DOES UNCERTAINTY REDUCE GROWTH? USING DISASTERS AS NATURAL EXPERIMENTS

Scott R. Baker[a] and Nicholas Bloom[b] and Stephen J. Terry[c]

May 2018

Abstract: A growing body of evidence suggests that uncertainty is countercyclical, rising sharply in recessions and falling in booms. But what is the causal relationship between uncertainty and growth? To identify this 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 use natural disasters, terrorist attacks and unexpected political shocks as instruments for our stock market proxies of first and second moment shocks. We find that both the first and second moments are highly significant in explaining GDP growth, with second moment shocks accounting for at least a half of the variation in growth. Variations in higher moments of stock market returns appear to have little impact on growth.

JEL No. D92, E22, D8, C23.

Keywords: uncertainty, natural disasters, political shocks, growth

Acknowledgements: We would like to thank the National Science Foundation and the Sloan Foundation for their financial support. We appreciated feedback from discussants Jonathan Goldberg, Ayhan Kose and Aart Kray, seminars participants at the AEA, the Chicago Fed, Maryland, IMF, Stanford, and the World Bank, and from Megha Patnaik and Stephen Terry.

[a] Northwestern University, Kellogg School of Management
[b] Stanford and NBER
[c] Boston University

1. Introduction

A rapidly growing literature is centered on investigating the relationship between uncertainty and growth. One emerging fact from this literature is that both macro and micro uncertainty is counter cyclical, rising steeply in recessions and falling in booms.[1] For example, Figure 1 plots five different proxies for uncertainty – macro and micro stock volatility, exchange rate volatility, bond yield volatility and GDP forecast disagreement - against GDP growth quintiles for 60 countries from 1970 to 2012. There is a clear downward relationship between uncertainty and GDP growth, which is robust to splits by country (e.g. developed and developing) and time period (e.g. pre and post 2000).

What is not clear, however, is to what extent this relationship is casual. Does uncertainty drive recessions, do recessions drive uncertainty, or does something else drive both? Since theoretical models of uncertainty and economic activity predict effects in both directions[2], identifying the direction of causation is ultimately an empirical question.

Identifying the direction of this relationship is difficult because most macro variables move together over the business cycle, without any obvious causal direction. In large part this is because, as Kocherlakota (2009) aptly noted, "*The difficulty in macroeconomics is that virtually every variable is endogenous*". As a result, the prior literature has either assumed the direction of causation, or relied on timing for identification in various Vector Autoregression estimators. This is problematic, however, because of the contemporaneous movement of macro variables and the forward looking nature of investment and hiring.[3]

In this paper we take what we believe is a more robust approach, involving two steps.

[1] See, for example, evidence of counter-cyclical volatility in: macro stock returns in the US in Schwert (1989), in firm-level stock returns in Campbell et al. (2001), Bloom, Bond and Van Reenen (2007) and Gilchrist et al (2009); in plant, firm, industry and aggregate output and productivity in Bloom, Floetotto, Jaimovich, Saporta and Terry (2011), Kehrig (2010) and Bachman and Bayer (2011); in price changes in Berger and Vavra (2010); and in consumption and income in Storesletten et al (2004), Meghir and Pistaferri (2004) and Guvenen, Ozkan and Song (2013). Other papers find that GDP and prices forecasts have a higher within-forecaster dispersion and cross-forecaster disagreement in recessions, for example, Bachman et al (2010), Popescu and Smets (2009) and Arslan et al (2011); that the frequency of the word "uncertainty" close to the word "economy" rises steeply in recessions (e.g. Alexopoulos and Cohen (2011)), and a broad uncertainty factor indicator is counter-cyclical (Jurado, Ludvigson and Ng, 2013).

[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 (1976) and Abel (1983)); (c) real-options effects (for example Bernanke (1983), Bertola and Caballero (1994), Dixit and Pindyck (1996), Hassler (1996), Gilchrist and Williams (2005), Sim (2008)); and (d) via financial contracting frictions (for example, Arrellano et al. (2010), and Narita (2011)). There are also models predicting effects of economic activity on uncertainty, for example on information collection in Van Nieuwerburgh and Veldkamp (2006) and Fajgelbaum et al. (2012), on noise-trading in Albagli (2011), on R&D in D'Erasmo and Moscoso Boedo (2011), on experimentation in Bachman and Moscarini (2011) and on policy in Bianchi and Melosi (2012).

[3] For example, Bloom (2009), Christiano et al. (2010), Arslan et al. (2011), Fernandez-Villaverde (2011) and Alexopoulos and Cohen (2011) report a large impact of uncertainty on recessions in their VARs, while Bachman and Bayer (2010) and Bachman et al. (2011) report the reverse (a large effect of recessions on uncertainty).

First, we combine measures of *macro* stock-market volatility (i.e. the volatility of the S&P500) with measures of *micro* stock-returns volatility (i.e. the dispersion across individual firm returns). Given the emphasis in literature on the importance of macro and micro uncertainty, we take the principal factor component of our macro and micro proxies as our 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 are more first moment shocks, while other shocks like coups lead more to changes in stock-market volatility, implying they are more of a second moment shock.

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 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 2 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, and an increase of 39% over the fifteen days after the event. For comparison Figure 3 shows the media coverage around general elections, showing no jump in the days after compared to 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 leads to an approximate 2% increase and a 3% decrease in GDP growth, respectively. That is, first and second moment effects are both significant drivers of growth, with second moment effects having equal or higher impact.

There are clearly some potential issues with this identification strategy. One of these is whether stock market volatility is a good indicator of second moment shocks to business conditions. As alternative estimation approaches, we also try using solely cross-firm stock-price returns dispersion, solely broad stock index volatility, as well as bond-price volatility

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

to proxy for second moment shocks, finding similar results. In addition, we construct alternative versions of our main instruments where we include shocks to regional economies and trade partners, finding that these also tend to drive similar effects.

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 date. Moreover, as shown in Figure 2, 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 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 quarterly or annual 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 property 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 (see Imbens and Angrist, 2004), in that our identification is driven by the variation in our instrument, which comes mainly in developing countries, which experience many more shocks than developed countries.

We investigate the impact of skewness of stock-market returns– and find little significance, controlling for first and second moments. Hence, this suggests that changes in the mean and variance of economic conditions appear to be sufficient statistics for the impact of disaster shocks on the economy in our quarterly and yearly analysis.[5]

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, country sizes and time periods.

Before presenting the empirical results we first run a micro-to-macro simulation model based on Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) in which we

[5] This does not mean that higher moments are not important, as shown for example by Barro et al. (2012) and Gourio (2012). Instead, these results suggest that higher moments do not change rapidly enough after major shocks to play an important role in determining their short-run (quarterly or yearly) impact.

introduce disaster shocks with first and second moment components. From this we generate simulated aggregate data on which we test the empirical identification strategy we use on actual data, and confirm that we can identify the true impact of first and second moment shocks. We do this simply to confirm there exists a reasonable macro framework in which the impact of first and second moment shocks can be identified using our disaster shocks methodology.

We also use this simulated data as a validation tool for an extension of our disaster instruments strategy to the Vector Autoregression setting, in which we use the disaster shocks as external instruments following the approach of Stock & Watson (2017). In the model data, this disaster instruments VAR recovers the true negative impact of uncertainty shocks on growth. We apply the same approach our empirical sample, again uncovering a negative impact of volatility shocks on growth.

This paper links to the literature on volatility and growth. Ramey and Ramey's (1996) influential 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. Carriere-Swallow and Cespedes (2013) demonstrate that this relationship appears much stronger for emerging countries with less developed financial systems relative to the United States. As with the business cycle literature the challenge with this literature is identifying the nature of causality underlying these relationships between growth and volatility.

In Section 2 we describe our estimating framework and run a simulation model to show that we obtain identification under this modeling null, in Section 3 we describe our economic and disaster data, while in Section 4 we run instrumental variable estimations. In Section 5 we estimate a series of robustness tests, and we discuss structural VAR results in Section 6. We conclude in Section 7.

2 Model and Simulation

To investigate the ability of our empirical approach to identify the impact of uncertainty shocks using natural disasters, terrorist attacks and political disasters we build a simulation model. This helps to both clarify the underlying economic model we have in mind, and also show that, at least in this set-up, our empirical approach is able to identify the parameters of interest.

2.1 A Model of Firm Investment and Uncertainty Shocks

We use the heterogeneous firms business cycle model with time varying uncertainty introduced in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Jaimovich (2018). That model features three crucial ingredients: a distribution of firms subject to micro and macro productivity shocks, time varying uncertainty or volatility in those shocks, and non-convex or lumpy adjustment costs for capital and labor.

A unit mass of ex-ante identical firms (j) produces output (y) at time (t) according to the Cobb Douglas production function:

$$y_{jt}=z_{jt}A_t k_{jt}^{\alpha} l_{jt}^{\nu}$$

This production function is characterized by micro-level idiosyncratic productivity z_{jt}, macro-level common productivity A_t, capital k_{jt}, and labor l_{jt}. The production function exhibits decreasing returns to scale with $\alpha+\nu<1$, implying that firms' possess an optimal scale and that the distribution of inputs across firms matters for aggregate productivity. Exogenous shocks to productivity evolve according to AR(1) processes in logs

$$\ln z_{jt+1} = \rho_Z \ln z_{jt} + \sigma_{Zt}\, \varepsilon_{Zjt+1}$$

$$\ln A_{t+1} = \rho_A \ln A_t + \sigma_{At}\, \varepsilon_{At+1}.$$

Based on empirical evidence of comovement in micro and macro uncertainty[6], we assume that the volatility of micro shocks σ_{Zt} – governing dispersion across firms in productivity shocks – and the volatility of macro shocks σ_{At} – governing the size or volatility of common shocks – move in sequence according to a two point Markov chain.

