Policy Uncertainty and Aggregate Fluctuations
Evidence from Emerging and Developed Economies

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Abstract

This paper identifies two types of policy uncertainty measures—government spending and real interest rates—and their impact on macroeconomic activity in 54 advanced, emerging, and developing economies. Policy uncertainty is defined as the inability to predict policy moves, that is, the conditional volatility of policy shocks. This is achieved in a panel vector autoregression model which allows, but does not require, the stochastic volatility of identified shocks to have direct and dynamic effects on macroeconomic outcomes. It shows that fiscal and monetary policy uncertainty are damaging to economic activity and act like negative supply shocks: raising prices while lowering output, investment and consumption. A one standard deviation government spending uncertainty shock decreases real gross domestic product (GDP) by a cumulative 1.0 percentage point and marginally increases inflation after two years. A one standard deviation real interest rate uncertainty shock lowers real GDP by a cumulative 1.3 percentage points after two years but raises inflation by 0.5 percentage point.

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Policy Uncertainty and Aggregate Fluctuations: Evidence from Emerging and Developed Economies*

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1 Introduction

Uncertainty about monetary and fiscal policy in the last few years is arguably at the highest it has been in recent history (Davis, 2016). Fiscal and monetary policy moves have been unprecedented in the past five decades and the likely future path of policy has become more unpredictable and uncertain. In response to the COVID-19 pandemic, policy makers unleashed fiscal stimulus to counter the steepest global output contraction in eight decades (World Bank, 2020). These stimulus measures were massive, raising global government debt by about 16 percentage points of output between 2019 and 2020. As the pandemic has evolved, compounded by the Russian Federation’s invasion of Ukraine, consumer inflation has shot up to rates not seen in four decades in advanced economies and since the 1990s in emerging market and developing economies (EMDEs).

In response to rising inflation, monetary policy makers have quickly ratcheted up interest rates, surprising financial markets. The U.S. Federal Reserve, for example, has implemented multiple consecutive 75 basis point hikes, a pace of increase not seen since the 1980s. Prior to this rapid adjustment, real interest rates in the United States (U.S.) reached a nadir not seen in almost 80 years. EMDEs saw equally rapid increases in policy rates.

Against this backdrop, this paper quantifies global monetary and fiscal policy uncertainty and quantifies the impact of policy uncertainty on the macroeconomy.\footnote{Global monetary policy uncertainty is defined as the median real interest rate uncertainty across all economies. Global fiscal policy uncertainty the median real government spending uncertainty. This paper will use “monetary policy uncertainty” and “real interest rate uncertainty”, on the one hand, and “fiscal policy uncertainty” and “government spending uncertainty” on the other, interchangeably.} It answers the following questions. First, what is the impact of fiscal and monetary policy uncertainty shocks on economic activity and prices? Second, does this impact differ across advanced economies and EMDEs? Finally, how has fiscal and monetary policy uncertainty evolved in recent history, particularly in EMDEs?

To do so the model of Mumtaz and Surico (2018)—a vector autoregression (VAR) model which allows, but does not require, the stochastic volatility of identified shocks to have
direct and dynamic effects on the endogenous variables—is extended along two key dimensions. First, while previous work has focused on the United States, this paper looks at 54 economies including 32 advanced economies and 22 EMDEs. Second, this paper allows for (but again does not require) fat-tailed shocks. That is, it distinguishes between slow-moving and fast-moving volatility, the latter measure reducing the possibility that the estimates of policy uncertainty are contaminated by volatility induced by transitory events or data outliers, and a way to deal with including data from the COVID-19 pandemic.  

Policy uncertainty is defined in this paper as in Jurado et al. (2015): the conditional volatility of policy shocks or, more specifically, the part of policy that cannot be forecasted by economic agents. What matters for households and firms that make decisions about spending and saving, or producing and investing, is not whether a particular outcome has become more or less disperse (for example, whether sales will rise or collapse) but rather whether it has become more or less predictable (that is, more difficult to predict a rise or collapse in sales).

This paper reports the following findings. First, policy uncertainty shocks have a material impact on real activity and prices. An increase in fiscal policy uncertainty (specifically real government spending uncertainty) is associated with a statistically significant drop in real GDP, private consumption, and fixed investment. Prices also increase. Monetary policy uncertainty (or real interest rate uncertainty) follows a similar dynamic, being associated with a statistically significant decrease in real GDP and increase in prices. There is no a priori theoretical basis for whether uncertainty shocks should act like supply or demand shocks (see Fernández-Villaverde et al., 2015; Fernández-Villaverde and Guerrón-Quintana, 2020).

Second, policy uncertainty affects advanced economies and EMDEs differently, although given the lower precision in estimating with smaller samples, these should be interpreted
with caution. Monetary policy uncertainty is much more detrimental in EMDEs and is associated with a decline in output and rising inflation. This may just reflect the higher levels of monetary policy uncertainty in EMDEs. It may also reflect inflation expectations that are less well-anchored, as firms raise prices as they have less faith that the central bank will be able to maintain its inflation target. It may also reflect the role external debt plays in consumption smoothing in these economies increasing their sensitivity to changes in, or the unpredictability of, real interest rates. Fiscal policy uncertainty is more detrimental to advanced economies and associated with a greater fall in output. This may reflect the fact that these economies have more efficient spending with larger fiscal multipliers such that firms and households benefit even less from rising fiscal policy uncertainty.

Third, policy uncertainty plays a non-negligible role in driving variations in, and understanding the dynamics of, activity and prices. Monetary and fiscal policy uncertainty explain about 5 percent of the variation in output within two years and about 12 percent of its variation in the longer-run. For prices, fiscal and monetary uncertainty drive about 2 percent of the variation after two years and about 9 percent in the longer-run. Counterfactual exercises show that fiscal and monetary policy uncertainty have been detrimental to output growth during the mid-1980s (when EMDEs faced crisis), the 2009 great recession, and during the COVID-19 pandemic. Low policy uncertainty between 2012 and 2019, in contrast, helped to boost output growth on average.

Fourth, the VAR model provides a narrative of the evolution of individual country-specific and global uncertainty, defined as the median uncertainty across countries, from a unified framework. Fiscal and monetary policy uncertainty has risen rapidly since the COVID-19 pandemic reaching levels not seen in decades. In the two decades prior to the pandemic, fiscal policy uncertainty related to government spending had steadily declined in advanced economies but rose rapidly during the 2008-09 global financial crisis (GFC). In contrast, government spending uncertainty rose rapidly during the GFC in EMDEs and is yet to return to pre-GFC levels. The GFC also reflected a period of high monetary pol-
icy uncertainty but EMDEs saw even higher levels of uncertainty in the early 2000s when many economies were adjusting to inflation targeting frameworks and bringing down inflation expectations.

This paper makes a number of contributions to the literature. First, it extends the analysis of the impact of fiscal and monetary policy uncertainty in a VAR model beyond the United States to 54 economies, including 32 advanced economies and 22 EMDEs. As such, this paper is the first to provide a perspective on policy uncertainty in both advanced economies and EMDEs. Second, the VAR model used in this paper generates country and global fiscal and monetary policy uncertainty from a unified framework and provides the most comprehensive analysis of fiscal and monetary policy uncertainty to date. It also provides an important alternative to the common approach of measuring uncertainty adopted in the literature following the work of Baker et al. (2016), and in line with Jurado et al. (2015). Third, it is the first to try and explicitly account for other factors that may drive uncertainty by removing transitory events and data outliers that may contaminate uncertainty measures. Finally, this paper provides a perspective on the evolution of monetary and fiscal policy uncertainty during the COVID-19 pandemic.

2 Related literature

This paper contributes to a growing literature on the importance of policy uncertainty in driving macroeconomic outcomes and on measuring this uncertainty.

2.1 Measures of policy uncertainty

There are four broad approaches to measuring uncertainty: textual analysis, market data, surveys, and models with time-varying volatility. The most prolific source of measuring this uncertainty started with Baker et al. (2016) who use newspaper coverage frequency (textual analysis) to develop an economic policy uncertainty (EPU) measure. The au-
Authors have subsequently extended this approach to a number of advanced economies and EMDEs. The popularity and simplicity in implementing this approach has led to similar measures for several other EMDEs. This work was also extended to specific policies such as monetary policy in Husted et al. (2020) for the United States and Arbatli et al. (2017) for Japan. In Holda et al. (2019), fiscal and monetary policy uncertainty is identified separately. A strand of textual analysis has also focused specifically on text released by central banks (see, for example, Ehrmann and Fratzscher, 2007).

Another method to measure policy uncertainty is to use statistical models with heteroskedastic errors where the second moments of policy variables vary over time. Fernández-Villaverde et al. (2015) use this approach to define tax and fiscal spending uncertainty. Mumtaz and Surico (2018) use this approach to identify both fiscal and monetary policy uncertainty in the United States employing a methodology that can solve the problem of the causal link between measures of uncertainty and other macroeconomic variables reported in Baker et al. (2016), Caggiano et al. (2014), and Stock and Watson (2012).

