasters are notoriously hard to predict, while coups and terrorist attacks by their nature tend to be planned in secret. Revolutions also appear hard to predict, presumably because otherwise they could be diverted by the government in power.

One initial issue is that the number of events covered by natural, political and terrorist disasters is extremely large, typically with several events per week around the world. So, we need to apply a filter to focus only on major events. With this aim, we include a shock only if it fulfills at least one of the following conditions: 1) more than 0.001% of the population in deaths, 2) more than 0.01% of GDP in damages, or 3) a successful coup or regime change.[7]

Table 1 contains some summary statistics on our full country sample for economic and shock variables. We have around 7000 quarterly observations for the 60 countries with GDP growth and stock returns data, with over 700 shocks occurring over this period. We now discuss the definitions of each of the groups of shocks in turn.

<u>Natural Disasters</u>: Our natural disaster data has been obtained from the Center for Research on the Epidemiology of Disasters (CRED).[8] This dataset contains over 15,000 extreme weather events such as, droughts, earthquakes, insect infestations, pandemics, floods, extreme temperatures, avalanches, landslides, storms, volcanoes, fires, and hurricanes from 1960 to 2019. The dataset includes the categorized event, its date and location, the number of deaths, the total number of people affected by

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[7]Our results are robust to modification of filters for both deaths and monetary damages, or by utilizing a filter that is measured in absolute rather than relative terms. These conditions are shocks that kill more than 100 people or do more than $1 billion in damages.

[8]See http://www.emdat.be/database CRED is a research center which links relief, rehabilitation, and development. They help to promote research and expertise on disasters, specializing in public health and epidemiology. Their EM-DAT database is an effort to provide a standardized and comprehensive list of large-scale disasters with the aim of helping researchers, policy-makers, and aid workers better respond to future events.

the event, and the estimated economic cost of the event. The CRED dataset also includes industrial and transportation accidents which we exclude in our analysis.

Terrorist Attacks: To define terrorist events we use the Center for Systemic Peace (CSP): High Casualty Terrorist Bombing list, which extends from 1993-2019 and includes all terrorist bombings which result in more than 15 deaths.[9] This data includes the location and date of each event as well as the number of deaths and an indicator for the magnitude of the attack ranging from 1 to 6.

Political Shocks: For political shocks, we utilize data from the Center for Systemic Peace (CSP): Integrated Network for Societal Conflict Research. To define political shocks, we include all successful assassination attempts, coups, revolutions, and wars, from 1970-2019.

We include two types of political shocks, each derived from the CSP's categorization of political shocks which is based on the types of actors and motives involved. The first is composed of coup d'états and other regime changes. Coup d'états are defined as forceful or military action which results in the seizure of executive authority taken by an opposition group from within the government. This opposition group is already a member of the country's ruling elites, rather than, for example, an underground opposition group. Typically, these are coups brought by the military or former military officers in government in a right-wing action against left-wing governments.

Our second type of political shock denotes a revolutionary war or violent uprising, excluding ethnic conflict which the CSP considers as a separate class. These are composed of events featuring violent conflict between a country's government and politically organized groups within that country who seek to replace the government or substantially change the governance of a given region. These groups were not previously part of the government or ruling elite and generally represent left-wing rebels overthrowing a right-wing or military regime.

Within each category, by country and quarter, we give a value of one if a shock has occurred and a zero otherwise. This means that if a country has, for example, three earthquakes in one quarter, it still receives a value of one. When using the media-weighted shocks, we use the shock with the highest jump in media citations

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[9]See http://www.systemicpeace.org/inscr/inscr.htm The CSP is a research group affiliated with the Center for Global Policy at George Mason University. It focuses on research involving political violence in the global system, supporting research and analysis regarding problems of violence in societal development. The CSP established the Integrated Network for Societal Conflict Research in order to coordinate and standardize data created and utilized by the CSP.

for that category in that quarter. The reason is to avoid double counting recurring but linked events within a quarter – such as an earthquake with multiple aftershocks.

2.2 Economic Data

Output Data: Real GDP is obtained from the Global Financial Database for all but 15 countries. GDP data for Mexico, Venezuela, Chile, Greece, and Singapore was obtained from the IMF Statistics division. GDP data for Pakistan was obtained from the World Bank. Saudi Arabian GDP data was obtained from the World Development Indicators Database. GDP data for Bangladesh, Kenya, Kuwait, Serbia, and Vietnam was obtained from the World Economic Outlook database. We proxy for GDP data with industrial production for Poland, Romania, and Nigeria. Real GDP data is denominated in the local currency and its reference year varies. As we deal with percentage changes, the different denominations and base years of different countries do not matter, in practice.

We use yearly real GDP growth by quarter (year-on-year growth) as our dependent variable to remove seasonality and reduce the impact of high frequency measurement errors.

Annual population data was obtained from the Global Financial Database. Population data is taken from national estimates and represents annual December 31st population levels. Data on monthly Consumer Price Indexes is obtained for all countries from a variety of sources, primarily the GFD, OECD, and the IMF.

Macro Uncertainty Proxy – Stock Market Index Data: Data on stock indices was obtained from the Global Financial Database, using the broadest general stock market index available for each country. Wherever possible we used daily data, but for six countries we used weekly or monthly data in the 1980s and early 1990s to construct stock returns and volatility indices when daily data was not available.[10] Our results are robust to the exclusion of observations taken from non-daily stock data and to excluding all observations from these countries. All stock indices in our analysis are normalized by the country level CPI data to obtain real returns.

In the empirical specifications, we generate yearly stock returns in each quarter, defined as the cumulative return over the proceeding four quarters, in order to match the timing of our yearly GDP growth rates. This serves as our first-moment series.

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[10]These countries are Saudi Arabia, Mexico, South Africa, Ireland, Russia, and Turkey.

A measure of average yearly volatility is created by taking the average of quarterly standard deviations of daily stock returns over the previous four quarters.

Micro Uncertainty Proxy – Cross Sectional Firm Return Data: As a micro-focused measure of first- and second-moment shocks, we look at returns across individual firms. We employ data from the WRDS international equity database, using data from all countries in our sample which have daily data from greater than 10 listed firms (comprising 39 of the 60 countries in our main sample). We then use the standard deviation of quarterly returns across firms to construct our second-moment series.

'Overall' uncertainty: As our overall or 'micro + macro' measure of uncertainty we combine our macro uncertainty (stock market index) and micro uncertainty (firm dispersion of returns) measures into a single standardized index. We first normalize both measures to a zero mean and unit standard-deviation series and take their average (then renormalizing the final index to a unit standard-deviation).[11] As such, our measure places equal weight on macro and micro variations in stock returns, so we also investigate the impact of other weightings which tend to yield relatively similar results because macro and micro stock returns and volatility are quite highly correlated.[12]

2.3 Newspaper Citations

Two natural concerns are that the shocks we utilize as instruments are either not unexpected or relatively small in magnitude. In order to help alleviate both of these potential problems, we turn to a measure of unexpectedness and impact derived from news article mentions of the countries in question.

Using the Access World News Newsbank service, we construct an "attention" index surrounding each event. We limit our attention to English-language newspapers based in the United States which number approximately 2,500 in our sample period. Blogs and other online news sources are excluded from the search.

For each event we search the Access World News archive using the name of the country the event occurred in. We then observe a 15-day period on either side of the day of each event, counting the number of articles written each day about the

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[11]This simple index is, of course, technically equal to the first principal component factor of the two uncertainty measures.

[12]Our macro and micro stock-returns and volatility correlations are 0.73 and 0.48 respectively.

country. Figure 1 reports the average number of articles on the country surrounding the event, where each event's coverage has been normalized to 1 in the 15 days prior to the event. For events in the United States, our search is the state in which the event primarily took place.

We use this data to construct a measure of the jump in attention paid to the country subsequent to an event or disaster. This will help to distinguish events which were both unexpected and large enough in magnitude to plausibly affect national returns or volatility from those which were not. For example, if we observe a similar number of articles regarding the country before and after the event date, we can assume that the event was predicted ahead and/or it was not that important. In contrast, observing a large jump in news articles just after the event makes it likely this was (at least in part) both unexpected and important enough to command additional news attention.

The way we define our jump in coverage index is to compute the percentage increase in the number of articles written in the 15 days after the event compared to the 15 days before the event. We choose this narrow 15-day window either side of the event to maximize our ability to detect discrete jumps in coverage (longer windows will also increase the measured impact of gradual trends) and to minimize the chances of feedback from economic impacts of event onto our index. As an illustration of this approach if we see 15 articles written about a country in the 15 days prior to the event and 30 articles written about a country in the 15 days following an event, we would assign this event a weight of 1 as it reflects a 100% jump in citations. Results are robust to using narrower or wider windows, like 5 or 30 days, surrounding the event.

3 The Impact of Uncertainty on Output

We display results from our primary specifications in Table 2. Column (1) gives results from an OLS regression of national GDP growth on our overall (macro and micro) stock market returns and volatility measures. We find a significant positive coefficient on stock return levels and a significant negative coefficient on stock market volatility. However, we worry about a high degree of endogeneity in these OLS results, so we proceed to our IV regressions in columns (2)-(5). Here we instrument for stock returns and volatility with our set of scaled natural and political disaster shocks. This set

consists of four series defined above: natural disasters, political shocks, revolutions, and terrorist attacks. Intuitively, our empirical identification strategy exploits the fact that each category of these political and disaster shocks generates a distinct combination of levels vs volatility effects.

The first shock type corresponds to natural disasters. In practice, such events often generate adverse short-term impacts on the economy but not much change in volatility. For example, the 1995 Japan Kobe earthquake led to a 19% drop in the stock-market but little increase in quarterly stock-market volatility.

