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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 returns to proxy for first- and second-moment shocks and instrument these with natural disasters, terrorist attacks, and political shocks. Our IV regression results reveal a robust negative short-term impact of second moments (uncertainty) on growth. Employing multiple VAR estimation approaches, relying on a range of identifying assumptions, also reveals a negative impact of uncertainty on growth. Finally, we show that these results are reproducible in a conventional micro-macro business cycle model with time-varying uncertainty.

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A data appendix is available at http://www.nber.org/data-appendix/w27167
A data and code packet is available at http://people.bu.edu/stephent/files/BBT_Packet.zip

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 has proven 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]

[1]See, for example, evidence of countercyclical volatility in: macro stock returns in the US in Schwert (1989), in firm-level 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 (Alexopoulos and Cohen, 2009), and that a broad uncertainty factor indicator is countercyclical (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 from information collection in Van Nieuwerburgh and Veldkamp (2006) and Fajgelbaum, Schaal, and Taschereau-Dumouchel (2017), from noise-trading in Albagli (2011), on R&D in Decker, D'Erasmo, and Moscoso Boedo (2016), from experimentation in Bachmann and Moscarini (2011) and from 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

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 return 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 many exogenous shocks that occur in a quarterly panel of nearly sixty countries from 1970Q1 to 2020Q1. 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 different types of shocks lead to differing bundles of impacts on first and second moments of stock markets and the economy. A series of IV estimations exploits these differences to separately identify the impact of first- vs second-moment shocks on the economy.

To refine this analysis, we weight each event by the increase in the 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 approach ensures that only events that are unanticipated are included, since anticipated events like elections and major sports events do not generate jumps in newspaper 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 plot shows that 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 days before the event.[4]

large impact of uncertainty on recessions in their VARs, while Bachmann and Bayer (2013) report the reverse (a large effect of recessions on uncertainty).

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

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 a greater than 1% increase and a 4% decrease in GDP growth, respectively. That is, first- and second-moment effects are both significant drivers of macroeconomic growth.

There are clearly some potential issues with this identification strategy. One of these is whether our 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 employ different media weighting strategies or include shocks to geographically neighboring economies and trade partners, finding that these also tend to drive similar effects. We also utilize several alternative proxies of macroeconomic uncertainty: exchange rate volatility, dispersion in GDP forecasts, Economic Policy Uncertainty (EPU) and the World Uncertainty Index (WUI). These measures exhibit substantial correlation with one another and our baseline results – positive impacts of first-moment shocks and negative impacts of second-moment shocks – are similar when using these alternate uncertainty proxies.[5] Finally, we also reproduce our IV empirical results using simulated data from a micro-macro model with adjustment costs, heterogeneous firms and time-varying uncertainty in which uncertainty shocks drive recessions through a wait-and-see channel. This exercise shows these empirical results are consistent with a standard real-options model of uncertainty shocks.

A second concern is whether these events are really shocks or 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 that 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

[5]As one example, we plot 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) showing strong correlations.

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 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 (e.g., 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 like buildings and equipment after a natural disaster and the closure of the banking system after a revolution. The maintained exclusion restriction in our IV analysis is that any of these effects are reflected in shifts in the first and second moments of stock returns after these shocks. So we conflate these channels together when obtaining causal identification of the impact of first- and second-moment effects of shocks on the economy.

Finally, our results are 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 occurs to a greater extent in less developed countries.

Moving on from our univariate IV regressions, we also employ two different vector autoregression (VAR) approaches to estimating the impact of uncertainty. Our first strategy follows the event restrictions methodology proposed by Ludvigson, Ma, and Ng (2021). The basic idea is to assume that first- and second-moment shocks move in a certain fashion on our pre-specified set of disaster event dates, e.g., with positive shifts in uncertainty during revolutions. We then consider many candidate responses of growth to uncertainty, discarding any which don't deliver first- and second-moment shock series which behave in the prescribed manner on our disaster dates.

In our estimates, the resulting set of admitted responses implies that a one standard deviation increase in uncertainty leads to around a 2% immediate decline in GDP, followed by a recovery of growth in around two years. This estimated path of growth after an uncertainty shock is robust to a range of alternative econometric approaches. The benefit of the event restrictions VAR approach is that at no point do we impose IV-style exclusion restrictions. In other words, we only must assume that disaster events cause impacts on first and second moments, while leaving open the possibility that disaster events may also operate through channels not reflected in the first two moments of stock returns. The cost of this more general, weaker identifying assumption is that the event restrictions VAR only yields set identification rather than point identification of the impact of uncertainty on growth.

In our second VAR estimation, therefore, we employ an identification approach based on stronger assumptions which yield point identification. We use our disaster shocks as external instruments 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 IV strategy, relying on analogous identifying assumptions for instrument relevance and exclusion. Using this approach, we also uncover a negative impact of uncertainty on growth, with a one standard deviation shock leading to an initial GDP decline of around 3.5% which proves robust across a range of alternative VAR specifications and subsamples.

To summarize, we find that both a VAR strategy tied closely to our univariate IV analysis and another VAR estimation imposing substantially weaker but more robust identifying assumptions reveal a negative short-term impact of uncertainty on growth.

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 broader disasters 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 impact (Gabaix, 2012; Gourio, 2012; Nakamura et al., 2013). We view our work as complementary, 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.

Our analysis of the impact of uncertainty on business cycles links to a rich and rapidly growing set of work in empirical macroeconomics seeking to uncover the causal impact of uncertainty on the economy.[6] Ludvigson, Ma, and Ng (2021) 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. Our event restrictions VAR approach employs their strategy in our context, applying the method to a different sample of countries outside of the US, a new set of event dates based on disasters rather than financial crises, and alternative cross-country measures of first- and second-moment fluctuations.

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) use a penalty function identification strategy and find an important role for both financial and uncertainty shocks in driving cycles. Stein and Stone (2013) exploit heterogeneous exposure of firms to volatility in energy markets and exchanges rates, finding that uncertainty causes investment and hiring declines but boosts R&D spending. Klepacz (2020) also exploits variation in exposure to energy prices, finding that uncertainty causes a decline in price adjustment at the micro level.

In Section 2 we describe our economic and disaster data. In Section 3 we run IV regressions to uncover the impact of uncertainty on GDP growth. In Section 4 we introduce and employ two VAR strategies to estimate the impact of uncertainty. In Section 5 we briefly overview a structural model which reproduces our IV results. We conclude in Section 6. Online appendices provide more details regarding our data

[6]The analysis of the disasters in our paper also links – at a broad level – to a rapidly growing body of work on the economics of the COVID-19 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., 2020a; 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 this line of work, although we do not exploit any unique features of epidemic events in our analysis.

and analysis.

2 Data

We use 59 countries in our analysis, spanning the period 1970Q1-2020Q1. 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, so we start our sample at that point.

2.1 Economic and Disaster Shock Data

We collect economic data on real GDP growth from the Global Financial Database, the OECD, the IMF, and the World Bank. We also construct a number of measures of first and second moments of national business conditions.

Our primary metrics that track first and second moments are based on national stock market movements using both an aggregate and a cross-sectional lens. First, as our "macro" measure, we calculate stock returns of the broadest national index and then define volatility as the quarterly standard deviations of daily stock returns. Our "micro" stock-market measure relies on individual firm-level returns. We calculate average quarterly returns across all firms in a country that are listed in the WRDS international equity database (only 39 of our countries have sufficient data for this measure) and then form the micro volatility measure as the cross-sectional standard deviation of quarterly returns. We also combine these micro and macro measures into an index by normalizing both to zero mean and unit standard deviation and taking their average.

