

Online Appendix

A Data Appendix

A.1 Disaster Shock Data

We discuss the details of the definitions of each of the groups of disaster shocks in this section.

Natural Disasters: Our natural disaster data has been obtained from the Center for Research on the Epidemiology of Disasters (CRED).¹² This dataset contains over 15,000 extreme weather events such as, droughts, earthquakes, insect infestations, pandemics, floods, extreme temperatures, avalanches, landslides, storms, volcanoes, fires, and hurricanes throughout our sample period. 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. We limit our sample to natural disasters that cause either 100 deaths or deal damages more than 0.1% of national GDP.

Terrorist Attacks: To define terrorist events we use the Center for Systemic Peace (CSP): High Casualty Terrorist Bombing list, which extends from 1993-2020. We include all terrorist bombings or attacks that cause over 50 deaths in our sample.¹³ 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

¹²See <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.

¹³See <http://www.systemicpeace.org>. 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 to coordinate and standardize data created and utilized by the CSP.

shocks, we include all successful assassination attempts, coups, revolutions, and wars, from 1970Q1-2020Q1.

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

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

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

In Table A1 we report forecasting specifications for these various shocks and demonstrate that they are not anticipated by the market in advance and are not predictable from national economic trends.

A.2 Economic Data

Output Data: Real GDP is obtained from the Global Financial Database (GFD) wherever possible. Data from the IMF, World Bank, and World Development Indicators and World Economic Outlook databases was used for a subset of countries.¹⁴ Real GDP data is denominated in the local currency and its reference year varies.

¹⁴We proxy for GDP data with industrial production for Poland, Romania, and Nigeria.

As we deal with percentage changes, the different denominations and base years of different countries do not matter, in practice. We use yearly real GDP growth by quarter (year-on-year growth) as our dependent variable to remove seasonality and reduce the impact of high-frequency measurement errors.

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

Macro Uncertainty Proxy – Stock Market Index Data: Data on stock indices was obtained from the Global Financial Database, using the broadest general stock market index available for each country.¹⁵ 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, to match the timing of our yearly GDP growth rates. This serves as our first-moment series. A measure of average yearly volatility is created by taking the average of quarterly standard deviations of daily stock returns over the previous four quarters.

Micro Uncertainty Proxy – Cross Sectional Firm Return Data: As a micro-focused measure of first- and second-moment shocks, we look at returns across individual firms. We employ data from the WRDS international equity database, using data from all countries in our sample which have daily data from greater than 10 listed firms (comprising 39 of the 59 countries in our main sample). We then use the standard deviation of quarterly returns across firms to construct our second-moment series.

“Overall” stock market uncertainty: As our overall or “micro + macro” measure of uncertainty we combine our macro uncertainty (stock market index) and micro uncertainty (firm dispersion of returns) measures into a single standardized index. We first normalize both measures to a zero mean and unit standard deviation series and take their average. As such, our measure places equal weight on macro and micro variations in stock returns, though we also investigate the impact of other weightings

¹⁵Wherever possible we used daily data, but for six countries (Saudi Arabia, Mexico, South Africa, Ireland, Russia, and Turkey) 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. Our results are robust to the exclusion of observations taken from non-daily stock data and to excluding all observations from these countries.

which tend to yield relatively similar results because macro and micro stock returns and volatility are quite highly correlated.

Other Uncertainty Measures: We also compile a number of other proxies of macroeconomic uncertainty including data on exchange rates, forecaster disagreement, and news-based measures of uncertainty.

We collect daily exchange rate data from the Global Financial Database whenever available (excluding periods of fixed exchange rates) and use the quarterly volatility of daily percentage change of exchange rates as an alternative measure of uncertainty. Exchange rates are measured as 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. Additionally, we do not use values of 0 for exchange rate volatility, which affects 548 quarters due to fixed exchange rates.

We use the Consensus forecast database which collects data from forecasters for a variety of outcomes including GDP across different countries. For each country, we utilize the standard deviations of one year ahead GDP growth forecasts as a measure of uncertainty.

