Disentangling the Effects of Uncertainty, Monetary Policy, and Leverage Shocks on the Economy*

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In this paper, we assess the information content and predictive ability of various risk and uncertainty measures in predicting various measures of real economic activity as well as undertake a comparative analysis of the relative importance of uncertainty, monetary policy, and leverage shocks in the macroeconomic business cycle. We find that the Jurado et al. (2015) macroeconomic uncertainty index and the Chicago Fed national financial conditions risk index have the strongest predictive relationship with economic activities. Also, in the context of a Bayesian monetary structural VAR, we use the penalty function approach to a sequential identification of uncertainty, monetary policy, and leverage shocks, and find that uncertainty shocks are a relatively more important source of variations in the economy than traditional monetary policy shocks. However, monetary policy shocks still outperform uncertainty shocks in explaining inflation dynamics.

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1 Introduction

How important are uncertainty shocks compared to monetary policy and leverage shocks? High uncertainty, whether caused by political unrest, trade restrictions, or the Covid-19 crisis, generally has a negative effect on the level of economic activity. For example, increased uncertainty typically leads to declines in real GDP, consumption, investment, employment, inflation and interest rates — see Bloom (2009), Mumtaz and Zanetti (2013), Jurado et al. (2015), Fernandez-Villaverde et al. (2015), Bloom et al. (2018), Davis (2019), and Caldara et al. (2016, 2020), among others. In recent years, as Cascaldi-Garcia et al. (2020) put it, “researchers, policymakers, and market participants have become increasingly focused on the effects of uncertainty and risk on financial market and economic outcomes.” On the other hand, financial intermediaries have also been shown to be more active players in the economy than was previously assumed. In this paper, we examine the interaction between uncertainty and the traditional sources of macroeconomic instability — monetary policy and leverage shocks — in the context of a Bayesian monetary structural vector autoregressive (VAR) model using the penalty function approach to sequentially identify multiple shocks. We find that uncertainty shocks explain a significant fraction of economic fluctuations, but monetary policy shocks outperform uncertainty shocks in explaining inflation dynamics.

Theoretical and empirical background. The information-based monetary misperceptions model of Lucas (1972), developed initially by Friedman (1968) and Phelps (1970), is one of the most celebrated business cycle models in the past 50 years. According to the model, in a rational expectations setting, economic agents have incomplete information about prices in the economy, and monetary shocks are a principal cause of business cycles. In recent years, however, most economists think that monetary shocks are not the principal cause of business cycle fluctuations. For example, Baumeister and Hamilton (2018) use a Bayesian structural VAR model, based on the new Keynesian approach to macroeconomics, and show that monetary policy shocks are relatively unimportant in explaining key macroeconomic variations compared to demand and supply shocks. However, the new Keynesian approach to macroeconomics ignores the financial intermediary sector. In this regard, as policy rates around the world reached the zero lower bound in the aftermath of the global financial crisis, banks and a number of market-based financial intermediaries have attracted a great deal of attention, and there is now almost universal agreement that the global financial crisis originated in the banking system. As Dery and Serletis (2020b) recently put it, “financial firms issue leverage, to acquire assets in excess of net worth, and also issue deposit liabilities, which are included in measures of the money supply. The question then is whether there is a useful role of leverage and the aggregate quantity of money in monetary policy and business cycle analysis.”

Regarding leverage, Adrian and Shin (2010) argue that “the evidence points to financial intermediaries adjusting their balance sheets actively, and doing so in such a way that leverage is high during booms and low during busts.” In fact, Geanakoplos (2012, p. 389)
argues that “leverage can be more important to economic activity and prices than interest rates, and more important to manage.” In this regard, Istiak and Serletis (2017) investigate the macroeconomic effects of leverage and the interdependence between monetary policy and leverage and conclude that the role played by leverage shocks seems more important than interest rate policy. Regarding the role of money, McCallum and Nelson (2011, p. 147) argue that “too much in the reaction to problems in measuring money has taken the form of abandoning the analysis of monetary aggregates, and too little has taken the form of more careful efforts at improved measurement.” In this regard, Dery and Serletis (2020b) complement and extend the Baumeister and Hamilton (2018) model by including financial intermediary leverage and money supply measures. They show that monetary policy shocks account for a nontrivial proportion of the variation in output when Divisia monetary aggregates are included in traditional interest rate monetary policy rules.