The second shock type represents coups, typically the takeover of a government by a right leaning military group. On average these lead to positive jumps in the market together with increased uncertainty. For example, after Musharraf led a military coup against the elected government in Pakistan in 1999 the stock market rose by 15% and quarterly volatility increased by nearly 200%.

The third shock type approximates a revolution - a change of power instigated by a group outside the government – which is often associated in the data with a large drop in markets together with much higher volatility. For example, after the revolution in Indonesia in 1998, the stock-market fell by 66% and quarterly volatility was 219% above average.

The final shock type corresponds a terrorist attack, often associated with a negative impact on the economy and increased uncertainty. For example, after the 9/11 terrorist attacks in the US the stock-market fell by 12% and quarterly volatility rose by 300%.

By comparing the response of the economy across these differing bundles of first- and second-moment events, our IV estimation isolates the separate roles of shifts in levels vs uncertainty in driving economic activity. Column (2) reports our baseline IV estimates. Before discussing the second stage results, we first check the first-stage results. The F-tests on the set of disaster shocks are reassuring. In terms of specification tests, the Sargan over-identification test is not rejected in any specification, suggesting that the impacts of these four types of disaster shocks are fully captured by stock-market levels and volatility. That is, we cannot reject the null that observing the impact of these disaster shocks on stock market levels and volatility is a sufficient statistic for their one-year impact on GDP growth.

In terms of the first stage results for volatility, we find that there is a significant positive effect for political shocks and revolutions, and terrorist attacks, but no

significant impact for natural disasters. This suggests that while sudden changes in government or terrorism increase uncertainty, natural disasters do not. This may be driven by the fact that the outcome of a natural disaster is a more known quantity than the other components and so does not have the same level of second moment impact.

Looking at the first stage for levels, we find negative effects for revolutions and terrorist attacks, but, perhaps surprisingly, large and positive effects of political shocks on stock market returns. This stems from the nature of these political shocks, which are generally right-wing military coups that take power from left-wing governments. In contrast, revolutions are generally left-wing groups overthrowing military or right-wing governments. Intriguingly we find negative but only marginally significant effects of natural disasters on stock market returns. One possible explanation is because increased foreign aid and reconstruction following natural disasters offsets some of the capital destruction they cause (Fomby, Ikeda, and Loayza 2013). Restricting estimates to the largest natural disasters (e.g. increasing the threshold at which we include a natural disaster in our estimates) does increase the impact of natural disasters on stock market levels, but at the cost of excluding many diasters across a wide range of countries.

Turning to the second stage results, we see a significant causal impact of both first and second moment effects on economic activity. The magnitudes of the impacts are large. All of the first and second moment series are scaled to have unit standard deviation for easy interpretation. In column (2), for example, we find that a one-standard deviation first-moment shock increases GDP by about 1.7% over the following year (about a half a standard deviation of GDP growth) and a one standard-deviation second moment shock reduces GDP by about 6.5% (about 3 standard deviations of GDP growth).

In columns (3) - (5), we decompose our combined macro+micro measure of first and second moment shocks into the individual components. Columns (3) and (4) look at only the volatility of daily aggregate stock-market indices to measure uncertainty (with either the full macro sample or the set of observations that is consistent with the 'micro' measure). Column (5) instead uses the micro measure, i.e., the cross sectional variance of quarterly returns across individual companies. We find qualitatively similar results in the same direction as in column (2), though point estimates shift somewhat.

Interestingly, all IV specifications give point estimates higher than those found in the corresponding OLS regressions. We posit that this could be due to a number of factors. The first is endogeneity, where for example positive first moment shocks could generate increased stock-market volatility and second-moment shocks could have first moment effects on stock returns. This causes OLS coefficients to be downward biased for both the levels and volatility terms. The second is measurement error stemming from noise trading and the imperfect match in economic coverage between real activity and stock-market returns.[13] Finally, an element of the Latent Average Treatment Effect (LATE) may be present. Our disaster shock instruments are more prevalent among the poorer countries in our sample where the impact of volatility may be higher than in rich countries.

From these results, we can discern three primary points. The first is that we find both first- and second-moment shocks matter to growth. This is consistent with the finance literature which uses a different empirical strategy to come to the conclusion that first- and second-moment effects are both important for determining asset prices (e.g. Bansal and Yaron (2004)).

Second, the causal effect of uncertainty on growth appears higher than OLS estimates suggest, likely due to factors such as measurement error and endogeneity, consistent with our simulation results in the next section.

Finally, we find that our strategy passes the Sargan over-identification test, suggesting that we cannot reject the null that controlling for the first two moments of business condition shocks (here, stock returns and stock volatility) is sufficient to capture the full short-run effect of such shocks.

3.1   Robustness and Heterogeneity

In this section we investigate the robustness of these results to allowing for cross-country spillover effects, including higher moments in the estimation, to different

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[13]As mentioned earlier, stock market indices cover publicly quoted firms global activities while GDP figures cover all firms' domestic activities. These can differ for at least two reasons. The first is that many large companies have much of their operations abroad, so for that example firms like General Electric, British Petroleum and Nissan have more than 50% of their employees abroad but their full market capitalization is captured in their domestic stock-market indices. Second, almost all small and medium companies, and even many large companies are privately held so that stock-market indices do not cover them. Beyond this other differences arise due from, for example, timing (Calendar year versus account years) and accounting rules (Census versus GAAP rules on capital equipment depreciation).

measures of first and second moments, and to a variety of sample splits.

To start, Table 3 reports the results of two exercises which construct alternative disaster instrument series. These checks are motivated by the idea that a nation's economic conditions may depend not only upon their own shocks but also those of "nearby" nations, defining nearby-ness according to a range of different metrics. First, in a set of trade-weighted exercises, we construct new disaster instruments for each country equal to the sum of the domestic disaster series plus other nations' disaster series weighted by the bilateral trade to GDP ratio. Second, in a set of inverse distance-weighted exercises, we construct a new set of disaster instruments for each country equal to the sum of the domestic disaster series plus other nations' disaster series, with weights linearly declining in distance. Columns (1) - (2) report IV regressions based on these two new instrument definitions with our composite uncertainty series used as an endogenous variable. We obtain results which are comparable to those in the baseline Column (2) of Table 2. Columns (3) - (4) use the new instruments in an IV regression using the macro uncertainty definition, again finding similar results to the relevant specification, in this case Column (3) of Table 2. Then, Columns (5) - (6) repeat the IV regression with each new disaster series for the micro uncertainty measure, with results comparable to Column (5) in Table 2. For each of the two spillover-based instrument definitions, and for each of the uncertainty series we consider, we robustly recover precise negative impacts of uncertainty on growth.

We now move on to a distinct set of robustness checks in Table 4. Column (1) gives our baseline IV regression for comparison. In column (2), we weight by country population, allowing for more weight to be given to larger countries. We find largely similar and still significant results. Column (3) shows results when we exclude our media-citation weighting of the disaster shocks, simply leveraging the disasters that drove larger increases in coverage greater than the median shock. Here, we do not see a significant impact of levels shocks on GDP, though we do uncover a less precisely estimated but still significant negative effect of uncertainty on growth. We take this as evidence that the media scaling provides valuable information about how impactful these disasters are on business conditions and economic activity of the countries in question.

In column (4), we include the third moment of our main returns proxy, skewness, and find little additional explanatory power.[14] However, it should be noted that

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[14]One point to clarify, however, is that this does not mean that disaster shocks' higher moments do

the first moment or levels series and the third moment or skewness series are quite correlated in this sample. Therefore, column (5) omits the levels term, uncovering a negative impact of both increased uncertainty and declines in skewness on GDP growth. Such patterns are consistent with the patterns related to skewness in Salgado, Guvenen, and Bloom (2020).

Finally, in column (6) we examine to what extent our results are heterogeneous across countries. We include interactions with being a "rich" country, defined as being above the sample-average GDP per capita of $25,000. Interestingly, we find no significant interaction (albeit with a large magnitude suggestive of a smaller impact of uncertainty in developed countries).[15]

3.2   Vector Autoregression

In this section, we adapt our disaster instruments approach to the analysis of growth and uncertainty in a structural vector autoregression (VAR) analysis. We consider a parsimonious three-variable VAR using the same series we've analyzed so far: GDP growth (g_{it}), the first moment of stock returns (F_{it}), and the second moment of stock returns (S_{it}) for country i in quarter t. Collecting these variables into a vector $X_{it} = (g_{it}, F_{it}, S_{it})'$ of endogenous variables, we can write our VAR in the form

$$X_{it} = \sum_{k=1}^{p} A_k X_{it-k} + \eta_{it}.$$

VAR analyses are attractive because they account for a flexible set of dynamic relationships between the included variables, summarized in the matrices A_k. As usual in this type of model, we can consistently estimate the coefficients in A_k with straightforward regressions. Now, we wish to uncover the causal impact of an underlying structural shock to second moments or uncertainty on GDP growth. We assume that the second-moment shock is one element of a larger vector of structural shocks e_{it}. After estimating the coefficients in A_k, we can only directly observe the properties of reduced-form innovations η_{it}. We make the conventional assumption

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not matter, but rather that these are not time-varying. This is in fact consistent with the frameworks of, for example, Nakamura et al. (2013) and Gourio (2012), who model higher moments as important but time stationary, even if some of the first and second moments vary over time.

