Economic Quarterly—Volume 105, Number 2—Second Quarter 2019—Pages 59–103

Time-Varying Skewness and Real Business Cycles

Lance Kent and Toan Phan

A growing literature in macroeconomics and finance has found important economic effects of variations in risk, in particular shocks to the *volatility* of key macroeconomic variables (such as total factor productivity). However, much less is known about the importance of shocks to the *skewness* of macroeconomic variables.[1]

In this paper, we seek to quantify the economic effects of skewness shocks. To this end, we augment a small open economy real business cycle model with a novel feature: discrete regime changes in the higher-order moments of exogenous shocks, modeled as shocks to total factor productivity (TFP). We assume that in each period the economy can be in one of two possible Markov states: an *unrest* state or a *quiet* state. The unrest state is assumed to be associated with a substantial increase in volatility and negative skewness of shocks. This assumption is motivated by our empirical findings about the moments of business cycles of many countries that experience political unrest (see the discussion of our calibration below). Hence, unrest is effectively a shock to the second-order and third-order moments of the distribution of economic shocks.

[redacted] Amazon, lanckent@amazon.com (work completed while the author was affiliated with the College of William & Mary); Federal Reserve Bank of Richmond, toanvphan@gmail.com. This paper supersedes an earlier working paper entitled "Business Cycles and Revolutions." The authors are grateful for helpful discussions with Daron Acemoglu, Filipe Campante, Matthias Doepke, B.R. Gabriel, Elias Papaioannou, and Romain Wacziarg. The authors would also like to thank seminar participants at the Atlanta Fed, Midwest Macro, the National University of Singapore, the 2014 ASSA Meetings, Duke University, the 2014 ISNIE meetings, the 2014 ESEM meetings in Toulouse, Queen's University Belfast, Utrecht University, and Maastricht University for their suggestions and feedback. The views expressed herein are those of the authors and not those of the Federal Reserve Bank of Richmond or the Federal Reserve System. DOI: https://doi.org/10.21144/eq1050201

[1] See the related literature section for a discussion of existing studies.

To solve the model, we develop a third-order perturbation method to approximate the endogenous reactions to shocks to the second-order and third-order moments of TFP. Existing methods to solve and simulate models (including global approximations to policy functions as in Judd [1996] or Richter et al. [2014] or perturbation methods as in Andreasen et al. [2017]) rely on Monte Carlo simulations to calculate the dynamics of third-order moments of endogenous quantities such as output and consumption. However, Monte Carlo simulations are problematic for the computation of higher-order moments such as skewness because these higher-order moments are more sensitive to simulation error.[2] To overcome this problem, we build upon the method of Andreasen (2017) to calculate generalized impulse response functions (GIRF) of third-order approximations of third-order moments of endogenous variables. Our solution method exploits computational symbolic algebraic manipulation to calculate the third-order moments *without* Monte Carlo simulations. This technical innovation is nontrivial, since it requires solving for the dynamics of over 20,000 polynomials, in the presence of a Markov-switching state, that are up to ninth order in the state variables. Furthermore, our approach is readily applicable to other DSGE models, especially those for which the dynamics of higher-order moments of endogenous variables are of interest.

Calibration: To calibrate the model, we document and exploit the substantial changes in higher-order moments of aggregate economic variables during periods of mass political unrest. Unrest episodes, which are well-documented by the political science literature (Chenoweth and Lewis 2013), are helpful in identifying higher-order moment shocks for several reasons. First, we find that these episodes are associated with substantial increases in the volatility and negative skewness of growth rates of output, consumption, and investment. For instance, on average, a year during an unrest episode is associated with a more than 50 percent increase in the volatility and a more than three times increase in the negative skewness of output growth. The changes in higher-order moments of aggregate variables (output growth, consumption growth, and investment growth) associated with an episode of unrest can be estimated with reasonable precision, since the database provides a relatively large number of country-year observations (with

[2] The calculation of skewness and other higher-order moments is sensitive to the tails of the distribution of interest. Since realizations on the tails are rare, many Monte Carlo draws are needed to ensure that the tails are sufficiently sampled. Therefore, for a given simulation length, the influence of Monte Carlo simulation error is going to be much more pernicious for higher-order moments, such as skewness, than for lower-order moments, such as the mean.

eighty-four unrest episodes between 1960 and 2006, each lasting more than five years on average).

Second, since the model assumes that shocks are common knowledge, we ideally want to identify shocks using events that are easily observed for all agents, at home or abroad. Mass unrest episodes are appropriate for this end, as they are major events, and agents in the economy as well as investors abroad do not need to be econometricians to learn that a campaign of mass political unrest is underway. Hence, the onset of an unrest episode is likely to have a direct effect on economic agents' perceptions of risk. Furthermore, since the impulse response exercises assume unanticipated shocks, we ideally want to use events that are ex-ante difficult to predict. Unrest episodes are again appropriate for this end, as it has been well-documented that mass unrest is largely unanticipated because it requires unpredictable shocks that enable a large number of nonstate actors to overcome informational and coordination problems.[3]

Results: Our model shows that the increase in volatility and especially negative skewness when the economy enters an episode of unrest has quantitatively substantial impacts on economic activities. In the baseline calibration, the observed changes in volatility and negative skewness can explain 21 percent of the observed drop in average output growth, 45 percent of the drop in average consumption growth, and 51 percent of the drop in average investment growth during unrest episodes. More importantly, *the increase in negative skewness accounts for about half of these drops in growth.*

Intuitively, when shocks become more negatively skewed, risk-averse agents know that realizations on the left tail of the distribution of shocks have become more likely. The increase causes agents to shift their portfolios to safer assets abroad and accumulate stocks of these safer assets, leading to capital outflow and drops in domestic investment and output. The consequences of this increased mass on the left tail are heightened under Epstein-Zin preferences. A Taylor expansion of the household's Bellman equation reveals that Epstein-Zin preferences punish and reward, respectively, the second and third central moments of the future value function. To a second-order approximation, Epstein-Zin preferences penalize the second central moment, i.e., variance. To a third-order approximation, the preferences gain an additional term that rewards the third central moment, which is the product of skewness and variance raised to the power of 3/2. Therefore, the quantitative

[3] See, e.g., Kuran (1989), Chenoweth and Stephan (2011), and Edmond (2013). We also verify this in our probit analysis to predict the onset of unrest in Appendix A.2.

effects of time-varying variance is amplified by time-varying negative skewness.

We demonstrate the quantitative significance of skewness by comparing the losses in economic activities during unrest under a second-order approximation to the same losses under a third-order approximation. The second-order approximation can account for only half of the economic losses that the third-order approximation can. Therefore, negative skewness is revealed as an important component of risk.

Related literature. Our paper is related to several strands of the literature on higher-order moments of business cycles. First, there is a growing body of research that emphasizes the importance of the time-varying volatilities of economic variables (e.g., Justiniano and Primiceri 2008; Caldara et al. 2012; Arellano et al. 2012; Christiano et al. 2014; and Gilchrist et al. 2014. The study that is the closest to ours in quantifying the impact of time-varying higher-order moments is Fernández-Villaverde et al. (2011). They consider a stochastic volatility process for the real interest rate and explore the impacts of interest rate volatility shocks to economic activities. The primary difference between our paper and this literature is that while they focus only on shocks to second moments, we focus on shocks to both second-order and third-order moments.

Second, there is a related body of macro-finance research that stresses the importance of skewness (e.g., Rancière et al. 2008; Barberis and Huang 2008; Guvenen et al. 2014; Salgado et al. 2015; Feunou et al. 2015; and Colacito et al. 2015). Our analysis is most related and complementary to that of Colacito et al. (2015), who show the importance of time-varying skewness in a macro-finance model with Epstein-Zin preferences. The major difference is that while they focus on the effects of skewness on financial variables (implied equity Sharpe ratios and equity risk premia), we focus on the effects on real economic variables (the growth rates of output, consumption, and investment). Also, while they focus on the United States, we focus on emerging and developing economies. Finally, while they calibrate the model by looking at analysts' forecasts for the U.S. economy, we look at the changes in higher-order moments of real economic variables during unrest episodes.

Finally, our paper is also related to a body of literature that emphasizes the importance of rare disasters in explaining macroeconomic phenomena (e.g., Barro 2006; Gourio 2012; Andreasen 2012; Gabaix 2012). A key insight from this literature is that variations in the probability of rare disasters, modeled as events on the far left tail of the distribution of shocks, can have first-order macroeconomic effects, as they influence the precautionary behaviors of risk-averse agents. Our paper points out that time-varying negative skewness has similar effects. This is because an increase in negative skewness implies a higher probability of states with very low consumption. However, our estimation approach is different and complementary to existing approaches in this literature. Since rare disasters occur infrequently in data, the literature usually does not estimate the time variation in the probability of disasters from data,[4] or it employs calibrations to proxies such as time-varying volatility of equity returns (e.g., Gourio et al. 2013). In contrast, we exploit the uncertainty associated with episodes of unrest to estimate the time variation in the skewness of economic shocks when the economies enter and exit unrest.[5]

Our paper is organized as follows. Section 1 describes our data sources and documents several stylized facts on business cycles during unrest episodes. Section 2 introduces unrest to a standard small open economy model and calculates how much of the stylized facts can be explained by changes in the distribution of shocks. Section 3 concludes.

1. DATA AND STYLIZED FACTS

Data Sources and Definitions

For economics and other data, we use annual panel macroeconomic data from 154 countries listed in the World Bank's World Development Indicators (WDI) database over the interval 1960-2006. This includes three time series: real output, real investment, and real consumption. We also use WDI data on the Gini coefficient and Alesina et al.'s (2003) data on ethnic, linguistic, and religious fractionalization as control variables

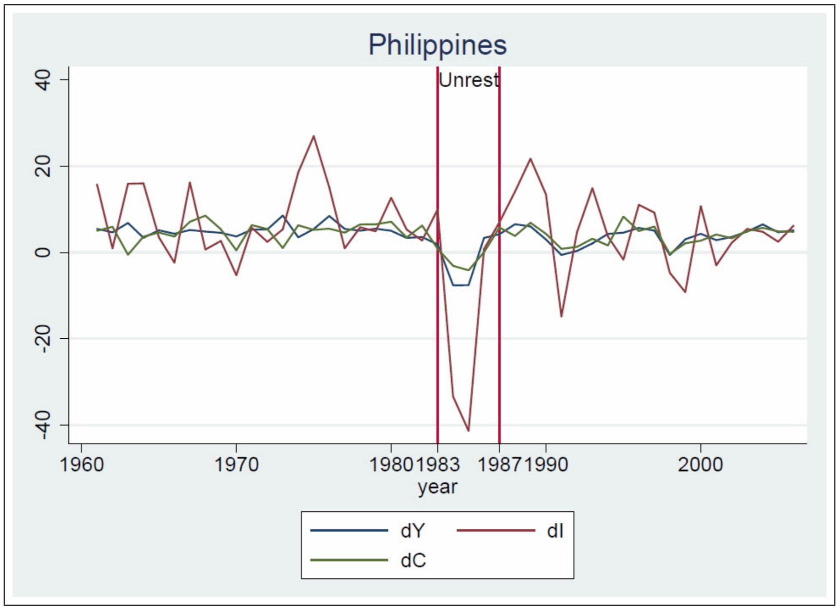
For mass unrest episodes, we use the Nonviolent and Violent Campaigns and Outcomes (NAVCO) dataset, version 2.0 (Chenoweth and Lewis 2013). NAVCO 2.0 provides a "consensus population" of all known continuous and large (having at least 1,000 observed participants) organized unrest campaigns between 1945 and 2006[6] that satisfy a series of conditions, as detailed in Appendix C. Each episode has an onset year and an end year. The onset year is defined as the first year with a series of coordinated, contentious collective actions with at least 1,000 observed participants. The episode is recorded as over when peak

[4] E.g., Nakamura et al. (2013) allow disasters to be correlated across countries but suppose that the probability of a given country entering into a disaster "on its own" is fixed over time.

[5] It is important to note that we do not identify unrest episodes themselves as disasters.

[6] More recent versions of the dataset include more recent years.

Figure 1 Example of Business Cycles Around Unrest



Notes: Growth rates of output, consumption, and investment (dY, dC, and dI respectively) of the Philippines around the People's Power Revolution (1983-87).

participation drops below 1,000. Overall, the NAVCO dataset provides 157 episodes of nonviolent and violent mass political unrest around the world between 1945 and 2006. Of these, there are eighty-four episodes in the years between 1960 and 2006, the period for which we have both unrest and economic data. Over this period, the average duration of an episode is 5.99 years.

Examples include many pro-democracy movements of civil unrest in Latin America, the Philippines's People Power Revolution (1983-87), Indonesia's civil unrest against Suharto (1997-98), and Mozambique's RENAMO resistance movement (1979-1992); for a complete listing of these episodes, see Appendix A.1. As an illustration, Figure 1 plots the time series of the growth rate in aggregate economic variables for the Philippines around the People's Power Revolution.