However, as Caldara et al. (2016, p. 185) put it, “the acute turmoil that swept through global financial markets during the 2008-2009 financial crisis and the depth and duration of the associated economic downturn, both in the United States and abroad, have cast a considerable doubt on the traditional sources of business cycle fluctuations. In response, recent theoretical and empirical research aimed at understanding these extraordinary events has pointed to financial and uncertainty shocks — or their combination — as alternative drivers of economic fluctuations.” Moreover, Davis (2019, p. 13) argues that “a variety of studies find evidence that high (policy) uncertainty undermines economic performance by leading firms to delay or forego investments and hiring, by slowing productivity-enhancing factor reallocation, and by depressing consumption expenditures. This evidence points to a positive payoff in the form of stronger macroeconomic performance if policymakers can deliver greater predictability in the policy environment.”

**Contribution.** In this paper, in the spirit of Adrian and Shin (2010), Caldara et al. (2016), Baumeister and Hamilton (2018), and Dery and Serletis (2020a) we assess the relative importance of uncertainty, monetary policy, and leverage shocks as sources of macroeconomic fluctuations. In doing so, we ignore real shocks, fiscal shocks, and other shocks (such as oil shocks), leaving their investigation for future work — see Cochrane (1994) and Ramey (2016) for a discussion of the shocks that drive economic fluctuations. We follow Caldara et al. (2016) and use the penalty function approach to a sequential identification of multiple shocks in the context of a Bayesian monetary structural VAR framework. This approach, initially developed by Faust (1998) and Uhlig (2005), and further extended by Mountford and Uhlig (2009), selects a structural VAR model by maximizing a criterion function subject to inequality constraints, with the criterion function consisting of the sum of the impulse response functions of the target variable(s) and the inequality constraints corresponding to sign restrictions on these impulse response functions over a pre-specified horizon. As Caldara et al. (2016, p. 186) argue, “compared with identification schemes based on sign restrictions, this framework allows us to distinguish empirically between shocks that have otherwise very similar qualitative effects on the economy.”
We find that most measures of risk and uncertainty are informative for predicting real economic activities and produce statistically and economically significant forecasts of economic activities. Based on the information content analysis of the various risk and uncertainty measures, we conclude that macroeconomic uncertainty and the Chicago Fed national financial conditions risk index are the most informative for predicting real economic activity. Based on our structural VAR analysis, we find that uncertainty shocks are more important in explaining fluctuations in the real sector of the economy than monetary policy and leverage shocks. We find that a positive uncertainty shock results in declines in the growth rate of real GDP, investment, consumption, and employment and increases in the unemployment rate. The contraction in the real economy from an adverse uncertainty shock is more pronounced and persistent relative to a contractionary monetary policy shock. In terms of forecast error variance decomposition, uncertainty shocks account for an overwhelming proportion of the variation of all real variables that we consider, ranging from 38% to 61% over a 3 year average, depending on the variable, while the corresponding proportion for monetary policy shocks ranges from 3% to 10%. However, monetary policy shocks outperform uncertainty shocks in explaining inflation fluctuations. On average, 27% of the variation in inflation is attributable to monetary policy while the corresponding proportion for uncertainty is approximately 18%. We also show that even though leverage is important in other regards, it does not seem to be an important source of macroeconomic instability relative to uncertainty and monetary policy shocks. Our findings are robust to six alternative proxies of risk and uncertainty, three broad Divisia monetary aggregates as well as four measures of leverage.