As alternative measures of national uncertainty, we also use the volatility of national exchange rates, the dispersion in professional forecasts of national growth rates, and two different text-based measures of country-level economic uncertainty (the EPU index and the WUI). These broader indicators of uncertainty rely less on the assumption that equity markets provide a high-quality view of national business conditions. We discuss our economic data in more detail in Appendix A.

Overall, the data span around 7000 quarterly observations for the 59 countries where we can obtain both GDP growth and index-level stock returns data, with over 500 shocks during this period. We use four major categories of disaster shocks that are discussed in more detail in Appendix A.

Natural Disasters: Extreme weather events such as, droughts, earthquakes, insect infestations, pandemics, floods, extreme temperatures, avalanches, landslides, storms, volcanoes, fires, and hurricanes.

Terrorist Attacks: Bombings and other non-state-sponsored attacks.

Coups: Military action which results in the seizure of executive authority taken by an opposition group from within the government.

Revolutions: A violent uprising or revolution seeking to replace the government or substantially change the governance of a given region.

Within each category, by country and quarter, we give a value of one if a disaster shock has occurred and a zero otherwise. This means that if a country has 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 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. We summarize our full sample for economic and shock variables in Table 1.

To obtain the causal impact of first- and second-moment shocks on GDP growth, we want to instrument using arguably exogenous shocks. This consideration leads us to focus on natural disasters, terrorist attacks, and political shocks as outlined above. Each of these shocks are arguably exogenous 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 or Hoover and Perez (1994) using oil price shocks as instruments for aggregate productivity shocks.

Of course, 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 exactly December 2010 was arguably unexpected.

Second, as discussed in more detail below, 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 large run-ups 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. Later, we also demonstrate the robustness of our results to a range of other measures of changes in media coverage or attention.

Third, we confirm in Table A1 using predictive regressions that these events appear to be surprises. This finding 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.

2.2 Newspaper Citations

Using the Access World News Newsbank service, we construct an "attention" index surrounding each event to construct media weights for our disaster shock instruments. 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. For our primary weighting approach, we observe a 15-day period on either side of the day of each event, counting the number of articles written each day about the 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 after an event or disaster. 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 relatively 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 assign this event a value of 1 as it reflects a 100% jump in citations. We also later demonstrate the robustness of our results to a number of alternative weighting approaches such as narrower windows or using alternative sets of global newspapers.

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 overall stock market returns and our micro + macro volatility measure. 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). In these specifications, we instrument for stock returns and volatility with our set of scaled natural and political disaster shocks. This set consists of the 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 level and volatility effects.

The first shock type corresponds to natural disasters. In practice, such events can 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 versus uncertainty. Column (2) reports our baseline IV estimates for both first and second stages. 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 statistically insignificant 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 disasters across a wide range of countries.

In terms of the first-stage results for volatility, we find that there is a significant positive effect for coups, revolutions and terrorist attacks in some specifications, but no significant impact for natural disasters. This suggests that while sudden changes in government or terrorism can 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. Additionally, while natural disasters and terrorist attacks are not strong drivers of first or second moments of stock returns in this IV setting, we find that the inclusion of these events does have the beneficial property of substantially constraining the range of potential estimates in our event restrictions VAR approach below.

Turning to the second-stage results, we see a significant causal impact of both first and second moments on economic activity. The magnitudes of the impacts are large. All 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 1.2% over the following year and a one standard deviation second-moment shock reduces GDP by about 4.2%.

In columns (3) - (5), we decompose our combined micro + macro measure of second-moment shocks into its 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 pattern 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.[7] Finally, an element of 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: average GDP per capita across our sample is more than $20,000 (approximately the GDP per capita of Hungary, Portugal, or Saudi Arabia), but the average shock occurs in a country with GDP per capita closer to $10,000 (approximately the GDP per capita of South Africa or Brazil).

[7]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 fiscal years) and accounting rules (Census versus GAAP rules on capital equipment depreciation).

We also perform several tests designed to analyze the validity and power of our chosen set of instruments. The reported F-tests of excluded instruments on the set of disaster shocks go some ways to reassure us that we do not suffer from weak-instrument issues. We also have considerable freedom for Sargan-Hansen tests of IV validity given that our specifications are over-identified, where a rejection of the null hypothesis of instrumental validity would cause doubt of the validity of our estimates. We find that the baseline Sargan over-identification test is not rejected in any specification, suggesting that the impacts of these four types of disaster shocks are 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.[8]

We go further and report results of difference-in-Sargan statistics below our baseline Sargan test results. This test allows us to test a strict subset of the original orthogonality conditions and is computed by calculating the difference between two Sargan statistics: one stemming from estimated the original baseline regression and the other stemming from the same regression run when removing one of the original instruments.[9] This test can more explicitly home in on the potential validity of any particular problematic instrument. The test is distributed χ^2 with degrees of freedom equal to the change in overidentifying restrictions with the null that the specified variables are valid instruments. We conduct this test for each instrument in turn, displaying the p-value of the χ^2test with one degree of freedom. We find that, in all cases, we fail to reject the null of instrument validity for all instruments in all specifications.

From these results, we can discern three primary points. The first is that we find both first- and second-moment shocks matter for growth, consistent with a finance literature using different empirical strategies and finding that first- and second-moment effects matter for asset prices (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.

Finally, we find that our strategy passes the Sargan over-identification tests and

[8]While there can be small-sample concerns about the power of the Sargan-Hansen test to detect invalid instruments, we do not think that these concerns apply in our large sample with thousands of country-quarters included (Bowsher, 2002).

[9]See Hayashi (1988), Eichenbaum, Hansen, and Singleton (2000), and Ruud (2000) who discuss this "difference-in-Sargan" (or "distance difference" or "C statistic") in more detail.

difference-in-Sargan tests, suggesting that we cannot reject the null that controlling for the first two moments of business condition shocks (stock returns and stock volatility) is sufficient to capture the full short-run effect of such shocks.

3.1 Alternative Measures of Stock Return Moments

We now move on to our first set of empirical robustness checks in Table 3. Column (1) reproduces 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. In column (3), we include the third moment of our main returns proxy, skewness, and find little additional explanatory power but a decline in the precision of our first- and second-moment coefficients. However, it should be noted that the first-moment or levels series and the third-moment or skewness series are quite correlated in this sample. Therefore, column (4) omits the first-moment term, uncovering a negative impact of increased uncertainty on GDP growth. Although we do not have the power to precisely estimate the impact of skewness here, the large positive, albeit noisy coefficients, are consistent with the idea that declines in skewness cause declines in growth (Salgado, Guvenen, and Bloom, 2020).[10]

Finally, we adjust both our micro and macro measures of stock returns to remove predictable components of stock returns and volatility using two separate approaches. First, we take a Heterogeneous Autoregressive (HAR) approach as in Campbell et al. (2001). Before aggregating our first-moment measure to a quarterly level, we regress each day's return on the past day's, past 5 days,' and past 22 days' returns and then utilize these residuals in the place of raw stock returns. That is, we strip each day's return of the predictable component given pre-existing trends in returns. For our second-moment measure, we perform the same regression but instead utilize daily squared returns in the place of daily returns. We have extremely low predictive power on returns and only slightly higher predictive power for squared returns (R-squared values of approximately 0.00 and 0.07 for first and second moments). We combine these adjusted series into a composite index in place of our baseline independent variables, with results in column (5) revealing effects similar to our baseline.