Stylized Facts on Business Cycles During Unrest

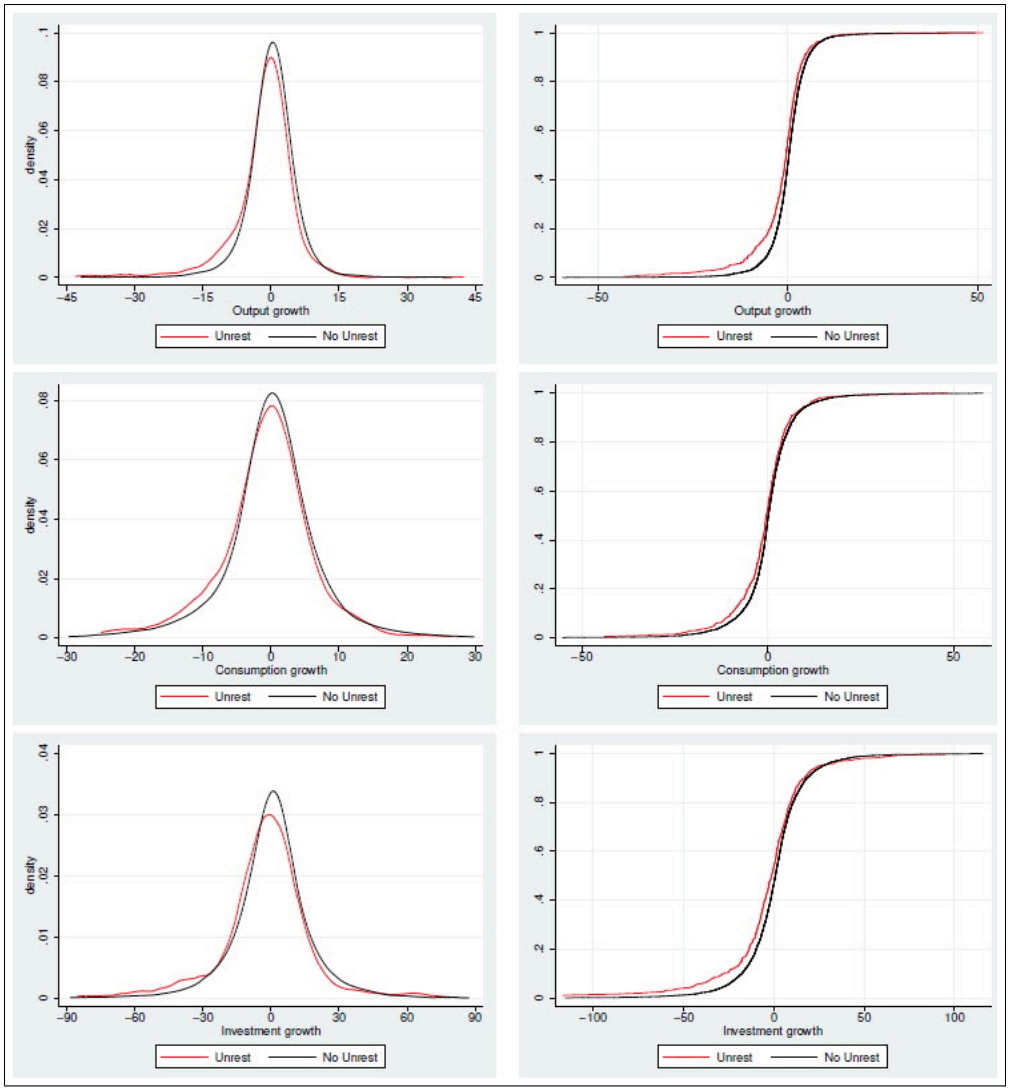
We now investigate the relationship between unrest and macroeconomic activities. The goal of this section is to arrive at a set of moments that will be used as calibration targets for the structural model of the following section. We focus on the contemporaneous association between unrest in a given country-year and the growth rates of output, consumption, and investment. We follow others in the macroeconomic literature (e.g., Fernández-Villaverde et al. 2011) and do not explicitly model why the higher-order moments change, nor do we attempt to make any causal claims about the contemporaneous causal impacts of unrest on output or vice versa.

We calculate the growth rates of output, consumption, and investment by the first difference in logs of the variable at constant 2005 USD and then remove a country-specific average growth rate from each series. That is, if the real output for country i in year t is Y_{it}, then we calculate the raw growth rate as $\Delta Y_{it} \equiv 100(\ln Y_{it} - \ln Y_{it-1})$. Then we take out the country's average growth rate to yield a demeaned output growth rate of $g_{Y,it} \equiv \Delta Y_{it} - \frac{1}{T_i}\sum_t \Delta Y_i$. A similar method is applied to demean consumption and investment growth. We demean to isolate fluctuations at the business cycle frequency and to control for differences in country-specific average growth rates.

We then contrast the distributions of growth rates during unrest $(g_{it}|U_{it} = 1)$ against moments during quiet times of no unrest $(g_{it}|U_{it} = 0)$ in Figure 2. The left column of Figure 2 displays smoothed kernel estimates of the empirical probability density functions for the growth rates of output, consumption, and investment, and the right column displays the corresponding empirical cumulative distribution functions. The probability density functions are estimated by Epanechnikov kernels with a bandwidth of 2 percentage points for output and consumption, and 4 percentage points for investment. The figures suggest that the distributions of the growth rates are more negatively skewed during unrest episodes.

To have numerical comparisons, Table 1 displays the means, standard deviations, skewnesses, and kurtoses of (country-demeaned) output growth, consumption growth, and investment growth during and outside of unrest episodes. All confidence intervals are bootstrapped with 500 replications and are reported at the 95 percent level. The first two columns report the estimated moments. The third column reports the difference in the estimated moments, along with the p-value for a test of the null hypothesis that there is no difference between the corresponding moments. The fourth column reports the ratio of the estimated standard deviations, along with the p-value for the Levene

Figure 2 Distribution Functions of Macro Variables



Notes: Smoothed empirical probability density functions and empirical cumulative distribution functions of output, consumption, and investment growth, unrest vs. no unrest.

test of the equality of variances. The fifth column reports the p-value for the Kolmogorov-Smirnov test of whether the two distributions of shocks (under unrest and no unrest) are the same.

Table 1 Empirical Moments In and Out of Unrest

	No unrest (c.i.)	Unrest (c.i.)	Difference [p-value]	Ratio [p-value]	K-S test [p-value]
Output growth					[0.00]
Mean	0.17	-1.75	-1.92		
	(0.03,0.32)	(-2.46,-1.04)	[0.00]		
Standard Dev.	5.62	8.63		1.53	
	(5.30,5.95)	(7.05,10.20)		[0.00]	
Skewness	-0.69	-2.26	-1.57		
	(-1.68,0.30)	(-4.16,-0.35)	[0.15]		
Kurtosis	23.61	23.38	-0.23		
	(15.95,31.27)	(13.86,32.91)	[0.97]		
Consumption grth					[0.00]
Mean	0.12	-1.10	-1.22		
	(-0.11,0.36)	(-1.90,-0.31)	[0.00]		
Standard Dev.	8.34	9.80		1.17	
	(7.69,8.99)	(7.30,12.29)		[0.00]	
Skewness	0.40	-2.96	-3.36		
	(-1.38,2.17)	(-6.52,0.60)	[0.10]		
Kurtosis	33.46	39.88	6.42		
	(17.34,49.57)	(6.66,73.10)	[0.73]		
Investment grth					[0.00]
Mean	0.40	-3.56	-3.96		
	(-0.19,1.00)	(-6.00,-1.12)	[0.00]		
Standard Dev.	20.29	27.45		1.35	
	(18.69,21.89)	(22.93,31.96)		[0.00]	
Skewness	-0.94	-0.71	0.24		
	(-2.52,0.64)	(-2.14,0.73)	[0.83]		
Kurtosis	31.78	15.11	-16.66		
	(17.77,45.80)	(11.21,19.00)	[0.03]		

Notes: Empirical moments in and out of unrest with bootstrapped 95 percent confidence intervals (in brackets) and p-values (in square brackets) on hypothesis tests that there is no difference between the two distributions. The first two columns report the estimated moments. The third column reports the difference in the estimated moments, along with the p-value for a test of the null hypothesis that there is no difference between the corresponding moments. The fourth column reports the ratio of the estimated standard deviations, along with the p-value for the Levene test of the equality of variances. The fifth column reports the p-value for the Kolmogorov-Smirnov test of whether the two distributions of shocks (under unrest and no unrest) are the same.

Table 1 shows that a period of unrest is associated with significant losses in growth. The per-year loss in output growth (relative to periods without unrest) is 1.92 percent, statistically significant at the 1 percent level. This estimated per-year loss is nontrivial, especially given that unrest is persistent once started. The estimated cumulative loss is relatively substantial at 11.50 percent of the base (pre-onset) year's output.[7] The annual loss in consumption growth is 1.22 percent, which is smaller than that of output growth. At the same time, investment growth losses are larger than output growth, at 3.96 percent. In cumulative terms, consumption and investment losses amount to 7.31 percent and 23.71 percent, respectively. Note that this ordering of the loss in investment, output, and consumption is consistent with the permanent income hypothesis, which predicts that investment is more sensitive to shocks than output, which is in turn more sensitive than consumption.

Furthermore, Table 1 shows that the standard deviations of the growth rates of output, consumption, and investment substantially increase during unrest episodes. The fourth column of Table 1 displays the ratio of standard deviations. We can see that the standard deviation of output growth is 53 percent larger in unrest, and the standard deviations of consumption and investment growth are 17 percent and 35 percent larger, respectively. The column also reports the p-values of Levene's test of equality of variances between various forms of unrest against the baseline of no unrest. The p-values show that all of these increases are highly statistically significant: well below 0.01 for all three.

Table 1 also shows that both output and consumption growth becomes more negatively skewed during unrest. The difference in the skewness between unrest and no unrest is -1.57 for output growth and -3.36 for consumption growth. The bootstrapped p-value for the hypothesis that the difference in skewness is equal to zero is 0.15 for output growth and 0.10 for consumption growth. While it is generally difficult to estimate higher-order moments of relatively infrequent events with great confidence, we believe that these differences in skewness are economically significant. The greater variance and larger left tail of many distributions are also visually discernible in Figure 2.[8] This discernible mass on the left tail corresponds to a continuous range from moderately to extremely bad outcomes. The difference between a period of unrest and a period with no unrest then is not the increased probability of a single disaster but an increase in the probability of a whole range of bad outcomes.

---

[7] If p is the continuation probability and x is the annual loss, then the cumulative loss is estimated to be $\frac{x}{1-p}$.

[8] While there is also a visibly larger left tail for the distribution of investment growth, the bootstrapped difference in the skewness in investment growth between unrest and no unrest is not significantly different from zero, with a p-value of 0.83. This is because there are a few observations of investment growth that are very large in absolute value on both sides of the distribution (consistent with sharp falls in investment and subsequent rebounds), and the bootstrapped estimate of the difference in skewness is sensitive to these outliers.

Finally, as the fifth column of Table 1 shows, under the Kolmogorov-Smirnov test, we can reject the hypothesis that the two distributions of shocks (under unrest and under no unrest) are the same, as the associated p-value is zero for each series (output growth, consumption growth, or investment growth).

We summarize our results in the following stylized fact:

Fact: *Episodes of mass political unrest are associated with statistically and economically significant economic costs: the distributions of output, investment, and consumption growth during unrest have lower means and higher variances than the distributions in periods of no unrest. In addition, the distributions of output and consumption growth are more negatively skewed during unrest.*

One potential mechanism that could explain the increased volatility and negative skewness in economic activities is that unrest is associated with substantial increases in the probability of institutional disruptions. In Appendix A.3, we document that the probabilities of large political and government changes, including major changes in polity and coups, substantially increase during unrest episodes. Large political changes are often associated with significant changes in legal and economic institutions, such as the protection of property and investment, which are key determinants of investment and growth (Acemoglu and Robinson 2005; and Acemoglu et al. 2014). Therefore, unrest episodes can increase the probability and severity of economic disasters.

2. QUANTITATIVE ANALYSIS

Model

How much of observed declines in average output, consumption, and investment growth during unrest, as reported in the previous section, can be attributed to volatility and skewness shocks? To answer this question, we augment a standard small open economy with a regime-switching process for the volatility and skewness of TFP. We calibrate the regime-switching process to moments that were estimated from data in the previous section.

Consider a canonical small open economy model with a representative household. Domestic firms competitively produce a numeraire good Y_t using capital K_{t-1} and labor H_t, subject to TFP ζ_t:

$$Y_t = \zeta_t K_{t-1}^{\alpha} (H_t)^{1-\alpha}.$$

These firms take factor prices R_t and W_t as given. Their first-order conditions on their optimal choices of capital and labor equate these factor prices with the corresponding marginal products in production:

$$W_t = (1-\alpha)\zeta_t K_{t-1}^{\alpha} H_t^{-\alpha}$$
$$R_t = \alpha\zeta_t K_{t-1}^{\alpha-1} H_t^{1-\alpha}.$$

Unrest shock. We introduce a regime-switching process. Let u_t be an exogenous two-state Markov process, with $u_t = 1$ representing the country being in unrest in period t and $u_t = 0$ representing no unrest, or a quiet time, in period t. Transitional probabilities are calibrated to match the probability of unrest onset and the persistence of unrest observed in data.

To model how unrest affects economic activities in the most tractable way, we assume that unrest affects the TFP process. Intuitively, as unrest episodes are associated with significant economic and political instability, they will affect the productivity of many economic sectors by, for instance, affecting the efficiency of resource allocation (Acemoglu et al. 2014). Such effects can be captured in a reduced form by a wedge to TFP, as in Chari et al. (2007).

Remark. Recall that our goal is to analyze the extent to which the shocks to higher-order moments of aggregate macroeconomic variables that we observe during unrest can explain the observed average losses in output, consumption, and investment growth. To conduct this analysis in the simplest and clearest possible way, we assume that unrest is a shock *only* to higher-order moments of the TFP process and not to the first moment. Obviously, this is a simplifying assumption and will likely lead to underestimations of the economic impacts of unrest. The model can be extended to allow for the possibility that unrest affects the first moment as well, but this will complicate the analysis. We will show that, even without an immediate associated fall in average productivity, a higher-order moment shock is enough to generate large changes in macroeconomic aggregates in line with the data.

Specifically, assume that TFP ζ_t consists of a growth component $(g^t)^{1-\alpha}$ and a level component A_t:

$$\zeta_t = (g^t)^{1-\alpha} A_t,$$

where, for numerical simplicity, we have assumed that growth rate is a constant g. However, level component A_t follows an autoregressive process with autoregressive parameter ρ and i.i.d. shocks ε_t:

$$\ln A_t = \rho \ln A_{t-1} + \varepsilon_t.$$

The stochastic process for ε_t depends on whether the economy is currently experiencing unrest. While in unrest ($u_t = 1$), shock ε_t is distributed Normal Inverse Gaussian with mean 0, standard deviation σ_u, skewness s_u, and kurtosis κ_u. While not in unrest ($u_t = 0$), shock ε_t is distributed Normal Inverse Gaussian with mean 0, standard deviation σ_q, skewness s_q, and kurtosis κ_q. The Normal Inverse Gaussian distribution has been used in the finance literature to model skewed distributions with fat tails (e.g. Barndorff-Nielsen 1997; Andersson 2001; and Mencía and Sentana 2012). The fact that the mean of ε_t is the same whether $u_t = 0$ or $u_t = 1$ reflects the assumption that unrest only affects higher-order moments of TFP.[9]

Preferences: As is now standard in the macro-finance literature (e.g., Gourio 2012; and Colacito and Croce 2013), we assume the representative household has recursive preferences as in Epstein and Zin (1989). These preferences allow us to distinguish between the intertemporal elasticity of substitution and risk aversion (captured by ζ and γ below). Moreover, these preferences nest the standard expected utility with constant relative risk aversion (CRRA) as a special case.