Apart from differences in the information set, this paper differs from Dery and Serletis (2020a) in two important ways. First, Dery and Serletis (2020a) consider only macroeconomic uncertainty, whereas in this paper we consider two proxies for risk — geopolitical risk and the Chicago financial conditions risk — and five proxies for uncertainty — financial uncertainty, macroeconomic uncertainty, real uncertainty, economic policy uncertainty, and trade policy uncertainty. In doing so, we provide a comprehensive analysis of the information content and predictive abilities of these risk and uncertainty measures. We test for Granger causality from each of the risk and uncertainty measures to real GDP as well as several other measures of real economic activity. We investigate the ability of each risk and uncertainty measure to forecast real economic activity, thus contributing to the literature by showing which measures of risk and uncertainty are more informative for predicting real economic activity. Second, we provide a comprehensive comparative analysis of monetary policy, uncertainty, and leverage shocks, focusing on the effects of these shocks on a broad range of economic variables, including real GDP, investment, consumption, employment, the unemployment rate, and the inflation rate. Our paper therefore is a more comprehensive and provides a more systematic treatment of some of the issues raised by Dery and Serletis (2020a). For example, Dery and Serletis (2020a) using macroeconomic uncertainty conclude that uncertainty shocks are more important in explaining output variation than monetary policy shocks. We generalize this empirical observation by showing that not only are uncertainty shocks more important
than monetary policy shocks in explaining output variations, but uncertainty shocks are also more important than monetary policy shocks in accounting for the variation in several other important macroeconomic variables such as investment, consumption, employment, and the unemployment rate. We also show that the use of several other measures of uncertainty leads to this conclusion.

**Layout.** The paper is organized as follows. Section 2 discusses the data and presents the various risk and uncertainty indicators, monetary aggregates, and leverage measures. Section 3 provides a preliminary investigation of the information content of the (eight) risk and uncertainty measures in the context of two classes of empirical models — Granger causality tests and a forecasting regression. Section 4 presents the structural VAR model and discusses the identification of uncertainty, monetary policy, and leverage shocks using the penalty function approach. Section 5 presents the empirical results while Section 6 performs robustness checks to assess the sensitivity of our findings to alternative uncertainty measures, identification schemes, monetary supply measures, and leverage measures. The final section concludes regarding the implications for business cycle analysis.

2 **The Data**

We use quarterly data for the United States, over the period from 1973:q1 to 2020:q2, to study the information content and predictive ability of various risk and uncertainty measures in predicting various measures of real economic activity and to undertake a comparative analysis of the relative importance of uncertainty, monetary policy, and leverage shocks in affecting macroeconomic variations. Our measure of real economic activity is real GDP. However, we also examine alternative indicators of economic activity, such as industrial production, capacity utilization, real private gross investment, the level of employment for all persons in the United States aged 15 to 64 years, the unemployment rate, housing starts, real disposable personal income, real per capita disposable personal income, personal consumption expenditure, and consumption expenditure for durable goods. We use the personal consumption expenditure deflator as the relevant price level variable and the Wu and Xia (2016) shadow federal funds rate as the policy variable to also capture the stance of monetary policy during the zero lower bound period. All these series, except for the policy rate, are obtained from the Federal Reserve Economic Database (FRED), maintained by the Federal Reserve Bank of St. Louis. The Wu and Xia (2016) shadow federal funds rate is from the Federal Reserve Bank of Atlanta.

Due to the recent proliferation of different risk and uncertainty indicators, we use two proxies for risk (geopolitical risk and the Chicago financial conditions risk) and six proxies for uncertainty (financial uncertainty, macroeconomic uncertainty, real uncertainty, economic policy uncertainty, trade policy uncertainty, and the CBOE S&P 100 volatility index). As noted by Cascaldi-Garcia *et al.* (2020), in their comprehensive survey of the many existing
measures of risk, uncertainty, and volatility, these measures are not interchangeable and may
or may not capture the same source of uncertainty. They have different information content,
because they are informative about different events, and thus cause different responses.

For geopolitical risk, we use the Caldara and Iacoviello (2019) index. This index is
constructed by counting the number of articles related to geopolitical risk (as a share of the
total number of news articles for each month), in the electronic archives of eleven national
and international newspapers. However, to obtain a long time series for our analysis, we use
the historical version of the series which is constructed based on three national newspapers.
See Caldara and Iacoviello (2019) for a detailed discussion of the geopolitical risk index.
We obtain the Chicago Fed national financial conditions risk index from FRED. It provides
a comprehensive update on the financial conditions in debt and equity markets, money
markets, and the traditional as well as shadow banking systems in the United States. Positive
values of the index indicate tighter than usual financial conditions while negative values of
the index indicate relatively lax financial conditions. Figure 1 plots the geopolitical risk and
the Chicago financial conditions risk indices; shaded areas indicate NBER recessions.