A third approach uses market data such as options and futures. Monetary policy uncertainty can be measured from the implied volatility of option prices on interest rates and realized volatility from futures (see, for example, Chang and Feunou, 2013; Bauer et al., 2012; and Carlson et al., 2005).

Finally, uncertainty measures can be constructed through survey data by asking participants about their perceptions of uncertainty. In the context of policy uncertainty, the Federal Reserve Bank of New York’s Survey of Primary Dealers (which started in 2004) asks primary dealers to provide their forecast of policy rates and their forecast uncertainty. Husted et al. (2020) use these survey responses to compare their news-based measure of monetary policy uncertainty. Dahlhaus and Sekhposyan (2018) use survey-based expectations of the policy rate to define a monetary policy uncertainty measure based on the underlying distribution of expectations.

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3These include South Africa (Redl, 2018), Poland (Holda et al., 2019), China (Davis et al., 2019), Turkey (Jirasavetakul and Spilimbergo, 2018), and Pakistan (Choudhary et al., 2020).
2.2 The role of policy uncertainty in economic outcomes

Interest in policy uncertainty and its impact on economic activity is rooted in fundamental questions about the role of macroeconomic stabilization policies. Chief among these questions is the role of the Federal Reserve, particularly during the Great Depression. Friedman (1968), for example, highlighted the role of policy uncertainty (using language such as ‘wide swings’ and ‘steady course’) stating that:

Short of the adoption of... a publicly stated policy of a steady rate of monetary growth, it would constitute a major improvement if the monetary authority followed the self-denying ordinance of avoiding wide swings. It is a matter of record that periods of relative stability in the rate of monetary growth have also been periods of relative stability in economic activity... By setting itself a steady course and keeping to it, the monetary authority could make a major contribution to promoting economic stabilization.

The focus on the role of policy uncertainty during the great depression went beyond the U.S. Federal Reserve, with Higgs (1997) arguing that government policy uncertainty—the security of property rights among others—kept investment low. The pervasive role of government in all aspects of society means that policy uncertainty could take many forms including in tax policy, expenditure policy, trade policy, monetary policy, structural policy, and regulatory policy. Fernández-Villaverde et al. (2011) show that rising real interest rate volatility, one possible measure of monetary policy uncertainty, is associated with a fall in output, consumption, investment and hours worked.

The focus on policy uncertainty was also present in answering questions on the impact

\footnote{The focus of this literature review is on policy uncertainty. There is also a literature focusing on uncertainty more broadly or defined along specific but unrelated dimensions. See Cascaldi-Garcia et al. (2020) for an overview.}

\footnote{Hassett and Metcalf (1999) and Alvarez et al. (1998) show that tax policy uncertainty affects firm’s investment choices. Caldara et al. (2020) show that trade policy affects investment and export decisions. More broadly uncertainty entices investors to wait by increasing the returns to waiting for more information (Bernanke, 1983; Pindyck, 1990).}
of failed stabilization and structural policies in EMDEs facing crises in the 1980s. Rodrik (1991), for example, showed that “even moderate amounts of policy uncertainty can act as a hefty tax on investment...”

The literature has also evolved to build models that explicitly include policy uncertainty including in Born and Pfeifer (2014), Fernández-Villaverde et al. (2015), Pastor and Veronesi (2012), and Pásstor and Veronesi (2013).

The evidence of the economic effects of policy uncertainty are almost exclusively focused on advanced economies. Notable exceptions include Balcilar et al. (2017) and Choi and Shim (2019). Choi and Shim (2019) compare financial and policy uncertainty in six emerging market economies and find that financial uncertainty has much larger impacts on output than policy uncertainty shocks (in contrast with advanced economies where the effects are about the same size).

3 Methodology

3.1 Baseline model

Our baseline empirical model is the following panel VAR:

\[ Z_{it} = c_i + \tau_t + \sum_{j=1}^{P} \beta_j Z_{it-j} + \sum_{k=0}^{K} b_k \tilde{h}_{it-k} + v_{it} \] (1)

where \( Z_{it} \) is an \( N \times 1 \) matrix of endogenous variables defined as \( Z_{it} = [G_{it}, Y_{it}, \pi_{it}, R_{it}, T_{it}] \). \( G_{it} \) denotes real government consumption expenditure, \( Y_{it} \) is real GDP, \( \pi_{it} \) is GDP deflator inflation, \( T_{it} \) is real government revenue and \( R_{it} \) is an ex-ante real short-term interest rate. Cross-sections (economies) and time are indexed by \( i = 1, 2, ..., M \) and \( t = 1, 2, ..., T \), respectively. Fixed effects and time effects are denoted by \( c_i \) and \( \tau_t \) respectively.

Before describing the regressors in equation 1 it is instructive to note that the variance covariance matrix \( \text{cov}(v_{it}) = \Omega_{it} \) is time-varying and heterogenous across economies. This
matrix is factored as:
\[
\Omega_{it} = A^{-1} H_{it} A^{-1}'
\]  
(2)

where \(A\) is a lower triangular matrix with ones on the main diagonal. \(H_{it}\) is a diagonal matrix \(H_{it} = \text{diag}\left(\exp\left(\tilde{h}_{it}\right) \cdot \frac{1}{\tilde{\lambda}_{it}}\right)\) where \(\tilde{h}_{it} = [h_{1,it}, h_{2,it}, \ldots, h_{N,it}]\) and \(\tilde{\lambda}_{it} = [\lambda_{1,it}, \lambda_{2,it}, \ldots, \lambda_{N,it}]\).

The volatility of the orthogonalized shocks has two components: \(\tilde{h}_{it}\) denotes a slower moving component that follows a panel VAR(1) process:
\[
\tilde{h}_{it} = \alpha_i + \theta \tilde{h}_{it-1} + b_0 \tilde{\eta}_{it}, \tilde{\eta}_{it} \sim N(0, 1)
\]  
(3)

where \(\alpha_i\) denotes country fixed effects, \(b_0\) is a lower triangular matrix and \(\tilde{\eta}_{it} = [\tilde{\eta}_{1,it}, \tilde{\eta}_{2,it}, \ldots, \tilde{\eta}_{N,it}]\) denotes uncertainty shocks. The volatilities \(\tilde{h}_{it}\) appear as regressors on the right hand side of the model in equation 1. If \(b_k \neq 0\), then shocks to \(\tilde{h}_{it}\) can affect \(Z_{it}\).

Higher frequency movements in the shocks (such as outliers) are captured by \(\tilde{\lambda}_{it}\). Geweke (1993) shows that assuming a Gamma prior for \(\lambda_{K,it}, K = 1, 2, \ldots, N\) of the form
\[
p\left(\tilde{\lambda}_{K,it}\right) = \prod_{m=1}^{NT} \Gamma(1, \nu_{K,\lambda})
\]
leads to a scale mixture of normals for the orthogonalized residuals \(\tilde{e}_{it} = Av_{it}\) where \(\text{cov}(v_{it}) = \text{diag}\left(\exp\left(\tilde{h}_{it}\right)\right)\). In other words, the \(k^{th}\) column of \(\tilde{e}_{it}\) follows a student t-distribution with \(\nu_{K,\lambda}\) degrees of freedom and time-varying volatility given by \(\tilde{h}_{it}\) (see also Chiu et al., 2017).

The model described in this section is an extended version of the VAR used in Mumtaz and Surico (2018). We extend the model of Mumtaz and Surico (2018) along two key dimensions. First, as in Alessandri and Mumtaz (2021), the model is estimated using a panel of economies covering both advanced economies and EMDEs. Second, and in contrast to Alessandri and Mumtaz (2021), we allow for fat-tailed disturbances. This reduces the possibility that the estimates of policy uncertainty are contaminated by volatility induced by transitory events or data outliers.
3.2 Identification

The first shock $\tilde{e}_{1t}$ is interpreted as a shock to government spending. The triangular structure of $A$ implies that spending is unaffected by shocks to the remaining variables for one period. As discussed in Blanchard and Perotti (2002), this is plausible as changes in spending take time to be legislated and implemented. The ordering of the real interest rate reflects the argument that the policy instrument responds contemporaneously to developments in real activity and inflation while monetary disturbances affect the economy with a lag. $T_{it}$ is ordered after the interest rate as tax revenue is not net of interest payments (see Caldara and Kamps, 2008).

The series $h_{it}$ represents the (log) volatility of the orthogonal shocks $\tilde{e}_{it}$. As the shocks associated with $G_{it}$ and $R_{it}$ are interpreted as policy shocks, the associated stochastic volatility captures policy uncertainty and $\tilde{\eta}_{it}$ are the uncertainty shocks. As noted above, the contemporaneous effect of these shocks on $h_{it}$ is assumed to be recursive and we order the volatilities in the same manner as the endogenous variables.

3.3 Estimation

The model is estimated using Bayesian techniques. We approximate the posterior distribution via an extended version of the Gibbs algorithm introduced in Alessandri and Mumtaz (2021). The details of the algorithm are given in appendix A1 and we present a summary of the key steps in this section.