Finally, we utilize the World Uncertainty Index (WUI) and Economic Policy Uncertainty Indexes (EPU) as alternative proxies for macro uncertainty. The WUI measures levels of uncertainty across countries using mentions of uncertainty contained in Economist Intelligence Unit reports, while EPU mainly tracks discussion of articles that mention economic policy uncertainty within newspaper articles in each country.

B Event Restrictions VAR

As noted in the text, in our first VAR approach we rely on an adaptation of the event restrictions approach for structural VAR identification in Ludvigson, Ma, and Ng (2021). The econometric framework is a three-variable VAR in the following series:

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

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

This VAR in the 3 variables growth (g_{it}), first moments (F_{it}), and second moments (S_{it}) has a panel structure running across nations i and quarters t . Without loss of

generality we describe a single-lag VAR since further lags can be accommodated in a similar equation in companion form. We allow for country and time effects f_i and g_t . The vector of innovations η_{it} reflects reduced-form disturbances to the VAR system, which are linked to a vector of random structural shocks e_{it} according to $e_{it} = B^{-1}\eta_{it}$ where B is a 3×3 matrix containing the contemporaneous impacts of each structural shock on the series in X_{it} . We assume the structural shocks are standardized with $e_{it} = (e_{Yit}, e_{Fit}, e_{Sit}) \sim (0, I_{3 \times 3})$.

Now, in this context the matrix A and fixed effects f_i and g_t can be consistently estimated via OLS, as usual. But since $A^s B$ is the impulse response matrix of interest at horizon s , we must also recover B . As usual, the covariance matrix of the reduced-form innovations $Cov(\eta_{it}, \eta_{it})$ contains only 6 unique elements, which in this case are given by $Cov(\eta_{it}, \eta_{it}) = BB'$. Since B has 9 elements, this information alone fails to independently identify the elements of the matrix B . So we then specify thresholds $k_{Revolution}^F, k_{Revolution}^S, k_{Coup}^F, k_{Coup}^S > 0$, and we define a list of differences linked to the inequalities listed in the main text which can be evaluated for any candidate matrix B .

1. Mean first-moment shocks on revolution dates, relative to the threshold:

$$g_{Revolution}^F(B) = -\mathbb{E}[e_{Fit}(B)|Revolution_{it}] - k_{Revolution}^F$$

2. Mean second-moment shocks on revolution dates, relative to the threshold:

$$g_{Revolution}^S(B) = \mathbb{E}[e_{Sit}(B)|Revolution_{it}] - k_{Revolution}^S$$

3. Mean first-moment shocks on coup dates, relative to the threshold:

$$g_{Coup}^F(B) = \mathbb{E}[e_{Fit}(B)|Coup_{it}] - k_{Coup}^F$$

4. Mean second-moment shocks on coup dates, relative to the threshold:

$$g_{Coup}^S(B) = \mathbb{E}[e_{Sit}(B)|Coup_{it}] - k_{Coup}^S$$

5. Mean first-moment shocks on terror attack dates:

$$g_{Terror}^F(B) = -\mathbb{E}[e_{Fit}(B)|Terror_{it}]$$

6. Mean first-moment shocks on natural disaster dates:

$$g_{NatDisaster}^F(B) = -\mathbb{E}[e_{Fit}(B)|NatDisaster_{it}]$$

The expectations are averages taken across the empirical sample of structural shocks implied by a candidate matrix B given by $e_{it}(B) = B^{-1}\eta_{it}$. We can collect the differences above into a vector

$$g(B) = (g_{Revolution}^F, g_{Revolution}^S, g_{Coup}^F, g_{Coup}^S, g_{Terror}^F, g_{NatDisaster}^F)'$$

where we note that a matrix B satisfies the inequalities listed in the main text exactly when $g(B) \geq 0$. Following the approach in Ludvigson, Ma, and Ng (2021), we first compute the lower-triangular Cholesky decomposition Σ of the reduced-form covariance matrix $Cov(\eta_{it}, \eta_{it})$. We then draw a group of candidate matrices B satisfying $Cov(\eta_{it}, \eta_{it}) = BB'$ via the orthogonal component Q of the QR decomposition of 1.5 million matrices with randomly drawn standard normal entries together with $B = \Sigma Q$. The set \mathcal{B} of admissible matrices is those candidates for which $g(B) \geq 0$, and we note that the matrices B in the set \mathcal{B} also define an associated group of admissible impulse responses $A^s B$ for horizon s .