We obtain the financial uncertainty, macroeconomic uncertainty, and real uncertainty
indices from the website of Sydney C. Ludvigson. Jurado et al. (2015) use 148 financial
indicators in constructing the financial uncertainty index. These include valuation ratios,
growth rates of aggregate dividends and prices, yields on corporate bonds of different ratings
grades, default and term spreads, yields on treasuries, and a broad cross-section of industry
equity returns, among others. They use 132 indicators — such as, for example, real output
and income, employment and hours, manufacturing and trade sales, consumer spending, in-
ventories and inventory sales ratios, housing starts, orders and unfilled orders, compensation
and labor costs, capacity utilization measures, bond and stock market indices, price indices,
and foreign exchange measures — in constructing the macroeconomic uncertainty index.
Given that real uncertainty is a subset of macroeconomic uncertainty, only the real activity
variables in the macro uncertainty index are used in the construction of the real uncertainty
index. See the appendix on the website of Sydney C. Ludvigson for a detailed discussion
regarding the construction of these indices and the list of variables in each of the indices.

The economic policy uncertainty index, developed by Baker et al. (2016), is from the Eco-
nomic Policy Uncertainty website. This measure of uncertainty is constructed from three
components. The first component results from searches of 10 large U.S. newspapers and
quantifies coverage of policy-related economic uncertainty. The second component draws on
reports by the Congressional Budget Office regarding the number of federal tax code provi-
sions set to expire in 10 years; as Baker et al. (2016) argue, the expiration of tax code creates
uncertainty. The third component is based on the Federal Reserve Bank of Philadelphia’s
Survey of Professional Forecasters, and uses any disagreement among economic forecasters

\footnote{See https://www.policyuncertainty.com/index.html. Note that this series is only available from 1985:q1,
so we augment the series with its historical version from 1973:q1 to 1984:q4.}
as a proxy for uncertainty. The trade policy uncertainty index, constructed by Caldara et al. (2020), is obtained from Matteo Iacoviello’s website. This index is constructed by counting the frequency of joint occurrences of trade policy and uncertainty terms as a share of the total number of news articles in automated text searches of the electronic archives of seven newspapers. Finally, the option-implied volatility on the S&P 500 stock futures index (VIX) is also a commonly used proxy for macroeconomic uncertainty — see Caldara et al. (2016). Because VIX is available since 1990:q1, we use the option-implied volatility on the S&P 100 stock futures index, constructed by the Chicago Board of Option Exchange (VXO), which is available over a longer period, since 1986:q1. It is to be noted that the correlation between the VXO and VIX, over the period from 1990:q1 to 2020:q1, is 0.99. We obtain the VXO from FRED. Figure 2 plots the financial uncertainty, macroeconomic uncertainty, real uncertainty, economic policy uncertainty, trade policy uncertainty, and the CBOE S&P 100 volatility index, with shaded areas indicating NBER recessions.

We also augment our model with measures of Divisia money, as Belongia and Ireland (2015, p. 268) “call into question the conventional view that the stance of monetary policy can be described with exclusive reference to its effects on interest rates and without consideration of simultaneous movements in the monetary aggregates.” They argue that properly measured monetary aggregates, such as the new Center for Financial Stability (CFS) Divisia monetary aggregates, can and should play an important role for the conduct of monetary policy, in addition to that of the short-term nominal interest rate. Thus, we follow Jadidzadeh and Serletis (2019) and Dery and Serletis (2021) and use the CFS broad Divisia monetary aggregates — Divisia M3, Divisia M4-, and Divisia M4. See Barnett et al. (2013) for a detailed documentation of the CFS Divisia monetary aggregates. In Figure 3, we present the log levels and annualized growth rates of the Divisia M3, Divisia M4-, and Divisia M4 monetary aggregates. Shaded areas indicate NBER recessions. As can be seen both in (log) levels and growth rates, the aggregates are clearly distinguishable. In our main analysis, we use the Divisia M3 aggregate, as it has been favored in the empirical analysis by Dery and Serletis (2021), but we also assess the robustness of our main findings to the use of the Divisia M4- and Divisia M4 monetary aggregates.