Let C_t denote household consumption in period t, and let $\tilde{C}_t \equiv C_t - \theta\omega^{-1}g^{t-1}H_t^{\omega}$ denote labor-adjusted consumption, where θ and ω are preference parameters. Then, we follow the sign convention of Rudebusch and Swanson (2012) and define the representative household's preferences as:

$$\tilde{V}_t \equiv \begin{cases} \left((1-\beta)\tilde{C}_t^{1-\varsigma} + \beta E_t\left[V_{t+1}^{1-\gamma}\right]^{\frac{1-\varsigma}{1-\gamma}}\right)^{\frac{1}{1-\varsigma}} & \text{if } \tilde{C}_t^{1-\varsigma} \text{ is always positive} \\ \left((1-\beta)\tilde{C}_t^{1-\varsigma} - \beta E_t\left[(-V_{t+1})^{1-\gamma}\right]^{\frac{1-\varsigma}{1-\gamma}}\right)^{\frac{1}{1-\varsigma}} & \text{if } \tilde{C}_t^{1-\varsigma} \text{ is always negative} \end{cases} \quad (1)$$

This convention ensures that the value function and the instantaneous payoff have the same sign.

Households supply capital and labor to the domestic firms, consume domestic goods, invest subject to an adjustment cost in capital, and trade noncontingent bonds in the international credit market:

$$V_t = \max_{C_t, D_t, I_t, H_t} \tilde{V}_t,$$

subject to:

$$\begin{aligned} C_t + D_{t-1} + I_t + \frac{\phi}{2}\left(\frac{K_t}{K_{t-1}} - g_t\right)^2 K_{t-1} &= R_t K_{t-1} + W_t H_t + \frac{D_t}{1+r_t} \\ K_t &= (1-\delta)K_{t-1} + I_t. \end{aligned}$$

[9] The unrest shock in each period t affects the distribution of the TFP in period t, and because TFP is autocorrelated, the unrest shock will affect the distribution of future TFP terms too. This is different from a "news shock" that does not affect current TFP, only future TFP.

We assume that the interest rate households borrow at is a function of the aggregate stock of debt D_t:

$$r_t = r^* + \psi(e^{D_t/g^t - \bar{d}} - 1),$$

where r_t is the interest rate, r^* is a constant representing the world's risk-free interest rate, and $\bar{d}$ and ψ are exogenous constants. This debt-elastic interest rate is a standard assumption to ensure that the equilibrium is stationary (e.g., Schmitt-Grohé and Uribe 2003).

Finally, a recursive equilibrium is defined as a set of policy functions for C_t, V_t, K_t, D_t, Y_t, r_t, I_t, H_t, W_t, and R_t as functions of K_{t-1}, D_{t-1}, A_t, and u_t such that all agent expectations are rational and the optimality conditions, constraints, and laws of motion described above hold.

Solution Method

One way to derive moments of output, consumption, and investment growth from the model is to simulate a very long time series in which the country transitions into and out of unrest with the same probabilities as in the data. But since unrest is rare, we would need an extraordinarily long simulated time series to reduce the Monte Carlo noise around our estimates of those higher-order moments. Instead, we adapt the pruning method from Andreasen et al. (2017) to get closed-form solutions for the paths of conditional moments of endogenous variables, the GIRF. We first describe how we calculate a GIRF and then how we use the GIRF to compare the model against the data. All details on the computational strategy, from approximation to pruning and the GIRF, are given in the Appendix.

We define the GIRF as follows. Let y_t denote the log-deviation of output Y_t from its steady-state value. Then Δy_t is the growth rate of output Y_t. Let X_t denote a vector of the first three powers of the growth rates of output, consumption, and investment:

$$X_t \equiv \left(\Delta y_t, \Delta i_t, \Delta c_t,\ (\Delta y_t)^2, (\Delta i_t)^2, (\Delta c_t)^2,\ (\Delta y_t)^3, (\Delta i_t)^3, (\Delta c_t)^3\right).$$

The GIRF is the evolution over time of the difference of conditional expectations of X_t between two conditioning sets, differing with respect to two given time series of realizations of unrest, $u = \{u_t, -\infty < t < \infty\}$ and $\tilde{u} = \{\tilde{u}_t, -\infty < t < \infty\}$:

$$GIRF^u(X_t) \equiv E[X_t|u] - E[X_t|\tilde{u}].$$

The first path, u, represents a country that starts with no unrest and then enters into unrest at $t = 1$ and stays there. That is, $u_t = 0$

$\forall t \leq 0$ and $u_t = 1\ \forall t \geq 1$. The second counterfactual path, $\tilde{u}$, is one where the country never enters unrest: $\tilde{u}_t = 0\ \forall t$.

Remark. The GIRF is useful for our purposes for several reasons. First, we want to calculate the moments that would be uncovered from a simulation. The conditional expectations in the GIRF allow us to consider the effects of shocks over the course of the GIRF. This is important, since under a nonlinear approximation to the policy function, the presence of shocks will cause the ergodic moments of all variables to differ from those in the absence of shocks. Second, since X_t contains powers and products of endogenous variables, we can find paths not just for conditional means, but also for conditional variances and skewnesses of the endogenous variables of interest given the paths for the components of X_t. Moreover, the GIRF allows us to avoid measurement error, which is a problem for estimating higher-order moments of simulated series from a finite simulation length. While Andreasen et al. (2017) rely on SMM for higher-order moments, we use the computer algebra software Mathematica to calculate GIRFs for these moments symbolically, term by term, and avoid Monte Carlo error.

The GIRF provides the conditional moments in the first year of an unrest episode, the second year, and so on. The moments from the data presented in the previous section are *weighted* averages over the years in observed unrest episodes because years that are closer to the beginning of an episode are more likely observed than years that are many years after the beginning of an episode. If $p = \Pr(U_t | U_{t-1} = 1)$, then the probability of a given observed year of unrest being the nth year of unrest ($n \geq 1$) within its respective episode is $(1-p)p^{n-1}$. Thus, to construct the single value for average value of X on unrest, we take a weighted average of a GIRF where a country enters into unrest and stays there but with smaller and smaller weight given to later periods of unrest. That is, we calculate $\sum_{t=1}^{\infty}(1-p)p^{t-1}GIRF^u(X_t)$.

Calibrations

First, we calibrate the model's basic parameters using standard values from the small open economy literature. These numbers are listed in the top panel of Table 2.[10] We allow the values for Epstein-Zin

[10] The sensitivity parameter of interest rate to debt is simply set to a small value to avoid a unit root, as in García-Cicco et al. (2010) and Schmitt-Grohé and Uribe (2003).

Table 2 Calibrated Parameters

	Parameter	Value	Source/Target
	From literature		
α	Capital share in production	0.32	García-Cicco et al. (2010)
β	Discount factor	0.922	–
δ	Depreciation	0.126	–
ϕ	Adjustment costs to capital	3.3	–
g	Trend growth rate	1.005	–
θ	Disutility from labor	0.224	–
ω	Disutility from labor	1.6	–
$\bar{d}$	Steady-state debt level	0.007	–
ψ	Interest rate sensitivity to debt	10^{-5}	–
ς	Inverse intertemporal elasticity of substitution	0.9 to 5	Table 3
γ	Risk aversion	5 to 20	Table 3
	Estimates from data		
p_{onset}	Probability of unrest onset	0.014	Appendix A.2
$p_{cont.}$	Probability of unrest continuation	0.833	Appendix A.2
	Chosen to match target		
σ_q	Std. of TFP shock ε_t in quiet times	2.75	Table 1
s_q	Skewness of TFP shock ε_t in quiet times	-1.10	Table 1
κ_q	Kurtosis of TFP shock ε_t in quiet times	22	(*)
σ_u	Std. of TFP shock ε_t during unrest	4.66	Table 1
s_u	Skewness of TFP shock ε_t during unrest	-2.83	Table 1
κ_u	Kurtosis of TFP shock ε_t during unrest	22	(*)

Notes: (*) means chosen sufficiently high to permit existence of Normal Inverse Gaussian distribution.

Table 3 Epstein-Zin Parameter Calibrations in the Literature

	ς	γ
Fernández-Villaverde et al. (2011)	5	5
Colacito et al. (2013)	0.9	10
Vissing-Jørgensen and Attanasio (2003)	0.9	20

preference parameters to vary within the standard range of values of the literature, surveyed in Table 3.[11]

[11] In Vissing-Jørgensen and Attanasio (2003), the estimated risk-aversion parameter can take a wide range of values, as large as thirty. To be conservative, we only set the maximum risk-aversion to be twenty.

Second, we calibrate parameters for the unrest process and the higher-order moments of TFP innovation ε_t to estimated moments from our empirical analysis in Section 1. Care must be paid to the calibration of the higher-order moments of TFP, both in unrest and in quiet times. The parameters chosen in the model govern the exogenous TFP process, but they are chosen to match the moments of endogenous quantities. It is relatively straightforward (as one could even rely on closed-form solutions) to choose the volatility of a shock process given a desired volatility of an endogenous quantity, such as output growth under a log-linear approximation to equilibrium. However, it is much less straightforward to choose higher-order moments of a shock process to match higher-order moments of a nonlinear approximation of the law of motion for an endogenous variable. Therefore, the parameters σ_q, σ_u, s_q, and s_u are chosen so that the ergodic standard deviation and skewness of output growth, and the average generalized impulse responses of the standard deviation and skewness of output growth, match those in the data.[12]

Results

Model's performance relative to data. We compare the average loss in output, investment, and consumption growth from the GIRF $\sum_{t=1}^{\infty}(1-p)p^{t-1}GIRF^u(\Delta y_t)$ to the corresponding observed average loss in growth as documented in Section 1. Table 4 reports the percentage of observed growth loss that can be explained by the calibrated model. The overall effect is an endogenous response of endogenous variables to an unrest shock that increases the volatility and negative skewness of TFP shocks, with an interplay of capital adjustment costs and preferences over the time resolution of risk. In each panel, we report the percentage obtained by using the first-, second-, and third-order approximations of the solution to the model. Note that by construction, the percentage explained using a first-order approximation is zero, as we assume that unrest does not affect the first moment of TFP shocks. The columns report the results with different preference parameters.

Table 4 shows that, under the baseline specification (the first column), the model explains 21 percent of the average output growth loss, 45 percent of the average consumption growth loss, and 51 percent of the average investment growth loss. This amounts to an output growth

[12] We do not attempt to match kurtoses exactly, since we approximate equilibrium only to third order. We choose the kurtosis of the TFP processes high enough to permit existence of the Normal Inverse Gaussian distribution for the calibrated second-order and third-order moments. The calibrated kurtosis of TFP is approximately equal to that of the empirical distribution of output growth.

Table 4 Numerical Results

	Numerical Results		
	Baseline $\varsigma = 0.9, \gamma = 10$	High risk av. $\varsigma = 0.9, \gamma = 20$	No EZ, low risk av. $\varsigma = 5, \gamma = 5$
Output growth			
First order	0	0	0
Second order	11	21	6
Third order	21	62	9
Consumption growth			
First order	0	0	0
Second order	22	742	7
Third order	45	128	11
Investment growth			
First order	0	0	0
Second order	27	51	16
Third order	51	148	23

Notes: Numerical results for the percentages of the empirically observed average losses in the growth rates of output, consumption, and investment that are explained by the model. The rows show the percentage explained by using first-order, second-order, and third-order approximations of the solution to the model.

loss of 0.40 percent per year, a consumption growth loss of 0.55 percent per year, and an investment growth loss of 2.01 percent per year. In cumulative terms over the average episode duration, this is an output growth loss of 2.41 percent, a consumption growth loss of 3.28 percent, and an investment growth loss of 12.09 percent.

The second column of Table 4 shows that, not surprisingly, the model can explain more with a larger coefficient of risk aversion ($\gamma = 20$ instead of $\gamma = 10$). There, the fractions of growth losses explained increase to 62 percent for output, 128 percent for consumption and 148 percent for investment (thus this calibration "overexplains" the losses in consumption and investment). On the other hand, when we shut down Epstein-Zin preferences and use a lower coefficient of risk aversion (the third column), the fractions of growth losses explained decrease to 9 percent, 11 percent, and 23 percent for output, consumption, and investment, respectively.

It is not surprising that the model cannot fully explain the observed losses, since we assume that unrest only affects higher-order moments of TFP shocks, and not the first-order moment, thus abstracting away from factors such as reallocation of resources between sectors of the economy that may directly affect the average productivity.[13]

However, the table shows that shocks to the higher-order moments of TFP alone can still explain a substantial fraction of the observed losses, especially in investment. Even without Epstein-Zin preferences and with a relatively low risk-aversion index, the model can still explain around a fourth of the observed loss in investment growth. Intuitively, in the model, when risk increases (either through the second-order or third-order moment of TFP), agents in the country shift away from domestic capital and into the internationally traded asset. This mechanism explains the drop in investment.

Role of negative skewness. One of our main findings is that negative skewness shocks play quantitatively important roles in driving business cycles. To see this, in rows labeled "second order" in Table 4, we show the fractions of observed losses explained under each calibration, but using an approximation of the solution of the model only to the second order, and thus effectively shutting down the endogenous response to the shock to the skewness of TFP. As the baseline column shows, *the reaction to skewness is substantial*: the fractions of average losses explained in the third-order rows are roughly doubling those explained in the second-order rows. Differences of comparable magnitudes are also found in the two other calibration columns.