Individual firms face nonconvex or lumpy costs of adjusting capital and labor, implying an optimal *Ss* adjustment strategy, with some firms actively investing and adjusting their labor and other firms pausing in an inaction region. As shown in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Jaimovich (2018), a positive shock to uncertainty in this model leads to a sharp drop in growth.

Intuitively, after an increase in uncertainty, the inaction regions for adjustment of capital and labor present because of lumpy adjustment costs increase in size. 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 the 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.

2.2 Simulating Disaster Shocks in the Model

Our goal is to use this model framework to analyze and validate our identification strategy based on stock returns and disaster events in our cross-country panel dataset. We start with the model from Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Jaimovich (2018), fixing parameters at the values structurally estimated in that paper based on establishment-level TFP dynamics in US Census manufacturing data and making several adaptations to this empirical framework.

First, because our sample of nations includes many small open economies, we use a partial equilibrium version of the model, fixing interest rates in a more plausible approximation of investment conditions faced by firms in our sample.

Second, we consider four exogenous disaster shocks in our simulation, each of which corresponds to a particular bundle of effects on aggregate levels (A_t) as well as uncertainty

[6] See the survey in Bloom (2014), for example.

or volatility (σ_t). We allow each of these shocks to occur with an arrival probability matched to their empirical frequency and an impact on first and second moments that is matched to our empirical sample. Before detailing our parameterization and the simulation results, we briefly introduce each disaster shock and discuss a representative example from our data.

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 no increase in quarterly stock-market volatility.

The second shock type represents coups, i.e., the takeover of a government by a military group. In our sample, each of these events represents the actions of a right wing group. Often such shifts lead to positive impacts on markets 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 1988, 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%.

We choose mappings from disaster types to a combination of first-moment and second-moment effects in our model. Each disaster type causes a shock to aggregate productivity of a fixed percentage (its first-moment impact), together with a movement to high uncertainty with a fixed probability (its second-moment impact). Given any set of first and second moment mappings from disasters in the model, we adjust the mean of the productivity process at the macro level as well as the frequency of uncertainty shocks in order to leave the overall parameterization of the model unchanged.

Finally, we generate a panel of GDP and first and second moment measures of stock returns at the country-quarter level in our model, simulating the returns for individual firms and summing value added across firms to compute GDP. We compute GDP growth in a given quarter as the growth rate over the past four quarters. From the stock return data, we compute a series of average levels or first moments by computing the mean of firm-level returns over the past four quarters, and we compute a proxy for uncertainty or second moments as the average variance of returns within firms over the past year, in logs.

We perform this simulation for 100 countries for 200 quarters each. We choose the values of the mappings from disasters to productivity and uncertainty in order to roughly approximate the first-stage regressions of the first and second moments of stock returns of disasters in our empirical analysis in Table 3 below. Appendix A2 contains more details on the simulation exercise.

2.3 Results on the Simulated Data

In Table 1, we report results from our simulated economy with disaster shocks, first from OLS and then instrumenting for volatility and stock market returns with the four types of simulated disaster shocks (natural, political, revolution, terrorist). We cluster at the country level. We also normalize the first and second moment series to a unit standard deviation in order to aid in the interpretation of the table.

Column (1) shows our OLS results. The coefficients reveal a positive association between the level of stock returns and growth as well as a positive association between the variance of stock returns and growth. The reason for the positive association between the variance of stock returns and growth – counterintuitive given the negative causal link between exogenous uncertainty shocks and growth in this model - is the fact that decreasing returns imply that the production function is convex in productivity. By extension firm valuations exhibit convexity and hence higher variance when productivity is high.[7] In other words, first and second moments can be endogenously linked to growth when examining OLS results alone, highlighting the need for an identification strategy to isolate the causal impact of second-moment shocks on growth.

In column (2) we report our IV results, instrumenting for the first and second moments of stock returns using our set of disaster shocks. The first-stage regressions – shown at the bottom of the column - exhibit signs matching the underlying model mappings. Natural disasters, revolutions, and terrorist attacks reduce the level of returns or first moments, while right-wing coups increase returns. Political coups and revolutions lead to large impacts on uncertainty. Moreover, both IV regressions pass weak instruments and over-identification tests. In the second-stage regression at the top, we see that the IV strategy correctly recovers the negative impact of uncertainty on growth, consistent with the true impact of uncertainty in the underlying model.

In summary, this short simulation section demonstrates that under the null of a standard heterogeneous firms business cycle model with uncertainty shocks and simulated stock returns, we can use disasters as instruments for stock-market valuations to correctly estimate the link between first and second moment shocks and GDP growth.

3 Data

In the estimations with real data we use up to 60 countries in our analysis. These 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

[7] This is a manifestation of the Oi (1961), Hartman (1972), Abel (1983) effect, through which convexity in input demands endogenously generates a positive link between levels and volatility.

countries in our panel. The data can be divided into disaster shock data and economic data, which we now discuss in turn, and are summarized in Table 2.

3.1 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 a paper by Jones and Olken (2005) looking at successful assassinations of national leaders as an instrument for leadership change and in 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, as in 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, looking only at one year impacts in the regressions. At these short-run frequencies it is easier to argue shocks are exogenous. For example, while many commentators expected revolutions in the Middle East at some point over the next couple of decades, 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 2 shows this media coverage on average for all shocks combined, displaying a large 39% jump after the shocks and no obvious run-up in coverage before the event. In comparison, Figure 3 shows the media coverage in the one month around general elections with no jump in the 15 days after the event.

Third, we do a variety of robustness tests and tests of the exogeneity of our shocks and find the results reassuringly robust. For example, as shown in Table A1 these shocks cannot be forecast in advance by stock market data, suggesting they are not anticipated by the market at a quarterly or annual level.

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:[8]

1. More than 100 deaths
2. More than $1 billion in damages
3. A successful coup or regime change

[8] Our results are robust to modification of filters for both deaths and monetary damages, or by utilizing a filter that is measured relative to a country's characteristics, as shown in our data file. These conditions are shocks that kill more than .001% of a country's population or do more than .01% of GDP in damages.

Table 3 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. Included for each shock, in parenthesis, are the quarter the shock occurred in, the ratio of news citations for the 15 days following the shock to the 15 days preceding it, and the type of shock (Natural Disaster, Political, Revolution, or Terrorism).

We now discuss the definitions of each of these three groups of shocks in turn.

Natural Disasters: Our natural disaster data has been obtained from the Center for Research on the Epidemiology of Disasters (CRED).[9] This dataset contains over 15,000 extreme weather events such as, droughts, earthquakes, epidemics, floods, extreme temperatures, insect infestations, avalanches, landslides, storms, volcanoes, fires, and hurricanes from 1960 to 2017. The dataset includes the categorized event, its date and location, the number of deaths, the total number of people affected by 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 1993-2017 and includes all terrorist bombings which result in more than 15 deaths.[10] 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 1970-2017.

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.

[9] 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.

[10] 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.

Typically these are coups brought by the military or former military officers in government against left-wing governments.

Our second type of political shock denotes a revolutionary war or violent uprising. 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. This category also does not include political violence stemming from ethnic grievances.

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 only 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.

3.2 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 does not matter.

We use yearly real GDP growth by quarter (year-on-year growth in quarterly) as our primary dependent variable to remove seasonality and quarterly effects, and reduce the impact of high frequency measurement errors. In some specifications we also use quarterly GDP growth defined as growth in GDP between the current and preceding quarter.

Annual population data for all 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 seven 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.[11] Our results are robust to the

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

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 our yearly GDP growth rates. A measure of average yearly volatility is created by taking the average of quarterly standard deviation of stock daily returns over the last four quarters. We also utilize a number of alternate measures of first and second moment shocks as robustness.

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).

In the empirical specifications we use the average of firm-level stock returns within a country as a measure of first moment shocks. We then use the standard deviation of quarterly returns across firms as our second moment.

'Overall' uncertainty: As our overall measure of uncertainty we take the principal component factor (PCF) of our macro uncertainty (stock market index) and micro uncertainty (firm dispersion of returns) measures. Because there are only two variables in this PCF analysis, this is equivalent to normalizing both measures to a zero mean and unit standard-deviation series and taking the average (and then renormalizing the final index to a unit standard-deviation). As such it places equal weight on macro and micro variations in stock-returns, so we also investigate the impact of other weightings, which tend to yields relatively similar results because macro and micro stock returns and volatility are quite highly correlated.[12]

Bond Yield Data: We take daily 10-year Government bond yield rates as an additional measure of volatility. We construct volatility from the quarterly volatility of daily percentage changes in bond yields, and the first moment from the mean quarterly bond yield.

3.3 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

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

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 country. Figure 2 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 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 include 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 broadly robust to using narrower or wider windows, like 5 or 30 days, surrounding the event.

4 The Impact of Uncertainty on Output

We display results from our primary specifications in Table 3. Column (1) gives results from an OLS regressions of national GDP growth on our overall (macro and micro) stock market returns and volatility measures. We find an insignificant positive coefficient on stock returns and a significant negative coefficient on stock market volatility, broadly similar to our simulation results.[13]

However, we worry about a high degree of endogeneity in these OLS results, so we proceed to our instrumental variable (IV) regressions in columns (2)-(4). 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.

[13] Note that while the relative parameter values are similar in the simulation and actual data the levels are different, due to relative differences in units and measurement error. By rescaling the units of the simulated data we could more closely align the parameters values, but since the objective is to show relative differences across parameters we have not done this to increase transparency.