[15]In an exercise along these lines, Karaman and Yıldırım-Karaman (2019) considers various measures of financial development, applying our methodology and finding evidence of heterogeneity or a more muted impact of uncertainty in contexts with more financial development.

that the two objects are linked by an impact matrix B translating the underlying shocks to observed innovations according to

$$\eta_{it} = Be_{it}.$$

Under this structure, the effect of an uncertainty shock to second moments S_{it} at any horizon is a straightforward function of the elements in the matrices A_k and B. So, we must turn to estimating the elements of B. Ex-ante, allowing for arbitrary structure in the matrix B and hence for flexible relationships between the VAR's series in the period of a shock, makes sense in many dynamic equilibrium economic models–including ours introduced later–in which variables may jump and interact immediately in response to shocks. However, a classic identification problem presents itself. If the elements of B are allowed to take arbitrary values in principle, then the feasibly estimated reduced-form innovations η_{it} will reflect a combination of the underlying structural shocks e_{it}. In general, the observed covariances between the elements of η_{it} are not enough to identify the elements of B and hence the impact of underlying shocks. Note that although the dynamics are generalized in the VAR context, the intuitive problem faced here is the exact same challenge we face in our univariate OLS analysis: a given correlation pattern between second-moment shocks and growth can reflect endogenous links between the series or an underlying causal link.

One classic econometric solution to the VAR identification problem, i.e., the problem of identifying and estimating B, is to impose recursive or timing assumptions on the underlying shocks to endogenous series which amount to zero restrictions for certain elements of B. However, as mentioned above, given the forward looking nature of stock-returns and (at least) the investment component of GDP, such timing assumptions are not ideal in our context.

Therefore, we rely on an alternative identification strategy which can be thought of as a generalization of our univariate disaster instruments strategy. In particular, we follow a version of the IV-VAR approach in Stock and Watson (2018) and Mertens and Ravn (2013). We assume that a four-element vector of independent disasters d_{it}, including each of the types of disasters we have studied so far, influence and form part of the structural shocks to first and second moments in e_{it}. As we detail in Appendix C, the extra information in the disaster series d_{it} allows us to identify the elements of the matrix B via a straightforward GMM exercise targeting the moments contained

in both the covariance matrix of the reduced-form residuals $Cov(\eta_{it}, \eta_{it})$ as well as the covariances $\mathbb{E}(\eta_{it}d'_{it})$ between the reduced-form innovations η_{it} and the disasters d_{it}. By exploiting the observed comovement between disasters and VAR innovations, which is the rough VAR equivalent of an univariate IV first-stage regression, we can piece apart the underlying shocks to first and second moments and the response of growth to a second-moment or uncertainty shock. This procedure is valid under the assumption that there are stable mappings between a given type of disaster and shocks to first and second moments, i.e., under the same assumptions embedded in our previous univariate IV exercise. See Appendix C for more information on the details of the underlying econometric approach and the manner in which we adapt it to the panel structure of our cross-country data.

Using our IV-VAR identification strategy to analyze our empirical sample of GDP growth, stock returns, and volatility, Figure 3 plots the impulse response of GDP growth to a second-moment shock. A one-standard deviation increase in uncertainty here leads to an immediate drop of just over 3.5% in GDP growth. Figure 4 – which adds the response computed under a range of alternative sample cuts, lag lengths, and specifications – demonstrates that the negative impact of second-moment shocks on GDP growth is robust in this IV-VAR analysis.

To summarize, a VAR extension of our disaster instrument IV regressions uncovers a negative impact of volatility shocks on growth in our empirical sample.

4 Model and Simulation

We introduce a heterogeneous firms business cycle model with micro and macro productivity fluctuations. The model features time variation in the uncertainty or volatility of shocks, building on Khan and Thomas (2008) and Bloom et al. (2018). Given our empirical sample of nations, we use a small open economy model with fixed prices. To validate our empirical identification strategy, we link fluctuations in simulated disaster shocks to movements in the level and volatility of shocks in the model. We then run counterparts to our disaster instruments empirical regressions on simulated data, structurally estimating the parameters governing disaster shocks in our quantitative model via indirect inference targeting these regressions. This is similar to the "identified moments" approach outlined by Nakamura and Steinsson (2018) of matching a model to causally identified empirical moments. The results demonstrate that in

this conventional model of uncertainty fluctuations and firm investment, a disaster instruments approach correctly uncovers the impact of uncertainty on growth. We also show that the IV-VAR estimates align closely in the data and the model, further validating the ability of our empirical strategy to correctly uncover the impact of uncertainty on growth.

4.1 Uncertainty at the Firm Level

The model centers on a unit mass of ex-ante identical firms, each of which produces a homogeneous output good y by combining capital k and labor n as inputs

$$y = zAk^{\alpha}n^{\nu}$$

with decreasing returns to scale or $\alpha + \nu < 1$. Time is discrete. A firm's productivity is subject to both micro shocks z and macro shocks A. Using $'$ to denote future periods, each process follows an AR(1) in logs

$$\ln A' = \rho_A \ln A + \sigma^A \varepsilon_A$$
$$\ln z' = \rho_z \ln z + \sigma^z \varepsilon_z$$

where the innovations ε_A and ε_z are independently distributed $N(0,1)$. Because of the high correlation of micro and macro uncertainty we assume that the micro ($\sigma^z \in \{\sigma_L^z, \sigma_H^z\}$) and macro ($\sigma^A \in \{\sigma_L^A, \sigma_H^A\}$) volatilities of shocks both move according to a common two-point Markov chain for uncertainty $S \in \{L, H\}$ with $\mathbb{P}(S' = H|S = L) = \pi_{L,H}$ and $\mathbb{P}(S' = H|S = H) = \pi_{H,H.}$

Two implications of this formulation bear further discussion. First, the timing convention used here ensures that firms observe the level of uncertainty S and hence the volatility of shocks they face for the next period when making choices in the current period. Second, note that changes in the uncertainty governing the two shocks facing firms lead to shifts in two distinct outcomes. While changing volatility of macro shocks σ^A leads to shifts in the volatility of macro aggregates, the coincident shifts in micro volatility σ^z lead to higher variance in the cross-section of firm-level outcomes.

4.2 Firm Investment and Value Maximization

Each period a firm chooses investment i in capital k' for the next period, accumulating capital with one-period time-to-build

$$k' = (1 - \delta_k)k + i$$

where capital depreciation satisfies $0 < \delta_k < 1$. Investment incurs adjustment costs AC^k according to

$$AC^k(i, k) = \mathbb{I}(|i| > 0)yF^k + |i|\mathbb{I}(i < 0)S^K$$

reflecting a fixed or disruption cost component $F^k > 0$ and partial irreversibility with loss of a share S^K of capital's purchase price. Each firm also hires labor in a competitive labor market with wage w. Each period a fraction satisfying $0 < \delta_n < 1$ of the firm's labor departs due to exogenous factors. So, hiring an increment s of new labor relative to the previous level n_{-1} results in a new level of labor given by

$$n = (1 - \delta_n)n_{-1} + s.$$

Hiring new labor also incurs adjustment costs AC^n given by

$$AC^n(s, n_{-1}) = \mathbb{I}(|s| > 0)yF^l + |s|H^l w,$$

with a fixed disruption component $F^n > 0$ and linear costs of hiring or firing $H^l > 0$. The framework here implies that both capital k and labor n_{-1} are state variables for the firm. In our small economy framework, the firm maximizes firm value taking as given the global real interest rate leading to a discount rate $0 < \beta < 1$. The firm's value is given by the expected present discounted value of payouts

$$V(z, k, n_{-1}; A, S) = \max_{k', n} \left\{ y - i - wn - AC^k - AC^n + \beta \mathbb{E}V(z', k', n; A', S') \right\}$$

subject to each of the constraints and stochastic processes laid out above. Numerically solving this model with five states and two endogenous policies is computationally intensive. As laid out in Appendix B, we apply conventional but efficient applied dynamic programming techniques in our solution and simulation of the model.

4.3 The Impact of an Uncertainty Shock in the Model

As usual in this class of models, fixed adjustment costs lead to an optimal lumpy adjustment strategy for each input, with some firms actively investing and adjusting their labor and other firms pausing in an inaction region. After an increase in uncertainty S, the inaction regions for investment in capital k or hiring more labor n increase in size because a firm's option value to delay such investments increases. In other words, more firms "wait and see," delaying input adjustment in order to respond optimally to more uncertain or volatile shocks in future. The result is a drop in hiring and investment that drives a recession. Because inactive firms also respond less to their micro-level shocks in the face of increased uncertainty, misallocation also rises and leads to amplification and propagation of the recession.

4.4 Simulating the Model with Disasters

Macro fluctuations in the model are driven by a combination of two shocks. The levels or first-moment shock A directly drives business cycles through its impact on the production function. At the same time, the uncertainty or second-moment shock S indirectly causes fluctuations through effects such as the wait-and-see channel outlined above. We quantitatively embed the notion of disaster shocks into our simulation of the model for each of the four types of events we analyze above. For each disaster type $i = 1, ..., 4$ we choose a parameter governing the first-moment impact

$$\lambda_i^F \in \mathbb{R}$$

and a parameter governing the second-moment impact

$$0 < \lambda_i^S < 1.$$

During the simulation of the model, we allow for iid occurrence of a disaster of type i with probability p_i. We indicate disaster occurrence with the dummy variables d_{it}. If a disaster of type i occurs in period t, we first shift the current *levels* of macro productivity

$$A_t \rightarrow A_t + \sigma_L^A \lambda_i^F,$$

where σ_L^A is the low-uncertainty standard deviation of the macro productivity

innovations. Then, we increase the level of *volatility* S_t to a high state

$$S_t \to H$$

with probability λ_i^S.

In all other respects, the simulation of the model follows a conventional structure. The nature of the heterogeneous firms model here means that in each period t we obtain a simulated cross-sectional distribution $\mu_t(z, k, n_{-1})$ across the unit mass of firms. Also, to align with the later structure of our data which reflects a panel across nations we simulate $k = 1, ..., N$ nations for $t = 1, ..., T$ periods each, delivering a set of simulated data

$$\{A_{kt}, S_{kt}, d_{1kt}, d_{2kt}, d_{3kt}, d_{4kt}, \mu_{kt}\}_{k,t}$$

including information on the first-moment A_{kt}, second-moment S_{kt}, disasters d_{ikt} for $i = 1, ..., 4$, and cross-sectional distribution μ_{kt} for country k at time t. We provide further detail on the computational approach employed here in Appendix B.