In our baseline implementation in the text, we employ a VAR with 12 lags and set $k_{Revolution}^S = k_{Coup}^S = 15\%$ together with $k_{Revolution}^F = k_{Coup}^F = 10\%$. We use the macro first- and second-moment series to maximize the sample size and number of disaster events in our group of restrictions. Figure 3 plots the baseline horizon-by-horizon upper and lower bounds of the admissible impulse responses in \mathcal{B} (blue lines) together with the horizon-by-horizon median response (green line with \times markers). The figure also plots (red lines with circles) the IRF associated with the “maxG” matrix $B \in \mathcal{B}$ which maximizes the collective size of the inequality restrictions $g(B)'g(B)$. Figure B1 plots the upper and lower bounds of the admissible impulse responses in \mathcal{B} for all variables and shocks in our baseline estimation. Figure 4 plots the distribution of elements $B(1, 3)$ – corresponding to the immediate impact of a one-standard deviation shock to uncertainty — across the matrices in \mathcal{B} in the baseline estimation

(blue bars), disregarding g_{Error}^F and $g_{\text{NatDisaster}}^F$ (green bars), and only considering $g_{\text{Revolution}}^F$ and $g_{\text{Revolution}}^S$ (red bars). Figure 5 plots the upper and lower boundaries of the admissible impulse responses in \mathcal{B} for a range of alternative lag lengths, looser event restrictions ($k_{\text{Revolution}}^S = k_{\text{Coup}}^S = 14\%$, $k_{\text{Revolution}}^F = k_{\text{Coup}}^F = 9\%$), tighter event restrictions ($k_{\text{Revolution}}^S = k_{\text{Coup}}^S = 16\%$, $k_{\text{Revolution}}^F = k_{\text{Coup}}^F = 11\%$), and alternative VAR specifications without time or country effects, etc. In the cases without country fixed effects or time fixed effects, the meaningful unabsorbed country-level heterogeneity or common time shifts imply that a looser set of event restrictions are required to generate non-empty admissible sets of responses. In all cases, the admissible set of impacts of uncertainty on growth includes only negative responses.

C Disaster Instruments IV-VAR

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

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

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

This VAR in the 3 variables growth (g_{it}), first moments (F_{it}), and second moments (S_{it}) has a panel structure running across nations i and quarters t . Without loss of generality we describe a single-lag VAR since further lags can be accommodated in a similar equation in companion form. We allow for country and time effects f_i and g_t . The vector of innovations η_{it} reflects reduced-form disturbances to the VAR system, which are linked to a vector of random structural shocks e_{it} according to $e_{it} = B^{-1}\eta_{it}$ where B is a 3×3 matrix containing the contemporaneous impacts of each structural shock on the series in X_{it} . We assume that the structural shocks e_{it} can be decomposed as

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

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

four types described in the main text satisfying $d_{it} \sim (0_{4 \times 1}, I_{4 \times 4})$. We also assume that the remaining disturbances are independent of the disasters and satisfy $\varepsilon_{it} \sim (0_{3 \times 1}, I_{3 \times 1})$. We assume that the disaster shocks influence the first- and second-moment structural innovations e_{Fit} and e_{Sit} alone according to the matrix D which has the following form

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

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

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

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

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

$$\mathbb{E}(\eta_{it} d_{it}') = B D$$

Together, $Cov(\eta_{it}, \eta_{it}) = B \Lambda B'$ and $\mathbb{E}(\eta_{it} d_{it}') = B D$ contain $6 + 12 = 18$ moments which are a function of the 17 parameters in B and D . This allows us to employ straightforward overidentified GMM estimation. We numerically implement the optimization using a diagonal weighting matrix and a quasi-Newton method. For the model and empirical results, we estimate the VAR using 3 lags with our composite micro + macro uncertainty index unless elsewhere specified. The figures report an

impulse response generating a second-moment increase of one standard deviation of the uncertainty series ex-time and country effects in our data. We compute empirical standard errors in the figures involving VAR results via a stationary block bootstrap of our empirical sample.