Before discussing the second stage results we first check the first-stage results. The F-tests on the set of disaster shocks look reassuring, having values of around 50 or above. 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, it appears that 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 of the first moment, 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.[14]

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. 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 3.4% (about 1.5 standard deviations of GDP growth).

In column (3) and column (4), we decompose our combined macro+micro measure of first and second moment shocks into the individual components. Column (3) looks at only the volatility of daily aggregate stock-market indices to measure uncertainty. Column (4) instead uses the cross sectional dispersion of quarterly returns across individual companies These provide two alternative measures of uncertainty that have been used frequently in the literature (for example, Campbell et al. (2002)). We find qualitatively similar results in the same direction as in column (2), though point estimates shift somewhat.

Interestingly, all IV specifications give points 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, as in our simulation results, whereby positive first moment shocks can generate increased stock-market volatility and second-moment shocks can have first

[14] See, for example, Fomby, Ikeda and Loyaza (2011)

moment effects. 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.[15] 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 and that excluding either will lead to misspecification bias. In terms of magnitudes in our preferred annualized IV specification we see that a one-standard deviation shock to uncertainty has a larger impact on GDP growth relative to shocks to the first moment, suggesting second moment shocks are as least as important as first moment shocks in explaining yearly GDP growth. Interestingly, this is consistent with the finance literature which uses a different empirical strategy to come to a similar conclusion that first and second moment effects are about equally important for determining asset prices (e.g. Bansal and Yaron, 2004).

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

5 Robustness and Heterogeneity

In this section we investigate the robustness of these results to including higher-moments, to different measures of first and second moments, and to a variety of sample splits. Table 5 gives the results of a number of robustness exercises. Column (1) gives our baseline yearly IV regression for comparison.

Column (2) utilizes a measure of first and second moment shocks based on sovereign bond yields rather than stock prices, finding qualitatively similar results though with an insignificant first moment. In column (3) we weight by country population. We find largely similar and still significant results. Column (4) shows results when we exclude our media-citation weighting of the disaster shocks.

In columns (5) and (6), we include the third moment of our main returns proxy, skewness, and find little additional explanatory power. Additional higher moments like kurtosis have similarly insignificant results. In short, there appears to be no strong evidence for any

[15] 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 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).

additional impact of higher moments from disasters shocks once the first and second moments are controlled for. Thus, the first and second moments of stock returns appear to be adequate proxies for the one-year impacts of disaster shocks.[16]

Finally, in columns (7) and (8) we examine to what extent our results are heterogeneous across countries. To do this we include various dummies based on sample characteristics, splitting these at the sample mean, and investigating if our first or second moment proxies vary across these subgroups. In column (7) 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). In column (8) we interact by pre/post 2000 and again find no significant differences.

6 Vector Autoregressions

In our simulation exercise we demonstrated that our IV identification strategy based on disasters uncovers a negative link between uncertainty and growth under the null of a standard business cycle model with heterogeneous firms and uncertainty. In this section, we adapt our disaster instruments approach to the analysis of growth and uncertainty in a structural Vector Auto-Regression (VAR) analysis.

We consider a parsimonious three-variable VAR using the same series we've analyzed so far: GDP growth, the first moment of stock returns, and the second moment of stock returns. VAR analyses are attractive because they account for a flexible set of dynamic relationships between the included variables, but a classic identification problem presents itself. In particular, we wish to uncover the causal impact of a structural shock to second moments on GDP growth. However, if there are endogenous links between the included series, the observed or reduced-form innovations to second moments will in general reflect a combination of the underlying structural shocks to first and second moments in the model. Although the dynamics are generalized in the VAR context, the intuitive problem is the exact same challenge faced 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 is to impose recursive or timing assumptions on the underlying shocks to endogenous series. Such assumptions seem particularly strong in our context however, especially given that we seek to use an identification strategy which would apply in our simulation model with contemporaneously determined output, first moment shocks, and second moment shocks.

Therefore, we rely on an alternative identification strategy, which can be thought of as a generalization of our univariate disaster instruments approach. In particular, we follow a

[16] One point to clarify, however, is that this does not mean that disaster shocks' higher moments do not matter, but rather that these are not time-varying. This is in fact consistent with the frameworks of, for example, Barro et al. (2012) and Gourio (2012), who model higher moments as important but time stationary, even if some of the first and second moments vary over time.

version of the IV-VAR approach in Stock & Watson (2017). We exploit the observed covariances of reduced-form shocks or observed innovations in our VAR system with the set of disasters introduced above, the VAR equivalent of our univariate first stage regressions. If a given disaster is associated with stable mappings to first and second moments, these extra covariances allow us with a straightforward GMM exercise to piece apart the underlying shocks to first and second moments and the response of growth to a second-moment or uncertainty shock. Appendix A3 contains more information on the underlying econometric approach, which we adapt to our panel structure of cross-country data.

Using our IV-VAR identification strategy to analyze our empirical sample of GDP growth, stock returns, and volatility, Figure 4 plots the impulse response of GDP growth to a second moment shock in the empirical sample of data used in Table 3. The one-standard deviation shock to the volatility of stock returns plotted here leads to a drop of around 3% in GDP growth. As Figure 5 – which adds the response computed under a range of alternative sample cuts, lag lengths, and specifications – demonstrates, the negative impact of second-moment shocks on GDP growth is robust in this IV-VAR analysis.

As in the univariate IV case, we can validate the IV-VAR in simulated data. Figure 6 plots our baseline empirical IV-VAR response of growth to a volatility shock against the same IV-VAR impulse response computed from the simulated model data used to produce Table 1. Not only does the IV-VAR approach recover the negative impact of an exogenous volatility shock on GDP growth in the simulated data, the two responses correspond relatively closely to one another.

To summarize, a VAR extension of our disasters instrument IV regressions – which is validated by application to our simulated model data – uncovers a negative impact of volatility shocks on growth in our empirical sample.

7 Conclusions

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 two analyses designed to determine the direction of causality. First, we perform a simulation in which a modeled economy undergoes shocks to business conditions and test the effects of these shocks, finding significant effects of both first and second moment shocks. Second, 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 change in daily newspaper coverage they induce.

Using these shocks to instrument our stock market proxies for first and second moment shocks, we find that both first and second moment shocks are highly significant in driving business cycles, conforming well to our simulated results. And controlling for first and second moments is sufficient to determine true effects of shocks on growth, with no significant impact on growth of higher moment shocks. These results are consistent across a number of different measures of first and second moment shocks to business conditions. We also find that IV estimates of the effects of uncertainty are much larger than OLS estimate, suggesting that measurement error and endogeneity are significant concerns in OLS analyses.

We also extend our univariate analysis to a VAR setting, exploiting our disaster instruments to uncover a negative impact of volatility on growth in an IV-VAR approach that can also be validated using our simulated model data.

Bibliography:

Abel, Andrew. (1983): "Optimal Investment Under Uncertainty," *American Economic Review*, 73, pp. 228-233.

Albagli, Elias (2011), "Amplification of Uncertainty in Illiquid Markets", USC mimeo.

Alexopoulos, M. and J. Cohen, 2009a. "Nothing to Fear but Fear itself? Exploring the effect of economic uncertainty", Manuscript, University of Toronto working paper.

Arrellano, Cristina, Bai, Yan and Kehoe, Patrick (2010): "Financial Markets and Fluctuations in Uncertainty," Federal Reserve Bank of Minneapolis Research Department Staff Report.

Arslan, Yavuz, Atabek, Ashhan and Sahinoz, Saygin (2011), "Expectation errors, uncertainty and economic activity", Bank of Turkey mimeo.

Bachmann, Ruediger, Elstner, S, and Sims, Erik (2011): "Uncertainty and Economic Activity: Evidence from Business Survey Data", NBER WP 16143.

Bachmann, Ruediger. and Christian. Bayer (2011): "Uncertain business cycles: really?", CESIFO-WP 2844.

Bachmann, Ruediger, Ricardo. Caballero and Eduardo. Engel (2010): "Aggregate Implications of Lumpy Investment: New Evidence and a DSGE Model", mimeo Yale University.

Bachmann, Ruediger., and Giuseppe. Moscarini. (2011) "Business Cycles and Endogenous Uncertainty," Yale mimeo.

Bansal, R. and Yaron, A. (2004), "Risks for the long run: a potential resolution of asset pricing puzzles", Journal of Finance LIX(4), 1481-1509.

Barro, Robert, 1992, "Economic Growth in a Cross Section of Countries," *Quarterly Journal of Economics*, Vol. 106, No. 2, pp. 407-443.

Barro, Robert, Nakamura, E., Steinsson, J and Ursua, J., (2012), "Crises and recoveries in an empirical model of consumption disasters", Harvard mimeo.

Berger, D., and J. Vavra (2010): "Dynamics of the U.S. Price Distribution," Yale mimeo

Bernanke, B. (1983): "Irreversibility, Uncertainty and Cyclical Investment," *Quarterly Journal of Economics*, 98, pp. 85–106.

Bertola, G., and R. Caballero. (1994): "Irreversibility and Aggregate Investment," *Review of Economic Studies*, 61, pp. 223–246.

Bianchi, Francesco, and Melosi, Leonardo (2012), "Dormant shocks and fiscal virtue", Duke/Chicago Fed mimeo

Bloom, Nick. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77, pp. 623-685.

Bloom, Nick. (2014): "Fluctuations in Uncertainty," *Journal of Economic Perspectives*, 28(2), pp. 153-176.

Bloom, Nick., S. Bond, and J. Van Reenen (2007): "Uncertainty and Investment Dynamics," *Review of Economic Studies*, 74, pp. 391–415.