4.5   Estimating the Model with Indirect Inference

To use our environment as a quantitative laboratory for exploring our empirical identification strategy, we must first parameterize the model. We do this in a two-step process. First, we fix the values of a range of model parameters to conventional values for a quarterly solution from the literature, reporting these in Table 5. We also fix the arrival probabilities of disasters p_i to their empirical averages in our cross-country sample. Second, we structurally estimate the values of all the parameters λ_i^F and λ_i^S governing the disaster shock process through an indirect inference procedure targeting the cross-country panel instrumental variables regressions discussed in Section 3. This matches the empirically estimated impact of each type of disaster shock on stock-market returns and volatility with its equivalent estimated on model data.

In particular, we collect the first- and second-stage coefficients for our IV estimates in two versions using both micro and macro second-moment proxies, i.e., we target the first-stage and second-stage coefficients in columns (4) and (5) of Table 2.[16] The

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[16]The target coefficients in Table 6 slightly differ from those reported in Table 2. The reason is that the model is solved at quarterly frequency, while the empirical macro stock return index involves daily standard deviations of stock returns. So when computing the target regression coefficients we

result is a total of 16 first-stage coefficients and 4 second-stage coefficients, or 20 target coefficients. Our structural estimation of the model through indirect inference chooses the set of parameters λ_i^F and λ_i^S for $i = 1, ..., 4$, a total of 8 parameters, to minimize the weighted difference between simulated and empirical estimates of the target coefficients.

Intuitively, the first-stage target coefficients rely on heterogeneity in the parameters λ_i^F and λ_i^S mapping different disasters to observable first and second moment shifts. The second-stage target coefficients reflect the impact of each innovation on macro growth, which is indirectly a function of the size and sign of the disaster mappings λ_i^F and λ_i^S in our nonlinear model. We provide further detail on the structural estimation approach employed here in Appendix B.

4.6   Parameter Estimates and Model IV Regressions

The bottom panel of Table 6 reports the structurally estimated disaster impacts λ_i^F and λ_i^S. Revolutions and terrorist attacks dominate the impact of disasters on first moments or levels, while political coups, revolutions, and terror attacks increase uncertainty or second moments appreciably. In the top panel, we examine the targeted IV regression coefficients, comparing the data versus the model. Give the overidentified nature of the estimation, with 8 parameters and 20 target regression coefficients, the model fits well. The first-stage regression coefficients based on both the micro and macro measures of uncertainty broadly mirror the underlying estimated disaster mappings in both the data and the model. Both of the micro and macro second-stage estimates in the data reveal a strong positive impact of levels shocks on growth, with a strong negative impact of uncertainty on growth, a pattern replicated in the model estimates.

Crucially, the second-stage coefficients run on simulated data in columns (2) and (3) of Table 6 reveal that our IV approach correctly uncovers a negative impact of uncertainty on GDP growth.

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have to slightly modify the definition of the macro second moment in both the model and the data. Details are provided in Appendix B.

4.7 The IV-VAR on Simulated Data

Armed with our structurally estimated model, we then estimate our IV-VAR on the simulated model data. Figure 5 plots two lines. The blue line with circles duplicates the baseline empirical IV-VAR estimates, uncovering an estimated drop in GDP growth after an uncertainty shock. The red line with plus signs plots the estimated impulse response of GDP growth to an uncertainty shock in simulated data. The magnitude of the drop and the recovery path are similar across the empirical dataset vs simulated data. The estimation exercise for the model targeted only the univariate panel IV regressions, but clearly the model matches both the initial impact and dynamics of the estimated VAR path quite closely.

5 Real-Time Forecasts of the Impact of COVID-19 on US GDP

The COVID-19 pandemic generated a steep decline in the aggregate stock market as well as a large spike in volatility. The pandemic likely combines multiple underlying shocks, with a direct impact on the average level of business activity together with increased uncertainty about the future path of the economy. Our IV estimation methodology, designed to exploit variation from disruptive events which embed a bundle of first- and second-moment shocks, is a natural laboratory in which we can seek to understand and forecast the impact of the pandemic on US GDP growth.

Deep shifts in previously buoyant equity markets began in late February. From the US market's peak on February 19, through to the end of the quarter on March 31, the decline in the aggregate return of the total market was 28%. Simultaneously, the cross-sectional standard deviation of US returns increased by around 150%. In our estimated IV-VAR, both of these shifts represent large shocks relative to the historical norm. In the US, the first-moment (levels series) dropped by over two standard deviations.[17] Our second-moment uncertainty index simultaneously spiked by over one standard deviation in this short period.[18]

In an earlier (Baker, Bloom, and Terry 2020) version of this paper circulated in

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[17]While the stock market recovered somewhat subsequently, we did not include this rebound as it reflects the response of fiscal and monetary policy.

[18]See Appendix D for more of the underlying details of our empirical exercise.

May 2020, we used our IV-VAR to produce forecasts of the impact of the COVID shock on the US economy using only real-time, forward-looking asset pricing data available through to the end of March 2021. In particular, we fed in these immediate, measurable changes in first and second moments, which arrived late in 2020Q1, as shocks to the economy in 2020Q2 within our VAR estimated from pre-pandemic data. Figure 6 plots the resulting forecast path of US year-on-year GDP growth over the next several years. The red line with square markers plots the impact of the uncertainty shock alone, while the blue line with circular markers plots the impact of the combined uncertainty and first-moment shocks. The forecast path of growth included a 7% drop in US GDP in 2020Q2. High uncertainty around our baseline forecast path is evident from the figure.

Our point forecast of a 7% drop in 2020Q2 was quite similar to the observed year-on-year drop of 9%. In 2020Q3, perhaps due to factors such as the unprecedentedly large fiscal stimulus embedded in policies such as the CARES Act not included in our forecast, US GDP rebounded sharply. We conclude based on the initial success of this forward-looking forecasting exercise that our sample of events, based on disasters in a wide sample of nations, and our IV strategy is an attractive framework for the analysis of the impact of large disruptions on economic activity.

6   Conclusion

A recent body of research has highlighted how uncertainty is counter cyclical, rising sharply in recessions and falling in booms. But what is the causal relationship? Does rising uncertainty drive recessions, or is uncertainty just an outcome of economic slowdowns?

In this paper, we perform multiple analyses designed to determine the direction of causality. We construct cross-country panel data on stock market levels and volatility as proxies for the first and second moments of business conditions. We then build a panel of indicators for natural disasters, terrorist attacks and political shocks and weight them by the changes in daily newspaper coverage that they induce.

Using these shocks to instrument for our stock market proxies for first- and second-moment shocks, we find that both first- and second-moment shocks are highly significant in driving national business cycles. In particular, second-moment or uncertainty shocks cause a decline in short-term growth in panel IV regressions. These results

are consistent across a range of specifications. A negative impact of uncertainty on growth also appears in an estimated multivariate IV-VAR.

To validate our disaster shock-based identification strategy, we build and solve a rich micro-macro model of business cycles and heterogeneous firms subject to disaster shocks. In this benchmark quantitative model, comparable to many used in the literature on uncertainty, volatility shocks cause a robust decline in growth. We structurally estimate this model, targeting our baseline IV regressions using simulated data to parameterize the disaster shock process. Our estimated model reveals that both our IV regressions and the IV-VAR correctly uncover a negative impact of uncertainty on growth.

Armed with our structurally validated empirical estimates, we then turn to an analysis of the COVID-19 pandemic, which initially combined a sharp drop in the level of equity markets with a jump in volatility. We produced a forecast in early 2020 in real time, feeding the observed COVID-19 asset price shock into our IV-VAR and making predictions, quite accurate ex-post, of large declines in US GDP early in the pandemic.

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Figure 1: Daily counts of newspaper articles mentioning country names in the weeks around natural disasters, political or terrorist shocks
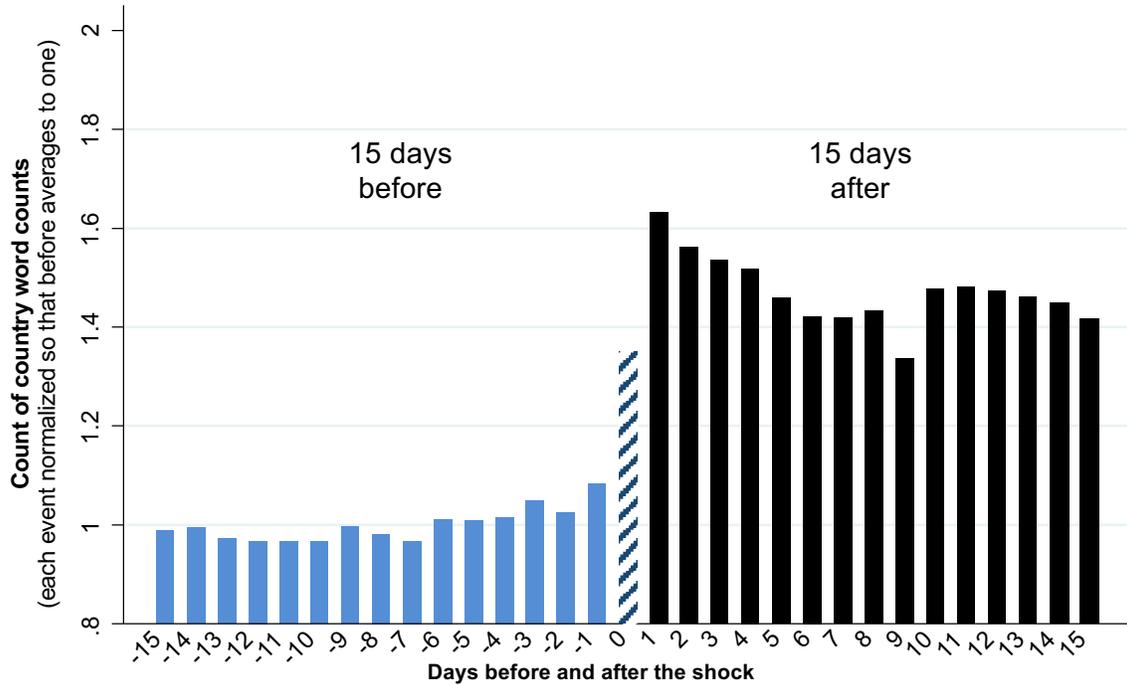
Notes: Shows the daily count of the name of the impacted country in the fifteen days before and after the shock, averaged over the universe of shocks (spanning the period from 1970 to 2020) studied in the regression analysis. For graphing purposes, the series for each event is normalized so that over the 15 days before the shock it has a mean of one. In the regressions events are weighted by the increase in cites in the 15 days after the event compared to the 15 days before to focus on the jump in cites after an event.