Finally, we consider four measures of leverage — commercial bank leverage, broker-dealer leverage, shadow bank leverage, and household leverage. In doing so, we are also making a distinction between traditional banks and shadow banks; by shadow banks we mean finance companies, funding corporations, and asset-backed securities issuers. We use data from the Board of Governors of the Federal Reserve System, and calculate the leverage measures following Adrian et al. (2014), as $A_t/(A_t-L_t)$, where $A_t$ denotes total financial assets and $L_t$ liabilities other than net worth — see also Istiak and Serletis (2016, 2017). In calculating net financial assets, we follow Istiak and Serletis (2017) and exclude total miscellaneous liabilities from total liabilities. Istiak and Serletis (2017) argue that this avoids extreme leverage values.

as well as negative leverage in some quarters. Figure 4 shows the levels and Figure 5 the annualized growth rates of each of the four leverage measures, with shaded areas indicating NBER recessions. Because one of the important results in the paper is related to the effects of monetary policy shocks, we use commercial bank leverage in our main analysis, but also investigate the robustness of our results to alternative leverage measures, including broker-dealer leverage that has attracted a great deal of attention during and in the aftermath of the global financial crisis.

3 The Information Content of Risk and Uncertainty

In this section, we perform Granger causality tests to investigate the information content of each of the risk and uncertainty measures in predicting real economic activities. In doing so, we follow Bernanke and Blinder (1992), Belongia and Ireland (2015), and Dery and Serletis (2021) and use the following regression equation

\[ Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j X_{t-j} + \sum_{k=1}^{r} \lambda_k P_{t-k} + e_t \]

where \( Y_t \) is a measure of real economic activity, \( X_t \) is a measure of risk or uncertainty, and \( P_t \) is the personal consumption expenditure deflator which acts as an adjustment variable to remove the effects of general prices from the estimates.

As already noted, our measure of real economic activity is real GDP. However, we also use alternative indicators of economic activities. These alternative indicators are more disaggregated proxies of economic activity relative to real GDP. These other measures are industrial production, total capacity utilization, real gross private investment, the employment rate (for all persons aged 15 to 64 years), the unemployment rate, total new privately owned housing units started (housing starts), real personal disposable income, per capita real personal disposable income, personal consumption expenditure, and consumption expenditure on durable goods. We test for Granger causality in the context of a flexible lag structure optimally chosen by the Akaike information criterion (AIC) after letting each of \( p, q, \) and \( r \) in the above equation take values from 1 to 12. We report the Granger causality test results in Table 1. Each entry in the table represents the marginal significance level of the test statistic testing the null hypothesis that all lags of the uncertainty variable (the \( X \) variable in the above equation) can be excluded from the regression; that is \( \theta_j = 0, \forall j \). Therefore, smaller \( p \)-values indicate a stronger role for that risk or uncertainty variable.

As shown in column 1 of Table 1, only geopolitical risk and the CBOE S&P 100 volatility index are not informative for predicting real GDP. That is, we are unable to reject the null hypothesis of no Granger causality at the 5% significance level. In general, the geopolitical risk index does not have any informative content for predicting any of the ten measures of
economic activities that we used, except for investment. Aside from geopolitical risk, the CBOE S&P 100 volatility index is the least informative among the risk and uncertainty measures that we used. It has information content for predicting 7 out of the 11 measures of economic activity. In addition to not being informative for predicting real GDP, using the CBOE S&P 100 volatility index, we are unable to reject the null of no causality at the 5% significance level for disposable income both in aggregate and at per capita level as well as personal consumption expenditure. Real uncertainty and trade policy uncertainty are informative for predicting 8 of the 11 measures of economic activity while the Chicago financial conditions risk and macroeconomic uncertainty measures are informative for predicting 9 out of 11 measures of economic activity. In the literature, financial frictions are an important transmission mechanism of uncertainty shocks, as noted by Arellano et al. (2019). Our results suggest that financial frictions may be better captured by the Chicago Fed national conditions risk index, which provides a comprehensive update on the financial conditions in debt and equity markets, money markets, and the traditional as well as shadow banking systems in the United States. Our results suggest that the CBOE S&P 100 volatility index (one of the most watched) does not seem to capture financial frictions through which uncertainty shocks are most likely to be transmitted. Lastly, financial uncertainty and economic policy uncertainty have information content for predicting all the measures of economic activity that we use in this study. In summary, we find that apart from geopolitical risk, all other measures of uncertainty are quite informative for predicting most measures of real economic activities.