Bloom, N. M. Floetotto, N. Jaimovich, I. Saporta and S. Terry, (2018): "Really Uncertain Business Cycles," *Econometrica*, 86(3), pp. 1031-1065.

Bloom, N., and J. Van Reenen (2007): "Measuring and Explaining Management Practices Across Firms and Countries," *Quarterly Journal of Economics*, 122, pp. 1351–1408.

Campbell, J., Lettau, M., Malkiel B. and Xu, Y. (2001), "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk", *Journal of Finance*, 56(1), 1-43.

Carriere-Swallow, Yan and Luis F. Cespedes, 2013, "The Impact of Uncertainty Shocks in Emerging Economies", Journal of International Economics 90(2): 316-325

Christiano, Lawrence, Motto and Rostagno. (2010): "Financial Factors in Business Cycles," mimeo Northwestern University.

D'Erasmo, Pablo and Moscoso-Boedo, Hernan (2011), "Intangibles and endogenous firm volatility over the business cycle", UVA/Maryland mimeo.

Dixit, A. and R. Pindyck (1996): *Investment Under Uncertainty*. Princeton, NJ: Princeton University Press.

Engle, R.F. and Rangel, J.G. (2008), "The Spline-GARCH Model for Low-Frequency Volatility and Its Global Macroeconomic Causes", Review of Financial Studies, 21(3), 1187-1222.

Fajgelbaum, Pablo, Schaal, Eduardo and Matthieu Taschereau-Dumouche (2012), "Uncertainty traps" UCLA mimeo

Fernandez-Villaverde, Jesus, Pablo Guerron, Juan Rubio-Ramirez & Martin Uribe (2011), "Risk Matters: the real effects of volatility shocks", forthcoming American Economic Review.

Fomby, T, Ikeda, Y. and Loyaza, N. (2011), "The growth aftermath of natural disasters", Journal of Applied Econometrics.

Gilchrist, S., J. Sim and E. Zakrajsek (2009). "Uncertainty, Credit Spreads and Aggregate Investment", Boston University mimeo.

Gilchrist, S., and J. Williams. (2005): "Investment, Capacity and Uncertainty: A Putty–Clay Approach," Review of Economic Dynamics, 8, 1–27.

Gourio, Francois (2012), "Disaster risk and business cycles", forthcoming *American Economic Review.*

Guvenen, Fatih, Ozkan, Serder and Song, Jae (2013), "The nature of countercyclical income risk", university of Minnesota mimeo.

Hamilton, J.D. and Lin, G. (1996), "*Stock Market Volatility and the Business Cycle"*, Journal of Applied Econometrics, 11(5), 573-593.

Hartman, Richard (1972), "The effect of price and cost uncertainty on Investment", Journal of Economic Theory, 5, 258-266.

Hassler, J. (1996): "Variations in Risk and Fluctuations in Demand—A Theoretical Model," *Journal of Economic Dynamics and Control*, 20, 1115–1143.

Hoover, Kevin and Perez, Steven, (1994), "Post Hoc Ergo Propter Hoc one more: an evaluation of 'Does Monetary Policy Matter' in the spirit of James Tobin", *Journal of Monetary Economics*, vol. 34, 89-99.

Imbens, Guido and Angrist, Joshua (1994), "Identification and estimation of local average treatment effects", *Econometrica* 62, 467-475.

Jones, Ben and Olken, Ben (2005), "Do Leaders Matter? National Leadership and Growth since World War II", *Quarterly Journal of Economics,* 120(3), 835-864.

Jurado, K, Ludvigson, S. and Ng, Serena (2013), "Measuring Uncertainty", NBER WP19456.

Kehrig, M. (2010): "The Cyclicality of Productivity Dispersion", mimeo Texas University.

Kjetil Storesletten, Christopher I. Telmer, and Amir Yaron. (2005): "Consumption and risk sharing over the life cycle" *Journal of Monetary Economics* 52, 1331-1358.

Koren, M. and Tenreyro, S. (2007), "Volatility and development", *Quarterly Journal of Economics*, pp. 243-287.

Kocherlakota, N. (2009): "Some thoughts on the state of macro", Minneapolis Fed mimeo.

Meghir, C., and L. Pistaferri. (2004): "Income Variance Dynamics and Heterogeneity," *Econometrica*, 72, 1–32.

Narita, F. (2011): "Hidden Actions, Risk-Taking and Uncertainty Shocks", mimeo University of Minnesota.

Oi, Walter (1961), "The desirability of price stability under perfect competition", *Econometrica* vol 29(1), pp. 58-64.

Popescu, A. and F. Smets (2009). "Uncertainty, Risk-Taking and the Business Cycle", mimeo.

Ramey, G., and V. Ramey, (1996) "Cross-country evidence on the link between volatility and growth," American Economic Review, LXXXV (1995), 1138–51.

Schwert, G. W. (1989): "Why Does Stock Market Volatility Change Over Time?" Journal of Finance 44, 1115-1153.

Shiller, R. (1987), "The volatility of stock market prices", *Science*, volume 235, pp. 33-37.

Sim, J. (2008): "Uncertainty, Irreversible Investment and General Equilibrium," Mimeo, Boston University.

Stock, James H. and Mark W. Watson (2017). "Identification and Estimation of Dynamic Causal Effects in Macroeconomics using External Instruments," Sargan lecture.
Van Nieuwerburgh, Stijn and Veldkamp, Laura (2006), "Learning asymmetries in real business cycles" *Journal of Monetary Economics,* v53(4), p753-772.
Zussman, Assaf and Zussman, Noam and Nielsen, Morten (2008): "Asset Market Perspectives on the Israeli-Palestinian Conflict" Economica 75, 84-115.

APPENDIX

A1) Data Cleaning:

Data on GDP growth, stock volatility, stock returns, and exchange rate volatility is windsorized 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 or data is missing. This affects 4 quarters of data in Mexico, Morocco, Saudi Arabia, and Pakistan. Additionally, we do not use values of 0 for exchange rate volatility, which affects 548 quarters due to fixed exchange rates.

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. This impacts 5 quarters for terrorism shocks, 186 quarters for natural disaster shocks, and 1 quarter for political coup shocks. In addition, despite being included in the Center for Research on the Epidemiology of Disasters list of disasters, disease-based disasters, insect-based disasters, and industrial accidents are excluded from the sample.

Bond yields are daily 10-year government bond yields at the close of the day. Exchange rates are the exchange rate at the close of the day relative to the US Dollar. US exchange rate measured against a trade-weighted basket of currencies.

A2) Simulation Model

We rely on the model and estimated parameters introduced in Bloom, Floetotto, Jaimovich, and Saporta-Eksten (2018). The parameterization of the uncertainty process as well as all the other parameters we use can be found in Tables 4-5 of that paper.

As noted in the main text, we incorporate several modifications to the baseline structure, including the following:

- <u>A partial equilibrium analysis with a fixed interest rate.</u> Implementation of this change requires only that we set the value of *p* in Bellman equation (18) equal to a constant value, numerically solving and simulating the model in an otherwise identical fashion.
- <u>Incorporation of disaster shocks.</u> We include four disaster shock types i = 1,…,4, and for each we choose a parameter $\lambda^F{}_i$ and a parameter $\lambda^S{}_i$. Upon arrival of a disaster of type i, which occurs with an iid probability equal to its sample frequency, we reduce the value of macro productivity by $\lambda^F{}_i$ standard deviations, and we also

impose a high uncertainty state with probability λ^{S}_{i}. The four shocks correspond to the following events in our data

- 1: Natural disasters (λ^F = -0.75, λ^S = 0.01, freq = 8.6%)
- 2: Political coups (λ^F = 1.46, λ^S = 0.65, freq = .25%)
- 3: Revolutions (λ^F = -6.01, λ^S = 0.96, freq = 0.1%)
- 4: Terrorist attacks (λ^F = -0.9, λ^S = 0.06, freq = 0.5%)

The parameters listed above were chosen in order to roughly match the empirical first and second stage mappings in Table 3, although given the larger number of targets than parameters the fit is imperfect.

- Simulating stock returns. The Bellman equation (10) in Bloom, Floettoto, Jaimovich, Saporta-Eksten, and Terry (2018) defines the valuation and stock return for a given firm. We compute these returns as well as value added for a simulated panel of firms at quarterly frequency for 100 nations for 200 quarters each. The aggregate value added defines GDP in a given quarter, and we take four-quarter growth rates to compute the model equivalent of GDP growth in our sample of data. Similarly, we compute the mean stock return cumulated over the last four quarters as the first moment of stock returns. We compute the mean within-firm standard deviation of stock returns, taking logs to obtain our second-moment measure of stock returns in the model.

A3) 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 (2017). The econometric framework is a three-variable VAR in the following series:

$$X_{it} = (Growth_{it}, Levels_{it}, Volatility_{it})'$$
$$X_{it} = f_i + g_t + AX_{it-1} + \eta_{it}$$

This 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. The vector of innovations η_{it} reflect reduced-form disturbances to the VAR system, which are linked to a vector of iid mean zero and unit standard deviation random structural shocks e_{it} according to $\eta_{it} = Be_{it}$ where *B* is a 3 x 3 matrix containing the contemporaneous impacts of each structural shock on the series in X_{it}. The matrix A can be consistently estimated via OLS, as usual. Since A^sB is the impulse response matrix at horizon s, we must also recover B. As usual, the covariance matrix of the reduced-form innovations $\Omega=\mathrm{cov}(\eta_{it}, \eta_{it})$ contains only 6 unique elements, failing to independently identify the elements of the matrix B. However, we assume that the structural shocks to first and second moments are generated by a combination of iid disturbances ε_{it} as well as iid realizations of the disaster shock series D_{it} according to

$$e^F_{it} = \sum_{i=1}^{4} d_{iF} D_{it} + \varepsilon_{Fit} \qquad e^S_{it} = \sum_{i=1}^{4} d_{iS} D_{it} + \varepsilon_{Sit}\,.$$

Now, identification of the VAR is based on recovery of the 9 elements in B together with the 8 parameters d_{iF}, d_{iS}, i=1,…,4. But the covariances of the reduced-form innovations η_{it} with the external instruments or disaster shocks D_{it} can be estimated with available information and provide another 12 moments. The result is a system of 18 moments which depend upon 17 parameters, allowing for straightforward over-identified 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.