D Simulation Model and Structural Estimation

We introduce a heterogeneous firms business cycle model with micro and macro productivity fluctuations along the lines of Bloom et al. (2018). The model features time variation in the uncertainty or volatility of shocks. Given our empirical sample of nations, we use a small open economy model with fixed prices. To validate our empirical identification strategy, we link fluctuations in simulated disaster shocks to movements in the level and volatility of shocks in the model. We then run counterparts to our disaster instruments empirical regressions on simulated data, structurally estimating the parameters governing disaster shocks in our quantitative model via indirect inference targeting these regressions. This is similar to the “identified moments” approach outlined by Nakamura and Steinsson (2018) of matching a model to causally identified empirical moments. The results demonstrate that in this conventional model of uncertainty fluctuations and firm investment, a disaster instruments approach correctly uncovers the impact of uncertainty on growth. We also show that the IV-VAR estimates align closely in the data and the model, further validating the ability of our empirical strategy to correctly uncover the impact of uncertainty on growth.

D.1 Uncertainty at the Firm Level

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

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

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

$$\ln A' = \rho_A \ln A + \sigma^A \varepsilon_A$$

$$\ln z' = \rho_z \ln z + \sigma^z \varepsilon_z$$

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

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

D.2 Firm Investment and Value Maximization

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

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

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

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

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

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

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

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

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

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

subject to each of the constraints and stochastic processes laid out above. Numerically solving this model with five states and two endogenous policies is computationally intensive. We apply conventional but efficient applied dynamic programming techniques in our solution and simulation of the model. Given parameters, we solve the model numerically using a discretized grid and employing policy iteration in heavily parallelized Fortran. With the model solution in hand, we simulate the model by directly tracking the period-by-period distribution of firm states across periods subject to aggregate shocks which reflect both the standard driving processes for macro productivity A and macro uncertainty S as well as the arrival of iid disaster events described below.

D.3 The Impact of an Uncertainty Shock in the Model

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

and investment that drives a recession. Because inactive firms also respond less to their micro-level shocks in the face of increased uncertainty, misallocation also rises and leads to amplification and propagation of the recession.

D.4 Simulating the Model with Disasters

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

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

and a parameter governing the second-moment impact

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

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

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

where σ_L^A is the low-uncertainty standard deviation of the macro productivity innovations. Then, we increase the level of *volatility* S_t to a high state

$$S_t \rightarrow H$$

with probability λ_i^S .

To maintain a constant mean macro productivity level A and uncertainty shock S transition frequency during the simulation given the values of λ_i^F and λ_i^S , we insert a constant term in the macro TFP process as well as modify the uncertainty frequency parameter $\pi_{L.H}$ appropriately.

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

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

including information on the first-moment A_{kt} , second-moment S_{kt} , disasters d_{ikt} for $i = 1, \dots, 4$, and cross-sectional distribution μ_{kt} for country k at time t .