In an online Appendix, we run the above regression without controlling for the price level, since it may be argued that all the variables are real and there is no need to control for prices. The results reported in the (online) Appendix Table A1 lead us to similar conclusions regarding the information content of the various risk and uncertainty measures. In (online) Appendix Table A2, we also test for Granger causality from real economic activity measures to the various risk and uncertainty measures. We find that (generally) most real economic activity measures do not Granger cause risk and uncertainty. This motivates our ordering choice of the shocks in the next section and our focus on the information content and the effects of risk and uncertainty on the real economy (and not on the effects of the real economy on risk and uncertainty).

Another way of assessing the predictive abilities of the various risk and uncertainty measures is in the context of a forecasting regression. In this context, we will be able to ascertain whether a particular measure of uncertainty can help us predict future levels of economic activity. We follow Caldara et al. (2016) and specify the following forecasting regression

\[ \Delta_h Y_{t+h} = \alpha + \theta U_t + \sum_{i=1}^{h+1} \beta_i \Delta Y_{t-i} + e_{t+h} \]

where \( \Delta_h Y_{t+h} = \frac{400}{h+1} \ln \left( \frac{Y_{t+h}}{Y_{t-1}} \right) \) and \( h \geq 0 \) is forecast horizon in quarters. \( U_t \) is one
of the eight measures of risk and uncertainty. We run this regression separately for each risk/uncertainty and economic activity measure and report the standardized values of $\theta$ in Table 2 (with $h = 1$) and Table 3 (with $h = 4$).

In Table 2, we find that except for geopolitical risk, economic policy uncertainty, trade policy uncertainty, and the CBOE S&P 100 volatility index, a one-standard deviation increase in any measure of uncertainty leads to a statistically (at 5% level) and economically significant reduction in real GDP. For example, a one-standard deviation increase in macroeconomic uncertainty is estimated to reduce real GDP by 0.447 of a standard deviation. Also, the decline in GDP is larger for macroeconomic uncertainty compared to any other measure of risk and uncertainty. We find that using geopolitical risk to forecast economic activity mostly does not produce any statistically significant results except in the case of industrial production. Also, using trade policy uncertainty we do not find any significant result for any measure of economic activity. In general, the Chicago financial conditions risk and macroeconomic uncertainty are informative for forecasting any measure of economic activity that we use. The CBOE S&P 100 volatility index is not useful for forecasting real GDP, employment, housing starts, real disposable income (both at the aggregate and in per capita), and personal consumption expenditure at the 5% significance level. Even though the economic policy uncertainty is informative in a Granger sense, it nonetheless has week forecasting performance, only being significant for forecasting 4 of the 11 measures of economic activity. We observe a similar pattern of informativeness and predictive ability of the various measures of uncertainty in Table 3 where we use risk and uncertainty measures to produce four quarter ahead forecasts of economic activity. We also note in Table 3 that the standard deviation change in any economic activity measure in response to a one-standard deviation increase in uncertainty is larger for macroeconomic uncertainty relative to any other measure of uncertainty. The estimated coefficients in Tables 2 and 3 in most cases are quite similar for any measure of risk and uncertainty and economic activity.