The parameters of the model can be collected into seven blocks: $\left( \Gamma, \bar{A}, \bar{B}, Q, \nu_{K,A}, \lambda_{it}, \tilde{h}_{it} \right)$. Here, $\Gamma = vec \left( [c_i, \tau_i, \beta_1, \ldots, \beta_P, b_1, \ldots, b_K] \right)$ denotes the coefficients of equation 1, $\bar{A}$ is a vector that collects the elements of $A$ that are not equal to 0 or 1, $\bar{B} = vec \left( [\alpha_i, \theta] \right)$ while $Q = b_0b_0'$ is the variance of the residual of the transition equation (3). Each iteration of the algorithm samples from the conditional posterior distributions of these parameter blocks.

Given $\tilde{h}_{it}, \lambda_{it}$ and $\bar{A}$, the model is simply a panel VAR with a known form of heteroscedasticity. Therefore, given a normal prior, the conditional posterior of $\Gamma$ is also normal after a
GLS transformation.
As described in Cogley and Sargent (2005), conditional on $\Gamma, \lambda_{it}$ and $\tilde{h}_{it}$, the elements of $\tilde{A}$ are coefficients in linear regressions involving the residuals of the panel VAR. Therefore, their conditional posterior is standard. Given $\tilde{h}_{it}$, equation 3 is simply a panel VAR with fixed effects. As we employ conjugate priors for $\tilde{B}$ and $Q$, their conditional posteriors are well known and easily sampled from. Geweke (1993) shows that the conditional posterior of $\lambda_{it}$ is a Gamma distribution and this set of parameters is easily drawn. We use a random walk Metropolis Hastings algorithm to draw from conditional posterior of the degrees of freedom parameters $\nu_{K,\lambda}$.
With a draw of $\Gamma, \tilde{A}, \tilde{B}, Q$ and $\lambda_{it}$ in hand, equations (1) to (3) constitute non-linear state space model for each country. To draw from the conditional posterior of $\tilde{h}_{it}$ we use the particle Gibbs sampler of Andrieu et al. (2010a) and Lindsten et al. (2014). We use 21,000 iterations and retain every 2nd draw after a burn-in period of 1,000 draws. In the technical appendix (figure A2.1) we show that the estimated inefficiency factors are low, providing evidence in favor of convergence of the algorithm.

4 Data

This section, along with Appendix A3, provide the definitions, transformations, and sources of the data used in the baseline model (and extensions). Data for 54 advanced economies and EMDEs are used in the baseline model from 1980Q1 to 2022Q4 (see table A3.1). The main variables are described in table 1 and the baseline model includes government spending, tax revenue, the real interest rate, real GDP, and the GDP deflator (figure 1). Appendix A3 provides details on the definition of the real interest rate.
For government spending, to get the greatest cross section both national accounts data—that is real public consumption expenditure on a seasonally adjusted basis—and data from government financial statements—usually collected as monthly nominal government ex-
penditure on a non-seasonally adjusted basis—are used. The government's financial statements across economies may be reported at the central government or general government level. For government revenue, both central government or general government level, data are collected based on availability. When national accounts data are used for government spending, and given the identifying assumptions used in model based on Ilzetzki et al. (2013), the data is checked to make sure it is not interpolated and avoid spurious results. Given the lack of tax only data for many economies, overall revenue including tax and non-tax sources of revenue are used. To model monetary policy, this paper uses the ex-ante real interest rate defined as the three-month interest rate less one-year-ahead consumer inflation forecasts.

As a rule, when official data is not available in real terms (constant prices) it is deflated using the GDP deflator. When data is not available from official sources as seasonally adjusted, and seasonality is present, the X13-ARIMA-SEATS method to seasonally adjust the data is implemented (US Census Bureau, 2016). When data is monthly, like reported for government spending and revenue, the data is summed (or averaged in the case of interest rates) to get to a quarterly frequency.

Table 1: Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Transformation</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_{it}$</td>
<td>Real public consumption expenditure, seasonally adjusted</td>
<td>Log level</td>
<td>Haver Analytics</td>
</tr>
<tr>
<td>$Y_{it}$</td>
<td>Real GDP, seasonally adjusted</td>
<td>Log level</td>
<td>Haver Analytics</td>
</tr>
<tr>
<td>$\pi_{it}$</td>
<td>GDP deflator, seasonally adjusted</td>
<td>Log level</td>
<td>Haver Analytics</td>
</tr>
<tr>
<td>$T_{it}$</td>
<td>Real general/central government revenue</td>
<td>Log level</td>
<td>Haver Analytics</td>
</tr>
<tr>
<td>$R_{it}$</td>
<td>Ex-ante real interest rate</td>
<td>Level</td>
<td>Haver Analytics; OECD</td>
</tr>
<tr>
<td>$C_{it}$</td>
<td>Real private consumption expenditure, seasonally adjusted</td>
<td>Log Level</td>
<td>Haver Analytics</td>
</tr>
<tr>
<td>$I_{it}$</td>
<td>Real gross fixed capital formation, seasonally adjusted</td>
<td>Log Level</td>
<td>Haver Analytics</td>
</tr>
<tr>
<td>$ER_{it}$</td>
<td>Real effective exchange rate, CPI-based</td>
<td>Log first difference</td>
<td>Bruegel; Haver Analytics</td>
</tr>
<tr>
<td>$S_{it}$</td>
<td>Equity prices</td>
<td>Log Level</td>
<td>Haver Analytics</td>
</tr>
</tbody>
</table>

*The VAR model assumes that fiscal policy makers require at least one quarter to respond to output shocks.*
5 Results

This section presents the results of the baseline model, and extensions, including measures of fiscal and monetary policy uncertainty, the impact of policy uncertainty on macroeconomic outcomes, the evolution of these uncertainty measures over the past two decades, and its contribution to the overall variation in economic activity and prices.

5.1 Measures of economic policy uncertainty

5.1.1 Baseline model

Uncertainty measures for 54 economies—32 advanced economies and 22 EMDEs—provide an opportunity to build a narrative of global fiscal and monetary policy uncertainty. Given the unbalanced nature of the panel data, fiscal and monetary policy uncertainty measures for the world, advanced economies and EMDEs are provided from 2000Q1 to 2022Q4 in figure 2. The COVID-19 pandemic represents an unprecedented shock to the global economy in both its nature and size, complicating the appropriate estimation of models that include these observations. The modeling strategy adopted, however, does include one possible solution to modeling the pandemic highlighted in Lenza and Primiceri (2022) and Carriero et al. (2021). The solution is to include stochastic volatility in the model that is fast-moving (that is, transient and infrequent).

Fiscal policy uncertainty related to government spending has experienced notable peaks and troughs over the last two decades. Uncertainty ratcheted up during the GFC, during the European debt crisis in 2012, during 2016 when several large EMDEs (Brazil, Russia) experienced recession and the U.S. Federal Reserve started raising interest rates, and most notably during and after the COVID-19 pandemic. These are likely periods when policy became less predictable. Fiscal policy uncertainty peaked in 2020Q2, subsequently

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7While data further back is available for several economies, restricting the sample to 2000Q1 ensures adequate country coverage for EMDEs.

8Another solution suggested by Ng (2021) is to “de-covid” the data by regressing the variables on COVID-19 indicators such as confirmed deaths and cases, among others.
declined through 2022Q4 but remains above pre-pandemic levels. There are large differences across economies with the interquartile range averaging about 2 percentage points, the variation particularly wide following the GFC and pandemic. The differences across economies are reflected in different experiences of advanced economies and EMDEs. Advanced economies saw government spending uncertainty rise during 2009, in 2012, and particularly following the pandemic. In contrast, EMDEs saw government spending uncertainty rise rapidly in 2008-09, and while it subsequently declined to lower levels, it never returned to the levels seen prior to the GFC. The trend among EMDEs likely reflects a loosening of fiscal policy that was never fully reversed leading to procyclical policy. Total expenditure among EMDEs increased from 25.7 percent of GDP in 2000-07 to 29.6 percent of GDP in 2008-2019. In the eleven years between 2009 and 2019, the primary budget in EMDEs was in deficit in nine of those years. As a consequence, government debt rose from 34 percent of GDP in 2008 to 54 percent of GDP in 2019. Uncertainty again rose rapidly during the pandemic, however, did not overtake uncertainty during the GFC.

There are three periods that reflected rising monetary policy uncertainty: the early 2000s, the GFC, and following the pandemic. There is significant country variation during these three periods typified by a wide interquartile range. During the early 2000s, many EMDEs were transitioning to inflation targeting frameworks and bringing down inflation expectations (Roger, 2009; Svensson, 2010). This period of changing frameworks was associated with elevated monetary policy uncertainty in these economies which lasted for several years. During 2008-09, both advanced economies and EMDEs saw rising monetary policy uncertainty, as the latter implemented unconventional policy measures, and central banks responded to significant financial turmoil and a global recession. Since then, monetary policy uncertainty has declined precipitously in both advanced economies and EMDEs until the pandemic. Monetary policy uncertainty went from a four decade low in 2018Q2 to its highest level since the early 2000s in 2022Q4, particularly among advanced economies.
The various policy uncertainty measures have some similarities but also differences to another measure of global economic policy uncertainty (EPU) in Davis (2016). The global EPU and the policy uncertainty measures in this paper show peaks of uncertainty in the early 2000s, during the GFC, and the pandemic. Fiscal policy uncertainty reflects rising uncertainty during the European debt crisis of 2012, in the mid-2010s, and during the pandemic in line with EPU peaks. Differences are also evident. Most notably, the global EPU suggests that policy uncertainty rose earlier, in 2018-19, than fiscal policy uncertainty before both reach new highs in 2020. Several factors could explain the differences across these measures. First, this paper uses a measure of policy uncertainty as in Jurado et al. (2015) which is fundamentally different from proxy-measures like the EPU. Second, measures of uncertainty are specific to the fiscal or monetary policy measure and not general policy uncertainty as in Davis (2016). Notable events in the EPU such as the European immigration crisis in 2015, the Brexit referendum, and political turmoil in several countries do not reflect as heavily in the unforecastable part of government spending or interest rate policy which is the focus of this paper. Third, as in Jurado et al. (2015), peaks in uncertainty occur far more infrequently compared to the EPU but have larger and more persistent correlations with economic activity.