D.5 Estimating the Model with Indirect Inference

To use our environment as a quantitative laboratory for exploring our empirical identification strategy, we must first parameterize the model. We do this in a two-step process. First, we fix the values of a range of model parameters to conventional values for a quarterly solution from the literature, reporting these in Table D1. We also fix the arrival probabilities of disasters p_i to their empirical averages in our cross-country sample. Second, we structurally estimate the values of all the 8 parameters λ_i^F and λ_i^S governing the disaster shock process through an indirect inference procedure targeting the cross-country panel instrumental variables regressions discussed in Section 3. To do so, we need to compute target statistics or moments in the data. We target the first- and second-stage panel IV regression coefficients based on both the micro and macro uncertainty indexes, i.e., we target versions of columns (4) and (5) of Table 2. The result is a total of 16 first-stage coefficients and 4 second-stage coefficients, or 20 target coefficients. We must also compute these target statistics or IV regression coefficients in the model. To do so, we simulate a panel of firms, using the Bellman equation directly to define the valuation and implied stock returns at the firm level. This series of stock returns can be used to compute all of the micro and macro stock return series underlying our first- and second-moment indexes. The one exception is the empirical macro second-moment series, which in Section 3 is defined using the average of daily stock return volatilities over the past four quarters. Since our model is solved at quarterly frequency, we instead use the rolling mean over the past four quarters of the squared deviations of the average stock return from its mean value.

This moderate change in definition of the macro uncertainty series is one reason the target coefficients reported in Table D2 differ from the related specifications in Table 2. Collecting the target regression coefficients or moments into a stacked vector $m(X)$ dependent on our sample X , our indirect inference approach seeks to structurally estimate the value of a stacked parameter vector θ containing the disaster mapping parameters. This is done by solving the problem:

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

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

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

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

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

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

Above, N_{sim} is the number of nations in our simulated panel, N is the number of nations in the data, and Ω is the joint covariance matrix of our target regression coefficients allowing for country-level clustering. We set W to the identity matrix. We compute the moment Jacobians $\frac{\partial m(\theta)}{\partial \theta'}$ using numerical differentiation at the estimated parameters $\hat{\theta}$. The standard errors reported at the bottom of Table D2 rely on our feasible estimate of Σ , while the t-statistics between model moments $m(\hat{\theta})$ and data $m(X)$ moments in the top panel of Table D2 are based on our feasible estimate of Ω .

Intuitively, the first-stage target coefficients rely on heterogeneity in the param-

eters λ_i^F and λ_i^S mapping different disasters to observable first- and second-moment shifts. The second-stage target coefficients reflect the impact of each innovation on macro growth, which is indirectly a function of the size and sign of the disaster mappings λ_i^F and λ_i^S in our nonlinear model.

D.6 Parameter Estimates and Model IV Regressions

The bottom panel of Table D2 reports the structurally estimated disaster impacts λ_i^F and λ_i^S . Revolutions and terrorist attacks dominate the impact of disasters on first moments or levels, while political coups, revolutions, and terror attacks increase uncertainty or second moments appreciably. In the top panel, we examine the targeted IV regression coefficients, comparing the data versus the model. Given the overidentified nature of the estimation, with 8 parameters and 20 target regression coefficients, the model fits well. The first-stage regression coefficients based on both the micro and macro measures of uncertainty broadly mirror the underlying estimated disaster mappings in both the data and the model. Both micro and macro second-stage estimates in the data reveal a strong positive impact of levels shocks on growth, with a strong negative impact of uncertainty on growth, a pattern replicated in the model estimates. Crucially, the second-stage coefficients run on simulated data in columns (2) and (3) of Table D2 reveal that our IV approach correctly uncovers a negative impact of uncertainty on GDP growth.

D.7 The IV-VAR on Simulated Data

Armed with our structurally estimated model, we then estimate our IV-VAR on the simulated model data. Figure D1 plots two lines. The blue line with circles duplicates the baseline empirical IV-VAR estimates, uncovering an estimated drop in GDP growth after an uncertainty shock. The red line with plus signs plots the estimated impulse response of GDP growth to an uncertainty shock in simulated data. The magnitude of the drop and the recovery path are similar across the empirical dataset vs simulated data. The estimation exercise for the model targeted only the univariate panel IV regressions, but clearly the model matches both the initial impact and dynamics of the estimated VAR path quite closely.