Figure 2: Daily counts of newspaper articles mentioning country names in the weeks around national elections
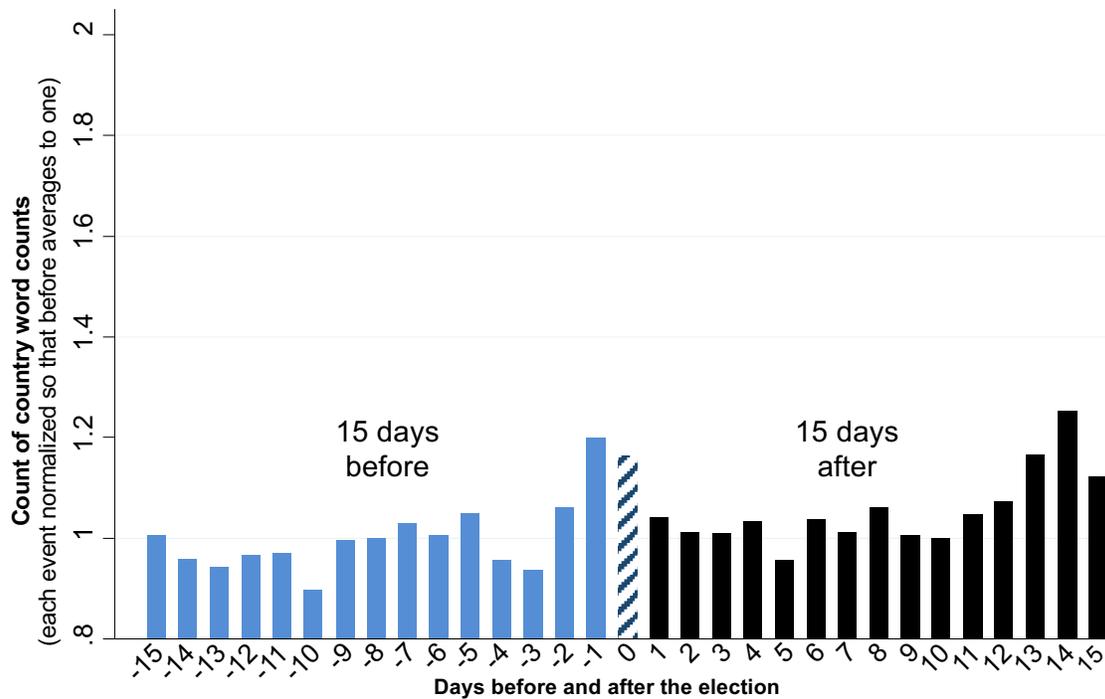
Notes: Shows the daily count of the name of the impacted country in the fifteen days before and after the election, averaged over 133 pre-scheduled elections in the G20 countries from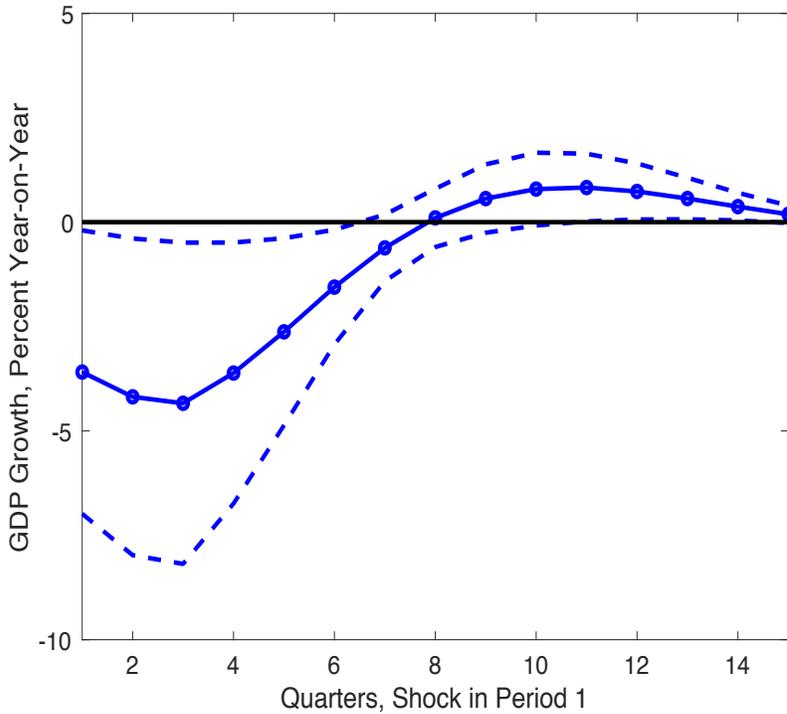 1970 to 2014. The series for each event is normalized for graphing so that over the 15 days before the election it has a mean of one.

Figure 3: An uncertainty shock causes a drop in GDP of around 3.5% in the disaster IV VAR

Notes: The figure shows the response of GDP growth to a one-standard deviation innovation in volatility in the disaster IV VAR. The sample is a panel of about 4,400 nation-quarters spanning around 40 nations from 1987Q1-2017Q3. GDP growth in period t is the percentage growth from quarter t-4 to t. The estimated VAR includes time + country effects, country dummies, 3 lags, with GDP growth, stock returns, and the stock return uncertainty index. The instruments include natural disasters, coups, revolutions, & terrorist attacks. 90% block bootstrapped bands plotted.

Figure 4: The drop in GDP after an uncertainty shock is robust across alternative disaster IV-VAR specifications
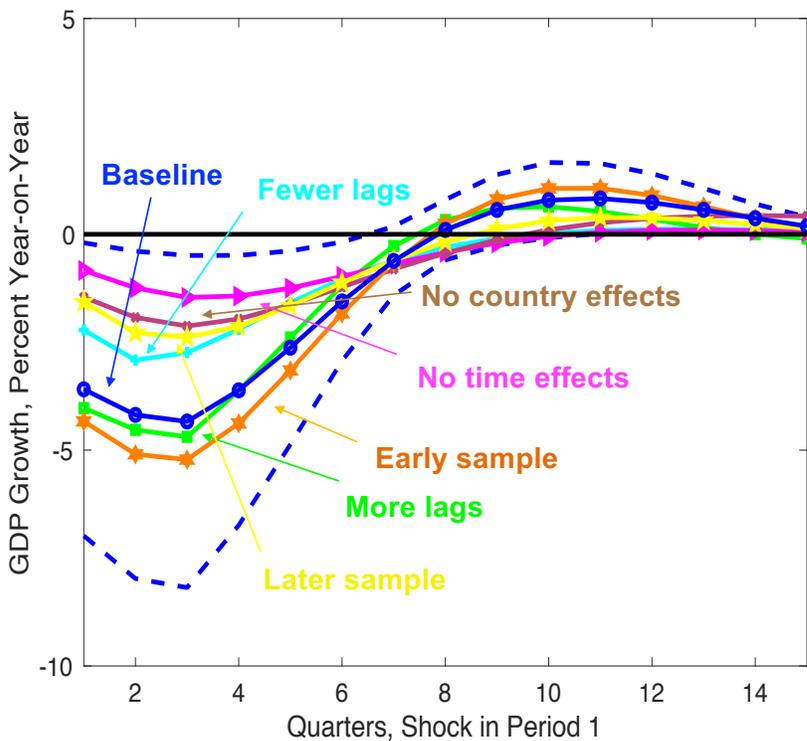
Notes: The figure shows the response of GDP growth to a one-standard deviation innovation in volatility in the disaster IV VAR. The responses are baseline (blue circles), pre-2003 (orange hexagrams), post-2003 (yellow stars), two lags (cyan + signs), four lags (green squares), no country trends (brown, x symbols), and no global time effects (pink, right arrows). The sample is a panel of about 4,400 nation-quarters spanning around 40 nations from 1987Q1-2017Q3. GDP growth in period t is the percentage growth from quarter t-4 to t. The baseline includes time + country effects, country dummies, 3 lags, with GDP growth, stock returns, and the stock return uncertainty index. The instruments include natural disasters, coups, revolutions, & terrorist attacks. 90% block bootstrapped bands plotted.

Figure 5: An uncertainty shock causes similar drops in GDP in the disaster IV-VAR in the data and the model

Notes: The figure shows the response of GDP growth to a one-standard deviation innovation in volatility in the disaster IV VAR. The responses include the baseline data (blue circles) and model (red + signs) estimates. The sample is a panel of about 4,400 nation-quarters spanning around 40 nations from 1987Q1-2017Q3. GDP growth in period t is the percentage growth from quarter t-4 to t. The estimated VAR includes time + country effects, country dummies, 3 lags, with GDP growth, stock returns, and the stock return uncertainty index. The instruments include natural disasters, coups, revolutions, & terrorist attacks. 90% empirical block bootstrapped bands plotted.

