Online Appendix

A Data Cleaning

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

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

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

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

B Simulation Model and Structural Estimation

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

B.1 Incorporating Disasters

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

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

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

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

B.2 Calibrating, Solving, and Simulating the Model

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

B.3 Structurally Estimating the Model

In Section 4.5 we structurally estimate the parameters λ_i^F and λ_i^S through indirect inference. To do so, we need to compute target statistics or moments in the data. We target the first- and second-stage panel IV regression coefficients based on both the micro and macro uncertainty indexes, i.e., we target columns (4) and (5) of Table 2. We must also compute these target statistics or IV regression coefficients in the model. To do so, we simulate a panel of firms, using the Bellman equation directly to define the valuation and implied stock returns at the firm level. This series of stock returns can be used to compute all of the micro and macro stock return series underlying our first- and second-moment indexes. The one exception is the empirical macro second-moment series, which in Section 3 is defined using the average of daily stock return volatilities over the past four quarters. Since our model is solved at quarterly frequency, we instead using the rolling mean over the past four quarters of the squared deviations of the average stock return from its mean value. This moderate change in definition of the macro uncertainty series results in the differences between the target coefficients reported in Table 6 and the equivalent specifications in Table 2. Collecting the target regression coefficients or moments into a stacked vector $m(X)$ dependent on our sample X, our indirect inference approach seeks to structurally estimate the value of a stacked parameter vector θ containing the disaster mapping parameters. This is done by solving the problem:

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

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

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

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

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

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

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

C Disaster Instruments VAR

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

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

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

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. 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 $e_{it} = B\eta_{it}$ where B is a 3×3 matrix containing the contemporaneous impacts of each structural shock on the series in X_{it}. The matrix A can be consistently estimated via OLS, as usual. Since $A^s B$ is the impulse response matrix at horizon s, we must also recover B. As usual, the covariance matrix of the reduced-form innovations $\Omega = cov(\eta_{it}, \eta_{it})$ 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 as well as iid realizations of the disaster shock series D_{it} according to the following formula:

$$e_{it}^{F} = \sum_{i=1}^{4} d_{iF} D_{it} + \varepsilon_{Fit}, \quad e_{it}^{S} = \sum_{i=1}^{4} d_{iS} D_{it} + \varepsilon_{Sit}.$$

Now, identification of the VAR is based on recovery of the 9 elements in B together with the 8 parameters $d_{iF}, d_{iS} \quad, i = 1, \ldots, 4$. But the covariances of the reduced-form innovations 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.

D COVID-19 Pandemic Forecast Exercise

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

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

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

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 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.