While there is no global monetary policy uncertainty measure to compare this paper’s results to, Husted et al. (2020) provide some guidance on the similarities and differences for the United States. Overall, the correlation between the newspaper-based measure of monetary policy uncertainty and in this paper is weak although there are similar spikes: elevated uncertainty can be seen in both measures in the early 2000s and following the COVID-19 pandemic. The measure in this paper, however, better reflects monetary policy uncertainty embedded in the Primary Dealers survey or implied volatility of options on one-year swap rates. Notably, monetary policy uncertainty is highest during the GFC in these measures, and it decreases precipitously through 2013 before rising again. There are also peaks in these measures during 1994/95 (bond market turmoil), and 2002/03.
The fast-moving volatility measures are provided in figure 3. There is a significant increase in transient and infrequent volatility during the COVID-19 pandemic, particularly 2020Q1 and 2020Q2.

5.2 Impact of policy uncertainty on macroeconomic outcomes

Fiscal and monetary policy uncertainty shocks have statistically significant and meaningfully large impacts on real GDP and the latter on prices (figure 4). The largest impact is from monetary policy uncertainty where a 1 standard deviation shock decreases real GDP by about 0.1 percentage point after three quarters and by a peak of 0.4 percentage point—the impact is statistically significant and long lasting. On a cumulative basis, after two years, monetary policy uncertainty lowers real GDP by 1.3 percentage points (figure 5). Monetary policy uncertainty shocks are particularly damaging by complicating future policy implementation by raising prices. A one standard deviation shock to monetary policy uncertainty raises prices on a cumulative basis by 0.2 percentage point after one year and by 0.5 percentage point after two years.

Government spending uncertainty shocks also have a significant impact damaging real GDP while at the same time raising prices, although the latter impact is not statistically significant. A one standard deviation increase in government spending uncertainty leads to a peak decrease in real GDP of 0.2 percentage point. On a cumulative basis a government spending uncertainty shock lowers output by 1.0 percentage point after two years. While prices rise in the case of a fiscal policy uncertainty shock the impact is not statistically significant.

There is no a priori theoretical basis to expect policy uncertainty shocks to present like either a demand or supply shock; that is decreasing output and prices in the former or decreasing output but increasing prices in the latter. There is little evidence in the literature that focuses on policy uncertainty shocks and even less on EMDEs (see Balcilar et al., 2017 and Choi and Shim, 2019). The theoretical model of Fernández-Villaverde et al. (2015) in-
icates that fiscal policy uncertainty shocks act like supply shocks, although the authors augment their Taylor rule to generate demand-like dynamics. Literature on uncertainty more broadly in Fernández-Villaverde and Guerrón-Quintana (2020), Born and Pfeifer (2014), and Bonciani and Van Roye (2016) show several channels through which uncertainty may raise prices. For example, higher prices could occur as firms increase prices, finding it less costly to set a price that is too high relative to competitors than too low (upward pricing bias channel). Redl (2018) show that in South Africa uncertainty shocks decrease output but raise prices because of countercyclical markups. Fasani and Rossi (2018)—in a follow-up paper to Leduc and Liu (2016) who argue that uncertainty shocks are like aggregate demand shocks—show that taking into account plausible interest rate smoothing in a Taylor rule generates responses that look like negative supply shocks. Mi-escu (2019) show, in a paper focused on EMDEs, that uncertainty shocks act like negative supply shocks, that is decrease output but raise prices, in these economies.

The impulse response functions for the endogenous variables of the VAR are presented in appendix A4. While not the focus of this paper, it is worth noting that the estimated responses are reasonable and in line with economic theory. Specifically, government spending shocks lead to an increase in real GDP and raise tax revenue. In the case of a monetary policy shock both real GDP and prices decline.

5.2.1 Extending the baseline model

The baseline model is extended in two ways. First, the baseline model is extended to include private consumption and fixed investment (sequentially) to understand policy uncertainty’s impact on the components of output. The variables replace real GDP in the identification step. Figure 6 shows the cumulative impact after one and two years of the policy uncertainty shocks on private consumption and fixed investment. Both fiscal policy and monetary policy uncertainty have large and statistically significant impacts on private consumption and fixed investment. A one standard deviation shock to government spend-
ing uncertainty decreases real private consumption by 0.5 percentage point after two years and real fixed investment by 3.4 percentage points. Monetary policy uncertainty lowers consumption by 1.3 percentage points and fixed investment by 5.6 percentage points after two years on a cumulative basis.

Second, figure 6 displays the cumulated impulse response of real GDP and GDP deflator to the policy uncertainty shocks, when the benchmark model is estimated separately for advanced economies and for EMDEs. While these sub-sample estimates are less precise due to the smaller sample size, they suggest that fiscal policy uncertainty is more important for GDP fluctuations in advanced economies. This outcome is consistent with smaller fiscal multipliers in EMDEs than advanced economies (Ilzetzki et al., 2013). This is also consistent with lower government spending efficiency in EMDEs (Schwartz et al., 2020 and Devadas and Pennings, 2018).

In contrast, monetary policy uncertainty has large effects on real GDP in EMDEs. Notwithstanding the caveats regarding the small sample, these results are consistent with the observation that monetary policy uncertainty has remained relatively low and stable in the developed world. Most EMDEs, however, experienced large fluctuations in this measure during the early 2000s and then during the GFC. This is also consistent with Fernández-Villaverde et al. (2011) which show that real interest rate volatility matters for economies that use external debt for consumption smoothing. Policy uncertainty’s impact on prices is more important in EMDEs than advanced economies with government spending and monetary policy uncertainty leading to inflation in EMDEs but not in advanced economies. This may reflect less well anchored inflation expectations.

5.3 Forecast error variance decomposition

Policy uncertainty shocks also play a non-negligible role in explaining the variation in output and prices. Figure 7 presents the median estimates of the forecast error variance decomposition for real GDP and the GDP deflator from the baseline model. In the case
of real GDP, policy uncertainty explains about 2 percent of its variation after one year, about 5 percent after two years, and about 11 percent after two decades. Most of this is due to government spending uncertainty followed by monetary policy uncertainty.\footnote{Uncertainty shocks play a larger role in explaining the variation in real GDP in line with Ramey (2016) who highlights the small proportion of variance explained by fiscal and monetary policy.} This is lower than the share of variation that policy uncertainty played in the United States at about 25 percent in Mumtaz and Surico (2018), although the model here does not include uncertainty related to government debt. Policy uncertainty plays less of a role in explaining the variation in the GDP deflator, at 1 percent after one year, just above 2 percent after two years, and about 9 percent after two decades. Here monetary policy uncertainty contributes the most.

5.4 Counterfactual analysis

One way to show the impact of policy uncertainty on economic outcomes is to compare actual real GDP growth (year-on-year) outcomes with a (model-based) counterfactual where there is no policy uncertainty. Figure 8 shows the difference between these two scenarios (actual less counterfactual such that negative numbers reflect the impact of rising uncertainty) for the world, advanced economies, and EMDEs across policy measures.

The impacts of policy uncertainty were largest on EMDEs, particularly during the mid-1980s and late 1990s reflecting widespread banking, currency and sovereign debt crises in these economies (Laeven and Valencia, 2020).\footnote{The number of EMDEs with data are limited during the 1980s, however, the results are still instructive as to the likely direction of impacts.} Both EMDEs and advanced economies experienced lower GDP growth than what would have been without policy uncertainty during the 2009 global recession, and the pandemic.

The counterfactual exercise can also be used to disentangle the roles of fiscal and monetary policy uncertainty in driving growth higher or lower. For EMDEs, monetary and fiscal policy uncertainty were both responsible for damaging real GDP growth during the
mid-1980s. In the early 2000s, strong growth and consolidating fiscal policy helped to improve growth prospects while the shift to inflation targeting in many EMDEs initially contributed to higher monetary policy uncertainty, damaging growth through the first half of the decade. The 2009 and COVID-19 recession again saw negative contributions from fiscal policy and monetary policy.

6 Robustness

The baseline model is extended in several directions to check the sensitivity of the main results.