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 (0.026)	0.044 (0.037)	-0.0003 (0.0006)	0.006 (0.014)				
Volatility of stock returns, last quarter	0.00001 (0.006)	0.009 (0.009)	0.002 (0.002)	0.0005 (0.003)				
GDP growth, last quarter	-0.0007 (0.0004)	0.0001 (0.0001)	-0.0001 (0.0001)	-0.001 (0.001)				
Volatility of stock returns, last year					0.006 (0.009)	0.006 (0.009)	0.002 (0.002)	-0.006 (0.005)
Level of stock returns, last year					-0.029 (0.045)	-0.029 (0.045)	-0.008 (0.008)	-0.011 (0.012)
GDP growth, last year					-0.001 (0.0007)	-0.001 (0.001)	-0.0001 (0.0001)	-0.001 (0.0007)
F-test p-value	0.154	0.486	0.808	0.832	0.396	0.462	0.776	0.452
Observations	5643	5643	5643	5643	6355	6355	6355	6355

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

Table D1: Calibrated model parameters

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

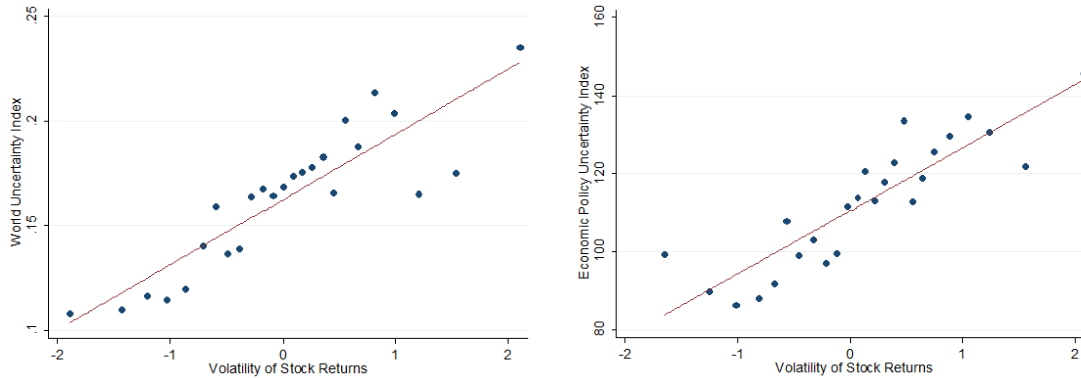
Notes: The table reports the values of calibrated parameters fixed before the structural estimation of the disaster mappings in the model. The values come from Khan and Thomas (2008) and Bloom, et al. (2018).

Table D2: Structurally estimated model parameters and fit

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

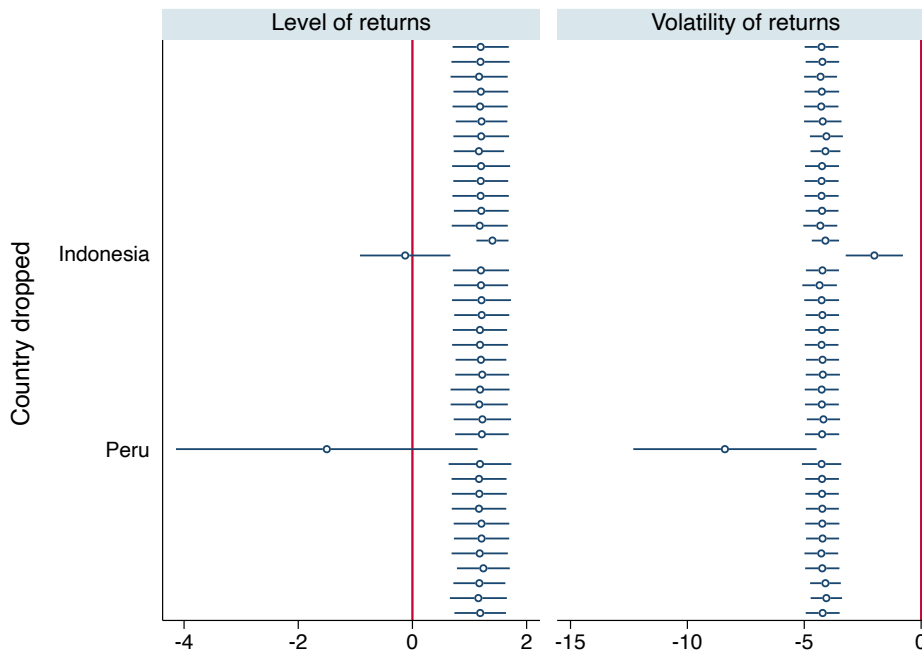
Notes: The top Panel A reports model vs data moments for the indirect inference estimation of the heterogeneous firms model. The target moments from the data are IV regression coefficients from the macro uncertainty measure (column (1)) and the micro uncertainty measure (column (3)). Year-quarter and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