Why does skewness matter? Intuitively, agents in our model dislike negative skewness. To see this, let $\tilde{C}_t = C_t - \theta\omega^{-1}g^{t-1}H_t^{\omega}$, the aggregate of utility from consumption and labor to the household. By the definition of household preferences, $V_t^{1-\varsigma} = (1-\beta)\tilde{C}_t^{1-\varsigma} + \beta E_t \left[V_{t+1}^{1-\gamma}\right]^{\frac{1-\varsigma}{1-\gamma}}$. Let $v_t \equiv V_t^{1-\varsigma}$ so that when $\gamma = \varsigma$ and thus Epstein-Zin preferences reduce to expected utility preferences, v_t is the usual definition of the value function for the household: $v_t = (1-\beta)\tilde{C}_t^{1-\varsigma} + \beta E_t \left[v_{t+1}^{\frac{1-\gamma}{1-\varsigma}}\right]^{\frac{1-\varsigma}{1-\gamma}}$. The third-order Taylor approximation for v_t around

[13] For example, if sectors of the economy differ not only with respect to average productivity, but also exposure to political uncertainty under unrest, we might see a reallocation of capital to relatively inefficient sectors, driving up the share of output growth loss explained. Recent work by Acemoglu et al. (2014) provides evidence that, during the Egyptian experience of the Arab Spring, firms that had closer ties to the threatened regime suffered greater losses on the Egyptian stock market than firms that did not. Exploring the macroeconomic significance of this and other *micro* risks associated with political unrest would be complementary to our analysis and is outside of the scope of this paper.

$v_{t+1} = \mu \equiv E_t[v_{t+1}]$ is:

$$\begin{aligned} v_t = & \quad (1-\beta)\tilde{C}_t^{1-\varsigma} \\ & + \beta E_t\left[v_{t+1}\right] \\ & - \beta \frac{\gamma-\varsigma}{2\mu(1-\varsigma)} Var_t\left[v_{t+1}\right] \\ & + \beta \frac{(\gamma-\varsigma)(\gamma+1-2\varsigma)}{6(\mu(1-\varsigma))^2} Skew_t\left[v_{t+1}\right] Var_t\left[v_{t+1}\right]^{3/2}. \end{aligned} \quad (2)$$

The first three terms of the continuation payoff are well-known in the literature on Epstein-Zin preferences (e.g., Colacito et al. 2013). The first term is current utility. The second is the same discounted continuation payoff that appears in non-Epstein-Zin expected utility preferences. The third term is a "correction" to expected utility that penalizes future variance of the value function as long as $\gamma > \varsigma$.[14] The fourth term is novel to a third-order approximation. Under the same assumption that $\gamma > \varsigma$ and $\varsigma < 1$, this term rewards positive skewness of the future value function and penalizes negative skewness. As γ increases, the penalties for both volatility and negative skewness increase.

The term $Skew_t\left[v_{t+1}\right] Var_t\left[v_{t+1}\right]^{3/2}$ is equal to $E_t[(v_{t+1}-\mu)^3]$, the third central moment of the value function. It shows that, for a given amount of skewness, the size of the third central moment increases in the variance. This is why skewness and variance are complementary in giving rise to precautionary motives in equilibrium.

Expression (2) is another way to see how these higher-order moments relate to a disaster risk. A disaster is an outcome on the far left tail. If variance increases, extreme events on both tails become more likely. If in addition skewness becomes more negative, the events far out on the lower tail specifically become more likely. Though we do not calculate a fourth-order approximation to this model, one can easily show that the next term in the above expansion would penalize the fourth central moment of the value function. An increase in the fourth-order moment, like an increase in negative skewness for a given second-order moment, also makes outcomes on the tails more likely. Therefore, by taking a higher-order approximation to the value function and by considering shock distributions with fat and skewed tails, we can recover some of the effects of what has been explored in the rare disaster literature.

Comparison with other studies. How do the results in Table 4 compare with other studies in the literature on the macroeconomic effects

[14] Remember, we are using a calibration where $\varsigma < 1$, so $\mu > 0$ and $\mu(1-\varsigma) > 0$.

of risk? It is well-known that increases in second-order moments lead to economic slowdowns, though the range of models in the literature is wide and none are exactly comparable with the model in this paper in terms of modeling assumptions or forcing processes. For example, while using a very different model (a closed economy with heterogeneous firms, subject to a transitory shock to the second-order moment of a composite of technology and demand, on the monthly frequency), Bloom (2009) obtains effects of risk that are of the same order of magnitude as here, i.e., doubling the standard deviation of the forcing process leads to a decline in the level of output by 2 percentage points within the first six months. For the canonical small open economy model considered here, Fernández-Villaverde et al. (2011) find that a transitory one-standard-deviation shock to second-order moment of innovations to the global interest rate (the interest rate that households in the small open economy pay on their international debt) can lead to declines in output levels in Argentina of 1.16 percentage points below steady state after sixteen quarters, or an average output growth loss of 0.29 percentage points per year, which is about 73 percent of what our baseline model predicts. Just as in Gourio's (2012) experiment with a transitory increase in the disaster probability, in our model, investment experiences the most significant decline and output contracts by a few percentage points. However, in that model, a disaster also entails some destruction of capital, so it is difficult to directly compare the two sets of numerical results.

Welfare. Finally, we evaluate the welfare loss due to the shock to the distribution of TFP. The change in the value function V_t experienced in the first period of an unrest episode corresponds to the welfare loss from facing the more negatively skewed distribution of TFP. The loss can be evaluated by considering the following counterfactual scenario: suppose that household consumption is dictated by a social planner who ensures that households enjoy labor-adjusted consumption $\bar{\tilde{C}}$ (the steady-state level of labor-adjusted consumption in the model) during each period the economy is not in unrest and $\bar{\tilde{C}}\Delta_C$, where $\Delta_C < 1$, during each period the economy is in unrest. Suppose additionally that unrest follows the same stochastic switching process as in the data and the model but there are no other sources of uncertainty to the households. The value function of the household in this scenario takes on two values: $\bar{V}$ while not in unrest, and $\bar{V}\Delta_V$, where $\Delta_V < 1$, while in unrest. The value function takes the following form:

$$\bar{V}\Delta_V = \left((1-\beta)(\bar{\tilde{C}}\Delta_C)^{1-\varsigma} + \beta\left(p(\bar{V}\Delta_V)^{1-\gamma} + (1-p)\bar{V}^{1-\gamma}\right)^{\frac{1-\varsigma}{1-\gamma}}\right)^{\frac{1}{1-\varsigma}}. \tag{3}$$

The log-linearization of the above:

$$\bar{V}^{1-\varsigma}\widehat{\Delta_V} \approx (1-\beta)\bar{\tilde{C}}^{1-\varsigma}\widehat{\Delta_C} + \beta p \bar{V}^{1-\varsigma}\widehat{\Delta_V}. \tag{4}$$

For a given $\widehat{\Delta_V}$, we can calculate the change in labor-adjusted consumption $\widehat{\Delta_C}$ that would give rise to a fall of $\widehat{\Delta_V}$ in the value function below its steady-state value for each period spent in unrest. We take $\widehat{\Delta_V}$ as calculated from our GIRF.

Our estimates imply a $\widehat{\Delta_C}$ equal to -6.1 percent. In other words, the welfare loss due to increased volatility and skewness during unrest is equal to the welfare loss if consumption were 6.1 percent lower than its steady-state value in each period of unrest. How does this number compare with those in other studies? Lucas (1987) shows that eliminating all business cycle fluctuations for a representative agent with expected-utility preferences corresponds to 0.1 percent to 0.5 percent of steady-state consumption. Dolmas (1998) finds that the same exercise under Epstein-Zin preferences yields 2 percent to 20 percent of steady-state consumption, depending on the degree of risk aversion.

3. CONCLUSION

We estimate shocks to the volatility and skewness of business cycles by exploiting the uncertainty associated with episodes of political unrest. A small open economy real business cycle model calibrated to the estimated moments from data shows that higher-order moment shocks, especially increased negative skewness, play important roles in explaining the observed average decline in economic activities. In short, the paper demonstrates the quantitative importance of time-varying skewness of shocks in the context of a small open economy real business cycle model. Our paper makes several contributions to different threads of the macroeconomic literature. In the context of real business cycle and DSGE models, the mapping from the higher-order moments of exogenous processes to moments of endogenous variables, such as the mapping studied in this paper, is relatively underexplored. While the literature has deployed a number of mechanisms (e.g., adjustment costs on investment, debt-elastic interest rates, habit in consumption, and interest rate smoothing; see Smets and Wouters 2007) to help log-linearized models better replicate the first-order and second-order moments of observed time series, it is less clear how these mechanisms affect the model's ability to match third-order moments as well. Our paper suggests it may be important to know more about the endogenous mechanisms that help or hinder matching higher-order moments of models, given that these moments could be important for the consequences of aggregate risk. Additionally, our method of accurately calculating the GIRF of third-order moments may help future researchers analyze the dynamics of higher-order moments of macroeconomic aggregates in DSGE models while avoiding Monte Carlo error.

APPENDIX: A. ONLINE APPENDIX: DATA

A.1 Details of NAVCO Unrest Data

NAVCO provides detailed information on 250 nonviolent and violent mass political campaigns between 1945 and 2006. These campaigns constitute a "consensus population" of all known cases satisfying the following conditions. Each episode is a series of observable (i.e., tactics used are overt and documented), continuous (distinguishing from one-off events or revolts) mass tactics or events that mobilize nonstate actors in pursuit of a political objective. The NAVCO dataset also provides, among other information, the country, the main participating groups, the documented objective of the movement in each year of the campaign, the presence of violence in each year of the campaign, and the degree to which the movement was successful at achieving the documented objective. We focus on episodes whose objectives belong to one of the following categories:

(0) *Regime change* indicates a goal of "overthrowing the state or substantially altering state institutions to the point that it would cause a de facto shift in the regime's hold on power."

(1) *Significant institution reform* indicates a goal of "changing fundamental political structures to alleviate injustices or grant additional rights."

(2) *Policy change* indicates a goal of "changes in government policy that fall short of changes in the fundamental political structures, including changes in a state's foreign policy."

For a complete listing of NAVCO unrest episodes, see the Online Appendix C.

A.2 Estimates of Onset and Continuation Probabilities

We investigate how likely unrest is to start and how persistent it is once it starts. We establish that unrest is rare but persistent. These facts are important for understanding the economic consequences of higher-order shocks to business cycles.

Let a dummy variable U_{it} take the value of one during episodes of unrest and zero during years with no unrest, where i denotes a country and t denotes a year. We estimate both the probability of unrest onset (i.e., the probability of unrest conditional on no unrest the previous year) and the probability of unrest continuation (i.e., the probability of unrest conditional on there being unrest in the previous year). To assess whether the probability of unrest is a function of other observable characteristics of a country, we estimate two probit models, one for onset and one for continuation. Each probit predicts $U_{it} = 1$ as a function of a constant and a vector Z_{it} of control variables, including lagged real GDP growth minus the country-specific average growth rate $\Delta Y_{i,t-1} - \frac{1}{T_i}\sum_t \Delta Y_{it}$, religious, ethnic, and linguistic fractionalization (all on a scale of 0 to 1), and income inequality (measured with the Gini coefficient). To control for region-specific factors that might influence the overall probability of a given country experiencing unrest, we include a term $\gamma_{Region(i)}$ as a region-fixed effect.[15] We do not include country-fixed effects because this would effectively exclude any country from our sample that has never experienced unrest. Instead, we want to include all countries in our sample to exploit not just variation within countries but between them as well. The fact that many countries never experience unrest is informative to estimating the probability of onset. The two probit regressions are:

$$\Pr(U_{it}|U_{it-1} = 0) = \Phi\left(\gamma_{Z0}Z_{it} + \gamma_0 + \gamma_{0,Region(i)}\right) \text{ (onset)} \tag{5}$$

$$\Pr(U_{it}|U_{it-1} = 1) = \Phi\left(\gamma_{Z1}Z_{it} + \gamma_1 + \gamma_{1,Region(i)}\right) \text{ (continuation)} \tag{6}$$

where Φ is the cumulative distribution function of the standard normal distribution.

Our baseline estimations, reported in Table 5, indicate that the onset of unrest is rare: the estimated onset probability is 1.4 percent per year. However, once it starts, unrest tends to last for several years: the estimated continuation probability in Table 6 is 83.3 percent per year. This continuation probability implies that the average duration of unrest episodes is 5.99 $(= \frac{1}{1-0.833})$.

In summary, we find that the onset of unrest is rare. But once started, unrest is persistent, leading to relatively lengthy episodes.

A.3 Political Risks Associated with Unrest

We document that the probability of large political changes increases significantly in each year of unrest. To the extent that any large po-

[15] The regions, as classified by the World Bank, are: East Asia and Pacific, Europe and Central Asia, Latin America and Caribbean, Middle East and North Africa, South Asia, and sub-Saharan Africa.

Table 5 Estimated Onset Probability

Onset	Baseline	(2)	(3)	(4)	(5)
$\Delta Y_{i,t-1} - \frac{1}{T_i}\Sigma_t \Delta Y_{it}$		-0.003	-0.004	-0.005	-0.001
		(0.01)	(0.01)	(0.02)	(0.01)
Ethnic Frac			0.500**		
			(0.24)		
Language Frac			-0.050		
			(0.21)		
Religion Frac			-0.227		
			(0.18)		
Gini				-0.014	
				(0.01)	
Europe, Central Asia					-0.095
					(0.15)
Latin America, Caribbean					0.021
					(0.15)
Middle East, North Africa					-0.005
					(0.18)
North America					*no obs.*
South Asia					0.432**
					(0.19)
Sub-Saharan Africa					0.125
					(0.14)
constant	-2.209***	-2.147***	-2.240***	-1.386***	-2.182***
	(0.03)	(0.04)	(0.11)	(0.46)	(0.11)
$\Pr(U_{i,t} \vert U_{i,t-1} = 0)$	0.014	0.016	0.013	0.083	0.01
	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)
N	9272	5910	5357	599	5771

Notes: Probit coefficient estimates to predict onset of unrest, U_{it}, and derived probabilities. ΔY_{it} denotes real GDP growth ($= 100\ x\ (\ln Y_t - \ln Y_{t-1})$). Standard errors in parentheses. East Asia is the baseline region for the specification with region FE. *: p < 0:10. **: p < 0:05. ***: p < 0:01.

litical change entails at least a temporary disruption of the economy, an increase in the probability of disruptive events might help make sense of the increase in the left tail of the distributions of output and consumption growth documented in the next section. We estimate a series of probit regressions to predict a set of political disruptions: (1) coups, (2) positive changes in the Polity index, (3) negative changes in the Polity index, (4) large positive changes in the Polity index (greater than five points), and (5) large negative changes in the Polity index

Table 6 Estimated Continuation Probability

Continuation	Baseline	(2)	(3)	(4)	(5)
$\Delta Y_{i,t-1} - \frac{1}{T_i}\Sigma_t \Delta Y_{it}$		0.011*	0.009	-0.016	0.010
		(0.01)	(0.01)	(0.03)	(0.01)
Ethnic Frac'n			0.423		
			(0.34)		
Language Frac'n			0.406		
			(0.27)		
Religion Frac'n			-1.022**		
			(0.32)		
Gini				0.006	
				(0.02)	
Europe, Central Asia					-0.800***
					(0.26)
Latin America, Caribbean					0.317
					(0.22)
Middle East, North Africa					-0.044
					(0.28)
North America					*no obs.*
South Asia					-0.199
					(0.30)
Sub-Saharan Africa					0.007
					(0.20)
constant	0.967***	0.995***	0.974***	0.694	1.001***
	(0.06)	(0.06)	(0.18)	(0.75)	(0.18)
$\Pr(U_{i,t} \mid U_{i,t-1} = 1)$	0.833	0.840	0.835	0.756	0.842
	(0.01)	(0.02)	(0.04)	(0.24)	(0.04)
N	732	590	558	74	590

Notes: Probit coefficient estimates to predict onset of unrest, U_{it}, and derived probabilities. ΔY_{it} denotes real GDP growth ($= 100\ x\ (\ln Y_t - \ln Y_{t-1})$). Standard errors in parentheses. East Asia is the baseline region for the specification with region FE. *: p < 0:10. **: p < 0:05. ***: p < 0:01.