Our second approach is to regress quarterly returns and volatility (both macro

[10]See also the frameworks of Nakamura et al. (2013) and Gourio (2012) which model higher moments as important but time stationary.

and micro measures) on one-quarter lags of returns and volatility. Again, we retain the residual values of these regressions in the place of the original values to remove the predictable components of quarterly returns and volatility. Combining the two residualized metrics into a composite index, we display the results of this specification in column (6). Again, we cannot reject the null of the coefficients being equivalent to our baseline. While there are predictable components to both returns and volatility, in practice in our data such predictability does not greatly affect our results.

3.2 Trade and Distance Weighting

Table 4 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 nearness according to two 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 with the macro uncertainty definition, again finding similar results to the relevant specification, in this case column (4) 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.

3.3 Alternative Media Weighting Approaches

Table 5 explores variation in the media weighting scheme for our four disaster instruments. Recall that our baseline approach utilizes the change in media mentions of a country in the 30 days (15 on each side) surrounding the date of a disaster shock across over 2,500 US newspapers as a weight on the disaster itself. In Table 5, we adjust these weights in a number of ways. In column (2), we exclude the weights altogether, using only dummies for the disasters in our sample. With this specification, we find results that differ from our baseline. In general, not allowing for any weighting of these disasters yields an effective 'overweighting' of small and insignificant disasters, weaking instrument power and dramatically increasing standard errors. Column (3) mitigates this issue to some extent by again using only binary indicators for our disaster shocks but excluding any shock that sees an increase in media attention of less than 40% (the median increase in our sample) in the 15 days following a disaster. We find comparable effects of both first- and second-moment shocks when restricting to this subset of disaster events.

Returning to specifications that include a version of media weighting, column (4) uses a 5-day window on either side of a disaster to calculate the increase in media attention rather than our baseline 15-day window. This check helps to mitigate potential concerns about foresight and gradual trends around the disaster dates affecting our weights. For many countries and events, we obtain less precise estimates here due to the small number of articles within this smaller window of time, driving standard errors up. However, we cannot reject that the effects with this approach are the same as our baseline estimates. Column (5) also works to reduce any potential trends in media attention surrounding the date of the disasters. Here we utilize a discontinuity regression approach rather than simply the ratio of media articles to estimate the increase in media after the shock, regressing the number of articles in the days around each disaster on a trend and a post-disaster dummy. We then utilize the value of the coefficient on the post-disaster dummy as our media weighting. These weights are highly correlated with our baseline media weighting (correlation coefficient of approximately 0.75) and yield similar estimates.

One broad concern with all the weighting approaches above is that all of the media weights are derived from mentions of countries in US newspapers. US papers, or Western papers in general, might be systematically biased in their discussion of the less developed countries that more frequently see some of the disasters in our sample. In column (6) we utilize an analogous approach using data from non-Western newspapers (specifically, we use 1,329 non-North American and non-European papers) in the Access World News database. Due to smaller numbers of newspapers, we again suffer from larger standard errors driven by smaller sample sizes when comparing numbers of articles after disasters with those prior to disasters, but we nevertheless obtain results consistent with our baseline.

3.4 Alternative Measures of Uncertainty

While our primary approach utilizes stock market volatility to proxy for second-moment shocks to business conditions, we also examine other metrics of macroeconomic uncertainty given the potential differences between volatility and uncertainty highlighted by Berger, Dew-Becker, and Giglio (2020). In Table 6 we utilize a number of such alternative proxies for uncertainty while retaining our baseline first-moment measure.

Columns (1) and (2) utilize data from two different measures of macro uncertainty derived from textual analysis of Economist Intelligence Unit reports and newspapers, respectively.[11] Each of these metrics works to capture one element of macroeconomic uncertainty across a multitude of countries across recent decades. In each case, we see significant negative effects of uncertainty, instrumented with our disaster shocks, on GDP growth. Since the EPU metric only exists for a minority of countries in our sample, column (3) augments EPU with values of WUI within countries that are not covered by an EPU index. Again, we see significant effects for both first- and second-moment shocks.

Column (4) then turns to data from macroeconomic forecasters spanning 22 countries going back a maximum of 40 years as an additional second-moment proxy. Specifically, we utilize the standard deviation in forecasts of one-year ahead GDP growth to substitute for stock market volatility. We find sizable impacts of this second-moment proxy on GDP growth. Our final alternate proxy, exchange rate volatility, performs similarly: positive and significant impacts of first-moment shocks and large and negative impacts of second-moment shocks on GDP growth.

4 Vector Autoregressions

In this section we study growth and uncertainty using structural vector autoregression (VAR) analysis. We consider a parsimonious three-variable VAR using the same series

[11] These datasets are described in detail in Ahir, Bloom, and Furceri (2020) (WUI) and Baker, Bloom, and Davis (2016) (EPU).

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 OLS regressions. 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 estimate the properties of reduced-form innovations η_{it}. We make the conventional assumption 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 an 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 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 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, given the forward-looking nature of stock returns and many components of GDP, such timing assumptions are not ideal in our context.

Instead, we employ two methods for solving this classic VAR identification problem. First, we employ an event restrictions VAR based on Ludvigson, Ma, and Ng (2021). The approach identifies the matrix B, and hence the response of output to uncertainty shocks, by requiring that over our set of disaster event dates the VAR must generate structural shocks to first and second moments of a given average magnitude. This event restrictions approach has the advantage of imposing substantially looser identifying assumptions than our univariate IV regressions, since we need not impose an exclusion restriction ruling out shocks other than first- or second-moment innovations on disaster dates. The disadvantage of the approach turns out to be that the response of growth to uncertainty shocks is set identified rather than point identified. As an alternative, we also employ a second approach generalizing our disaster instruments strategy. This IV-VAR method, a version of Stock and Watson (2018) and Mertens and Ravn (2013), requires an assumption that disaster events serve as valid instruments for first and second moments in the GDP growth equation, allowing us to trace out a point-identified response of growth to an uncertainty shock in this case. Both the event restrictions VAR and IV-VAR identification strategies, despite the differences in their underlying identifying assumptions, reveal robust negative impacts of uncertainty shocks on growth.

4.1 Event Restrictions VAR

We first employ a version of the event restrictions VAR method of Ludvigson, Ma, and Ng (2021). We begin with the covariance matrix of the reduced-form residuals $Cov(\eta_{it}, \eta_{it})$ which can be readily estimated. If the structural shocks e_{it} are independent with unit standard deviations, the contemporaneous response of the economy to shocks is summarized in the matrix B which must satisfy $Cov(\eta_{it}, \eta_{it}) = BB'$. The left hand side of this equation from the data has fewer unique elements than the matrix B. In other words, the traditional VAR identification challenge applies here, and more restrictions must be imposed to identify B.

The event restrictions VAR approach places assumptions directly on the behavior of the structural shocks $e_{it}(B)$ implied by B, shocks which are given by a simple transformation of the reduced-form residuals η_{it} from the data: $e_{it}(B) = B^{-1}\eta_{it}$. We consider any potential response matrix B admissible in this event restrictions VAR strategy if the associated structural shocks $e_{it}(B)$ satisfy a set of pre-specified set of inequalities over our disaster event dates. In particular, let $e_{it} = (e_{Yit}, e_{Fit}, e_{Sit})'$ be the vector of structural shocks for country i in period t. Motivated by our evidence in Table 2 linking disasters to changes in both the first and second moments of stock returns, we require that the structural shocks to first and second moments increase or decrease by a given amount on average over our disaster dates. In particular, we impose the following inequalities for each disaster type:

1. Revolutions are linked on average to lower first moments and increased second moments

$$\mathbb{E}(e_{Fit}|Revolution_{it}) \leq -k^F_{Revolution}, \quad \mathbb{E}(e_{Sit}|Revolution_{it}) \geq k^S_{Revolution}$$

   for some threshold magnitudes $k^F_{Revolution}, k^S_{Revolution} > 0$.