Table A1: Economic variables cannot forecast disasters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shock type as dependent variable:	Natural	Political	Revolution	Terrorist	Natural	Political	Revolution	Terrorist
Level of stock returns, last quarter	-0.026	0.044	-0.0003	0.006				
	(0.026)	(0.037)	(0.0006)	(0.014)				
Volatility of stock returns, last quarter	0.00001	0.009	0.002	0.0005				
	(0.006)	(0.009)	(0.002)	(0.003)				
GDP growth, last quarter	-0.0007	0.0001	-0.0001	-0.001				
	(0.0004)	(0.0001)	(0.0001)	(0.001)				
Volatility of stock returns, last year					0.006	0.006	0.002	-0.006
					(0.009)	(0.009)	(0.002)	(0.005)
Level of stock returns, last year					-0.029	-0.029	-0.008	-0.011
					(0.045)	(0.045)	(0.008)	(0.012)
GDP growth, last year					-0.001	-0.001	-0.0001	-0.001
					(0.0007)	(0.001)	(0.0001)	(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 2013. 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.

Table A2: Correlations of Different Volatility Measures

Specification	**(1)** Stock Volatility	**(2)** Cross-Firm Volatility	**(3)** Bond Yield Volatility	**(4)** Exchange Rate Volatility
Stock Volatility	1.00 *1.00*	0. 4810*** *0.4332****	0.1985*** *0.1243****	0.1343*** *0.1670****
Cross-Firm Volatility		1.00 *1.00*	0.1831*** *0.1582****	0.0921*** *0.1837****
Bond Yield Volatility			1.00 *1.00*	-0.1064*** *-0.0899****
Exchange Rate Volatility				1.00 *1.00*

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Data is quarterly by country from 1970 until 2013. Table gives pairwise correlations of four measures of volatility. Italicized numbers give pairwise correlations of the measures after being demeaned by country and time.

Table 1: Simulated data – estimated impact of returns and volatility on GDP Growth

	(1)	**(2)**
Estimation	OLS	IV
Period:	Yearly	Yearly
Level of returns $_{t-1}$	2.933***	3.593***
	(0.0720)	(0.817)
Volatility of returns $_{t-1}$ (in logs)	2.955***	-4.143***
	(0.0905)	(1.177)
IV 1st stage: Levels		
Natural Disasters $_{t-1}$		-0.174***
		(0.0272)
Political Shocks $_{t-1}$		1.141***
		(0.219)
Revolutions $_{t-1}$		-0.105
		(0.498)
Terrorist attack $_{t-1}$		-0.167
		(0.121)
Instrument F-test		16.30
IV 1st stage: Volatility		
Natural Disasters $_{t-1}$		0.0577***
		(0.0211)
Political Shocks $_{t-1}$		0.656***
		(0.122)
Revolutions $_{t-1}$		0.911***
		(0.179)
Terrorist attacks $_{t-1}$		0.0177
		(0.103)
Instrument F-test		14.48
Sargan test p-value		0.625
Observations	20,000	20,000
Countries	100	100
Year-Quarter FE	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. The level of returns is the average stock return across firms in the panel of simulated data. The volatility of returns is the variance of returns in the cross section of firms in the simulated data. Standard errors clustered by country. Column (1) estimated by OLS and column (2) by instrumental variables. All columns include a full set of country dummies and a full set of year by quarter dummies. †significant at the 15% level, * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2: Descriptive Statistics (yearly frequency)

	Obs.	Mean	Median	Std. Dev.	Min	Max
Annual GDP Growth, %	9683	3.46	3.49	7.29	-38.02	25.98
Return Level Index	4416	-0.01	0.05	0.98	-5.21	4.79
Return Volatility Index	4406	-0.02	0.00	1.00	-5.19	2.90
Stock Returns, %	7047	0.01	0.01	0.08	-0.45	0.45
Log (Stock Ret. Volatility)	7047	-4.51	-4.53	0.49	-6.06	-2.59
Cross Sectional Returns	4573	0.00	0.00	0.09	-0.38	0.93
Log (Cross Sectional Volatility)	4533	-1.56	-1.56	0.35	-3.89	-0.39
Bond Yields, %	5149	7.28	6.81	4.25	-0.14	55.93
Log (Bond Yield Volatility)	5098	-4.35	-4.47	0.81	-8.56	-0.66
Log (Exchange Rates, per $)	9283	1.31	0.98	3.79	-27.12	10.03
Log(Exch. Rate Volatility)	9283	1.51	1.70	1.27	-3.80	3.67
Natural Disasters	9683	0.242	0	0.63	0	4
Natural Disasters (scaled by media increase)	9683	0.096	0	0.46	0	7.98
Political Shocks	9683	0.011	0	0.11	0	1
Political Shocks (scaled by media increase)	9683	0.030	0	0.41	0	14.07
Revolution shock	9683	0.011	0	0.10	0	1
Revolutions (scaled by media increase)	9683	0.003	0	0.06	0	2.47
Terrorist attacks	9683	0.008	0	0.09	0	1
Terrorist attacks (scaled by media increase)	9683	0.005	0	0.09	0	3.67
GDP Per Capita (2005 $US, World Bank PPP)	9683	24143	24643	16702	1335	78559

Notes: All values are yearly averages unless noted otherwise. Data from 60 countries from 1970 to 2017.

Table 3: Real data – estimated impact of returns and volatility on GDP Growth

	(1)	(2)	(3)	(4)
Estimation	OLS	IV	IV	IV
Period:	Yearly	Yearly	Yearly	Yearly
Stock Measure	Micro+Macro	Micro+Macro	Macro	Micro
Level of returns $_{t-1}$	0.589***	1.738***	3.070***	0.964**
	(0.110)	(0.243)	(0.391)	(0.406)
Volatility of returns $_{t-1}$ (in logs)	-0.607***	-6.874***	-7.093***	-9.818***
	(0.197)	(0.388)	(0.699)	(0.631)
IV 1st stage: Levels				
Natural Disasters $_{t-1}$		-0.237*	-0.0718	-0.3001*
		(0.130)	(0.176)	(0.162)
Political Shocks $_{t-1}$		2.19***	1.674***	1.86***
		(0.069)	(0.051)	(0.064)
Revolutions $_{t-1}$		-7.72***	-6.92***	-5.66***
		(0.394)	(0.3622)	(0.308)
Terrorist attack $_{t-1}$		-0.314	-0.1391	-0.357
		(0.518)	(0.501)	(0.361)
Instrument F-test		313.9	386.08	239.72
IV 1st stage: Volatility				
Natural Disasters $_{t-1}$		-0.0467	-0.0842	0.0121
		(0.181)	(0.1661)	(0.1363)
Political Shocks $_{t-1}$		1.094***	1.137***	0.5794***
		(0.083)	(0.08026)	(0.0833)
Revolutions $_{t-1}$		4.71***	3.319***	4.122***
		(0.274)	(0.2948)	(0.2642)
Terrorist attacks $_{t-1}$		0.186**	0.3457*	-0.058
		(0.094)	(0.194)	(0.1176)
Instrument F-test		158.01	104.04	84.55
Sargan test p-value		0.681	0.551	0.782
Observations	4,406	4,406	4,406	4,406
Countries	42	42	42	60
Year-Quarter FE	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, while column (3) is macro (index) and column (4) is micro (cross-firm) returns. Standard errors clustered by country. Data is quarterly by country from 1970 until 2013. 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. All columns include a full set of country dummies and a full set of year by quarter dummies. †significant at the 15% level, * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Real data – estimated impact of returns and volatility on GDP Growth (trade- and distance-weighted)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation:	IV	IV	IV	IV	IV	IV
Weighting:	Trade	Distance	Trade	Distance	Trade	Distance
Period:	Yearly	Yearly	Yearly	Yearly	Yearly	Yearly
Stock Measure	Micro+Macro	Micro+Macro	Macro	Macro	Micro	Micro
Level of returns $_{t-1}$	3.34***	2.38***	3.37***	2.33**	4.59**	1.62
	(1.22)	(0.716)	(0.563)	(0.974)	(2.19)	(1.45)
Volatility of returns $_{t-1}$ (in logs)	-5.11***	-6.62***	-6.63***	-5.15***	-5.04*	-6.84***
	(1.79)	(1.20)	(0.697)	(1.91)	(2.64)	(1.49)
IV 1st stage: Levels						
Natural Disasters $_{t-1}$	-0.130**	-0.047†	-0.119**	-0.060**	-0.165**	-0.026
	(0.057)	(0.032)	(0.061)	(0.033)	(0.069)	(0.042)
Political Shocks $_{t-1}$	0.894***	0.915***	1.51***	1.52***	0.261	0.264
	(0.115)	(0.100)	(0.565)	(0.511)	(0.211)	(0.224)
Revolutions $_{t-1}$	-6.33***	-4.94***	-5.51***	-1.98	-5.03***	-4.52***
	(0.417)	(1.38)	(0.392)	(2.96)	(0.366)	(0.745)
Terrorist attack $_{t-1}$	-0.187***	-0.108	-0.165***	-0.070	-0.184***	-0.155*
	(0.055)	(0.092)	(0.064)	(0.074)	(0.047)	(0.091)
Instrument F-test	104.2	35.8	66.38	4.54	73.58	24.89
IV 1st stage: Volatility						
Natural Disasters $_{t-1}$	-0.104	-0.020	-0.015	0.003	-0.72	0.019
	(0.082)	(0.033)	(0.089)	(0.031)	(0.074)	(0.038)
Political Shocks $_{t-1}$	0.584***	0.550***	0.804***	0.728***	0.340***	0.297***
	(0.054)	(0.077)	(0.298)	(0.286)	(0.049)	(0.048)
Revolutions $_{t-1}$	4.174***	3.53***	4.12***	4.068***	4.02***	3.46***
	(0.260)	(0.777)	(0.287)	(0.828)	(0.272)	(0.654)
Terrorist attacks $_{t-1}$	0.112**	0.112*	-0.015	0.005	0.167**	0.083
	(0.053)	(0.069)	(0.076)	(0.077)	(0.070)	(0.089)
Instrument F-test	109.9	24.39	54.14	7.87	84.57	30.4
Sargan test p-value	0.203	0.264	0.734	0.725	0.289	0.307
Observations	4,406	4,406	6,997	6,997	4,406	4,406
Countries	42	42	60	60	42	42
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