(greater than five points).[16] Each probit regression is specified as in equation (6), as a function of a constant, an indicator for current unrest, the difference between lagged real GDP growth and a country-specific average real GDP growth, and the interaction between current unrest and lagged real GDP growth. Let X_{it} be an indicator for one of the political disruptions. We estimate:

$$\Pr(X_{it}) = \Phi\left(\gamma_U U_{it} + \gamma_Z Z_{it} + \gamma_{ZU} Z_{it} U_{it} + \gamma_0\right) \tag{7}$$

[16] Data for coups come from Marshall and Marshall (2011) and data for Polity come from Marshall and Jaggers (2002).

Table 7 Estimated Probability of Political Events

	$Coup_{it}$	$\Delta Pol_{it} > 0$	$\Delta Pol_{it} < 0$	$\Delta Pol_{it} > 5$	$\Delta Pol_{it} < -5$
$U_{i,t}$	0.494***	0.802***	0.431***	0.849***	0.420**
	(0.07)	(0.07)	(0.09)	(0.10)	(0.13)
Lagged output growth†	-0.005	-0.017***	-0.005	-0.019**	-0.007
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
$U_{i,t}$*Lagged output growth†	-0.002	0.004	0.002	0.003	0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
constant	-1.585***	-1.696***	-1.937***	-2.397***	-2.437***
N	6500	6500	6500	6500	6500

Notes: Probit coefficient estimates to predict other political upheavals as functions of current unrest and derived probabilities. † relative to country-specific average output growth: $\Delta Y_{i,t-1} - \frac{1}{T_i}\Sigma_t \Delta Y_{it}$. Probabilities evaluated at lagged real output growth equal to country-specific average. Standard errors in parentheses. *: p < 0:10. **: p < 0:05. ***: p < 0:01.

There are a few differences between this specification and the specification of unrest onset and continuation in equation (6). First, we estimate one probit for each political disruption X_{it}. Second, in equation (6), we estimate the probits conditional on the presence of lagged unrest and the absence of lagged unrest separately. Here, we estimate one probit including both unrest and its interactions with the controls in one step. We do this to test hypotheses that the probability of each political disruption is significantly different in the presence and absence of unrest. Third, for simplicity, we include in the vector of controls Z_{it} just one control: the difference between lagged output growth and country-specific average output growth. We find that unrest is associated with increases in the probability of *all* kinds of political changes.

APPENDIX: B. ONLINE APPENDIX: MODEL DETAILS

B.1 Derivation of the Household Problem

First, we pose the problem in recursive form

$$V(K,D)^{1-\varsigma} = \max_{C,D',K',H} (1-\beta)\left(C-\theta\omega^{-1}ZH^{\omega}\right)^{1-\varsigma} + \beta E\left[V(K',D'^{1-\gamma}\right]^{\frac{1-\varsigma}{1-\gamma}} + \lambda\left((R+1-\delta)K + WH + \frac{D'}{1+r} - D - C - K' - \frac{\phi}{2}\left(\frac{K'}{K}-g\right)^2 K\right).$$

The associated first-order conditions and envelope condition are:

$$\lambda = (1-\beta)(1-\varsigma)\left(C-\theta\omega^{-1}ZH^{\omega}\right)^{-\varsigma}$$

$$-\frac{\lambda}{1+r} = \beta(1-\varsigma)E\left[V(K',D'^{1-\gamma}\right]^{\frac{1-\varsigma}{1-\gamma}-1} E\left[V(K',D'^{-\gamma}V_D(K',D')\right]$$

$$(1-\varsigma)V(K,D)^{-\varsigma}V_D(K,D) = -\lambda$$

$$\lambda\left(1+\phi\left(\frac{K'}{K}-g\right)\right) = \beta(1-\varsigma)E\left[V(K',D'^{1-\gamma}\right]^{\frac{1-\varsigma}{1-\gamma}-1} E\left[V(K',D'^{-\gamma}V_K(K',D')\right]$$

$$(1-\varsigma)V(K,D)^{-\varsigma}V_K(K,D) = \lambda\left(R+1-\delta+\phi\left(\frac{K'}{K}-g\right)\frac{K'}{K} - \frac{\phi}{2}\left(\frac{K'}{K}-g\right)^2\right).$$

These lead to:

$$V^{1-\varsigma} = (1-\beta)\tilde{C}^{1-\varsigma} + \beta\tilde{V}^{1-\varsigma}$$

$$\tilde{V}^{1-\gamma} = E\left[V'^{1-\gamma}\right]$$

$$\tilde{C} = C - \theta\omega^{-1}ZH^{\omega}$$

$$1 = \beta E\left[\left(\frac{V'}{\tilde{V}}\right)^{\varsigma-\gamma}\left(\frac{\tilde{C}'}{\tilde{C}}\right)^{-\varsigma}(1+r)\right]$$

$$1 = \beta E\left[\left(\frac{V'}{\tilde{V}}\right)^{\varsigma-\gamma}\left(\frac{\tilde{C}'}{\tilde{C}}\right)^{-\varsigma}\left(\frac{R'+1-\delta+\phi\left(\frac{K''}{K'}-g'\right)\frac{K''}{K'}-\frac{\phi}{2}\left(\frac{K''}{K'}-g'\right)^2}{1+\phi\left(\frac{K'}{K}-g\right)}\right)\right].$$

B.2 Full Set of Equilibrium Conditions

The equilibrium conditions are (with additional variables introduced for convenience):

$$V_t^{1-\varsigma} = (1-\beta)\tilde{C}_t^{1-\varsigma} + \beta\tilde{V}_t^{1-\varsigma} \tag{8}$$

$$\tilde{V}_t^{1-\gamma} = E\left[V_{t+1}^{1-\gamma}\right] \tag{9}$$

$$\tilde{C}_t = C_t - \theta\omega^{-1}Z_{t-1}H_t^{\omega} \tag{10}$$

$$W_t = \theta Z_{t-1}H_t^{\omega-1} \tag{11}$$

$$1 = \beta E_t\left[\left(\frac{V_{t+1}}{\tilde{V}_t}\right)^{\varsigma-\gamma}\left(\frac{\tilde{C}_{t+1}}{\tilde{C}_t}\right)^{-\varsigma}(1+r_t)\right] \tag{12}$$

$$1 = \beta E_t\left[\begin{array}{c}\left(\frac{V_{t+1}}{\tilde{V}_t}\right)^{\varsigma-\gamma}\left(\frac{\tilde{C}_{t+1}}{\tilde{C}_t}\right)^{-\varsigma}\\ \left(\frac{R_{t+1}+1-\delta+\phi\left(\frac{K_{t+1}}{K_t}-g_{t+1}\right)\frac{K_{t+1}}{K_t}-\frac{\phi}{2}\left(\frac{K_{t+1}}{K_t}-g_{t+1}\right)^2}{1+\phi\left(\frac{K_t}{K_{t-1}}-g_t\right)}\right)\end{array}\right] \tag{13}$$

$$Y_t = A_tK_{t-1}^{\alpha}(Z_tH_t)^{1-\alpha} \tag{14}$$

$$W_t = (1-\alpha)A_tK_{t-1}^{\alpha}Z_t^{1-\alpha}H_t^{-\alpha} \tag{15}$$

$$R_t = \alpha A_tK_{t-1}^{\alpha-1}Z_t^{1-\alpha}H_t^{1-\alpha} \tag{16}$$

$$Y_t + \frac{D_t}{1+r_t} = D_{t-1} + C_t + I_t + \frac{\phi}{2}\left(\frac{K_t}{K_{t-1}} - g_t\right)^2 K_{t-1} \tag{17}$$

$$I_t = K_t - (1-\delta)K_{t-1} \tag{18}$$

$$r_t = r^* + \psi(e^{(\tilde{D}_t/Z_t-\bar{d})} - 1). \tag{19}$$

The equilibrium conditions, scaled ($c_t = C_t/Z_{t-1}$, $\tilde{c}_t = \tilde{C}_t/Z_{t-1}$, $h_t = H_t$, $w_t = W_t/Z_{t-1}$, $v_t = V_t/Z_{t-1}$, $\tilde{v}_t = \tilde{V}_t/Z_{t-1}$, $y_t = Y_t/Z_{t-1}$,

$k_t = K_t/Z_t$, $a_t = A_t$) and simplified:

$$
\begin{aligned}
v_t^{1-\varsigma} &= (1-\beta)\tilde{c}_t^{1-\varsigma} + \beta\tilde{v}_t^{1-\varsigma} && (20)\\
\tilde{v}_t^{1-\gamma} &= E\left[(g_t v_{t+1})^{1-\gamma}\right] && (21)\\
\tilde{c}_t &= c_t - \theta\omega^{-1}h_t^{\omega} && (22)\\
w_t &= \theta h_t^{\omega-1} && (23)\\
\kappa_t &= \frac{k_t}{k_{t-1}} - 1 && (24)\\
1 &= \beta g_t^{-\gamma} E_t\left[\left(\frac{v_{t+1}}{\tilde{v}_t}\right)^{\varsigma-\gamma}\left(\frac{\tilde{c}_{t+1}}{\tilde{c}_t}\right)^{-\varsigma}(1+r_t)\right] && (25)\\
1 &= \beta g_t^{-\gamma} E_t\left[\left(\frac{v_{t+1}}{\tilde{v}_t}\right)^{\varsigma-\gamma}\left(\frac{\tilde{c}_{t+1}}{\tilde{c}_t}\right)^{-\varsigma}\left(\frac{R_{t+1}+1-\delta+\phi g_{t+1}^2(\kappa_{t+1}+\frac{1}{2}\kappa_{t+1}^2)}{1+\phi g_t\kappa_t}\right)\right] && (26)\\
y_t &= a_t k_{t-1}^{\alpha}(g_t h_t)^{1-\alpha} && (27)\\
w_t h_t &= (1-\alpha)y_t && (28)\\
R_t k_{t-1} &= \alpha y_t && (29)\\
y_t &= d_{t-1} - \frac{d_t g_t}{1+r_t} + c_t + i_t + \frac{\phi}{2}g_t^2\kappa_t^2 k_{t-1} && (30)\\
i_t &= k_t g_t - (1-\delta)k_{t-1} && (31)\\
r_t &= r^* + \psi(e^{(d_t-\bar{d})} - 1) && (32)\\
\log(a_{t+1}) &= \rho\log(a_t) + \eta(u_t\sigma_u + (1-u_t)\sigma_q)\epsilon_{t+1} && (33)\\
\log(g_t) &= \log(g_q) + \eta u_t \log(g_u) && (34)\\
\epsilon_{t+1} &\sim \text{i.i.d.}N(0,1) && (35)\\
u_{t+1} &\sim \text{Markov, 0 or 1 with constant transition matrix.} && (36)
\end{aligned}
$$

Steady state at $\eta = 0$:

$$v = \left(\frac{1-\beta}{1-\beta g^{1-\varsigma}}\right)^{\frac{1}{1-\varsigma}} \tilde{c} \tag{37}$$

$$\tilde{v} = gv \tag{38}$$

$$\tilde{c} = c - \theta\omega^{-1}h^{\omega} \tag{39}$$

$$w = \theta h^{\omega-1} \tag{40}$$

$$1 = \beta g^{-\varsigma}(1+r) \tag{41}$$

$$r = R - \delta \tag{42}$$

$$y = ak^{\alpha}(gh)^{1-\alpha} \tag{43}$$

$$wh = (1-\alpha)y \tag{44}$$

$$Rk = \alpha y \tag{45}$$

$$y = d\frac{1+r-g}{1+r} + c + i \tag{46}$$

$$i = k(g-1+\delta) \tag{47}$$

$$r = r^* \tag{48}$$

$$a = 1 \tag{49}$$

$$\kappa = 0 \tag{50}$$

$$g = g_q. \tag{51}$$

B.3 Notes on Solution Method and GIRFs

To approximate the solution to equilibrium of our model, we use a higher-order perturbation method with the pruning algorithm of Andreasen et al. (2017). Because we calculate GIRFs for higher-order moments of endogenous variables, deriving analytic representations for the GIRFs, as Andreasen et al. (2017) do, would be extremely algebraically tedious. Instead, we rely on the computer algebra software Mathematica to compute these higher-order moments. This section describes our computational strategy.