2. Coups are linked on average to higher first moments and increased second moments

$$\mathbb{E}(e_{Fit}|Coup_{it}) \geq k^F_{Coup}, \quad \mathbb{E}(e_{Sit}|Coup_{it}) \geq k^S_{Coup}$$

   for some threshold magnitudes $k^F_{Coup}, k^S_{Coup} > 0$.

3. Terror attacks are linked on average to lower first moments

$$\mathbb{E}(e_{Fit}|Terror_{it}) \leq 0.$$

4. Natural disasters are linked on average to lower first moments

$$\mathbb{E}(e_{Fit}|NatDisaster_{it}) \leq 0.$$

Before proceeding further, we must highlight one feature of the assumptions above, which is that they involve no IV-style exclusion restrictions whatsoever. More precisely, we do not require that disaster events only impact economic growth through their impacts on first- and second-moment shocks e_{Fit} and e_{Sit}. By contrast, the inequality restrictions allow flexibly for disasters to have arbitrary auxiliary impacts on the economy through the unrestricted growth innovations e_{Yit}. Intuitively, we only impose that at least some of the consequences of disaster events are reflected in changes in the first and second moments of stock returns, not that all the consequences of disaster events are accounted for by those channels.

To practically investigate the implications of these restrictions for our VAR, we follow the procedure in Ludvigson, Ma, and Ng (2021) and randomly generate a large number — 1.5 million — of candidate matrices B, each of which is consistent with the reduced-form covariance matrix and satisfies $Cov(\eta_{it}, \eta_{it}) = BB'$. The subset $\mathcal{B}$ of these candidate VAR responses consistent with our disaster event inequality restrictions provides a set identified estimate of the impact of structural shocks in the VAR. No candidate B in this set is more likely than another, but values outside of the set can be ruled out based our event restrictions. In our baseline estimation, we impose that revolutions and coup events cause mean increases in uncertainty of at least $k^S_{Revolution} = k^S_{Coup} = 15\%$, together with average changes in first moments of at least $k^F_{Revolution} = k^F_{Coup} = 10\%$. We chooser looser, less extreme thresholds than might be suggested at first glance by our univariate IV first-stage regressions in Table 2. This is a natural choice because, by contrast with those regressions which employ media weighting and can therefore exploit variation in disaster severity, our event date restrictions are based purely on the timing of the full set of disaster events with varying severity. Nevertheless, as we show below our results are robust to alternative choices of these parameters, and restricting to larger impacts of disaster events would in fact strengthen our key findings. See Appendix B for more information on the details of our underlying econometric approach and the way we adapt it to the panel structure of our cross-country data allowing for country and quarter effects in the specifications above.

Figure 3 plots our baseline estimates of the response of GDP growth to a one standard deviation uncertainty shock. The solid blue lines plot the upper and lower bounds of the responses implied by the admissible set $\mathcal{B}$ at each horizon, i.e., the lower and upper bounds of our estimated range of responses of GDP growth to uncertainty over time. We estimate that an uncertainty shock causes an immediate drop in GDP ranging from 1 to 2.5 percentage points, followed by a gradual recovery of GDP growth taking around two years. For reference, Figure 3 also includes two additional lines. The first is the median admissible response of GDP growth at each horizon (green with x markers) featuring an impact of just over 2%. The second (in red with circles) is what Ludvigson, Ma, and Ng (2021) refer to as the "max$G$" solution, i.e., the response associated with the admissible candidate matrix B^{maxG} for which the values of the inequality restrictions above are collectively maximized. In this max$G$ case an uncertainty shock causes an immediate drop in GDP of around 2.5%. The appropriate econometric approach to statistical inference isn't fully understood in this set identified VAR context, as emphasized by Ludvigson, Ma, and Ng (2021). However, to provide more context on our estimates of the initial drop in GDP, the blue bars in Figure 4 display the distribution of the contemporaneous impact of uncertainty on GDP over the full set of admissible responses $\mathcal{B}$ in our baseline estimation, a distribution which clusters towards more severe drops in GDP in the range of 2 to 2.5%. To understand which types of events drive our identification, in Figure 4 we also plot the distribution of GDP responses to uncertainty when only imposing coup and revolution event restrictions (green bars) and when only imposing revolution event restrictions (red bars). This exercise reveals that the information contained in revolution event dates alone is enough to rule out a positive response of GDP to uncertainty. But adding the additional event restrictions associated with coups, natural disasters, and terror attacks in our baseline estimation serves to quantitatively sharpen the bounds of our estimated set and in fact rules out some of the more extreme negative estimated responses which would otherwise be admissible.

Moving beyond the GDP growth response to uncertainty, Figure B1 plots the bounds of the admissible responses of all variables to all shocks in our VAR, revealing that while our event restrictions are informative for the dynamics of GDP growth after an uncertainty shock they are largely silent on the path of first and second moments after shocks to GDP growth itself. There is some evidence that first-moment shocks lead to a moderate increase in uncertainty, consistent with the idea that differences between our univariate OLS and IV estimates in Table 2 may stem from underlying endogeneity in the OLS specifications. We conclude that our VAR results allow us to identify a negative impact of uncertainty on GDP growth without limiting or taking any ex-ante stand on the nature of potential endogenous feedback mechanisms linking real activity to uncertainty.

Our baseline estimates of the drop in GDP growth after an uncertainty shock are robust to a range of alternative estimation choices. Figure 5 plots the admissible boundaries of the impact of an uncertainty shock in a number of robustness checks with different VAR lag lengths, tighter event restrictions, looser restrictions, and various other specifications. In all cases, we estimate a range of responses implying a substantial drop in GDP after an uncertainty shock. Taking stock, although the event restrictions VAR strategy requires substantially weaker identifying assumptions than our IV approaches, we nevertheless uncover a negative causal impact of uncertainty shocks on growth.

4.2 Disaster IV-VAR

In our second approach we rely on an alternative VAR identification strategy which can be thought of as a generalization of our univariate disaster IV regressions. We follow a version of the IV-VAR approach in Stock and Watson (2018) and Mertens and Ravn (2013). Working with this IV-VAR method rather than the event restrictions VAR approach detailed above requires more restrictive identifying assumptions, although we gain the benefit of point rather than set identification of the impulse responses. First, we assume that the four-element vector of independent disaster instruments d_{it}, including each of the types of disasters we studied in our univariate regressions, influence and form part of the structural shocks to first and second moments in e_{it}, a VAR version of the traditional IV relevance assumption. We also rely upon a second assumption – an exclusion restriction – stating that the disaster instruments d_{it} are correlated with the first- and second-moment shocks e_{Fit} and e_{Sit} but orthogonal to other shocks to GDP growth e_{Yit}. In words, our identifying assumption is that the impact of our disasters on GDP growth is fully reflected in shifts in the first and second moments of asset prices.

Under these two assumptions 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}. Intuitively, the information in the moments $\mathbb{E}(\eta_{it} d'_{it})$ provides the rough VAR equivalent of an univariate IV first-stage regression, which together with the observed reduced-form covariances $Cov(\eta_{it}, \eta_{it})$ allows us to piece apart the underlying shocks to first and second moments and the response of growth to a second-moment or uncertainty shock. See Appendix C for more information on the details of the underlying econometric approach and our practical choices when implementing the IV-VAR estimation.