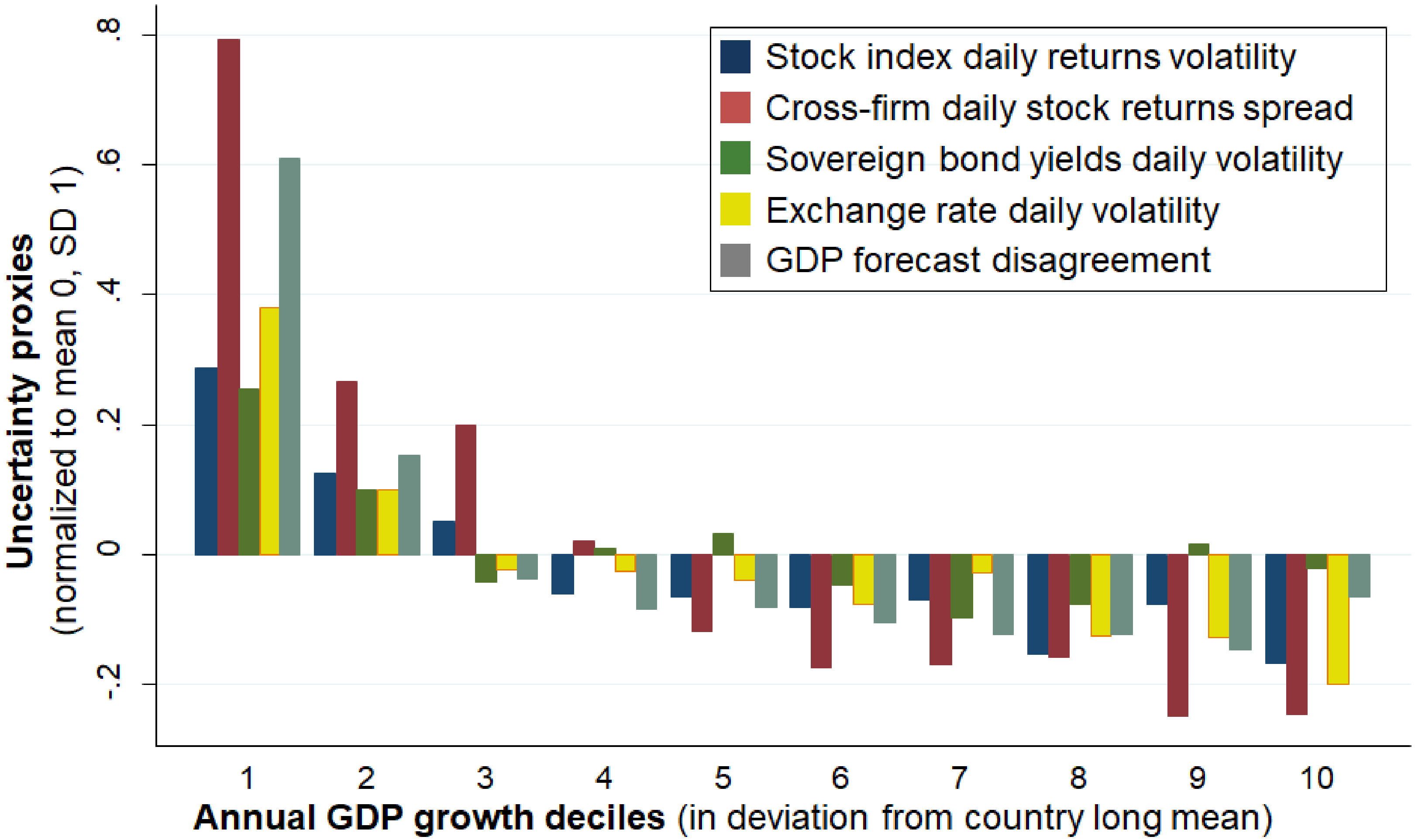
Notes: The dependent variable is GDP growth. †significant at 15%, * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by country. Data is quarterly by country from 1970 until 2017. All columns estimated by instrumental variables with a full set of quarter-by-year 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 borders; shocks occurring in bordering countries will receive a weight of 0.5).

Table 5: Robustness of Main Stock Returns Results to Alternate Specifications and Sample Splits

Specification	(1) Baseline Index	(2) Bond Yields	(3) Population Weighted	(4) No Media Scaling	(5) Add Skewness	(6) Only Skewness	(7) Split by GDP per capita	(8) Split by time period
Level of returns $_{t-1}$	1.738***	5.710	1.621**	0.326*	2.287		2.313*	1.408
	(0.243)	(8.014)	(0.774)	(0.181)	(1.423)		(1.41)	(0.383)
Volatility of returns$_{t-1}$	-6.874***	-5.283**	-4.100***	-0.572*	-6.281***		-5.348***	-6.657
(in logs)	(0.388)	(2.093)	(0.828)	(0.330)	(2.222)		(1.82)	(1.173)
Skewness of returns$_{t-1}$					-1.783	-4.853**		
					(9.444)	(2.454)		
Rich*Level of returns $_{t-1}$							2.236	
							(7.92)	
Rich*Volatility of returns$_{t-1}$							7.28	
							(5.49)	
Post2000*Level of returns $_{t-1}$								0.738
								(6.170)
Post2000*Vol of returns$_{t-1}$								-0.888
								(2.687)
Relative Magnitude vol to level	3.96	0.93	2.53	1.79	2.75	-	4.16	4.73
Sargan p-value	0.418	0.413	0.381	0.107	0.310	0.272	0.302	0.454
Observations	4,406	4,923	4,406	4,406	4,406	4,406	4,406	4,406

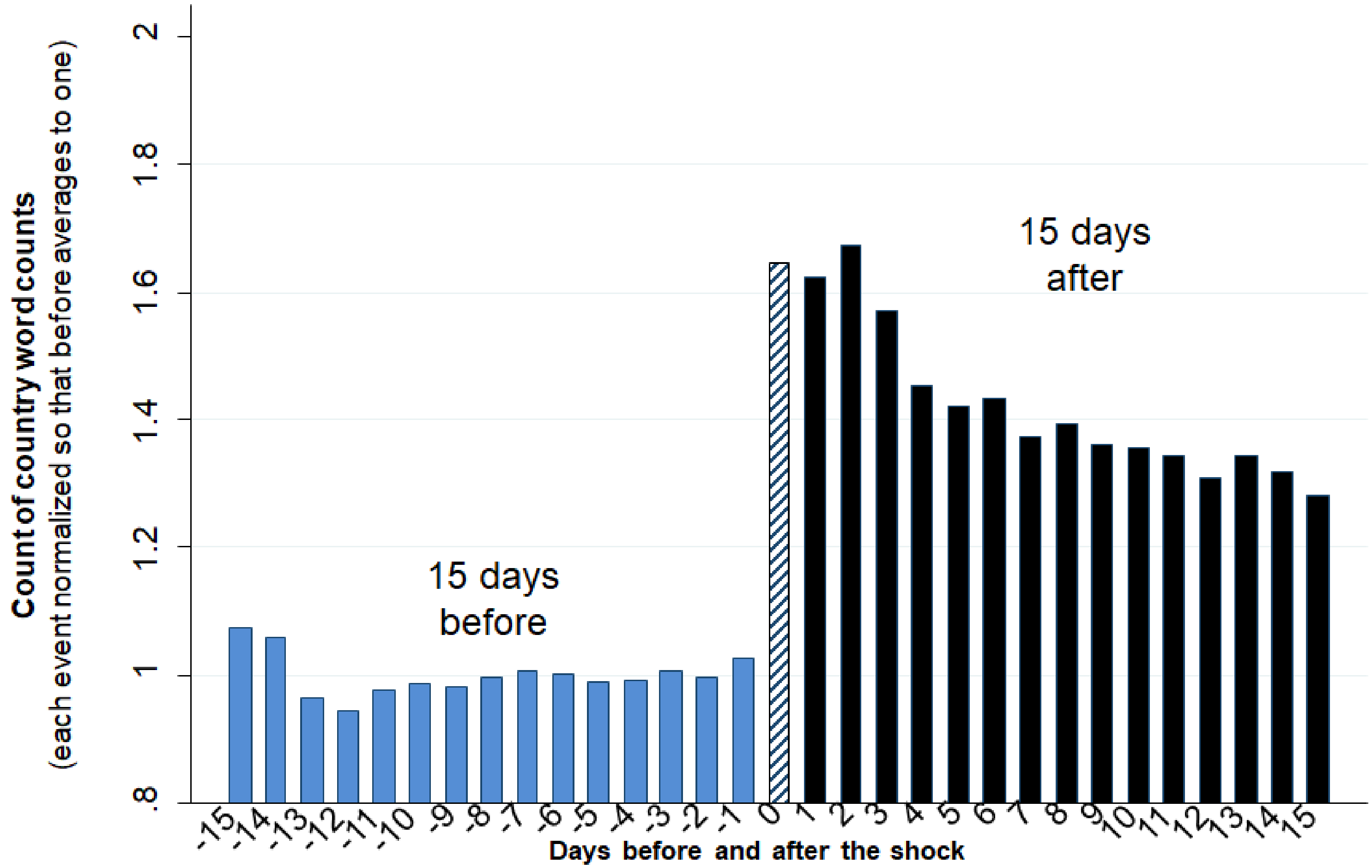
Notes: The dependent variable is GDP growth. †significant at 15%, * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered by country. Data is quarterly by country from 1970 until 2017. All columns estimated by instrumental variables with a full set of quarter-by-year 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, except for column (4) which is not multiplied at all. 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 (7) splits countries by the sample median of long-run GDP per capita, which is ~$25,000 (in 2010 dollars). The split in column (8) is by the time period being pre-2000 or greater than equal to 2000.