Figure 6: COVID-19 forecasted a sizable drop in US GDP in real time
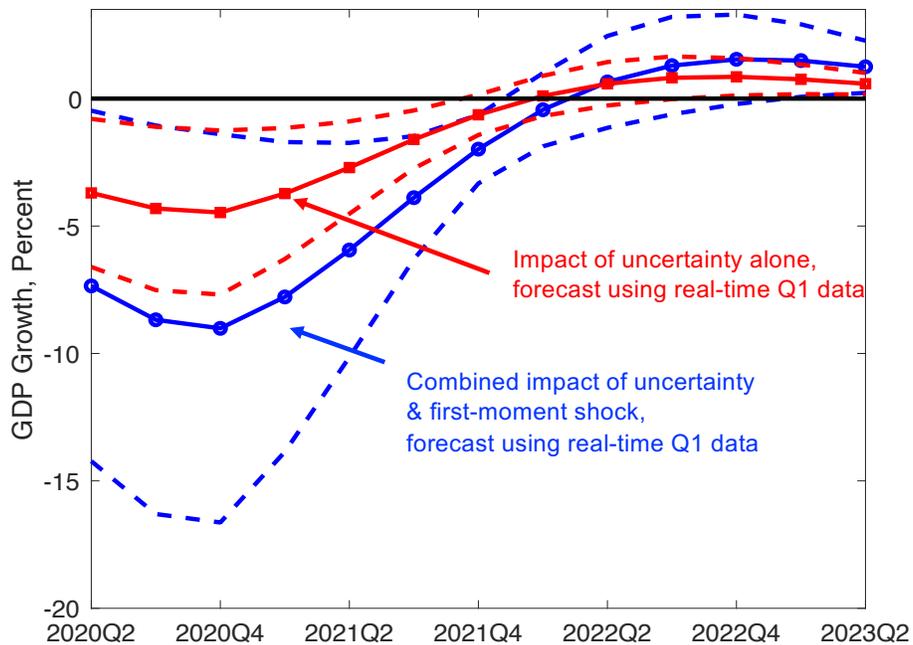
Notes: The estimation data spans 1 January 1987 to 31 March 2020. The forecast path of year-on-year real GDP growth is plotted. The first moment shock is estimated from an observed late 2020Q1 drop in stock returns of 2.3 standard deviations. The second moment shock is estimated from a combined micro and macro stock return volatility increase of increase of 1.04 standard deviations. The dashed lines are 90% confidence intervals computed with a stationary block bootstrap.

Table 1: Descriptive statistics

	Obs.	Mean	Median	Std. Dev.	Min	Max
Annual GDP Growth, %	10,095	3.46	3.44	7.16	-138.02	60.98
Return Level Index	4,445	-0.01	0.05	0.98	-5.20	4.79
Return Volatility Index	4,435	-0.03	0.00	1.00	-5.19	2.91
Stock Returns, %	7,396	0.01	0.01	0.07	-0.45	0.45
Log (Stock Return Volatility)	7,395	-4.52	-4.55	0.49	-6.05	-2.59
Cross Sectional Returns	4,582	0.00	0.00	0.09	-0.38	0.93
Log (Cross Sectional Volatility)	4,542	-1.56	-1.55	0.35	-3.89	-0.39
Natural Disasters	10,095	0.37	0	0.67	0	4
Natural Disasters (scaled by media increase)	10,095	0.20	0	0.61	0	7.99
Coups	10,095	0.01	0	0.11	0	2
Coups (scaled by media increase)	10,095	0.03	0	0.40	0	14.07
Revolutions	10,095	0.01	0	0.09	0	1
Revolutions (scaled by media increase)	10,095	0.00	0	0.06	0	2.47
Terrorist attacks	10,095	0.02	0	0.16	0	4
Terrorist attacks (scaled by media increase)	10,095	0.02	0	0.28	0	10.10
GDP Per Capita (2005 $US, World Bank PPP)	10,095	24,148.2	24,643	16,687.1	1,335	78,559

Notes: All values are yearly averages at quarterly frequency. Data from 60 countries from 1970 to 2019 wherever available.

Table 2: Estimated impact of levels and volatility on GDP Growth

	(1)	(2)	(3)	(4)	(5)
Estimation	OLS	IV	IV	IV	IV
Sample:	Common	Common	Macro	Common	Common
Stock Measure	Micro+Macro	Micro+Macro	Macro	Macro	Micro
Level of returns$_{t-1}$	0.592***	1.733***	2.874***	2.878***	1.806
	(0.110)	(0.239)	(1.004)	(0.420)	(1.370)
Vol of returns$_{t-1}$	-0.616***	-6.532***	-5.820***	-6.898***	-8.412***
(in logs)	(0.192)	(0.618)	(1.456)	(0.733)	(2.139)
IV 1st stage: Level					
Nat Disasters$_{t-1}$		-0.079	-0.019	-0.042	-0.099
		(0.107)	(0.129)	(0.106)	(0.088)
Coups$_{t-1}$		2.168***	1.917***	1.645***	0.931***
		(0.070)	(0.324)	(0.052)	(0.255)
Revolutions$_{t-1}$		-6.705***	-4.885***	-6.278***	-4.813***
		(1.415)	(1.386)	(1.109)	(0.946)
Terror attacks$_{t-1}$		-0.118*	-0.061	-0.053	-0.113**
		(0.061)	(0.073)	(0.065)	(0.058)
Instrument F-test		270.47	11.81	352.93	10.26
IV 1st stage: Vol					
Nat Disasters$_{t-1}$		-0.006	-0.068	0.004	0.023
		(0.157)	(0.136)	(0.160)	(0.079)
Coups$_{t-1}$		1.094***	0.887***	1.156***	0.515**
		(0.087)	(0.296)	(0.086)	(0.228)
Revolutions$_{t-1}$		3.866***	2.969***	2.894***	3.119***
		(1.146)	(1.076)	(0.603)	(0.845)
Terror attacks$_{t-1}$		0.159**	0.037	0.122	0.154
		(0.076)	(0.106)	(0.106)	(0.101)
Instrument F-test		50.17	4.79	51.41	5.27
Sargan p-value		0.381	0.430	0.305	0.126
Observations	4,435	4,435	7,347	4,435	4,435
Countries	42	42	58	42	42
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is GDP growth. The level and (log) volatility of returns are scaled for comparability across columns to have unit standard-deviation over the regression sample. In columns (1) to (2) stock returns and volatility are the principal component factor of the micro (cross-firm) and macro (overall index) returns. Columns (3) and (4) utilize the macro (index) stock returns and volatility while changing the sample to be the overlap between the macro and micro (column 4) or the full sample where we have macro index data (column 3). Column (5) is micro (cross-firm) returns. Standard errors clustered by country. Data is quarterly by country from 1970 until 2019. Column (1) estimated by OLS and (2) to (5) by instrumental variables. Instruments (disasters) are scaled by the increase in media mentions of the country in the 15-days after the shock compared to the 15-days before the shock. Sargan test is the over-identification test of instrument validity. All columns include a full set of country dummies and a full set of year by quarter dummies. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Estimated impact of trade-weighted and distance-weighted returns and volatility on GDP Growth

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation:	IV	IV	IV	IV	IV	IV
Weighting:	Trade	Distance	Trade	Distance	Trade	Distance
Stock Measure	Micro+Macro	Micro+Macro	Macro	Macro	Micro	Micro
Level of returns $_{t-1}$	1.666***	1.372***	2.929***	2.993***	1.519**	1.014*
	(0.301)	(0.359)	(0.830)	(0.716)	(0.621)	(0.611)
Volatility of returns $_{t-1}$ (in logs)	-6.351***	-6.353***	-5.405***	-6.624***	-7.858***	-7.981***
	(0.717)	(0.785)	(1.283)	(1.324)	(1.119)	(1.181)
Sargan test p-value	0.224	0.239	0.680	0.452	0.287	0.306
Observations	4,435	4,435	7,347	7,347	4,542	4,542
Countries	42	42	58	58	42	42
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is GDP growth. * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by country. Data is quarterly by country from 1970 until 2019. All columns estimated by instrumental variables with a full set of quarter-by-year time dummies. Instruments are all multiplied by the increase in media mentions of the country in the 15-days after the shock compared to the 15-days before the shock. All columns include a full set of country dummies and year by quarter dummies. Volatility is in logs in the regression. Levels and Volatility are the principal component factor of the micro (cross-firm) and macro (overall index) returns in (1) and (2), while columns (3)-(4) are macro (index) and columns (5)-(6) are micro (cross-firm) returns. Trade weighted regressions include both shocks (instruments) in a given country and also a weighted version of shocks in a country's trading partners (scaled by total trade/GDP). Distance weighted regressions include both shocks (instruments) in a given country and also a weighted version of shocks in a country's neighbors (shocks scaled on a 0-0.5 scale based on the linear distance between the borders of each country-pair; shocks occurring in bordering countries will receive a weight of 0.5).