Using our IV-VAR identification strategy to analyze the empirical sample of GDP growth, stock returns, and volatility, Figure 6 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 percentage points in GDP growth. Figure 7 – which adds the response computed under a range of alternative specifications – demonstrates that the negative impact of second-moment shocks on GDP growth is robust in this IV-VAR analysis.

To summarize, although our two VARs differ widely in terms of their underlying identifying assumptions and implementations, we still estimate a meaningful and negative causal impact of uncertainty shocks on growth somewhere at or above 2-3% depending upon the econometric approach.

5 Model and Simulation

Our contribution is empirical, but we also construct a partial equilibrium heterogeneous firms business cycle model with macro and macro uncertainty fluctuations, building on Khan and Thomas (2008) and Bloom et al. (2018). Within this model, output y at the firm level is given by $y = zAk^{\alpha}n^{\nu}$. Production stems from capital k and labor n, inputs with decreasing returns chosen subject to nonconvex adjustment costs and also reflects shocks to productivity at the micro (z) and macro (A) levels. Productivity shocks are subject to fluctuations in uncertainty at the micro (σ^z) and macro levels (σ^A) according to

$$\ln z' = \rho_z \ln z + \sigma^z \varepsilon'_z, \quad \ln A' = \rho_A \ln A + \sigma^A \epsilon'_A.$$

As detailed in Bloom et al. (2018), in this class of models the presence of nonconvex adjustment costs on inputs generates a "wait and see" effect after an uncertainty shock, driving a sharp recession as firms pause their hiring and investment activities. To reproduce our empirical IV approach in simulated data, we augment the productivity processes above to allow for first-moment (ε) and second-moment (σ) shocks to be influenced by the arrival of four different disaster events. We provide details and show in Appendix D that a structurally estimated version of this model can broadly reproduce our univariate IV estimates in simulated data, and our IV-VAR approach yields similar estimates of the impact of uncertainty on growth in the data versus the simulation. We conclude that our empirical findings in sections 3 and 4 are in line with one common theoretical framework linking uncertainty to the business cycle through firm decision making, albeit one with exogenous fluctuations in uncertainty.

6 Conclusion

A recent body of research highlights how uncertainty is countercyclical, rising sharply in recessions and falling in booms. But what is the causal relationship?

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. 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, and we also show that a micro-macro heterogeneous firms business cycle model with fluctuations in uncertainty is consistent with the IV estimates we uncover.

We also employ two different VAR approaches to identifying the impact of uncertainty on growth. The first is an event restrictions VAR which places only loose restrictions on the link between disasters and underlying shocks but comes at the cost of set rather than point identification. The second is a generalization of our panel IV approach to the VAR context. Under both VAR strategies, we estimate a robust negative effect of uncertainty on growth.

Although our analysis highlights the challenges associated with identifying the impact of uncertainty, we argue that these challenges are surmountable in practice and offer evidence that higher uncertainty reduces growth in the short term.

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Table 1: Descriptive statistics

	Obs.	Mean	Median	Std. Dev.	Min	Max
Annual GDP Growth, %	10,278	3.44	3.43	7.13	-138.02	60.98
Return Level Index	4,745	0.00	0.04	1.00	-5.21	4.99
Return Volatility Index	4,734	0.00	0.03	1.00	-5.17	2.95
Stock Returns, %	7,472	0.01	0.01	0.07	-0.45	0.45
Log (Stock Return Volatility)	7,471	-4.52	-4.55	0.49	-6.05	-2.59
Cross Sectional Returns	4,978	0.00	0.00	0.09	-0.35	0.95
Log (Cross Sectional Volatility)	4,938	-1.55	-1.54	0.35	-3.89	-0.36
Natural Disasters	10,278	0.24	0	0.59	0	4
Natural Disasters (scaled by media increase)	10,278	0.13	0	0.52	0	7.98
Coups	10,278	0.01	0	0.10	0	1
Coups (scaled by media increase)	10,278	0.03	0	0.39	0	14.07
Revolutions	10,278	0.01	0	0.09	0	1
Revolutions (scaled by media increase)	10,278	0.00	0	0.06	0	2.47
Terrorist attacks	10,278	0.02	0	0.16	0	3
Terrorist attacks (scaled by media increase)	10,278	0.01	0	0.12	0	4.12
GDP Per Capita (2005 $US, World Bank PPP)	10,278	23,946	24,643	16,606	1,335	78,559

Notes: All values are country-level yearly averages at quarterly frequency. Data spans 1970Q1 to 2020Q1 where 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$_{t-1}$	0.412***	1.197***	2.322**	2.233***	1.444***
	(0.068)	(0.246)	(0.996)	(0.505)	(0.473)
Vol of returns$_{t-1}$ (in logs)	-0.348***	-4.236***	-2.978**	-4.249***	-6.141***
	(0.111)	(0.364)	(1.215)	(0.557)	(1.079)
IV 1st stage: Level					
Nat Disasters$_{t-1}$		-0.104	-0.103	-0.027	-0.139
		(0.214)	(0.295)	(0.194)	(0.213)
Coups$_{t-1}$		3.181***	2.448***	2.089***	1.177***
		(0.108)	(0.412)	(0.072)	(0.154)
Revolutions$_{t-1}$		-9.577***	-6.078***	-7.758***	-5.852***
		(2.072)	(1.740)	(1.401)	(1.323)
Terror attacks$_{t-1}$		-0.753***	-0.400**	-0.435***	-0.560***
		(0.152)	(0.157)	(0.083)	(0.166)
Instrument F-test		264.59	13.02	328.26	20.35
IV 1st stage: Vol					
Nat Disasters$_{t-1}$		0.045	-0.231	-0.007	0.113
		(0.313)	(0.279)	(0.302)	(0.176)
Coups$_{t-1}$		1.914***	1.387***	1.871***	0.811***
		(0.156)	(0.460)	(0.143)	(0.115)
Revolutions$_{t-1}$		6.588***	4.502***	4.452***	5.054**
		(1.751)	(1.642)	(0.889)	(2.086)
Terror attacks$_{t-1}$		-0.161	0.015	0.395**	-0.382
		(0.157)	(0.374)	(0.155)	(0.381)
Instrument F-test		45.34	3.84	57.35	13.51
Sargan p-val		0.564	0.360	0.474	0.853
Diff p-val (Dropping Coups)		0.939	0.183	0.650	0.719
Diff p-val (Nat Disasters)		0.290	0.522	0.223	0.700
Diff p-val (Revolution)		0.310	0.165	0.261	0.833
Diff p-val (Terrorism)		0.292	0.470	0.223	0.689
Observations	4,734	4,734	7,422	4,734	4,734
Countries	42	42	58	42	42
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is GDP growth. The first- and second-moment series are scaled for comparability across columns to have residualized unit standard deviation over the regression sample. In columns (1) to (2) stock returns and volatility are an index of the micro (cross-firm) and macro (overall) returns. Columns (3) and (4) utilize the macro (overall) stock returns and volatility. Column (5) is micro (cross-firm) returns. Standard errors clustered by country. Data is quarterly by country from 1970Q1 until 2020Q1 where available. Column (1) estimated by OLS and (2) to (5) by instrumental variables. Instruments 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. Differenced p-values are Chi-squared tests with 1 degree of freedom on the difference between Sargan values of the full IV specification and running IV when dropping each of the individual instruments. 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: Robustness of main results to alternative stock return measures