6.1 Identification

As discussed above, the shocks in the benchmark model are identified using a Cholesky decomposition. Moreover, we impose the restriction that the level shocks are uncorrelated with the shocks to the transition equation for the volatility. In this section we relax both assumptions and estimate the following model based on Mumtaz (2018):

\[
\tilde{h}_{it} = \alpha_i + \theta \tilde{h}_{i,t-1} + \sum_{j=1}^{Q} d_j Z_{it-j} + S^{\frac{1}{2}} \eta_{it} \\
Z_{it} = c_i + \tau_t + \sum_{j=1}^{P} \beta_j Z_{it-j} + \sum_{k=1}^{K} \gamma_k \tilde{h}_{i,t-k} + H^{\frac{1}{2}} \epsilon_{it} \\
\epsilon_{it} = \begin{pmatrix} \eta_{it} \\ \epsilon_{it} \end{pmatrix} \sim N(0, \Sigma), \text{diag}(\Sigma) = 1 \\
\Sigma = \begin{pmatrix} \Sigma_{\eta_{it}} & \Sigma_{\eta_{it} \epsilon_{it}} \\ \Sigma_{\eta_{it} \epsilon_{it}} & \Sigma_{\epsilon_{it}} \end{pmatrix}
\]
To identify the policy uncertainty shocks we adopt the approach of Uhlig (2004). In other words, the government spending uncertainty shock is identified as the shock that makes the maximal contribution to the forecast error variance of the stochastic volatility $\tilde{h}_{it}$ associated with the government spending equation. Similarly, monetary policy uncertainty shock is defined as the shock that explains the largest proportion of the variance of the real interest rate conditional volatility.\(^{11}\) Figure A5.1 in appendix A5 presents the impulse responses to the policy uncertainty shocks identified using this alternative approach. These estimates support the benchmark conclusions. In particular, both shocks are associated with a decline in GDP and there is some evidence that prices increase in response to the shock.

6.2 Specification

The baseline model includes the contemporaneous value of stochastic volatility in the observation equation. This assumption is useful as it keeps the model parsimonious by reducing the number of unobserved state variables. We extend the model by including an additional lag of the volatility. As shown in the top panel of figure A5.2 in appendix A5, the estimated effect of policy uncertainty on GDP is very similar to the benchmark in this extended model. Next, we extend the benchmark model so that the level of the endogenous variables can affect the stochastic volatility. In other words, the transition equation of the model is extended as follows:

$$\tilde{h}_{it} = \alpha_i + \theta \tilde{h}_{i,t-1} + \sum_{j=1}^{\tilde{J}} j \tilde{z}_{i,t-j} + b_0 \tilde{\eta}_{it}, \tilde{\eta}_{it} \sim N(0, 1) \quad (8)$$

We set the lag length $\tilde{J}$ to 1. The second row of Figure A5.2 shows that, in qualitative terms, the impact of policy uncertainty shocks in this extended model is similar to the benchmark case. To check if the impulse responses are stable across time, the sample is restricted

\(^{11}\)The restrictions on FEV are imposed over the horizon 0 to 10 years.
to the post-1990 period. As shown in the third row of figure A5.2, the main results are mostly preserved. The IRFs also do not change much over the samples suggesting that the persistence of uncertainty shocks does not change much. Finally, we consider if adding additional variables to the benchmark model changes the results. The last row of figure A5.2 displays the response of real GDP from a model includes the real exchange rate and equity prices. Note that the model accounts for the level and conditional volatility of these additional variables. The estimates still suggest that policy uncertainty has a negative impact on GDP.

7 Conclusion

In the face of unprecedented moves in fiscal and monetary policy in recent years in response to unprecedented and unexpected shocks to the global economy, the path forward for policy makers and the ability to predict these paths is uncertain. Tightening monetary policy too much may cause a global recession. Tightening too little may de-anchor inflation expectations. Conflicting trade-offs, supporting households while maintaining fiscal sustainability, exist equally for fiscal policy makers. Reflecting the growing inability to predict future policy moves, measures of policy uncertainty have risen rapidly since 2020, damaging economic activity and raising prices.

This paper presents new global measures of two types of policy uncertainty: government spending and monetary policy. This is done for 54 advanced, emerging, and developing economies in a model that accounts for the causal spillovers of such uncertainty measures on economic activity. The model is unique in the literature as it allows for fat-tailed disturbances. That is, it distinguishes between slow-moving and fast-moving volatility, the latter measure reducing the possibility that the estimates of policy uncertainty are contaminated by volatility induced by transitory events or data outliers, and accounting for the COVID-19 pandemic.
The paper also shows that policy uncertainty shocks have a material impact on real activity and prices. An increase in fiscal (from government spending) and monetary (from real interest rates) policy uncertainty leads to a statistically significant drop in real GDP, private consumption, and fixed investment and an increase in prices. These uncertainty shocks, which act like supply shocks, are particularly detrimental in the current environment of high inflation and rising global recession risks.

Policy uncertainty also affects advanced economies and EMDEs differently although given the lower precision in estimating with smaller samples these should be interpreted with caution. Monetary policy uncertainty is much more detrimental for EMDEs where it is associated with a collapse in output and rising inflation. This may reflect higher levels of monetary uncertainty in EMDEs, inflation expectations that are less well-anchored, and the role of external debt in consumption smoothing in these economies making them more sensitive to real interest rate moves. Fiscal policy uncertainty is more detrimental to advanced economies, being associated with a greater fall in output. This may reflect larger fiscal multipliers and more efficient spending in these economies.
References

Alessandri, P. and H. Mumtaz (2021). The macroeconomic cost of climate volatility. 8, 9


Bauer, M. D. et al. (2012). Monetary policy and interest rate uncertainty. Federal Reserve Bank of San Francisco. 5


Miescu, M. S. (2019). Uncertainty shocks in emerging economies: A global to local approach for identification. *Available at SSRN* 4176889. 16


Pindyck, R. S. (1990). Irreversibility, uncertainty, and investment. 6


Figure 1: Main policy variables

A. Real government spending
Percent, year-on-year

C. Real government revenue
Percent, year-on-year

E. GDP deflator
Percent, year-on-year

B. Ex-ante real interest rate
Percent

D. Real GDP
Percent year-on-year

Sources: Consensus Economics; Haver Analytics; OECD.
Note: Based on a sample of 53 economies used in the baseline model. Last observation in 2022Q4.
Figure 2: Policy uncertainty measures

A. Fiscal spending uncertainty

B. Monetary policy uncertainty

C. Fiscal spending uncertainty

D. Monetary policy uncertainty

E. Fiscal spending uncertainty

F. Monetary policy uncertainty

Source: Authors’ calculations; Davis (2016).
Note: EMDEs = emerging market and developing economies. Results based on the benchmark structural panel VAR model with stochastic volatility. EMDEs and advanced economy outcomes are based on medians. Economic policy uncertainty index is based on Davis (2016).
Figure 3: Fast-moving uncertainty

A. Fast-moving volatility ($\tilde{\lambda}_i t$), fiscal spending

B. Fast-moving volatility ($\tilde{\lambda}_i t$), real interest rate

Source: Authors’ calculations; Davis (2016).
Note: Results based on the benchmark structural panel VAR model with stochastic volatility. Median across 54 economies.
Figure 4: Impulse response functions

A. Impact of a 1 standard deviation shock to government spending uncertainty on real GDP

B. Impact of a 1 standard deviation shock to government spending uncertainty on GDP deflator

C. Impact of a 1 standard deviation shock to monetary policy uncertainty on real GDP

D. Impact of a 1 standard deviation shock to monetary policy uncertainty on GDP deflator

Source: Authors’ calculations.

Note: Results based on the benchmark structural panel VAR model with stochastic volatility.
Figure 5: Impulse response functions: cumulative impact

A. Impact of a 1 standard deviation shock on real GDP

-2.5 -2.0 -1.5 -1.0 -0.5 0.0

Percentage points

1-year 2-years 1-year 2-years
Government spending uncertainty Monetary policy uncertainty

B. Impact of a 1 standard deviation shock on GDP deflator

0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

Percentage points

1-year 2-years 1-year 2-years
Government spending uncertainty Monetary policy uncertainty

Source: Authors’ calculations.
Note: Results based on the benchmark structural panel VAR model with stochastic volatility. Orange whiskers reflect the 16-84th percentile.
A. Impact of a 1 standard deviation shock on private consumption

B. Impact of a 1 standard deviation shock on fixed investment

C. Impact of a 1 standard deviation shock on real GDP, by regions

D. Impact of a 1 standard deviation shock on GDP deflator, by regions

Source: Authors’ calculations.

Note: Orange whiskers reflect the 16-84th percentile.

A.B. Results based on a structural panel VAR model with stochastic volatility based on the following ordering: government consumption; private consumption or fixed investment; GDP deflator; real interest rate; and tax revenue.

C.D. Based on separate panel VAR models for EMDEs and advanced economies. Figures show two-year cumulative IRFs.
Figure 7: Forecast error variance decomposition

A. Real GDP

B. GDP Deflator

Source: Authors' calculations.
Note: Results based on the benchmark structural VAR model with stochastic volatility. Median estimates of forecast error variance decompositions.
Figure 8: Counterfactuals: Real GDP

A. Impact of policy uncertainty on all economies

B. Impact of policy uncertainty, by subgroup

C. Impact of fiscal policy uncertainty on EMDEs

D. Impact of monetary policy uncertainty on EMDEs

Source: Authors’ calculations.