Figure A1: Correlation of the World Uncertainty and Economic Policy Uncertainty indices with stock return volatility



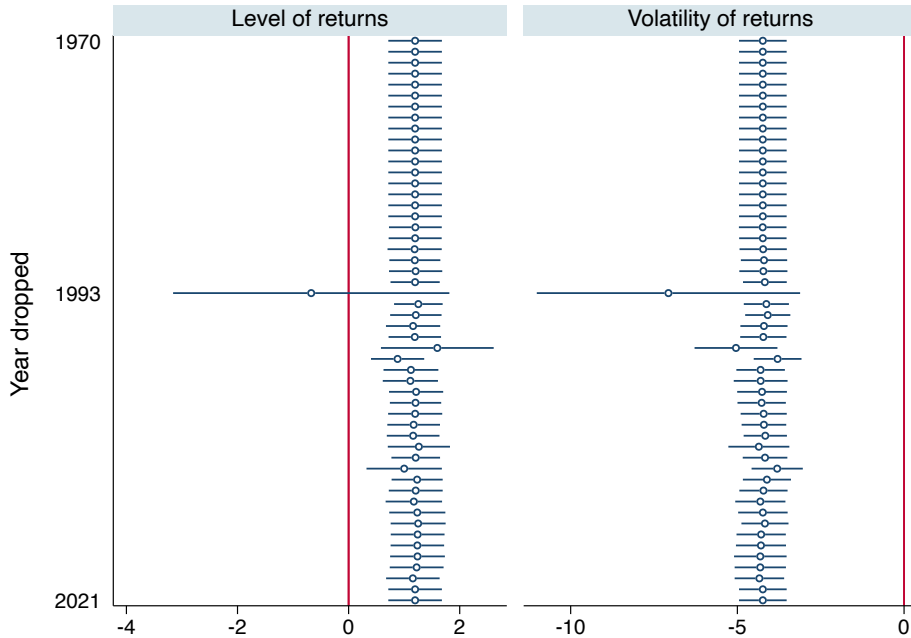
Notes: Left panel plots a bin-scatter (across 25 bins) of country-quarter values of the World Uncertainty Index (WUI) against a country-quarter measure of stock volatility. We are able to match this version of stock volatility and WUI values across 34 countries back to 1987. Right panel plots a bin-scatter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

Figure A2: Robustness of the estimated impact of levels and volatility on GDP Growth – Excluding countries one by one