Specification	(1) Baseline Index	(2) Population Weighted	(3) Add Skewness	(4) Just Vol and Skewness	(5) HAR-Adjusted Returns and Vol (Daily)	(6) Residualized Returns and Vol (Quarterly)
Level of returns $_{t-1}$	1.197***	1.123***	-0.464		0.993***	0.998**
	(0.246)	(0.309)	(5.709)		(0.185)	(0.477)
Volatility of returns$_{t-1}$	-4.236***	-4.298***	-7.447	-6.655*	-4.212***	-3.379***
	(0.364)	(0.407)	(10.765)	(3.604)	(0.371)	(0.460)
Skewness of returns$_{t-1}$			22.377	16.982		
			(71.403)	(20.773)		
Sargan p-value	0.564	0.533	0.933	0.989	0.653	0.550
Observations	4,734	4,734	4,734	4,734	4,734	4,692
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Country 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 1970Q1 until 2020Q1 where available. All columns estimated by instrumental variables. 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. Volatility of returns is in logs in all specifications. The first- and second-moment series are scaled for comparability across columns to have residualized unit standard deviation over the regression sample. All columns include a full set of country dummies and year by quarter dummies. HAR adjustments are done for both macro (overall) and micro (cross-firm) data, and then an index is constructed. Column (5) HAR adjustments are made by regressing daily returns (volatility) on the average returns (volatility) over the previous 1 trading day, 5 trading days, and 22 trading days and obtaining the residual. Column (6) returns and volatility series are adjusted by regressing each quarterly value on the lagged value and retaining the residual estimate across all countries.

Table 4: Trade- and distance-weighted measures

	(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 $_{t-1}$	1.027***	0.877**	1.886**	1.613**	0.912***	0.859
	(0.311)	(0.350)	(0.743)	(0.697)	(0.262)	(0.528)
Volatility of returns $_{t-1}$	-3.965***	-3.759***	-3.870***	-4.191***	-6.077***	-5.106***
	(0.370)	(0.453)	(0.846)	(0.754)	(0.452)	(0.783)
Sargan test p-value	0.570	0.601	0.377	0.610	0.423	0.095
Observations	4,734	4,734	4,734	4,734	4,734	4,734
Countries	42	42	42	42	42	42
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Country 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 1970Q1 until 2020Q1 where available. 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. Volatility is in logs in the regressions. The first- and second-moment series are scaled for comparability across columns to have residualized unit standard deviation over the regression sample. Levels and volatility are an index of the micro (cross-firm) and macro (overall) 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 each country and a weighted version of shocks in a country's trading partners (scaled by total trade/GDP). Distance-weighted regressions include both shocks (instruments) in each country and 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 5: Alternative instrument media weighting approaches

Specification	(1) Baseline Index	(2) Unscaled by Media	(3) Over Median Media Jump	(4) 5-day Media Jump Window	(5) Regression-Imputed Media Jump	(6) Non-Western Media Jump
Level of returns $_{t-1}$	1.197***	-0.270	1.002***	1.251	1.197**	1.452***
	(0.246)	(1.590)	(0.363)	(1.153)	(0.478)	(0.498)
Volatility of returns$_{t-1}$	-4.236***	-1.303	-4.098***	-4.504***	-3.777***	-3.973***
	(0.364)	(2.738)	(0.450)	(1.716)	(0.778)	(1.058)
Sargan p-value	0.564	0.735	0.530	0.529	0.964	0.919
Observations	4,734	4,734	4,734	4,734	4,734	4,734
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

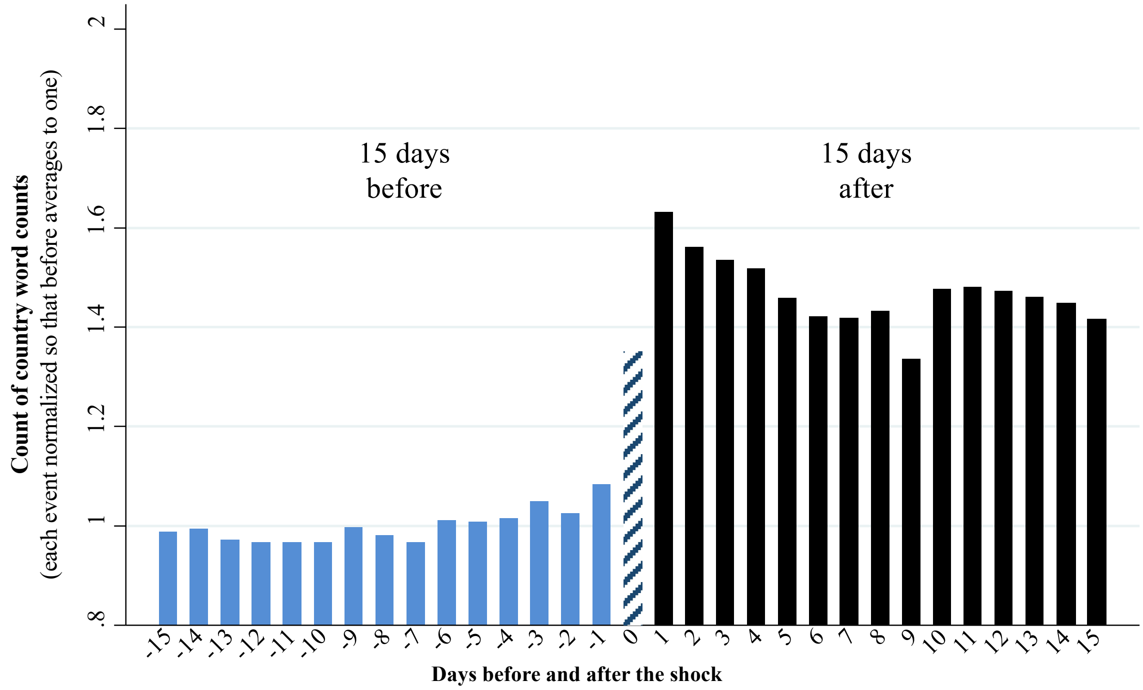
Notes: The dependent variable is GDP growth. * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by country. Data is quarterly by country from 1970Q1 until 2020Q1 where available. All columns estimated by instrumental variables with a full set of quarter-by-year time dummies. The first- and second-moment series are scaled for comparability across columns to have residualized unit standard deviation over the regression sample. Column (1) displays our baseline index where instruments (disasters) are weighted by the change in media mentions in American newspapers of a country's name in the 15 days after an event relative to the 15 days before the event. Column (2) is uses only disaster dummies rather than scaled disasters. Column (3) utilizes dummies for disasters only if they have a change in media mentions above the median (~40% increase). Column (4) uses a 5-day window rather than a 15-day window before and after the event. Column (5) regresses media mentions around each event against a time trend and a post-event dummy and then uses the value of the dummy as the media weighting. Column (6) uses only non-Western media sources (i.e., using all newspapers in Access World News excepting those from North America and Europe) and calculates the media weighting using all other world papers.