Table 4: Robustness of main stock results to alternate specifications and sample splits

Specification	(1) Baseline Index	(2) Population Weighted	(3) Above Median Shocks - Unscaled	(4) Add Skewness	(5) Just Vol and Skewness	(6) Split by GDP per capita
Level of returns $_{t-1}$	1.733***	1.746***	1.141	1.101		1.356**
	(0.239)	(0.237)	(1.417)	(1.268)		(0.602)
Volatility of returns$_{t-1}$	-6.532***	-6.634***	-3.358*	-9.172***	-10.285***	-5.687***
	(0.618)	(0.609)	(1.736)	(2.888)	(3.002)	(0.861)
Skewness of returns$_{t-1}$				6.451	8.146*	
				(4.678)	(4.932)	
Rich*Level of returns $_{t-1}$						-2.865
						(4.036)
Rich*Vol of returns$_{t-1}$						2.378
						(3.878)
Post2000*Level of returns $_{t-1}$						
Post2000*Vol of returns$_{t-1}$						
Sargan p-value	0.208	0.215	0.159	0.716	0.719	0.286
Observations	4,435	4,435	4,435	4,345	4,435	4,435

Notes: The dependent variable is GDP growth. * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by country. Data is quarterly by country from 1970 until 2019. All columns estimated by instrumental variables with a full set of quarter-by-year time dummies. Instruments (disasters) are all multiplied by the increase in media mentions of the country in the 15-days after the shock compared to the 15-days before the shock, except for column (3) which simply utilizes the unscaled disasters that are above the median of media attention. Volatility of returns is logged in all specifications. All columns include a full set of country dummies and year by quarter dummies. Volatility is in logs in the regression. The split by GDP per capita in column (6) splits countries by the sample median of long-run GDP per capita, which is ~$25,000 (in 2010 dollars).

Table 5: Calibrated model parameters

Parameter	Symbol	Value
Capital Elasticity	α	0.25
Labor Elasticity	ν	0.50
Discount Rate	β	0.99
Capital Depreciation	δ_k	0.03
Labor Depreciation	δ_n	0.09
Micro Persistence	ρ_z	0.95
Micro Low Volatility	σ^z_L	0.05
Micro Volatility Jump	σ^z_H/σ^z_L	4.12
Macro Persistence	ρ_A	0.95
Macro Low Volatility	σ^A_L	0.01
Macro Volatility Jump	σ^A_H/σ^A_L	1.61
Uncertainty Frequency	$\pi_{L,H}$	0.03
Uncertainty Persistence	$\pi_{H,H}$	0.94
Capital Fixed Cost	F^k	0.00
Capital Irreversibility	S^k	0.34
Labor Fixed Cost	F^l	0.10
Labor Linear Cost	H^l	0.07

Notes: The table reports the values of calibrated parameters fixed before the structural estimation of the disaster mappings in the model. The values come from Khan and Thomas (2008) and Bloom, et al. (2018).

Panel A: Model Fit	(1)	(2)	(3)	(4)
Model vs Data	Data	Model	Data	Model
Stock Measure	Macro	Macro	Micro	Micro
IV 1st stage: Level				
Nat Disasters$_{t-1}$	-0.071	-0.002	-0.147	-0.002
	(0.106)	[0.652]	(0.112)	[1.259]
Coups$_{t-1}$	1.657***	0.612	1.852***	0.612
	(0.055)	[-18.966]	(0.085)	[-14.590]
Revolutions$_{t-1}$	-6.154***	-3.275	-4.818***	-3.275
	(1.084)	[2.657]	(1.198)	[1.288]
Terror attacks$_{t-1}$	-0.047	-0.223	-0.117***	-0.223
	(0.051)	[-3.424]	(0.044)	[-2.409]
IV 1st stage: Vol				
Nat Disasters$_{t-1}$	-0.028	0.021	0.004	0.018
	(0.082)	[0.600]	(0.102)	[0.137]
Coups$_{t-1}$	1.693***	0.779	0.508***	0.391
	(0.116)	[-7.890]	(0.130)	[-0.903]
Revolutions$_{t-1}$	7.841***	2.490	3.201***	0.615
	(2.236)	[-2.393]	(1.275)	[-2.028]
Terror attacks$_{t-1}$	-0.011	0.266	0.133	0.058
	(0.049)	[5.653]	(0.083)	[-0.899]
IV 2nd Stage: GDP Growth				
Level of returns$_{t-1}$	1.557**	1.610	0.736	2.008
	(0.291)	[0.181]	(0.558)	[2.279]
Vol of returns$_{t-1}$	-3.859***	-1.326	-9.735***	-3.244
	(0.284)	[8.905]	(1.533)	[4.234]
Panel B: Estimated Model Parameters				
Disaster Type:	Nat Disasters	Coups	Revolutions	Terror Attacks
Level ($\sigma^A_L \lambda^F$)	-0.0002	0.0004	-0.277***	-0.0264***
	(0.0005)	(0.0015)	(0.008)	(0.0014)
Vol (λ^S)	0.014	0.853***	0.816***	0.110***
	(0.024)	(0.076)	(0.153)	(0.011)

Notes: The top Panel A reports model vs data moments for the indirect inference estimation of the heterogeneous firms model. The target moments from the data are IV regression coefficients from the macro uncertainty measure (column 1) and the micro uncertainty measure (column 3). Year-quarter and country dummies are included in all regressions, and standard errors clustered by country are reported in parentheses beneath the target moments. * significant at 10%; ** significant at 5%; *** significant at 1%. The simulated model moments, regression coefficients themselves, at the estimated parameters are reported in columns 2 and 3, with the t-statistic for the difference in model vs data moments reported in brackets below. The bottom Panel B reports the structurally estimated parameters mapping the four categories of disaster events to the macro TFP process and uncertainty process in the model. Standard errors, computed via the standard indirect inference formulas and clustered by country, are included in parentheses below the point estimates.

Online Appendix

A   Data Cleaning

Data on GDP growth, stock volatility, stock returns, and exchange rate volatility is winsorized at a 0.1% level. That is, the lowest and highest 0.1% of values are constrained to be equal to the 0.1th percentile and 99.9th percentile, respectively. This is done to prevent extreme outliers from driving the results. Censoring the data (dropping the top and bottom 0.1%) yields similar results.

We also drop data when the stock market has been suspended for the quarter. This affects 4 quarters of data in Mexico, Morocco, Saudi Arabia, and Pakistan. For the purposes of this project, shocks occurring in Hong Kong are considered to occur in China. Shocks occurring in Taiwan are considered separately and as a different country.

Shocks of each type are limited to one per quarter. In addition, disease-based disasters, insect-based disasters, and industrial accidents are excluded from the sample.

For the empirical exercises in Section 3, we compute first moments as the average of the aggregate quarterly stock return over the past four quarters. The micro first moment is based on the average of firm-level returns, while the macro first moment is based on pre-compiled aggregate indexes. The macro second-moment series is the average of the daily standard deviation of the aggregate stock return over the past four quarters. The micro second-moment series is the average of the cross-sectional variance of firm-level stock returns over the past four quarters. The micro+macro index of uncertainty is the standardized index of the micro and macro uncertainty series described in the main text.

B   Simulation Model and Structural Estimation

We extend the model introduced in Bloom et al. (2018) to incorporate disaster shocks which serve as a driver of uncertainty and levels fluctuations in TFP.

B.1 Incorporating Disasters

As noted in the main text, we incorporate several modifications to the baseline structure in order to generalize the model to allow for iid disaster shocks.

- A partial equilibrium analysis with a fixed interest rate. Implementation of this change requires only that we set the value of w in the Bellman equation in our main text equal to a constant value, numerically solving and simulating the model in an otherwise identical fashion.

- Incorporation of disaster shocks. We include four disaster shock types i = 1,...,4, and for each we choose a parameter λ_i^F and a parameter λ_i^S. Upon arrival of a disaster of type i, which occurs with an iid probability p_i equal to its sample frequency, we reduce the value of macro productivity by λ_i^F standard deviations, and we also impose a high uncertainty state with probability λ_i^S.

- Maintaining Constants Means in Simulation. To maintain a constant mean macro productivity level A and uncertainty shock S transition frequency during the simulation, we insert a constant term in the macro TFP process as well as modify the uncertainty frequency parameter $\pi_{L.H}$ appropriately.

B.2 Calibrating, Solving, and Simulating the Model

Before structurally estimating the disaster mappings, we first set the value of a range of conventional parameters for a quarterly solution in Table 5. Given parameters, we solve the model numerically using a discretized grid and employing policy iteration in heavily parallelized Fortran. With the model solution in hand, we simulate the model by directly tracking the period-by-period distribution of firm states across periods subject to aggregate shocks which reflect both the standard driving processes for macro productivity A and macro uncertainty S as well as the arrival of iid disaster events.

B.3 Structurally Estimating the Model

In Section 4.5 we structurally estimate the parameters λ_i^F and λ_i^S through indirect inference. To do so, we need to compute target statistics or moments in the data. We target the first- and second-stage panel IV regression coefficients based on both

the micro and macro uncertainty indexes, i.e., we target columns (4) and (5) of Table 2. We must also compute these target statistics or IV regression coefficients in the model. To do so, we simulate a panel of firms, using the Bellman equation directly to define the valuation and implied stock returns at the firm level. This series of stock returns can be used to compute all of the micro and macro stock return series underlying our first- and second-moment indexes. The one exception is the empirical macro second-moment series, which in Section 3 is defined using the average of daily stock return volatilities over the past four quarters. Since our model is solved at quarterly frequency, we instead using the rolling mean over the past four quarters of the squared deviations of the average stock return from its mean value. This moderate change in definition of the macro uncertainty series results in the differences between the target coefficients reported in Table 6 and the equivalent specifications in Table 2. Collecting the target regression coefficients or moments into a stacked vector $m(X)$ dependent on our sample X, our indirect inference approach seeks to structurally estimate the value of a stacked parameter vector θ containing the disaster mapping parameters. This is done by solving the problem:

$$\min_{\theta}(m(\theta) - m(X))'W(m(\theta) - m(X)),$$

where $m(\theta)$ is the set of moments or regression coefficients computed from simulated model data given the parameter vector θ. W is some weighting matrix for our regression coefficient moments. Our estimator is therefore a version of the standard overidentified simulated method of moments (Gourieroux et al. 1996). We refer to our estimation procedure as "indirect inference" because of the regression coefficient interpretation of our target moments, but we don't carry around the extra notation of the "auxiliary model" defined by Smith (2008).