The equilibrium conditions can be stated in the following form:

$$0 = E_t[F(\mathbf{y}_{t+1}, \mathbf{y}_t, \mathbf{x}_{t+1}, \mathbf{x}_t, u_{t+1}, u_t)]. \tag{52}$$

The vector of equations $\mathbf{F}$ includes all optimality conditions, constraints, and the law of motion for the exogenous process. The vector $\mathbf{y}_t$ is the vector of control variables: $[\log(y_t), \log(c_t), \log(i_t), \log(h_t), \log(r_{k,t}), \log(w_t), \log(r_t), \log(\tilde{c}_t), \kappa_t, \log(v_t), \log(\tilde{v}_t)]$. The perturbation parameter, η, is 1 in the model of interest but set to 0 at the point of approximation. The vector $\mathbf{x}_t$ is the vector of *continuous* states, including the perturbation parameter[17]: $[\log(k_{t-1}), d_{t-1}, \log(a_t), \eta]$. u_t is the indicator for unrest, which can only take the values 0 and 1.

The solution to this model is a set of policy functions of the following form, where $\epsilon_{t+1} = \begin{bmatrix} \epsilon^u_{t+1} \\ \epsilon^q_{t+1} \end{bmatrix}$ and the two shocks ϵ^u_{t+1} and ϵ^q_{t+1} follow two i.i.d. Normal Inverse Gaussian processes, described in the text:

$$\mathbf{y}_t = \mathbf{g}(\mathbf{x}_t, u_t) \tag{53}$$

$$\mathbf{x}_{t+1} = \mathbf{h}(\mathbf{x}_t, u_t) + \eta \mathbf{S}(u_{t+1})\epsilon_{t+1}. \tag{54}$$

More specifically, for the state vector,

$$\begin{bmatrix} \log(k_t) \\ d_t \\ \log(a_{t+1}) \\ \eta \end{bmatrix} = \mathbf{h}\left(\begin{bmatrix} \log(k_{t-1}) \\ d_{t-1} \\ \log(a_t) \\ \eta \end{bmatrix}, u_t \right) + \eta \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ u_{t+1} & (1-u_{t+1}) \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \epsilon^u_{t+1} \\ \epsilon^q_{t+1} \end{bmatrix}. \tag{55}$$

At the point of approximation, the system is at a nonstochastic steady state in $\mathbf{x}_t$ and $\mathbf{y}_t$: $\mathbf{x}_t = \mathbf{x}_{ss} = [\log(k_{ss}), d_{ss}, 0, 0]$ and $\mathbf{y}_t = \mathbf{y}_{ss}$. Since the unrest and no-unrest states are completely symmetric at $\eta = 0$ by construction, the process u_t is irrelevant for the steady states of $\mathbf{x}_t$ and $\mathbf{y}_t$. Therefore, the following is true for all values of u_{t+1} and u_t:

$$0 = F(\mathbf{y}_{ss}, \mathbf{y}_{ss}, \mathbf{x}_{ss}, \mathbf{x}_{ss}, u_{t+1}, u_t). \tag{56}$$

We use a standard third-order perturbation method (e.g., Judd 1996) to construct Taylor series approximations to $\mathbf{h}(\cdot, 0)$, $\mathbf{h}(\cdot, 1)$, $\mathbf{g}(\cdot, 0)$, and $\mathbf{g}(\cdot, 1)$. Those Taylor series approximations yield the coefficients $\mathbf{h}_{0\mathbf{x}} = \frac{\partial \mathbf{h}(\mathbf{x},0)}{\partial \mathbf{x}}|_{\mathbf{x}=\mathbf{x}_{ss}}$, $\mathbf{H}_{0\mathbf{xx}} = \frac{\partial^2 \mathbf{h}(\mathbf{x},0)}{\partial \mathbf{x}^2}|_{\mathbf{x}=\mathbf{x}_{ss}}$, and $\mathbf{H}_{0\mathbf{xxx}} = \frac{\partial^3 \mathbf{h}(\mathbf{x},0)}{\partial \mathbf{x}^3}|_{\mathbf{x}=\mathbf{x}_{ss}}$, conformably reshaped:

$$\mathbf{h}(\mathbf{x}, 0) \approx \mathbf{h}_{0\mathbf{x}}\mathbf{x} + \frac{1}{2}\mathbf{H}_{0\mathbf{xx}}(\mathbf{x} \otimes \mathbf{x}) + \frac{1}{6}\mathbf{H}_{0\mathbf{xxx}}(\mathbf{x} \otimes \mathbf{x} \otimes \mathbf{x}). \tag{57}$$

This implies that the law of motion for $\mathbf{x}_t$ and $\mathbf{y}_t$ can be approximated to third order as:

$$\mathbf{x}_{t+1}|u_t, u_{t+1} = \mathbf{h}_{u_t\mathbf{x}}\mathbf{x}_t + \frac{1}{2}\mathbf{H}_{u_t\mathbf{xx}}(\mathbf{x}_t \otimes \mathbf{x}_t) + \frac{1}{6}\mathbf{H}_{u_t\mathbf{xxx}}(\mathbf{x} \otimes \mathbf{x} \otimes \mathbf{x}) + \eta \mathbf{S}_{u_{t+1}}\epsilon_{t+1} \tag{58}$$

$$\mathbf{y}_t|u_t, u_{t+1} = \mathbf{g}_{u_t\mathbf{x}}\mathbf{x}_t + \frac{1}{2}\mathbf{G}_{u_t\mathbf{xx}}(\mathbf{x}_t \otimes \mathbf{x}_t) + \frac{1}{6}\mathbf{G}_{u_t\mathbf{xxx}}(\mathbf{x}_t \otimes \mathbf{x}_t \otimes \mathbf{x}_t). \tag{59}$$

[17] We include the perturbation parameter in the definition of the state vector to simplify notation. Andreasen et al. (2017) include a brief discussion of this notation in the extensive appendix to their paper.

However, it is well-known (e.g., in Kim et al. 2008; and Den Haan and De Wind 2012) that third-order approximations like the above can have undesirable statistical properties, such as explosive simulated paths and spurious steady states. Andreasen et al. (2017) extend Kim et al. (2008) and use a pruning algorithm to eliminate these undesirable properties. The second-order pruning algorithm separates simulated components of $\mathbf{x}_t$ and $\mathbf{y}_t$ into first-order components $\mathbf{x}_t^f$ and $\mathbf{y}_t^f$, second-order components $\mathbf{x}_t^s$ and $\mathbf{y}_t^s$, and third-order components $\mathbf{x}_t^r$ and $\mathbf{y}_t^r$. The simulated quantities of interest are $\mathbf{x}_t^f + \mathbf{x}_t^s + \mathbf{x}_t^r$ and $\mathbf{y}_t^f + \mathbf{y}_t^s + \mathbf{y}_t^r$, and the components evolve linearly.

Let $\mathbf{C}_{t+1} = \mathbf{S}_{u_{t+1}}\epsilon_{t+1} + [0,0,0,1]'$. The constant vector $[0,0,0,1]'$ reflects the fact that the law of motion for the perturbation parameter is simply $\eta = 1$.

Following the approach in Andreasen et al. (2017), we have:

$$\mathbf{x}_{t+1}^f = \mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^f + \mathbf{C}_{t+1} \tag{60}$$

$$\mathbf{x}_{t+1}^s = \mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^s + \frac{1}{2}\mathbf{H}_{\mathbf{xx},u_t}(\mathbf{x}_t^f, \mathbf{x}_t^f) \tag{61}$$

$$\mathbf{x}_{t+1}^f \otimes \mathbf{x}_{t+1}^f = (\mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^f + \mathbf{C}_{t+1}) \otimes (\mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^f + \mathbf{C}_{t+1}) \tag{62}$$

$$\mathbf{x}_{t+1}^r = \mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^r + \mathbf{H}_{\mathbf{xx},u_t}(\mathbf{x}_t^f \otimes \mathbf{x}_t^s) + \frac{1}{6}\mathbf{H}_{\mathbf{xxx},u_t}(\mathbf{x}_t^f \otimes \mathbf{x}_t^f \otimes \mathbf{x}_t^f) \tag{63}$$

$$\mathbf{x}_{t+1}^f \otimes \mathbf{x}_{t+1}^s = (\mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^f + \mathbf{C}_{t+1}) \otimes (\mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^s + \frac{1}{2}\mathbf{H}_{\mathbf{xx},u_t}(\mathbf{x}_t^f \otimes \mathbf{x}_t^f)) \tag{64}$$

$$\mathbf{x}_{t+1}^f \otimes \mathbf{x}_{t+1}^f \otimes \mathbf{x}_{t+1}^f = (\mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^f + \mathbf{C}_{t+1}) \otimes (\mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^f + \mathbf{C}_{t+1}) \otimes (\mathbf{h}_{\mathbf{x},u_t}\mathbf{x}_t^f + \mathbf{C}_{t+1}). \tag{65}$$

At this point, we deviate from the notation in Andreasen et al. (2017). Let

$$\mathbf{z}_t = \begin{bmatrix} \mathbf{x}_t^f \\ \mathbf{x}_t^s \\ \mathbf{x}_t^f \otimes \mathbf{x}_t^f \\ \mathbf{x}_t^r \\ \mathbf{x}_t^f \otimes \mathbf{x}_t^s \\ \mathbf{x}_t^f \otimes \mathbf{x}_t^f \otimes \mathbf{x}_t^f \end{bmatrix}.$$

Expanding the above, we find that

$$\mathbf{z}_{t+1} = \mathbf{A}_{u_t,u_{t+1}}(\epsilon_{t+1})\mathbf{z}_t + \mathbf{B}_{u_{t+1}}(\epsilon_{t+1}).$$

Remember that $\mathbf{C}_{t+1}$ is a function of ϵ_{t+1}.

$$\mathbf{A}_{u_t,u_{t+1}}(\epsilon_{t+1}) =$$

$$\begin{bmatrix} \mathbf{h}_{\mathbf{x},u_t} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{h}_{\mathbf{x},u_t} & \frac{1}{2}\mathbf{H}_{\mathbf{xx},u_t} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \tilde{\mathbf{H}}_{3,1} & \mathbf{0} & \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{h}_{\mathbf{x},u_t} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{h}_{\mathbf{x},u_t} & \mathbf{H}_{\mathbf{xx},u_t} & \frac{1}{6}\mathbf{H}_{\mathbf{xxx},u_t} \\ \mathbf{0} & \mathbf{C}_{t+1} \otimes \mathbf{h}_{\mathbf{x},u_t} & \mathbf{C}_{t+1} \otimes \frac{1}{2}\mathbf{H}_{\mathbf{xx},u_t} & \mathbf{0} & \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{h}_{\mathbf{x},u_t} & \mathbf{h}_{\mathbf{x},u_t} \otimes \frac{1}{2}\mathbf{H}_{\mathbf{xx},u_t} \\ \tilde{\mathbf{H}}_{6,1} & \mathbf{0} & \tilde{\mathbf{H}}_{6,3} & \mathbf{0} & \mathbf{0} & \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{h}_{\mathbf{x},u_t} \end{bmatrix}$$

where

$$\tilde{\mathbf{H}}_{3,1} = \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{C}_{t+1} + \mathbf{C}_{t+1} \otimes \mathbf{h}_{\mathbf{x},u_t} \tag{66}$$

$$\tilde{\mathbf{H}}_{6,1} = \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{C}_{t+1} \otimes \mathbf{C}_{t+1} + \mathbf{C}_{t+1} \otimes \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{C}_{t+1} + \mathbf{C}_{t+1} \otimes \mathbf{C}_{t+1} \otimes \mathbf{h}_{\mathbf{x},u_t} \tag{67}$$

$$\tilde{\mathbf{H}}_{6,3} = \mathbf{C}_{t+1} \otimes \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{h}_{\mathbf{x},u_t} + \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{C}_{t+1} \otimes \mathbf{h}_{\mathbf{x},u_t} + \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{h}_{\mathbf{x},u_t} \otimes \mathbf{C}_{t+1}. \tag{68}$$

$$\mathbf{B}_{u_{t+1}}(\epsilon_{t+1}) = \begin{bmatrix} \mathbf{C}_{t+1} \\ \mathbf{0} \\ \mathbf{C}_{t+1} \otimes \mathbf{C}_{t+1} \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{C}_{t+1} \otimes \mathbf{C}_{t+1} \otimes \mathbf{C}_{t+1} \end{bmatrix}.$$

Similarly, for controls $\mathbf{y}_t$, we have $(\mathbf{y}_t^f + \mathbf{y}_t^s + \mathbf{y}_t^r)|u_t = \mathbf{D}_{u_t}\mathbf{z}_t$, where

$$\mathbf{D}_{u_t} = \begin{bmatrix} \mathbf{g}_{u_t,\mathbf{x}} & \mathbf{g}_{u_t,\mathbf{x}} & \frac{1}{2}\mathbf{G}_{u_t,\mathbf{xx}} & \mathbf{g}_{\mathbf{x},u_t} & \mathbf{G}_{\mathbf{xx},u_t} & \frac{1}{6}\mathbf{G}_{\mathbf{xxx},u_t} \end{bmatrix}.$$

In this paper. we are interested in the growth rates of the controls.

$$\begin{aligned} (\Delta\mathbf{y}_{t+1})|u_t, u_{t+1} &= \left[(\mathbf{y}_{t+1}^f - \mathbf{y}_t^f) + (\mathbf{y}_{t+1}^s - \mathbf{y}_t^s) + (\mathbf{y}_{t+1}^r - \mathbf{y}_t^r)\right]|u_t, u_{t+1} \\ &= \mathbf{D}_{u_{t+1}}\mathbf{z}_{t+1} - \mathbf{D}_{u_t}\mathbf{z}_t \\ &= \mathbf{D}_{u_{t+1}}(\mathbf{A}_{u_t,u_{t+1}}(\epsilon_{t+1})\mathbf{z}_t + \mathbf{B}_{u_{t+1}}(\epsilon_{t+1})) - \mathbf{D}_{u_t}\mathbf{z}_t \\ &= (\mathbf{D}_{u_{t+1}}\mathbf{A}_{u_t,u_{t+1}}(\epsilon_{t+1}) - \mathbf{D}_{u_t})\mathbf{z}_t + \mathbf{D}_{u_{t+1}}\mathbf{B}_{u_{t+1}}(\epsilon_{t+1}) \\ &= \mathbf{A}^{\Delta\mathbf{y}}_{u_t,u_{t+1}}(\epsilon_{t+1})\mathbf{z}_t + \mathbf{B}^{\Delta\,\mathbf{y}}_{u_{t+1}}(\epsilon_{t+1}). \end{aligned}$$