Table 6: Alternative uncertainty measures

Specification	(1) World Uncertainty Index	(2) Economic Policy Uncertainty	(3) WUI and EPU	(4) GDP Forecast Dispersion	(5) Exchange Rate Volatility
Level of returns $_{t-1}$	3.545***	2.498	3.880***	1.045*	1.036**
	(0.638)	(2.257)	(0.639)	(0.534)	(0.449)
World Uncertainty Index$_{t-1}$	-3.636***				
	(1.319)				
Economic Policy Uncertainty$_{t-1}$		-1.123*			
		(0.650)			
WUI and EPU$_{t-1}$			-2.868***		
			(1.066)		
GDP Forecast Dispersion$_{t-1}$				-3.173***	
				(0.644)	
Exchange Rate Volatility$_{t-1}$					-8.163***
					(1.318)
Sargan p-value	0.595	0.596	0.518	0.858	0.473
Observations	4,506	1,806	4,087	1,749	4,616
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes

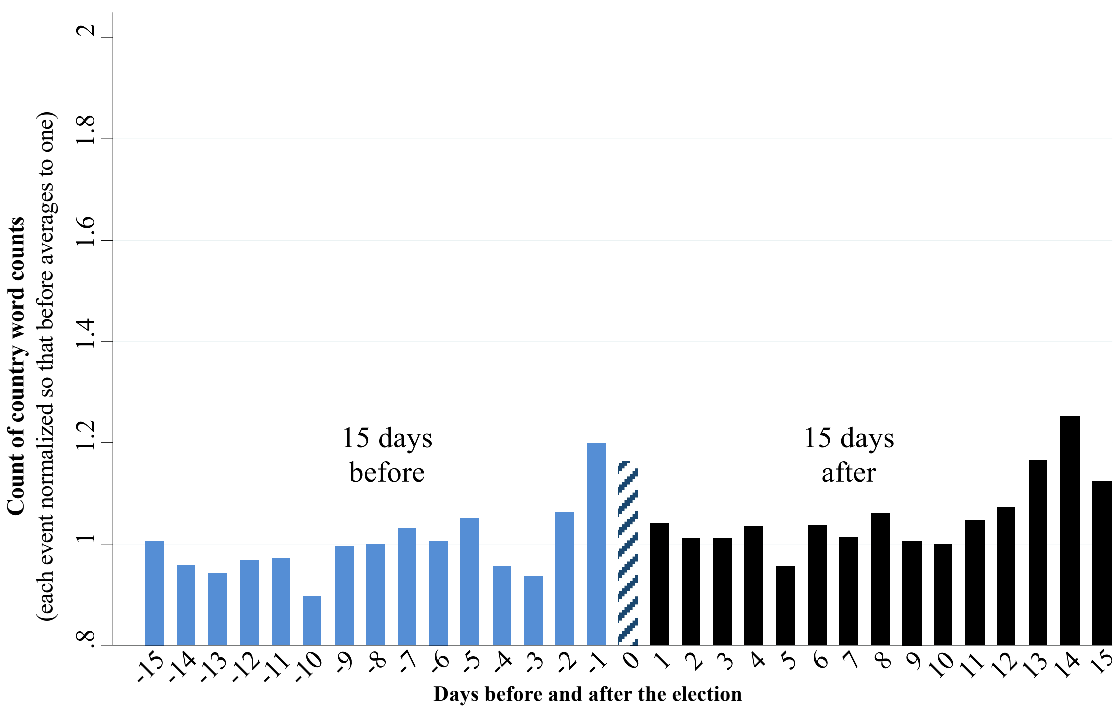
Notes: The dependent variable is GDP growth. * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by country. Data is quarterly by country from 1970Q1 until 2020Q1 where available. All columns estimated by instrumental variables with a full set of quarter-by-year time dummies. The first- and second-moment series are scaled for comparability across columns to have residualized unit standard deviation over the regression sample. Each column substitutes our baseline measure of second-moment shocks (stock market volatility) with another uncertainty proxy. Column (1) uses the World Uncertainty Index taken from Ahir, Bloom, and Furceri (2020). Column (2) uses the Economic Policy Uncertainty Index from Baker, Bloom, and Davis (2016). Column (3) combines both indexes (due to sparsity of country coverage for EPU) by country, such that countries covered by EPU use EPU data and all other countries utilize the WUI data. Column (4) uses the dispersion in 1-year-ahead GDP forecasts from a large macroeconomic forecasting company. Column (5) uses the standard deviation of exchange rates in a quarter relative to the dollar (for the US we use exchange rates against a trade-weighted basket of other currencies).

Figure 1: Daily counts of newspaper articles mentioning country names in the weeks around natural disasters, political, or terrorist shocks



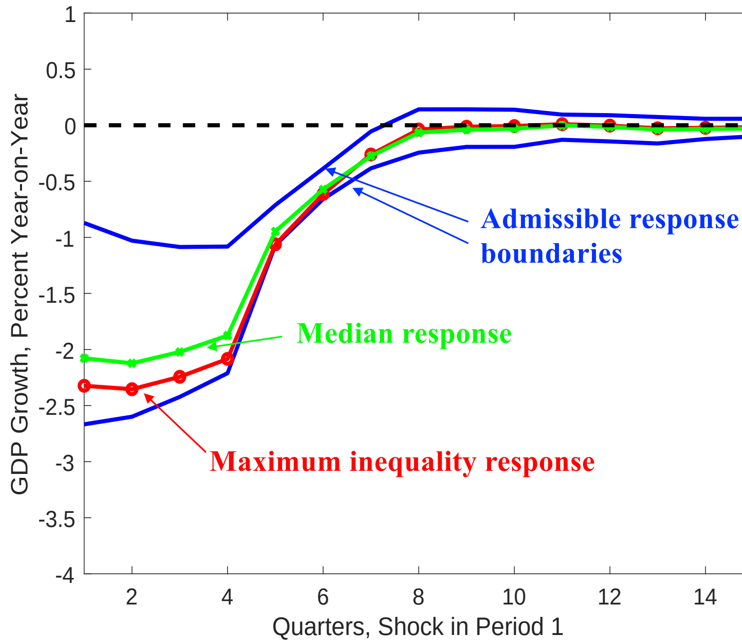
Notes: Shows the daily count of the name of the impacted country in the fifteen days before and after the shock, averaged over the universe of shocks (spanning the period from 1970 to 2020) studied in the regression analysis. For graphing purposes, the series for each event is normalized so that over 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



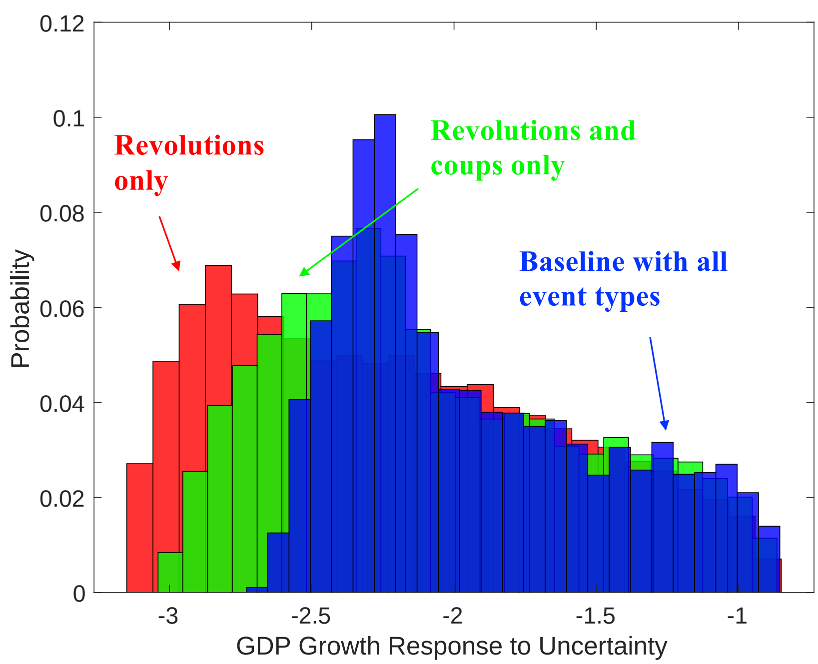
Notes: Shows the daily count of the name of the impacted country in the fifteen days before and after the election, averaged over 133 pre-scheduled elections in the G20 countries from 1970 to 2014. The series for each event is normalized for graphing so that over the 15 days before the election it has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