Figure 1: All our uncertainty proxies are negatively correlated with growth across our (unbalanced) panel for 60 countries, 1970-2012



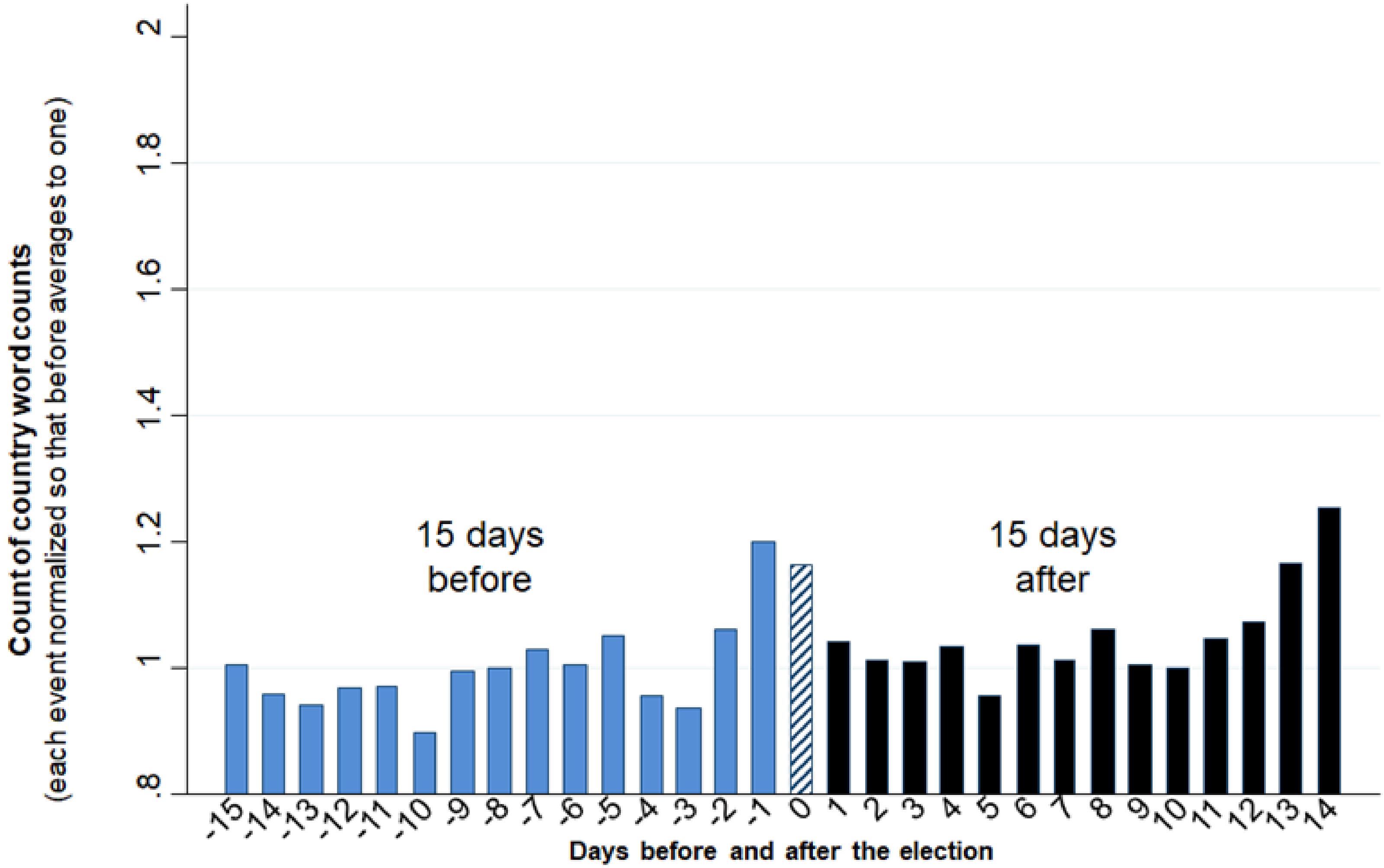
Notes: Volatility indicators constructed from the unbalanced panel of daily data from 1970 to 2012 from 60 countries. Volatility values are calculated across all trading days (1-year ahead GDP growth forecasts) within each year, and then normalized for presentational purposes so each of the five indicators has a mean of 0 and a standard-deviation of 1 over the sample. The GDP growth deciles are calculated using annual values in deviations from the country mean across the sample.

Figure 2: Newspaper daily word counts for the affected country in the one month around the natural disaster, political or terrorist shock



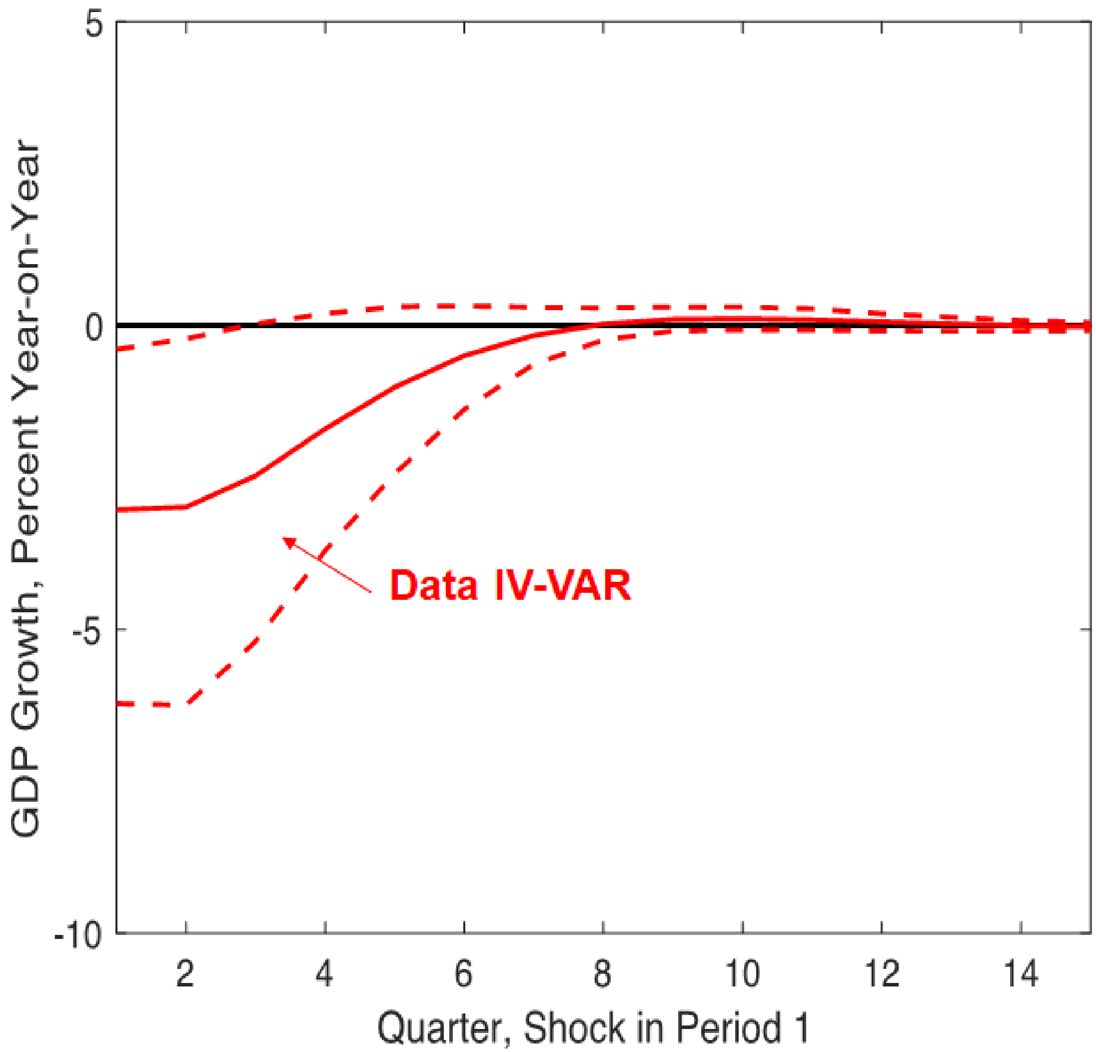
Notes for the figure: Shows the daily count of the name of the impacted country in the two weeks before and after the shock, averaged over the 1353 shocks studied in the regression analysis. For graphing purposes the series for each event is normalized so that over the 15 days before the shock it has 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 3: Newspaper daily word counts for the affected country in the one month around national elections