Note: Results based on the benchmark structural VAR model with stochastic volatility. Estimates reflect actual real GDP growth (year-on-year) less counterfactual real GDP excluding all (panel A and B) or certain policy uncertainty (panel C and D). Unweighted averages across all economies, advanced economies and EMDEs.
Appendix

A1 Model Estimation

The panel VAR with stochastic volatility in mean is defined as:

\[ Z_{it} = c_i + \tau_t + \sum_{j=1}^{P} \beta_j Z_{it-j} + \sum_{k=0}^{K} b_k \tilde{h}_{it-k} + v_{it} \quad (A1.1) \]

\[ \text{cov}(v_{it}) = \Omega_{it} \quad (A1.2) \]

\[ \Omega_{it} = A^{-1}H_{it}A^{-1}' \quad (A1.3) \]

\[ H_{it} = \text{diag} \left( \exp(h_{it}) \frac{1}{\lambda_{it}} \right) \quad (A1.4) \]

\[ \tilde{e}_{it} = Av_{it} \quad (A1.5) \]

\[ \tilde{h}_{it} = C_i + F\tilde{h}_{it-1} + N_{it}, N_{it} \sim N(0, \bar{Q}), \quad (A1.6) \]

\[ E(e_{it}, \eta_{it}) = 0, E(e_{it}, e_{jt}) = 0, E(N_{it}, \eta_{jt}) = 0 \text{ for } j \neq i \quad (A1.7) \]

Cross sections are indexed by \( i = 1, 2, \ldots, M \) while the time dimension is indexed by \( t = 1, 2, \ldots, T \). Equation A1.1 describes the observation equation of the system, where \( Z_{it} \) is a \( N \times 1 \) matrix of endogenous variables, \( c_i \) and \( \tau_t \) denote cross-section and time fixed effects.

The vector \( \tilde{h}_{it} \) collects the stochastic volatilities of the orthogonalized shocks \( \tilde{e}_{it} \) that are included as additional regressors and their lags: \( \tilde{h}_{it} = [h_{1,it}, \ldots, h_{N,it}, \ldots, h_{1,it-K}, \ldots, h_{N,it-K}] \).

Similarly \( \tilde{\lambda}_{it} = [\lambda_{1,it}, \ldots, \lambda_{N,it}] \).

In equation A1.3 \( A \) denotes a \( N \times N \) lower triangular matrix with ones on the main diagonal and \( H_{it} = \text{diag} \left( \exp(\tilde{h}_{it}), \exp(\tilde{h}_{it}), \ldots \right) \). The transition equation of the model is given by equation A1.6 where \( C_i \) denotes the cross-section specific intercepts (fixed effects) \( c \) in companion form. The stochastic volatilities are assumed to follow a VAR(1) process. The matrices \( F \) and \( \bar{Q} \) are \( n \times n \) and collect the coefficients \( \theta \) and covariance \( Q \) in companion form. For example, when \( N = 2, P = 1, K = 0 \), the observation equation of the model can be written as:

\[
\begin{pmatrix}
Z_{it}^{(1)} \\
Z_{it}^{(2)}
\end{pmatrix} =
\begin{pmatrix}
c_{i}^{(1)} \\
c_{i}^{(2)}
\end{pmatrix} +
\begin{pmatrix}
\tau_{t}^{(1)} \\
\tau_{t}^{(2)}
\end{pmatrix} +
\begin{pmatrix}
\beta_{11} & \beta_{12} \\
\beta_{21} & \beta_{22}
\end{pmatrix}
\begin{pmatrix}
Z_{it-1}^{(1)} \\
Z_{it-1}^{(2)}
\end{pmatrix} +
\begin{pmatrix}
b_{11}^{(1)} & b_{12}^{(1)} \\
b_{21}^{(1)} & b_{22}^{(1)}
\end{pmatrix}
\begin{pmatrix}
h_{1,it} \\
h_{2,it}
\end{pmatrix} +
\begin{pmatrix}
A_{11} & 0 \\
A_{21} & A_{22}
\end{pmatrix}^{-1}
\begin{pmatrix}
\exp(h_{1,it}) \frac{1}{\lambda_{1,it}} \quad 0.5 \\
0 & \left( \exp(h_{2,it}) \frac{1}{\lambda_{2,it}} \right)^{0.5}
\end{pmatrix}
\begin{pmatrix}
\tilde{e}_{it}^{(1)} \\
\tilde{e}_{it}^{(2)}
\end{pmatrix}
\]
The transition equation in this case (with \( n = 2 \)) is given by:

\[
\begin{pmatrix}
\hat{h}_{1,it} \\
\hat{h}_{2,it}
\end{pmatrix}
= \begin{pmatrix}
C_i^{(1)} \\
C_i^{(2)}
\end{pmatrix} + \begin{pmatrix}
\theta_{11} & \theta_{12} \\
\theta_{21} & \theta_{22}
\end{pmatrix} \begin{pmatrix}
\hat{h}_{1,it-1} \\
\hat{h}_{2,it-1}
\end{pmatrix} + \begin{pmatrix}
\eta_{it}^{(1)} \\
\eta_{it}^{(2)}
\end{pmatrix}
\]

where

\[
\tilde{Q} = \begin{pmatrix}
Q_{11} & Q_{12} \\
Q_{12} & Q_{22}
\end{pmatrix}
\]

### A1.1 Prior distributions and starting values

#### VAR coefficients

Let \( \Gamma = vec ([\beta_j; b_k; c_i, \tau_t]) \) and denote the number of regressors excluding the lags of \( Z_{it} \) as \( EX \). Note that the country and time-fixed effects are introduced into the model using dummy variables. Following Banbura et al. (2007), we employ a Normal prior implemented via dummy observations. The priors are implemented by the dummy observations \( y_D \) and \( x_D \) that are defined as:

\[
y_D = \begin{bmatrix}
diag(\gamma_1, \ldots, \gamma_n) \\
0_{N \times (P-1) \times N} \\
\vdots
\end{bmatrix}, \quad x_D = \begin{bmatrix}
J_P \otimes diag(s_1, \ldots, s_n) \\
0_{N \times (NP) + EX}
\end{bmatrix}
\]

\[(A1.8)\]

where \( \gamma_1 \) to \( \gamma_n \) denote the prior mean for the parameters on the first lag obtained by estimating individual AR(1) regressions, \( \kappa \) measures the tightness of the prior on the autoregressive VAR coefficients, and \( c \) is the tightness of the prior on the remaining regressors. We set \( \tau = 1 \) and \( c = 1000 \).

The priors for the coefficients are thus: \( N(\Gamma_0, P_0) \) where \( \Gamma_0 = (x_D'x_D)^{-1}(x_D'y_D) \) and \( P_0 = S \otimes (x_D'x_D)^{-1} \) where \( S \) is a diagonal matrix with an estimate of the variance of \( Z_{it} \).

#### Elements of \( \tilde{h}_{it} \)

To set initial values for the elements of \( \tilde{h}_{it} \), we estimate a VAR with stochastic volatility for each country and obtain an initial estimate of the stochastic volatilities, denoted by \( \mu_{it} \). The prior for \( \tilde{h}_{it} \) at \( t = 0 \) is defined as \( \ln h_{i0} \sim N(\ln \mu_{i1}, I) \).

#### Elements of \( A \)

Using the lags of \( \mu_{it} \) in equation 1, we estimate the equation \( Z_{it} = c_i + \tau_t + \sum_{j=1}^{P} \beta_j Z_{it-j} + \sum_{k=0}^{K} b_k \ln u_{it-k} + v_{it} \) by OLS and obtain an initial estimate of the residuals of the VAR \( v_{it} \). The prior for the off-diagonal elements \( A \) is \( A_0 \sim N(\hat{a}^{ols}, V(\hat{a}^{ols})) \) where \( \hat{a}^{ols} \) are the off-diagonal elements of the inverse of the Cholesky decomposition of \( \text{var} (v_{it}) \) where each row of the decomposition is divided by the corresponding element on the diagonal. \( V(\hat{a}^{ols}) \) is assumed to be diagonal with the elements set equal to 1.
Parameters of the transition equation

The prior on the coefficients of the transition equation A1.6 is implemented via dummy variables (see Banbura et al. (2007)), shrinking each equation towards an AR process. The prior tightness parameter controlling the strength of the prior on the coefficients on the lagged volatilities is set equal to 0.2. The prior for \( Q \) is inverse Wishart: \( IW(Q_0, T_0) \) where \( Q_0 = \text{diag}(g_0 \times T_0) \) with \( g_0 \) representing a vector that contains the average variance of the shocks to the transition equation obtained by the initial estimation of the VAR with stochastic volatility for each country. The degrees of freedom \( T_0 \) are set equal to \( N + 1 \).