Figure 3: An uncertainty shock causes a drop in GDP growth in the disaster event restrictions VAR



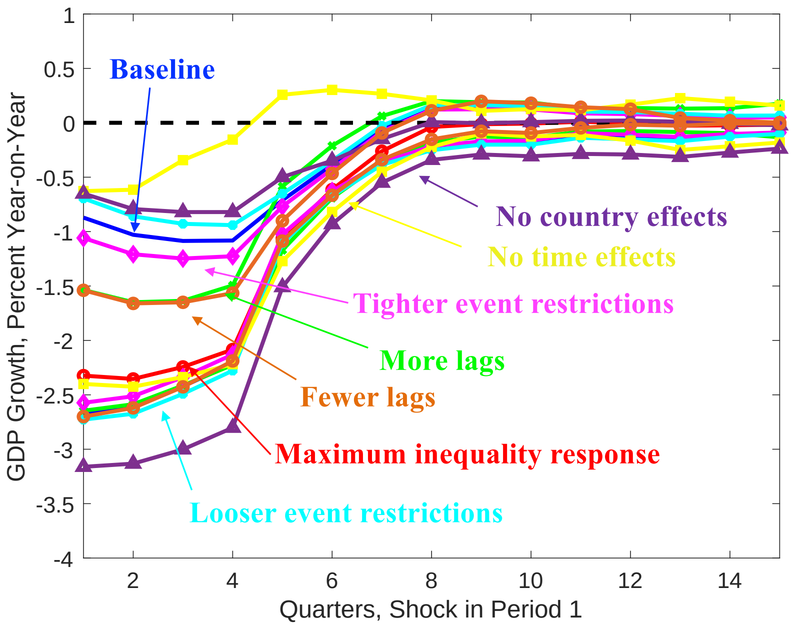
Notes: The figure plots responses of output growth to a one-standard deviation shock to uncertainty in the event restrictions panel VAR. The sample spans 58 countries for 6733 country-quarters over 1972Q2-2019Q4. The estimated VAR includes time and country effects, 12 quarterly lags, and links GDP growth, aggregate stock returns, and aggregate uncertainty. Maximum and minimum values of the set of admissible responses at each horizon consistent with the event restrictions are plotted in solid blue. The median response at each horizon is plotted in green with x markers. The "maxG" response maximizing the value of the event restriction inequalities is plotted in red with circles.

Figure 4: An uncertainty shock causes a drop in GDP in the disaster event restrictions VAR across a range of different disaster types



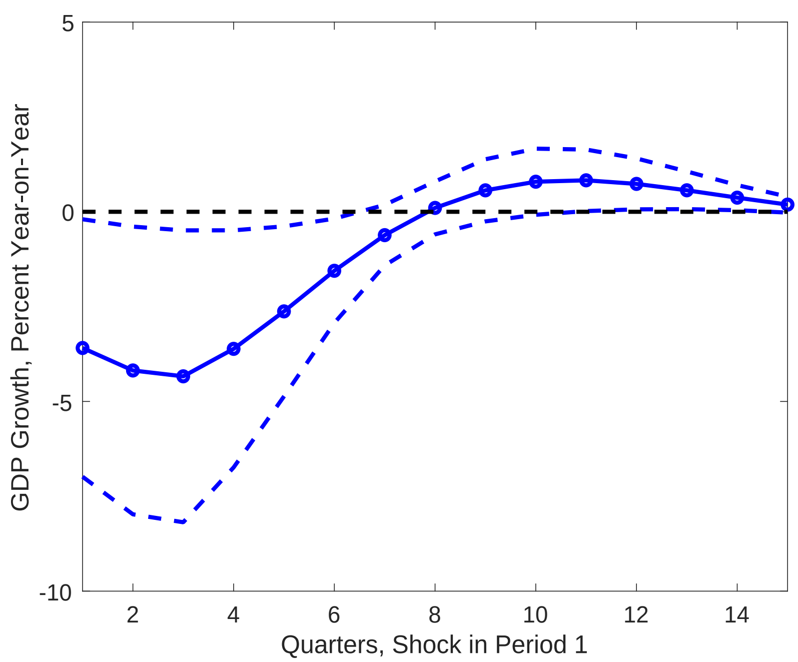
Notes: The histogram plots distributions of admissible contemporaneous responses of output growth to a one-standard deviation shock to uncertainty in the event restrictions panel VAR. The sample spans 58 countries for 6733 country-quarters over 1972Q2-2019Q4. The estimated VAR includes time and country effects, 12 quarterly lags, and links GDP growth, aggregate stock returns, and aggregate uncertainty. The blue bars use the baseline event restrictions with all disaster events including revolutions, coups, terror attacks, and natural disasters. The green bars use revolutions and coups only. The red bars use revolutions only.

Figure 5: An uncertainty shock causes a drop in GDP across a range of alternative disaster event VAR specifications



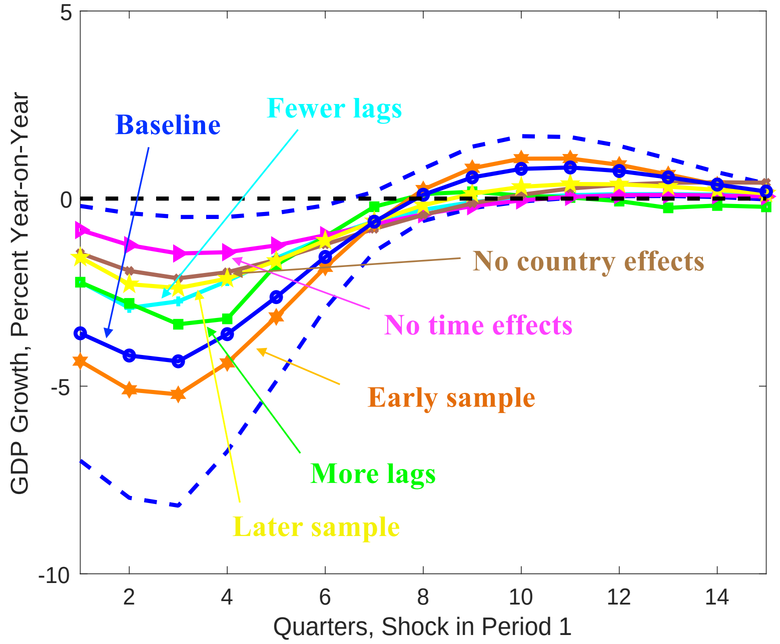
Notes: The figure plots responses of output growth to a one-standard deviation shock to uncertainty in the event restrictions panel VAR. The sample spans 58 countries for 6733 country-quarters over 1972Q2-2019Q4. The estimated VAR includes time and country effects, 12 quarterly lags, and links GDP growth, aggregate stock returns, and aggregate uncertainty. Maximum and minimum values of the set of admissible responses at each horizon consistent with the event restrictions are plotted in each case. The solid blue lines are the baseline, and the red line with circles is the inequality maximizing response. The cyan lines with stars loosen the event inequalities. The magenta lines with diamonds tighten the event inequalities. The green lines with x markers lengthen to 14 lags. The orange lines with circles shorten to 10 lags. The yellow lines with squares remove time effects. The purple lines with triangles remove country effects.

Figure 6: An uncertainty shock causes a drop in GDP 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, 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 7: An uncertainty shock causes a drop in GDP across a range of 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), twelve 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.