We compute the standard errors according to conventional asymptotics allowing for clustering at the nation level. The limiting distribution of our resulting point estimate $\hat{\theta}$ is given by:

$$\sqrt{N}(\hat{\theta} - \theta) \rightarrow_d N(0, \Sigma),$$

where the asymptotic variance is given by the usual sandwich formula:

$$\Sigma = \left(1 + \frac{N_{sim}}{N}\right) \left(\frac{\partial m(\theta)}{\partial \theta'} W \frac{\partial m(\theta)}{\partial \theta}\right)^{-1} \frac{\partial m(\theta)}{\partial \theta'} W \Omega W \frac{\partial m(\theta)}{\partial \theta} \left(\frac{\partial m(\theta)}{\partial \theta'} W \frac{\partial m(\theta)}{\partial \theta}\right)^{-1}.$$

Above, N_{sim} is the number of nations in our simulated panel, N is the number of nations in the data, and Ω is the joint covariance matrix of our target regression coefficients allowing for country-level clustering. We set W to the identity matrix. We compute the moment Jacobians $\frac{\partial m(\theta)}{\partial \theta'}$ using numerical differentiation at the estimated parameters $\hat{\theta}$. The standard errors reported at the bottom of Table 6 rely on our feasible estimate of Σ, while the t-statistics between model moments $m(\hat{\theta})$ and data $m(X)$ moments in the top panel of Table 6 are based on our feasible estimate of Ω.

C   Disaster Instruments VAR

As noted in the text we rely on an adaptation of the external instruments approach for structural VAR identification in Stock and Watson (2018) or Mertens and Ravn (2013). The econometric framework is a three-variable VAR in the following series:

$$X_{it} = (g_{it}, F_{it}, S_{it})'$$

$$X_{it} = f_i + g_t + A X_{it-1} + \eta_{it}$$

This VAR in the 3 variables growth (g_{it}), first moments (F_{it}), and second moments (S_{it}) has a panel structure running across nations i and quarters t. Without loss of generality we describe a single-lag VAR since further lags can be accommodated in a similar equation in companion form. We allow for country and time effects f_i and g_t. The vector of innovations η_{it} reflect reduced-form disturbances to the VAR system, which are linked to a vector of random structural shocks e_{it} according to $e_{it} = B\eta_{it}$ where B is a 3×3 matrix containing the contemporaneous impacts of each structural shock on the series in X_{it}. We assume that the structural shocks e_{it} can be decomposed as

$$e_{it} = (e_{Yit}, e_{Fit}, e_{Sit})' = D d_{it} + \varepsilon_{it},$$

where $d_{it} = (d_{1it}, d_{2it}, d_{3it}, d_{4it})'$ is a vector of independent disaster shocks of the

four types described in the main text satisfying $d_{it} \sim (0_{4\times1}, I_{4\times4})$. We also assume that the remaining disturbances are idependent of the disasters and satisfy $\varepsilon_{it} \sim (0_{3\times1}, I_{3\times1})$. We assume that the disaster shocks influence the first and second moment structural innovations e_{Fit} and e_{Sit} alone according to the matrix D which has the following form

$$D = \begin{pmatrix} 0 & 0 & 0 & 0 \\ D_{1F} & D_{2F} & D_{3F} & D_{4F} \\ D_{1S} & D_{2S} & D_{3S} & D_{4S} \end{pmatrix}.$$

In other words, we assume an exclusion restriction maintaining that the impact of disasters on GDP growth is mediated through their impact on first and second moments alone. Now, in this context the matrix A and fixed effects f_i and g_t can be consistently estimated via OLS, as usual. But since $A^s B$ is the impulse response matrix of interest at horizon s, we must also recover B. As usual, the covariance matrix of the reduced-form innovations $Cov(\eta_{it}, \eta_{it})$ contains only 6 unique elements, which in this case are given by

$$Cov(\eta_{it}, \eta_{it}) = B\Lambda B'$$

$$\Lambda = Cov(e_{it}, e_{it}) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \sum_{j=1}^{4} D_{jF}^2 + 1 & \sum_{j=1}^{4} D_{jF}D_{jS} \\ 0 & \sum_{j=1}^{4} D_{jF}D_{jS} & \sum_{j=1}^{4} D_{jS}^2 + 1 \end{pmatrix}.$$

Since B has 9 elements, this information alone fails to independently identify the elements of the matrix B. However, the observable covariances between the reduced-form innovations η_{it} and the disasters d_{it} are

$$\mathbb{E}(\eta_{it} d'_{it}) = BD$$

Together, $Cov(\eta_{it}, \eta_{it}) = B\Lambda B'$ and $\mathbb{E}(\eta_{it} d'_{it}) = BD$ contain $6 + 12 = 18$ moments which are a function of the 17 parameters in B and D. This allows us to employ straightforward overidentified GMM estimation. We numerically implement the optimization using a diagonal weighting matrix and a quasi-Newton method. For the model and empirical results, we estimate the VAR using 3 lags unless elsewhere specified. We compute empirical standard errors in the figures involving VAR results via

a stationary block bootstrap of our empirical sample.

D   COVID-19 Pandemic Forecast Exercise

We use the impulse responses of GDP growth to first and second moments from our estimated IV-VAR in Section 3 to compute the forecast path of US GDP growth in Figure 6.

First, we set the levels of the quarterly first-moment shock equal to the change in the US stock market overall from February 19 to March 31, 2020, which was -28.2% based on the Wilshire 5000 index. Then, we compute the variance in the cross section of stock returns in the US over the same period from the Compustat equities database. The standard deviation of the stock return jumped by about 150% in this short period, from to 8.8% to 21.8%. Since these quarterly changes occurred late in the quarter in 2020Q1, we attribute them to 2020Q2.

Combining these quarterly shifts into our rolling averages of first and second moments results in a first-moment shock of -2.33 standard deviations and a second-moment shock of 1.04 standard deviations. The red line in Figure 6 is equal to 1.04 times the baseline impulse response of year-on-year GDP growth to an uncertainty shock. The blue line in Figure 6 then further subtracts 2.33 times the impulse response of growth to a first-moment shock. The confidence intervals are based on stationary block bootstraps of these linear combinations, accounting for the covariances of the first-moment and second-moment impulse responses where appropriate.

Figure A1: Correlation of World Uncertainty Index and Economic Policy Uncertainty Index with Stock Volatility
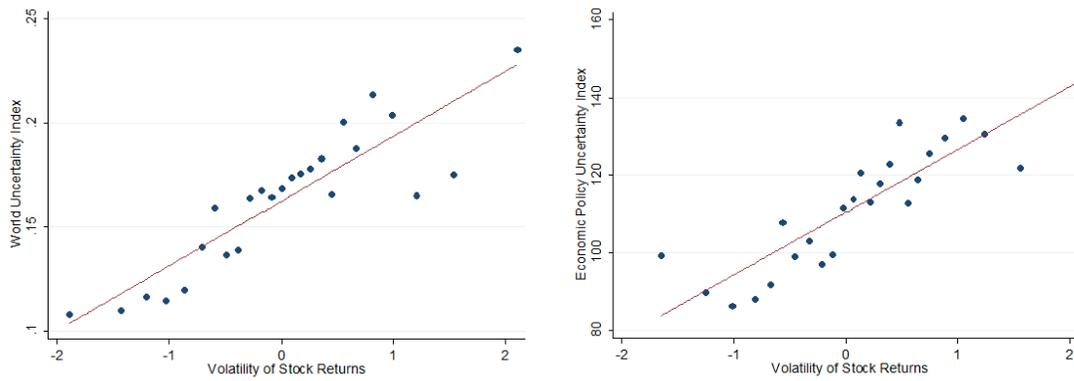
Notes: Left panel plots a bin-scatter (across 25 bins) of country-quarter values of the World Uncertainty Index (WUI) against a country-quarter measure of stock volatility. We are able to match this version of stock volatility and WUI values across 34 countries back to 1987. Right panel plots a bin-scatter (across 25 bins) of country-quarter values of Economic Policy Uncertainty against a country-quarter measure of stock volatility. We are able to match this version of stock volatility and EPU values across 20 countries back to 1987. WUI (Ahir, et al (2020)) measures uncertainty using frequency counts of "uncertainty" (and its variants) in the quarterly Economist Intelligence Unit country reports. EPU (Baker et al (2016)) measures uncertainty using the fraction of newspaper articles from major newspapers discussing topics regarding the economy, policy, and uncertainty.

Table A1: Economic variables cannot forecast disasters

Shock type as dependent variable:	(1) Natural	(2) Political	(3) Revolution	(4) Terrorist	(5) Natural	(6) Political	(7) Revolution	(8) Terrorist
Level of stock returns, last quarter	-0.026 (0.026)	0.044 (0.037)	-0.0003 (0.0006)	0.006 (0.014)				
Volatility of stock returns, last quarter	0.00001 (0.006)	0.009 (0.009)	0.002 (0.002)	0.0005 (0.003)				
GDP growth, last quarter	-0.0007 (0.0004)	0.0001 (0.0001)	-0.0001 (0.0001)	-0.001 (0.001)				
Volatility of stock returns, last year					0.006 (0.009)	0.006 (0.009)	0.002 (0.002)	-0.006 (0.005)
Level of stock returns, last year					-0.029 (0.045)	-0.029 (0.045)	-0.008 (0.008)	-0.011 (0.012)
GDP growth, last year					-0.001 (0.0007)	-0.001 (0.001)	-0.0001 (0.0001)	-0.001 (0.0007)
F-test p-value	0.154	0.486	0.808	0.832	0.396	0.462	0.776	0.452
Observations	5643	5643	5643	5643	6355	6355	6355	6355

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. All columns are estimated in OLS with standard-errors clustered at the country level, and all shocks weighted by their increase in media coverage. Data is quarterly by country from 1970 until 2019. All columns include a full set of country dummies and year by quarter dummies. The F-test p-value is the probability value of the F-test of the three economic variables in each column.