A1.1.1 Elements of \( \tilde{\lambda}_{it} \)

We employ a hierarchical prior for elements of \( \tilde{\lambda}_{it} \) (see Koop (2003))). The prior for \( \lambda_{K,it} \) is a Gamma distribution \( \Gamma(1, \upsilon_K) \). The degrees of freedom parameter \( \upsilon_K \) is treated as an unknown parameter with the prior: \( \Gamma(\upsilon_0, 2) \). We set \( \upsilon_0 = 20 \) in our application.

A1.2 Simulating the conditional posterior distributions

VAR coefficients

Conditional on all other parameters, the model in equation A1.1 is a panel VAR with a known form of heteroscedasticity. The conditional posterior distribution is normal: \( N(\Gamma_{T\setminus T_0}, P_{T\setminus T_0}) \).

The model in A1.1 can be written at each time period \( t \) as:

\[
y_{it} = x_{it} \Gamma_{i} + \tilde{e}_{it}
\]

where:

\[
y_{it} = \text{vec}(Z_{it})
\]

\[
x_{it} = \\
\begin{pmatrix}
X_{1,t} \\
. \\
X_{M,t}
\end{pmatrix}
\]

\[
X_{it} = I_N \otimes \bar{x}
\]

\( \bar{x} \) denotes all the RHS variables in equation A1.1 at time \( t \) for country \( i \). The variance of the error term \( \tilde{e}_{it} \) is:

\[
\text{var} (\tilde{e}_{it}) = R_t = \text{blkdiag} \left( [A^{-1}H_{11}^{1/2}A^{-1'}, \ldots, A^{-1}H_{M1}^{1/2}A^{-1'}] \right)
\]

Finally, we assume that the transition equation for \( \Gamma_{t} \) is \( \Gamma_{t} = \Gamma_{t-1} \). These equations form a conditionally linear and Gaussian state-space system. Following Carter and Kohn (1994) we use the Kalman filter to calculate the mean and the variance of the conditional posterior
distribution of $\Gamma$. The Kalman filter is initialized at $\Gamma_0$ and $P_0$ and the recursions are given by the following equations for $t = 1, 2, \ldots T$

$$\Gamma_{t \setminus t-1} = \Gamma_{t-1 \setminus t-1}$$
$$P_{t \setminus t-1} = P_{t-1 \setminus t-1}$$
$$\eta_{t \setminus t-1} = y_t - x_t^{'}\Gamma_{t \setminus t-1}$$
$$f_{t \setminus t-1} = x_t^{'} P_{t \setminus t-1}^{-1} x_t + R_t$$
$$K_t = P_{t \setminus t-1}^{'} f_{t \setminus t-1}^{-1}$$
$$\Gamma_{t \setminus t} = \Gamma_{t \setminus t-1} + K_t \eta_{t \setminus t-1}$$
$$P_{t \setminus t} = P_{t \setminus t-1} - K_t x_t P_{t \setminus t-1}$$

The final iteration of the Kalman filter at time $T$ delivers $\Gamma_{T \setminus T}$ and $P_{T \setminus T}$, the mean and the variance of the conditional posterior. This application of the Carter and Kohn (1994) algorithm to this heteroscedastic VAR model is equivalent to a GLS transformation of the model.

**Element of $A$**

Given a draw for $\Gamma$, $\tilde{\lambda}_{it}$ and $\tilde{h}_{it}$ the VAR model can be written as $A' (v_{it}) = \tilde{e}_{it}$ where $v_{it} = Z_t - (c_i + \tau_t + \sum_{j=1}^{p} \beta_j Z_{it-j} + \sum_{k=0}^{K} b_k \tilde{h}_{it-k})$ and $VAR(\tilde{e}_{it}) = H_{it}$. This is a system of linear equations with a known form of heteroscedasticity. The conditional distributions for a linear regression apply to each equation of this system after a simple GLS transformation to make the errors homoscedastic. The $kth$ equation of this system is given as $v_{it}^k = -v_{it}^{-k} \alpha + \tilde{e}_{it}$ where the superscript $k$ denotes the $kth$ column of the residual matrix while $-k$ denotes columns 1 to $k - 1$. Note that the variance of $\tilde{e}_{it}$ is time-varying and given by $\exp \left( \tilde{h}_{it} \tilde{\lambda}_{it} \right)$. A GLS transformation involves dividing both sides of the equation by $\sqrt{\exp \left( \tilde{h}_{it} \tilde{\lambda}_{it} \right)}$ to produce $v_{it}^* = -v_{it}^{-k} \alpha + e_{it}^*$ where $*$ denotes the transformed variables and $\text{var} (e_{it}^*) = 1$. The conditional posterior for $\alpha$ is normal with mean and variance given by $M^*$ and $V^*$:

$$M^* = \left( V \left( \hat{a}_{ols} \right)^{-1} + v_{it}^{k*} v_{it}^{-k*} \right)^{-1} \left( V \left( \hat{a}_{ols} \right)^{-1} \hat{a}_{ols} + v_{it}^{k*} v_{it}^{k*} \right)$$
$$V^* = \left( V \left( \hat{a}_{ols} \right)^{-1} + v_{it}^{k*} v_{it}^{-k*} \right)^{-1}$$

**Elements of $\tilde{h}_{it}$**

Conditional on the VAR coefficients and the parameters of the transition equation, the model has a multivariate non-linear state-space representation for each cross-section given by equations A1.1 and A1.6. Following recent developments in the seminal paper by Andrieu et al. (2010b), we employ a particle Gibbs step to sample from the conditional pos-
terior of $\tilde{h}_{it}$. Andrieu et al. (2010b) show how a version of the particle filter, conditioned on a fixed trajectory for one of the particles can be used to produce draws that result in a Markov Kernel with a target distribution that is invariant. However, the usual problem of path degeneracy in the particle filter can result in poor mixing in the original version of particle Gibbs. Recent developments, however, suggest that small modifications of this algorithm can largely alleviate this problem. In particular, Lindsten et al. (2014) propose the addition of a step that involves sampling the ‘ancestors’ or indices associated with the particle that is being conditioned on. They show that this results in a substantial improvement in the mixing of the algorithm even with a few particles. As explained in Lindsten et al. (2014), ancestor sampling breaks the reference path into pieces and this causes the particle system to collapse towards something different than the reference path. In the absence of this step, the particle system tends to collapse to the conditioning path. We employ particle Gibbs with ancestor sampling in this step to draw $\tilde{h}_{it}$ for $i = 1,2, \ldots, M$.

Let $\tilde{h}_{it}^{(d-1)}$ denote the fixed the fixed trajectory, for $t = 1,2, \ldots, T$ obtained in the previous draw of the Gibbs algorithm for country $i$. We denote the parameters of the model by $\Xi$, and $j = 1,2, \ldots, S$ represents the particles. The conditional particle filter with ancestor sampling proceeds in the steps described below. We suppress the cross-section index $i$ in $\tilde{h}_{it}$ to keep the notation simple. In other words $\tilde{h}_{it}$ refers to the stochastic volatility for the $ith$ cross-section. The steps described below are repeated for $i = 1,2, \ldots, M$.

1. For $t = 1$
   
   (a) Draw $\tilde{h}_{1}^{(j)} \mid \tilde{h}_{0}^{(j)}, \Xi$ for $j = 1,2, \ldots, S - 1$. Fix $\tilde{h}_{1}^{(S)} = \tilde{h}_{1}^{(d-1)}$
   
   (b) Compute the normalized weights $p_{t}^{(j)} = \frac{w_{t}^{(j)}}{\sum_{j=1}^{M} w_{t}^{(j)}}$ where $w_{t}^{(j)}$ denotes the conditional likelihood: $\left| \Omega_{i1}^{(j)} \right|^{-0.5}$
   
   $$\tilde{c}_{i1} = Z_{it} - \left( c_{i} + \tau_{i} + \sum_{j=1}^{P} \beta_{j} Z_{it-j} + \sum_{k=0}^{K} b_{k} \tilde{h}_{1, [-k]}^{(j)} \right)$$
   
   and $\Omega_{i1}^{(j)} = A_{i1}^{-1} H_{i1}^{(j)} A_{i1}^{-1}$ with $H_{i1}^{(j)} = diag \left( \exp \left( \tilde{h}_{1, [0]}^{(j)} \right) \right)$. The subscript $[0]$ denotes the contemporaneous value in the state vector while $[-k]$ denote the $k$ lagged states.

2. For $t = 2$ to $T$

   (a) Resample $\tilde{h}_{t}^{(j)}$ for $j = 1,2, \ldots, S - 1$ using indices $a_{t}^{(j)}$ with $\Pr \left( a_{t}^{(j)} = j \right) \propto p_{t-1}^{(j)}$
   
   (b) Draw $\tilde{h}_{t}^{(j)} \mid \tilde{h}_{t-1}^{(a_{t}^{(j)})}, \Xi$ for $j = 1,2, \ldots, S - 1$ using the transition equation of the model (equation 3). Note that $\tilde{h}_{t-1}^{(a_{t}^{(j)})}$ denotes the resampled particles in step (a) above.
   