To calculate the average change in the first three moments of output, investment, and consumption growth during unrest, we use the concept of GIRF from Andreasen et al. (2017) and Koop et al. (1996). In particular, we calculate the unconditional moments of all endogenous variables for two fixed paths for the unrest process. The first path is for a country that starts with no unrest and then enters into unrest at $t = 1$ and stays there. That is, $u_t = 0\ \forall t \leq 0$ and $u_t = 1\ \forall t \geq 1$. Denote this path for u_t as u. The second counterfactual path is one where the country never enters unrest: $u_t = 0\ \forall t$. Denote this path for u_t as $\tilde{u}$. Andreasen et al. (2017) condition on an initial value of the state vector $\mathbf{z}_0$. We instead focus on an unconditional expectation over the entire range of t to be able to arrive at a single path of moments for our exercise. The generalized IRF for the state variables $\mathbf{z}_t$ is the difference, at each point in time t, of the unconditional mean of $\mathbf{z}_t$ along the path u and the unconditional mean of $\mathbf{z}_t$ along the path $\tilde{u}$:

$$GIRF^u(\Delta \mathbf{y}_{t+1}) = E[\Delta \mathbf{y}_{t+1}|u] - E[\Delta \mathbf{y}_{t+1}|\tilde{u}]. \tag{69}$$

Andreasen et al. (2017) derive separate expressions for the evolution over time of the variances of controls. We take a different approach, which we find to be simpler, especially in dealing with third-order moments. We expand the set of objects we find a GIRF of from $\Delta \mathbf{y}_t$ to $Y_t = \begin{bmatrix} \Delta \mathbf{y}_t \\ (\Delta \mathbf{y}_t) \otimes (\Delta \mathbf{y}_t) \\ (\Delta \mathbf{y}_t) \otimes (\Delta \mathbf{y}_t) \otimes (\Delta \mathbf{y}_t) \end{bmatrix}$, so that we can compute one GIRF for all the moments of interest in one pass. For example, $vec(Var(\Delta \mathbf{y}_t)) = E[(\Delta \mathbf{y}_t) \otimes (\Delta \mathbf{y}_t)] - E[\Delta \mathbf{y}_t] \otimes E[\Delta \mathbf{y}_t]$, and the skewness of $\Delta \mathbf{y}_t$ is similarly a function of $E[(\Delta \mathbf{y}_t) \otimes (\Delta \mathbf{y}_t) \otimes (\Delta \mathbf{y}_t)]$. Using the expression $\Delta \mathbf{y}_t = \mathbf{A}^{\Delta \mathbf{y}}_{u_t,u_{t+1}}(\epsilon_{t+1})\mathbf{z}_t + \mathbf{B}^{\Delta \mathbf{y}}_{u_{t+1}}(\epsilon_{t+1})$ and expanding the Kronecker products in X_t, we have matrices $\tilde{\mathbf{A}}^{\Delta \mathbf{y}}_{u_t,u_{t+1}}(\epsilon_{t+1})$ and $\tilde{\mathbf{B}}^{\Delta \mathbf{y}}_{u_{t+1}}(\epsilon_{t+1})$ such that

$$\{X_{t+1} = \tilde{\mathbf{A}}^{\Delta \mathbf{y}}_{u_t,u_{t+1}}(\epsilon_{t+1})\{Z_t + \tilde{\mathbf{B}}^{\Delta \mathbf{y}}_{u_{t+1}}(\epsilon_{t+1}) \tag{70}$$

where $Z_t = \begin{bmatrix} \mathbf{z}_t \\ \mathbf{z}_t \otimes \mathbf{z}_t \\ \mathbf{z}_t \otimes \mathbf{z}_t \otimes \mathbf{z}_t \end{bmatrix}$.

To calculate the law of motion for Z_t, we expand the Kronecker products in the definition of Z_t using the law of motion $\mathbf{Z}_{t+1} = \mathbf{A}_{u_t,u_{t+1}}(\epsilon_{t+1})\mathbf{z}_t + \mathbf{B}_{u_{t+1}}(\epsilon_{t+1})$ and arrive at the law of motion $Z_{t+1} = \tilde{\mathbf{A}}_{u_t,u_{t+1}}(\epsilon_{t+1})Z_t| + \tilde{\mathbf{B}}_{u_{t+1}}(\epsilon_{t+1})$ for matrices $\tilde{\mathbf{A}}_{u_t,u_{t+1}}(\epsilon_{t+1})$ and $\tilde{\mathbf{B}}_{u_{t+1}}(\epsilon_{t+1})$.

For any Z_0, the independence of ϵ_{t+1} and Z_t implies for states and controls (noting that $E[\tilde{\mathbf{A}}_{u_t,u_{t+1}}(\epsilon_{t+1})|Z_0, u] = E[\tilde{\mathbf{A}}_{u_t,u_{t+1}}(\epsilon_{t+1})|u]$ and similarly for $E[\tilde{\mathbf{A}}^{\Delta \mathbf{y}}_{u_t,u_{t+1}}(\epsilon_{t+1})|Z_0, u]$, $E[\tilde{\mathbf{B}}_{u_{t+1}}(\epsilon_{t+1})|Z_0, u]$ and $E[\tilde{\mathbf{B}}^{\Delta \mathbf{y}}_{u_{t+1}}(\epsilon_{t+1})|Z_0, u]$):

$$E[Z_{t+1}|Z_0, u] = E[\tilde{\mathbf{A}}_{u_t,u_{t+1}}(\epsilon_{t+1})|u]E[Z_t|Z_0, u] + E[\tilde{\mathbf{B}}_{u_{t+1}}(\epsilon_{t+1})|u] \tag{71}$$

$$E[Y_{t+1}|Z_0, u] = E[\tilde{\mathbf{A}}^{\Delta \mathbf{y}}_{u_t,u_{t+1}}(\epsilon_{t+1})|u]E[Z_t|Z_0, u] + E[\tilde{\mathbf{B}}^{\Delta \mathbf{y}}_{u_{t+1}}(\epsilon_{t+1})|u]. \tag{72}$$

Let Z_0 be the fixed point of the law of motion for $E[Z_{t+1}Z_0, u]$, conditional on $t < 0$, in other words, conditional on no unrest at time t or $t+1$.

$$Z_0 = E[\tilde{\mathbf{A}}_{0,0}(\epsilon_{t+1})]Z_0 + E[\tilde{\mathbf{B}}_0(\epsilon_{t+1})]. \tag{73}$$

From the elements of Z_0, we can calculate the ergodic means, variances, covariances, skewnesses, and sundry third moments of all elements of $\mathbf{z}_t$ conditional on no unrest. This is the starting point of our GIRF. For $t = 1, 2, 3...$, use the laws of motion for X_t and Z_t to iterate forward, conditional on both the path u and the counterfactual path $\tilde{u}$, and use those paths to calculate the GIRF for X_t:

$$GIRF^u(X_t) = E[X_t|u] - E[X_t|\tilde{u}]. \tag{74}$$

This notation is very condensed. For example, $\tilde{\mathbf{B}}^{\Delta\mathbf{y}}_{u_{t+1}}(\epsilon_{t+1})$ is a very large matrix, with very large polynomials containing terms with order as high as ϵ^9_{t+1}. There are a large number of terms in every element of these matrices, even if expressed as Kronecker products; that is why we rely on the symbolic manipulation of Mathematica to expand these polynomials. Even after exploiting the very high degree of symmetry and redundant terms in Z_t, there are over 20,000 unique elements in that vector. Mathematica can handle these calculations very quickly, calculating the GIRFs for both states and controls in under two minutes.

1. C. ONLINE DATA APPENDIX: LIST OF NAVCO UNREST EPISODES

Table 8 List of Episodes of Mass Political Campaigns

	Country	Begin year	End year	Campaign	Target
1	Afghanistan	1978	1978	Afghans	Afghan government
2	Afghanistan	1992	1996	Taliban/ Anti-Government Forces	Afghan regime
3	Afghanistan	2001	2006	Taliban Resistance	Afghan government
4	Albania	1989	1991	Albania Anti-Communist	Communist regime
5	Algeria	1962	1963	Former Rebel Leaders	Ben Bella regime
6	Algeria	1992	2006	Islamic Salvation Front	Algerian government
7	Angola	1975	2002	UNITA	Angolan government
8	Argentina	1973	1977	ERP/ Monteneros	Argentina regime
9	Argentina	1977	1983	Argentina pro-democracy movement	Military junta
10	Argentina	1987	1987	Argentiana coup plot	Attempted coup
11	Bangladesh	1987	1990	Bangladesh Anti-Ershad	Military rule
12	Belarus	1988	1991	Belarus Anti-Communist	Communist regime
13	Belarus	2006	2006	Belarus Regime Opposition	Belarus government
14	Benin	1989	1990	Benin Anti-Communist	Communist regime
15	Bolivia	1952	1952	Bolivian Leftists	Military junta
16	Bolivia	1977	1982	Bolivian Anti-Junta	Military juntas
17	Brazil	1984	1985	Diretas ja	Military rule
18	Bulgaria	1989	1989	Bulgaria Anti-Communist	Communist regime
19	Burma	1988	2006	Karens	Burmese government
20	Burma	1988	1990	Burma pro-democracy movement	Military junta
21	Burundi	1972	1973	First Hutu Rebellion	Tutsi influence in government
22	Burundi	1988	1988	Second Hutu Rebellion	Tutsi influence in government
23	Burundi	1991	1992	Tutsi supremacists	Buyoya regime
24	Burundi	1993	2002	Third Hutu Rebellion	Power-sharing/Tutsi-dominated government
25	Cambodia	1970	1975	Khmer Rouge	Cambodian government
26	Cambodia	1978	1979	Anti-Khmer Rouge	Cambodian government
27	Cambodia	1989	1997	Second Khmer Rouge	Cambodian government
28	Chad	1968	1990	Frolinat	Chadian government
29	Chad	1994	1998	Chad rebels	Chadian regime
30	Chile	1973	1973	Pinochet-led rebels	Allende regime
31	Chile	1983	1989	Anti-Pinochet Movement	Augusto Pinochet
32	China	1956	1957	Hundred Flowers Movement	Communist regime
33	China	1966	1968	Cultural Revolution Red Guards	Anti-Maoists
34	China	1976	1979	Democracy Movement	Communist regime
35	China	1989	1989	Tiananmen	Communist regime
36	Colombia	1946	1953	Liberals of 1949	Conservative govt
37	Colombia	1964	2006	Revolutionary Armed Forces of Colombia and National Liberation Army	Colombia govt and US influence
38	Costa Rica	1948	1948	National Union Party	Calderon regime
39	Croatia	1999	2000	Croatian Institutional Reform	Semi-presidential system
40	Cuba	1956	1959	Cuban Revolution	Batista regime
41	Czechoslovakia	1989	1990	Velvet Revolution	Communist regime
42	Djibouti	1991	1994	Afar insurgency	Djibouti regime
43	Dominican Republic	1965	1965	Dominican leftists	Loyalist regime
44	Egypt	2000	2005	Kifaya	Mubarak regime
45	El Salvador	1977	1991	Salvadoran Civil Conflict	El Salvador government
46	Ethiopia	1981	1991	Tigrean People's Liberation Front	Ethiopian government
47	France	1960	1962	Pro-French Nationalists	French withdrawal from Algeria
48	Georgia	2003	2003	Rose Revolution	Shevardnadze regime
49	Ghana	1949	1950	Convention People's Party movement	British Rule
50	Ghana	2000	2000	Anti-Rawlings	Rawlings govt
51	Greece	1963	1963	Anti-Karamanlis	Karamanlis regime
52	Greece	1973	1974	Greece Anti-Military	Military rule
53	Guatemala	1954	1954	Conservative movement	Arbenz leftist regime
54	Guatemala	1961	1996	Marxist rebels (URNG)	government of Guatemala

Table 9 List of Episodes of Mass Political Campaigns (continued)

55	Guyana	1990	1990 Anti-Burnham / Hoyte	Burnham/Hoyte autocratic regime
56	Haiti	1985	1985 Anti-Duvalier	Jean Claude Duvalier
57	Hungary	1956	1956 Hungary Anti-Communist	Communist regime
58	Hungary	1989	1989 Hungary pro-dem movement	Communist regime
59	India	1967	1971 Naxalite rebellion	Indian regime
60	Indonesia	1949	1962 Darul Islam	Indonesian government
61	Indonesia	1956	1960 Indonesian leftists / Anti Sukarno	Sukarno regime
62	Indonesia	1997	1998 Anti-Suharto	Suharto rule
63	Iran	1977	1978 Iranian Revolution	Shah Reza Pahlavi
64	Iran	1981	1982 Iranian Mujahideen	Khomenei regime
65	Iran	1982	1983 KDPI	Iranian regime
66	Iraq	1959	1959 Shammar Tribe and pro-Western officers	Qassim regime
67	Iraq	1991	1991 Shiite rebellion	Hussein regime
68	Ivory Coast	2002	2005 PMIC	Incumbent regime
69	Kenya	1990	1991 Anti-Arap Moi	Daniel Arap Moi
70	Kyrgyzstan	1990	1991 Kyrgyzstan Democratic Movement	Communist regime
71	Kyrgyzstan	2005	2005 Tulip Revolution	Akayev regime
72	Laos	1960	1975 Pathet Lao	Laotian government
73	Lebanon	1958	1958 Anti-Shamun	Shamun regime
74	Lebanon	1975	1975 Lebanon leftists	Lebanese government
75	Lebanon	2005	2005 Cedar Revolution	Syrian forces
76	Liberia	1989	1990 Anti-Doe rebels	Doe regime
77	Liberia	1992	1995 NPFL & ULIMO	Johnson regime
78	Liberia	1996	1996 National patriotic forces	Liberian govt
79	Liberia	2003	2003 LURD	Taylor regime
80	Madagascar	1991	1993 Active Forces	Didier Radsiraka
81	Madagascar	2002	2002 Madagasar pro-democracy movement	Radsiraka regime
82	Malawi	1959	1959 Nyasaland African Congress	British rule
83	Malawi	1992	1993 Anti-Banda	Banda regime
84	Maldives	2003	2006 Anti-Gayoom	Maumoon Abudul Gayoom's regime
85	Mali	1990	1992 Mali Anti-Military	Military rule
86	Mexico	1987	2000 Anti-PRI	Corrupt govt
87	Mexico	2006	2006 Anti-Calderon	Calderon regime
88	Mongolia	1989	1990 Mongolian Anti-communist	Communist regime
89	Mozambique	1979	1992 Renamo	Mozambique government
90	Nepal	1990	1990 The Stir	Monarchy/Panchayat regime
91	Nepal	1996	2006 CPN-M/UPF	Nepalese government
92	Nicaragua	1978	1979 FSLN	Nicaraguan regime
93	Nicaragua	1980	1990 Contras	Sandinista regime
94	Niger	1991	1992 Niger Anti-Military	Military rule
95	Nigeria	1993	1998 Nigeria Anti-Military	Military rule
96	Oman	1964	1976 Popular Front for the Liberation of Oman and the Arab Gulf (PFLOAG)	Oman government
97	Pakistan	1968	1969 Anti-Khan	Khan regime
98	Pakistan	1983	1983 Pakistan pro-dem movement	Zia al-Huq
99	Pakistan	1994	1995 Mohajir	Pakistani government
100	Panama	1987	1989 Anti-Noriega	Noriega regime
101	Papua New Guinea	1988	1988 Bougainville Revolt	Papuan regime
102	Paraguay	1947	1947 Paraguay leftist rebellion	Morinigo regime
103	Peru	1980	1995 Sendero Luminoso (The Shining Path) Senderista Insurgency	Peruvian government
104	Peru	1996	1997 Tupac Amaru Revolutionary Movement (MRTA) - Senderista Insurgency	Peruvian government
105	Peru	2000	2000 Anti-Fujimori	Fujimori govt
106	Philippines	1946	1954 Hukbalahap Rebellion	Filipino government
107	Philippines	1972	2006 New People's Army	Filipino government
108	Philippines	1983	1986 People Power	Ferdinand Marcos
109	Philippines	2001	2001 Second People Power Movement	Estrada regime
110	Poland	1956	1956 Poznan Protests	Communist regime