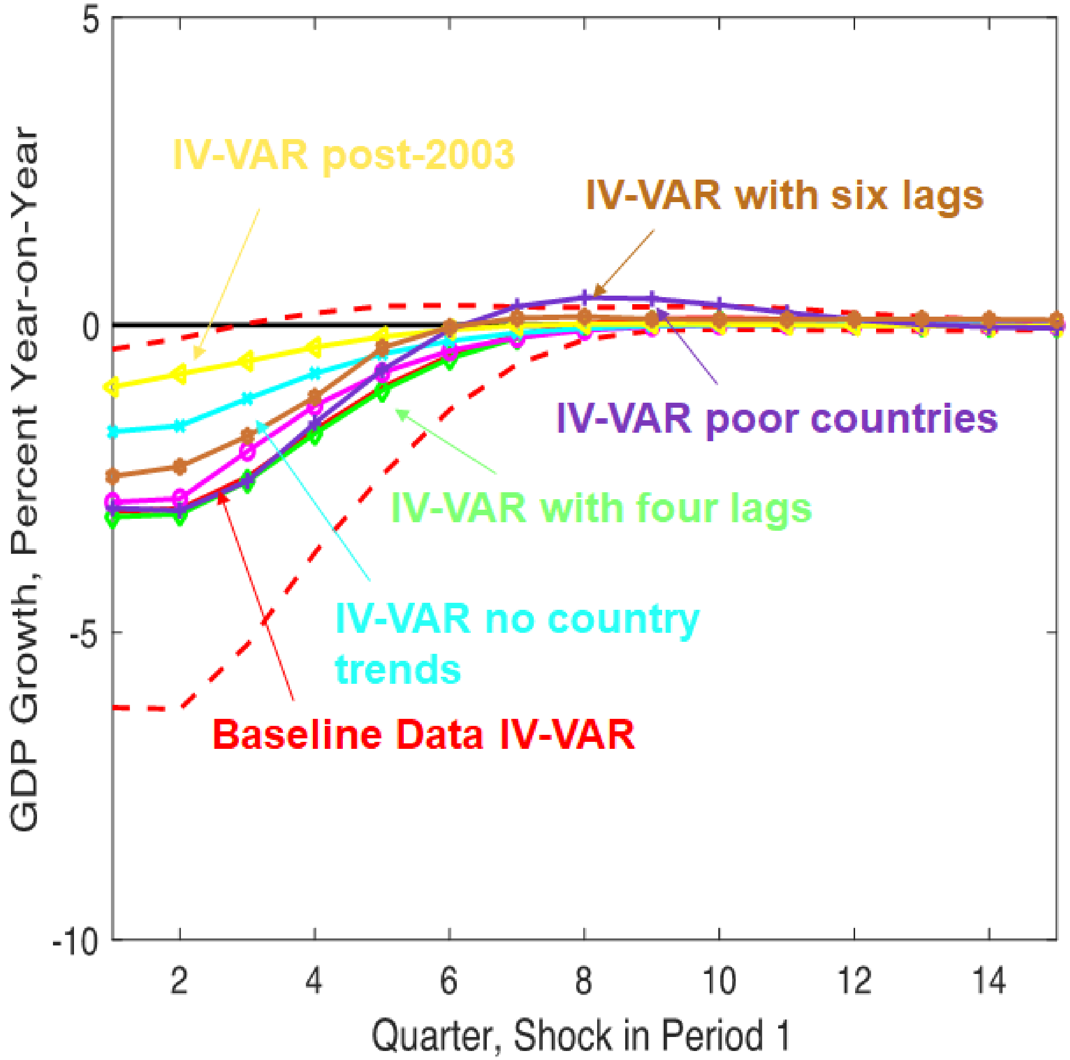
Notes for the figure: Shows the daily count of the name of the impacted country in the two weeks before and after the election, averaged over the 133 elections in the G20 countries our sample. The series for each event is normalized for graphing so that over the 15 days before the election it has a mean of one.

Figure 4: The disaster IV VAR reveals that an uncertainty shock causes a drop in growth of around 3%



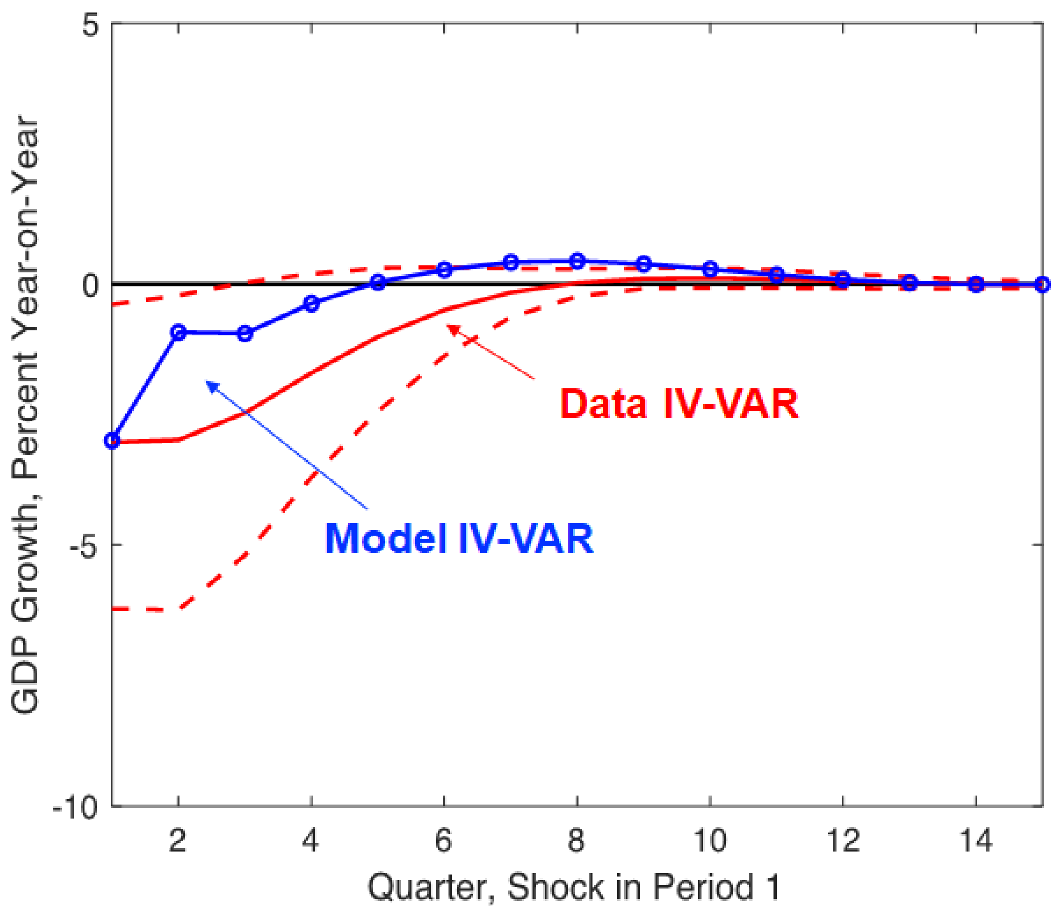
Notes: The figure shows the response of GDP growth to a one-standard deviation innovation in volatility estimated using the disaster instruments VAR. The plotted 90% error bands are based on a stationary block bootstrap. The sample is an unbalanced panel of 4,000 nation-quarters spanning 40 nations from 1987Q1-2017Q3. GDP growth in period t is the percentage growth from quarter t-4 to t. The estimated VAR includes time dummies, country dummies, and 3 lags of the endogenous vector with GDP growth, stock returns, and stock return volatility. The instruments include natural disasters, coups, revolutions, and terrorist attacks.

Figure 5: The drop in growth after an uncertainty shock is robust to different samples, lags, specifications etc



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 (red, no symbols), low-income nations (purple + signs), post-2003 (yellow triangles), with four lags (green diamonds), with six lags (orange hexagrams), and no country trends (cyan x signs). The plotted 90% error bands are based on a stationary block bootstrap. The sample is an unbalanced panel of 4,000 nation-quarters spanning 40 nations from 1987Q1-2017Q3. GDP growth in period t is the percentage growth from quarter t-4 to t. The baseline estimated VAR includes time dummies, country dummies, and 3 lags of the endogenous vector with GDP growth, stock returns, and stock return volatility. The instruments include natural disasters, coups, revolutions, & terrorist attacks.

Figure 6: The disaster instruments VAR yields similar impacts of an uncertainty shock in the data and the simulation



Notes: The figure shows the response of GDP growth to a one-standard deviation innovation in volatility estimated using the disaster instruments VAR. The empirical response is in red, while the response estimated on equivalent model data is in blue with circles. The plotted 90% error bands are based on a stationary block bootstrap. The empirical sample is an unbalanced panel of 4,000 nation-quarters spanning 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 dummies, country dummies, and 3 lags of the endogenous vector with GDP growth, stock returns, and stock return volatility. The instruments include natural disasters, coups, revolutions, and terrorist attacks.