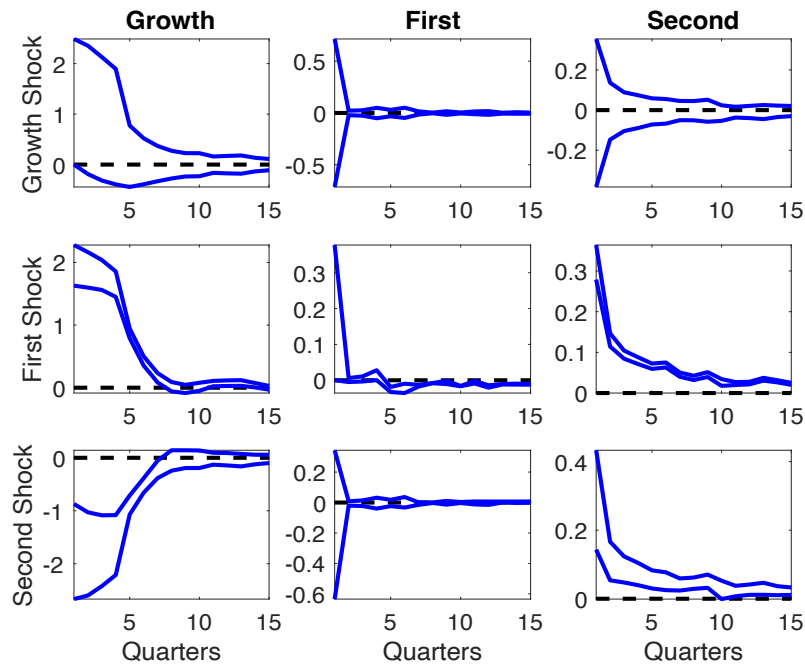
Notes: The figure plots the estimates for the level and volatility of stock returns in the IV estimation of Table 2 – Column (2) after removing (one by one) each of the 39 countries where the index of the micro (cross-firm) and macro (overall) stock returns can be calculated. The dependent variable is GDP growth. Standard errors are clustered by country and the regressions include year-quarter and country fixed effects. The countries which have a material impact on the estimation coefficients, Indonesia and Peru, are labelled.

Figure A3: Robustness of the estimated impact of levels and volatility on GDP Growth – Excluding years one by one



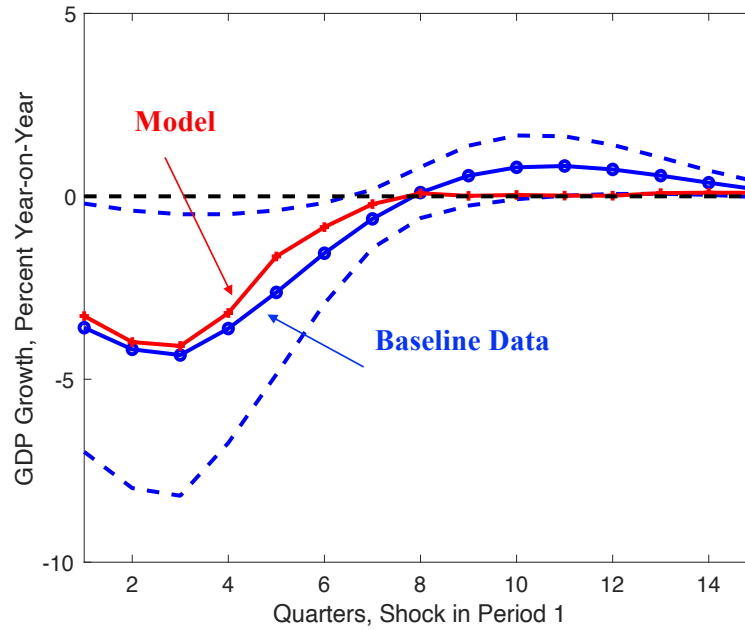
Notes: The figure plots the estimates for the level and volatility of stock returns in the IV estimation of Table 2 – Column (2) after removing (one by one) each year in the sample (1970 - 2021). The dependent variable is GDP growth. Standard errors are clustered by country and the regressions include year-quarter and country fixed effects. The year which has a material impact on the estimation coefficients, 1993, as well as the first and the last year of the sample are labelled.

Figure B1: The disaster event VAR restrictions offer discipline for the responses of GDP to first- and second-moment shocks



Notes: The figure plots admissible impulse responses to one standard deviation shocks to GDP growth, aggregate stock returns, and aggregate uncertainty in the event restrictions panel VAR. Each row plots admissible responses of all variables to a particular shock, and each column plots the responses of a particular variable to all shocks. The sample spans 58 countries for 6733 country-quarters over 1972Q2-2019Q4. The estimated VAR includes time and country effects, 12 quarterly lags. Maximum and minimum values of the set of admissible responses at each horizon consistent with the event restrictions are plotted in each case.

Figure D1: An uncertainty shock causes similar drops in GDP in the disaster IV-VAR in the data and the model



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