Table 10 List of Episodes of Mass Political Campaigns (continued)

111	Poland	1968	1968	Poland Anti-Communist I	Communist regime
112	Poland	1970	1970	Poland Anti-Communist II	Communist regime
113	Poland	1976	1976	Poland Warsaw worker uprising	Communist regime
114	Poland	1980	1989	Solidarity	Communist regime
115	Portugal	1973	1974	Carnation Revolution	Military rule
116	Romania	1987	1989	Anti-Ceaucescu rebels	Ceacescu regime
117	Russia	1990	1991	Russia pro-dem movement	Anti-coup
118	Rwanda	1961	1964	Watusi	Hutu regime
119	Rwanda	1990	1994	Tutsi rebels	Hutu regime
120	Rwanda	1994	1994	Patriotic Front	Hutu regime and genocide
121	Senegal	2000	2000	Anti-Diouf	Diouf govt
122	Serbia	1996	2000	Anti-Milosevic	Milosevic regime
123	Sierra Leone	1991	1996	RUF	Republican government
124	Slovenia	1989	1990	Slovenia Anti-Communist	Communist regime
125	Somalia	1982	1991	Somalia clan factions; SNM	Siad Barre regime
127	South Africa	1952	1961	South Africa First Defiance Campaign	Apartheid
128	South Africa	1984	1994	South Africa Second Defiance Campaign	Apartheid
129	South Korea	1960	1960	South Korea Student Revolution	Rhee regime
130	South Korea	1979	1980	South Korea Anti-Junta	Military junta
131	South Korea	1987	1987	South Korea Anti-Military	Military government
132	Sri Lanka	1971	1971	JVP	Sri Lankan government
133	Sri Lanka	1972	1972	LTTE	Sri Lankan occupation
134	Sudan	1985	1985	Anti-Jaafar	Jaafar Nimiery
135	Sudan	1985	2005	SPLA-Garang faction	Sudanese government
136	Sudan	2003	2006	JEM/SLA	Janjaweed militia
137	Syria	1980	1982	Muslim Brotherhood	Syrian regime
138	Taiwan	1979	1985	Taiwan pro-democracy movement	Autocratic regime
139	Tajikistan	1992	1997	Popular Democratic Army (UTO)	Rakhmanov regime
140	Tanzania	1992	1992	Tanzania pro-democracy movement	Mwinyi regime
141	Thailand	1966	1981	Thai communist rebels	Thai government
142	Thailand	1973	1973	Thai student protests	Military dictatorship
143	Thailand	1992	1992	Thai pro-dem movement	Suchinda regime
144	Thailand	2005	2006	Anti-Thaksin	Thaksin regime
145	Uganda	1980	1986	National Resistance Army	Okello regime
146	Uganda	1986	2006	LRA	Museveni government
147	Ukraine	2001	2004	Orange Revolution	Kuchma regime
148	Uruguay	1963	1972	Tupamaros	Uruguay government
149	Uruguay	1984	1985	Uruguay Anti-Military	Military rule
150	Venezuela	1958	1958	Anti-Jimenez	Jimenez dictatorship
151	Venezuela	1958	1963	Armed Forces for National Liberation (FALN)	Betancourt regime
152	Yugoslavia	1968	1968	Yugoslavia student protests	Communist regime
153	Yugoslavia	1970	1971	Croatian nationalists	Yugoslav government
154	Zambia	1990	1991	Zambia Anti-Single Party	One-party rule
155	Zambia	2001	2001	Anti-Chiluba	Chiluba regime
156	Zimbabwe	1974	1979	Zimbabwe African People's Union	Smith/Muzorena regime
157	Zimbabwe	1982	1987	PF-ZAPU guerillas	Mugabe regime

REFERENCES

Acemoglu, Daron, Tarek A. Hassan, and Ahmed Tahoun. 2014. "The Power of the Street: Evidence from Egypt's Arab Spring." Working Paper 20665. Cambridge, Mass.: National Bureau of Economic Research. (November).

Acemoglu, Daron, and James A. Robinson. 2005. *Economic Origins of Dictatorship and Democracy.* Cambridge: Cambridge University Press.

Alesina, Alberto, Arnaud Devleeschauwer, William Easterly, Sergio Kurlat, and Romain Wacziarg. 2003. "Fractionalization." *Journal of Economic Growth* 8 (June):155–94.

Andersson, Jonas. 2001. "On the Normal Inverse Gaussian Stochastic Volatility Model." *Journal of Business & Economic Statistics* 19 (January): 44–54.

Andreasen, Martin M. 2012. "On the Effects of Rare Disasters and Uncertainty Shocks for Risk Premia in Non-Linear DSGE Models." *Review of Economic Dynamics* 15 (July): 295–316.

Andreasen, Martin M., Jesus Fernández-Villaverde, and Juan F. Rubio-Ramírez. 2017. "The Pruned State-Space System for Non-Linear DSGE Models: Theory and Empirical Applications." *Review of Economic Studies* 85 (January): 1–49.

Arellano, Cristina, Yan Bai, Patrick J. Kehoe. 2012. "Financial Frictions and Fluctuations in Volatility." Federal Reserve Bank of Minneapolis Research Department Staff Report 466 (Revised November 2018).

Barberis, Nicholas, and Ming Huang. 2008. "Stocks as Lotteries: The Implications of Probability Weighting for Security Prices." *American Economic Review* 98 (December): 2066–100.

Barndorff-Nielsen, Ole E. 1997. "Normal Inverse Gaussian Distributions and Stochastic Volatility Modelling." *Scandinavian Journal of Statistics* 24 (March): 1–13.

Barro, Robert J. 2006. "Rare Disasters and Asset Markets in the Twentieth Century." *Quarterly Journal of Economics* 121 (August) :823–66.

Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks." *Econometrica* 77 (May): 623–85.

Caldara, Dario, Jesus Fernandez-Villaverde, Juan F. Rubio-Ramirez, and Wen Yao. 2012. "Computing DSGE Models with Recursive Preferences and Stochastic Volatility." *Review of Economic Dynamics* 15 (April): 188–206.

Chari, V. V., Patrick J. Kehoe, and Ellen R. McGrattan. 2007. "Business Cycle Accounting." *Econometrica* 75 (May): 781–836.

Chenoweth, Erica, and Orion A. Lewis. 2013. "Unpacking Nonviolent Campaigns: Introducing the NAVCO 2.0 Dataset." *Journal of Peace Research* 50 (May): 415–23.

Chenoweth, Eerica, and Maria J. Stephan. 2011. *Why Civil Resistance Works: The Strategic Logic of Nonviolent Conflict*. New York: Columbia University Press.

Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. 2014. "Risk Shocks." *American Economic Review* 104 (January): 27–65.

Colacito, Riccardo, Max Croce, Steven Ho, and Philip Howard. 2013. "BKK the EZ Way: An International Production Economy with Recursive Preferences." Working Paper (April).

Colacito, Riccardo, and Mariano M. Croce. 2013. "International Asset Pricing with Recursive Preferences." *Journal of Finance* 68 (December): 2651–686.

Colacito, Riccardo, Eric Ghysels, Jinghan Meng, and Wasin Siwasarit. 2015. "Skewness in Expected Macro Fundamentals and the Predictability of Equity Returns: Evidence and Theory." Working Paper (August).

Den Haan, Wouter J., and Joris De Wind. 2012. "Nonlinear and Stable Perturbation-Based Approximations." *Journal of Economic Dynamics and Control* 36 (October): 1477–497.

Dolmas, Jim. (1998). "Risk Preferences and the Welfare Cost of Business Cycles." *Review of Economic Dynamics* 1 (July): 646–76.

Edmond, Chris. 2013. "Information Manipulation, Coordination, and Regime Change." *Review of Economic Studies* 80 (October): 1422–458.

Epstein, Larry G., and Stanley E. Zin. 1989. "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework." *Econometrica* 57 (July): 937–69.

Fernández-Villaverde, Jesus, Pablo Guerrón-Quintana, Juan F. Rubio-Ramírez, and Martín Uribe. 2011. "Risk Matters: The Real Effects of Volatility Shocks." *American Economic Review* 101 (October): 2530–561.

Feunou, Bruno, Mohammed R. Jahan-Parvar, and Cédric Okou. 2015. "Downside Variance Risk Premium." Bank of Canada Working Paper 2015-36 (October).

Gabaix, Xavier. 2012. "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance." *Quarterly Journal of Economics* 127 (May): 645–700.

García-Cicco, Javier, Roberto Pancrazi, and Martín Uribe. 2010. "Real Business Cycles in Emerging Countries?" *American Economic Review* 100 (December): 2510–531.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajšek. 2014. "Uncertainty, Financial Frictions, and Investment Dynamics." Working Paper 20038. Cambridge, Mass.: National Bureau of Economic Research. (April).

Gourio, François. 2012. "Disaster Risk and Business Cycles." *American Economic Review* 102 (October): 2734–766.

Gourio, François, Michael Siemer, and Adrien Verdelhan. 2013. "International Risk Cycles." *Journal of International Economics* 89 (March): 471–84.

Guvenen, Fatih, Serdar Ozkan, and Jae Song. 2014. "The Nature of Countercyclical Income Risk." *Journal of Political Economy* 122 (June): 621–60.

Judd, Kenneth L. 1996. "Approximation, Perturbation, and Projection Methods in Economic Analysis." In *Handbook of Computational Economics* Vol. 1, edited by H.M. Amman, D.A. Kendrick, and J. Rust. Amsterdam: North Holland, 509–85.

Justiniano, Alejandro, and Giorgio E. Primiceri. 2008. "The Time-Varying Volatility of Macroeconomic Fluctuations." *American Economic Review* 98 (June): 604–41.

Kim, Jinill, Sunghyun Kim, Ernst Schaumburg, and Christopher A. Sims. 2008. "Calculating and Using Second-Order Accurate Solutions of Discrete Time Dynamic Equilibrium Models." *Journal of Economic Dynamics and Control* 32 (November): 3397–414.

Koop, Gary, M. Hashem Pesaran, and Simon M. Potter. 1996. "Impulse Response Analysis in Nonlinear Multivariate Models." *Journal of Econometrics* 74 (September): 119–47.

Kuran, Timur. 1989. "Sparks and Prairie Fires: A Theory of Unanticipated Political Revolution." *Public Choice* 61 (April): 41–74.

Lucas, Robert E. 1987. *Models of Business Cycles*, Volume 26. Oxford: Basil Blackwell.

Marshall, Monty G., and Keith Jaggers. 2002. "Polity IV Project: Political Regime Characteristics and Transitions, 1800-2002."

Marshall, Monty G., and Donna Ramsey Marshall. 2011. "Coup D'etat Events, 1946-2012 Codebook." Center for Systemic Peace.

Mencía, Javier, and Enrique Sentana. 2012. "Distributional Tests in Multivariate Dynamic Models with Normal and Student-t Innovations." *Review of Economics and Statistics* 94 (February): 133–52.

Nakamura, Emi, Jón Steinsson, Robert Barro, and José Ursúa. 2013. "Crises and Recoveries in an Empirical Model of Consumption Disasters." *American Economic Journal: Macroeconomics* 5 (July): 35–74.

Rancière, Romain, Aaron Tornell, and Frank Westermann. 2008. "Systemic Crises and Growth." *Quarterly Journal of Economics* 123 (February): 359–406.

Richter, Alexander W., Nathaniel A. Throckmorton, and Todd B. Walker. 2014. "Accuracy, Speed and Robustness of Policy Function Iteration." *Computational Economics* 44 (December): 445–76.

Rudebusch, Glenn D., and Eric T. Swanson. 2012. "The Bond Premium in a DSGE Model with Long-Run Real and Nominal Risks." *American Economic Journal: Macroeconomics* 4 (January): 105–43.

Salgado, Sergio, Fatih Guvenen, and Nicholas Bloom. 2015. "Skewed Business Cycles." Working Paper (June).

Schmitt-Grohé, Stephanie, and Martín Uribe. 2003. "Closing Small Open Economy Models." *Journal of International Economics* 61 (October): 163–85.

Smets, Frank, and Rafael Wouters. 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review* 97 (June): 586–606.

Vissing-Jørgensen, Annette, and Orazio P. Attanasio. 2003. "Stock-Market Participation, Intertemporal Substitution, and Risk-Aversion." *American Economic Review* 93 (May): 383–91.