   (c) Fix $\tilde{h}_{t}^{(S)} = \tilde{h}_{t}^{(d-1)}$
   
   (d) Sample $a_{t}^{(M)}$ with $\Pr \left( a_{t}^{(M)} = j \right) \propto p_{t-1}^{(j)} \Pr \left( \tilde{h}_{t}^{(d-1)} \mid \tilde{h}_{t-1}^{(j)}, \alpha, \theta, Q \right)$ where the density $\Pr \left( \tilde{h}_{t}^{(d-1)} \mid \tilde{h}_{t-1}^{(j)}, \alpha, \theta, Q \right)$ is computed as $|Q|^{-0.5} - 0.5 \exp \left( \tilde{h}_{it}^{(M)} (Q)^{-1} a_{it}^{(j)} \right)$, where $\tilde{h}_{it} = \tilde{h}_{t}^{(d-1)} - (\alpha + \theta \tilde{h}_{t-1}^{(j)})$. This constitutes the ancestor sampling step. If $a_{t}^{(M)} = M$ then the algorithm collapses to the simple particle Gibbs.
(e) Update the weights $p_t^{(j)} = \frac{w_t^{(j)}}{\sum_{m=1}^{M} w_t^{(m)}}$ where $w_t^{(j)}$ denotes the conditional likelihood: $\left| \Omega_{it}^{(j)} \right|^{-0.5} - 0.5 \exp \left( \tilde{e}_{it} (\Omega_{it}^{(j)})^{-1} \tilde{e}_{it}' \right)$, where

$\tilde{e}_{it} = Z_{it} - \left( c_i + \tau_t + \sum_{j=1}^{P} \beta_j Z_{it-j} + \sum_{k=0}^{K} b_k \tilde{h}_{[k]}^{(j)} \right)$,

$\Omega_{it}^{(j)} = A^{-1} H_{it}^{(j)} A^{-1'}$, with $H_{it}^{(j)} = \text{diag} \left( \exp \left( \tilde{h}_{it[0]}^{(j)} \right) \right)$.

3. End

4. Sample $\tilde{h}_{it}^{(i)}$ with $\Pr \left( \tilde{h}_{it}^{(i)} = \tilde{h}_{it}^{(j)} \right) \propto p_t^{(j)}$ to obtain a draw from the conditional posterior distribution

We use $M = 20$ particles in our application. The initial values $\mu_0$ defined above are used to initialize step 1 of the filter.

**Parameters of the transition equation**

Conditional on the draw for the volatilities, the conditional posterior for $\bar{B} = \text{vec} \left( [c_i, \theta] \right)$ the parameters of the panel VAR in equation A1.6 is Normal. Consider the VAR $y_t = c_i + y_{t-1} + \theta + \eta_t$, where $y_t = [h_{1,it}, h_{2,it}, \ldots, h_{N,it}]$ for $i = 1, 2, \ldots, M$. Let $x$ denote the regressors in each equation of this VAR. These include the lagged volatility and country dummies. The conditional posterior of the coefficients is defined as

$$
G \left( \bar{B} \setminus \Xi \right) \sim N (B^*, Q \otimes (x^* x^*)^{-1})
$$

where $B^* = (x^* x^*)^{-1} (x^* y^*)$ and $x^*$ and $y^*$ denote $x$ and $y$ appended with prior dummy observations.

The conditional posterior for $Q$ is inverse Wishart and is given by

$$
G \left( Q \setminus \Xi \right) \sim IW (S^*, T^*)
$$

where $T^* = MT + T_0$ with $MT$ the total number of observations in the stacked data $y$ and the scale matrix is $S^* = (y - x \bar{b})' (y - x \bar{b}) + Q_0$ where $\bar{b}$ denotes $\bar{B}$ reshaped to match the dimensions of $x$.

A1.2.1 **Elements of $\tilde{\lambda}_{it}$**

As described in Koop (2003), the conditional posterior of $\lambda_{K, it}, K = 1, 2, \ldots, N$ is a Gamma distribution with the following mean and degrees of freedom:

$$
m = (\nu_K + 1) / \left( \frac{1}{h_{K, it}} \tilde{e}_{K, it}^2 + \nu_K \right)
$$

$$
df = \nu_K + 1
$$
A1.2.2 Degrees of freedom \( \nu_K \)

This conditional distribution is non-standard and is given by:

\[
G(\nu_K) \propto \left( \frac{\nu_K}{2} \right)^{\frac{MT+K}{2}} \Gamma \left( \frac{\nu_K}{2} \right)^{-MT} \exp \left( - \left( \frac{1}{\nu_0} + 0.5 \sum_{t=1}^{MT} \left[ \ln \left(-\lambda_{K,t}^{-1}\right) + \lambda_{K,t} \right] \right) \nu_K \right)
\]

We use a random walk Metropolis Hastings algorithm to draw from this conditional posterior distribution.

A2 Convergence

Figure A2.1: Inefficiency factors

Source: Authors’ calculations.
Note: Inefficiency factors
A3 Data

A3.1 Real interest rate

The stance of monetary policy is often determined in the context of the real policy interest rate. Two things are needed to determine the real interest rate: the nominal policy interest rate, which the central bank usually sets, and some measure of inflation expectations. On the nominal interest rate, while there is often a short-term policy rate controlled directly by the central bank, in practice, the interest rate that prevails in the economy can be different. Also central banks could set many different interest rates, and use other tools, to control financial conditions. To best reflect the de facto stance of monetary policy, and the many different monetary policy frameworks across economies, a three-month market-based measure of interest rates is used; the short-term rate best reflecting what a central bank endeavors to control.

On inflation expectations, there are many measures that could be used to get to a real interest rate measure. Some use actual inflation outcomes—the resultant measure referred to as ex-post real interest rates—or some form of forward-looking inflation—an ex-ante real interest rate. Forward-looking inflation measures can come from various sources including forecast from a model or surveys of either households, businesses, experts, or all economic agents. While household surveys can be useful, their country and time coverage is limited. To best balance the need for a forward-looking measure with a significant country coverage a hybrid approach is followed that uses one-year-ahead consensus forecasts of CPI inflation extended by out-of-sample forecasts from ARIMA models.

A3.2 Inflation expectations

The hybrid approach to generating one-year-ahead inflation expectations has two components. First, all average consensus forecasts for CPI inflation starting in 2005 for the current year and one-year ahead are collected from Consensus Economics (covering 85 economies). Since consensus forecast report fixed event forecasts (for example, 2020 and 2021) every month that do not account for the time dimension of forecasts appropriately, the fixed horizon transformation in Siklos (2013) and Bordo and Siklos (2017) is used. The fixed horizon adjustment is as follows:

\[
\pi_{m,t}^{FH} = \left(\frac{13 - m}{12}\right)\pi_t^{FE} + \left(\frac{m - 1}{12}\right)\pi_{t+1}^{FE}
\]  

(A3.1)

where \(FH\) is the fixed horizon forecast which is a linear combination of the fixed event forecast at time \(t\) (for example, 2020) and \(t+1\) (for example, 2021) for month \(m\). This transformation ensures that inflation expectations are one-year-ahead.

Second, to extend the forecasts backwards 12-month-ahead inflation forecasts are produced using an automatic ARIMA model. The following steps are followed:

- Collect non-seasonally adjusted headline consumer price index data and log-linearize;
- Using the first three years of data, fit the best ARIMA model based on the automatic approach in Hyndman and Khandakar (2008) using the Akaike’s Information Criterion (AIC) to select the model;
- Generate the 12-month-ahead forecast using the iterated approach;
- Update the model sample by shifting one-month forward and repeat steps above.

Figure A3.1 plots the outcome of the preceding exercise for two countries included in the sample (the United States and South Africa). There is a strong correlation across measures of one-year-ahead inflation expectations. In the United States, all measures reflect the current rising inflation environment during 2022, the low inflation environment that preceded it since the global financial crisis, and the moderation in inflation since the early 1990s. In South Africa, CPI inflation forecast from automatic ARIMA process track consensus forecasts and household expectations of one-year-ahead inflation.

Figure A3.1: Inflation expectations

A. United States

B. South Africa

Sources: Bureau of Economic Research; Consensus Economics; Haver Analytics; University of Michigan.
Note: Reflects one-year-ahead inflation expectations.
Table A3.1: Economies in baseline VAR model

<table>
<thead>
<tr>
<th>Advanced economies</th>
<th>EMDEs</th>
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<tbody>
<tr>
<td>Australia</td>
<td>Portugal</td>
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<td>Iceland</td>
<td>Thailand</td>
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A11
A4 Baseline model full results

Figure A4.1: Impulse response function: volatility shocks

Source: Authors’ calculations.
Note: Results based on the benchmark structural VAR model with stochastic volatility. Shading reflects 68 percent and 90 percent highest posterior density interval.
Figure A4.2: Impulse response function: level shocks

Source: Authors’ calculations.
Note: Results based on the benchmark structural VAR model with stochastic volatility. Shading reflects 68 percent and 90 percent highest posterior density interval.
A5 Robustness analysis

Figure A5.1: Robustness checks using alternative model

Source: Authors’ calculations.
Note: Robustness checks using model that allows for correlation between level and volatility shocks. Policy uncertainty shocks are identified using the approach of Uhlig (2004)
Figure A5.2: Robustness checks: Impact on real GDP

Source: Authors’ calculations.

Note: Robustness checks using alternative model specifications. See section 6