In conclusion, we find that most measures of risk and uncertainty are informative for predicting real economic activities and do indeed produce statistically and economically significant forecasts of economic activities. We find generally consistent results between the Granger causality tests of informativeness of these risk and uncertainty measures and their predictive abilities based on forecasting regressions. The risk and uncertainty measures that have a stronger predictive relationship with economic activities are macroeconomic uncertainty, financial uncertainty, real economic uncertainty, and the Chicago Fed national financial conditions risk index. In fact, we conclude from our analysis that the most informative uncertainty measure for predicting economic activities are macroeconomic uncertainty and the Chicago Fed national financial conditions risk index. The finding that macroeconomic uncertainty has the most strongest information content for predicting economic activity is also consistent with Caldara et al. (2016), Meinen and Rohe (2017), and Shinohara et al. (2020). Therefore, in the structural VAR analysis in the next section, we start by using macroeconomic uncertainty as the main measure of risk and uncertainty. Nonetheless, we
also assess the robustness of our findings to all the risk and uncertainty measures except the CBOE S&P 100 volatility index. We do not use the CBOE S&P 100 volatility index in the structural VAR analysis, because it is only available from 1986:q1 compared to all the other series which start from 1973:q1.

4 The Structural VAR

4.1 The Model

A typical structural model is of the form

$$Z'_t A = \Gamma_0 + \sum_{k=1}^{p} Z'_{t-k} \Gamma_k + \varepsilon'_t$$

(1)

where $Z_t$ is a $n \times 1$ vector of the relevant variables, $A$ is a $n \times n$ matrix of contemporaneous coefficients, $\Gamma_0$ is a $1 \times n$ vector of constants, $\Gamma_k$, $k = 1, \ldots, p$, are $n \times n$ matrices of slope coefficients, and $\varepsilon_t$ is a $n \times 1$ vector of structural disturbances with variance-covariance matrix $D$. For convenience, we rewrite equation (1) compactly as

$$Z'_t A = X'_t B + \varepsilon'_t$$

where $B = [\Gamma'_1, \ldots, \Gamma'_p, \Gamma'_0]^\prime$, $X'_t = [Z'_{t-1}, \ldots, Z'_{t-p}, 1]$, and $B$ is $(np + 1) \times n$.

The reduced-form VAR is

$$Z'_t = X'_t \Phi + u'_t$$

where $\Phi = BA^{-1}$, $u'_t = \varepsilon'_t A^{-1}$, and $E[u_t u'_t] = \Omega$. The matrices $\Phi$ and $\Omega$ are the reduced-form parameter matrices. The reduced-form parameters can be estimated by OLS, but the unknown structural parameters in $A$, $B$, and $D$ will require further restrictions to be identified. In the following subsection, we discuss how we achieve identification in this paper.

4.2 Identification and Estimation

There are several methods of identifying the structural parameters, the most popular of which is recursive identification. In recent years, pure sign restrictions, as pioneered by Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005), have also become quite ubiquitous — see, for example, Dedola and Neri (2007), Pappa (2009), and Mumtaz and Zanetti (2012, 2015). However, despite the appealing simplicity of the pure sign restrictions approach, it suffers from the Preston (1978) “model identification problem,” as noted by Fry and Pagan (2011). Moreover, the pure sign restrictions approach may also suffer from misidentification of the shocks of interest, according to Wolf (2020).
In this paper, we follow Caldara et al. (2016) in using the penalty function approach, initially developed by Faust (1998) and Uhlig (2005), and further extended by Mountford and Uhlig (2009), to the identification of multiple structural shocks. See Caldara et al. (2016) or Dery and Serletis (2020a) for more details. However, for the purpose of this paper, it suffices to present the following brief exposition of the penalty function approach.

For any arbitrarily given structural parameters \(\{A, B\}\), denote \(L_h(A, B)_{ij}\) to be the impulse response function (IRF) of the \(i\)th variable to the \(j\)th structural shock at a finite horizon \(h\). Then \(L_h(A, B)_{ij}\) is row \(i\) and column \(j\) of \(hA_1J_0\ldots0\ldots0\)

\[
F = \begin{pmatrix}
B_1A^{-1} & I_n & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
B_pA^{-1} & 0 & \ldots & I_n \\
\end{pmatrix}
\quad \text{and} \quad
J = \begin{pmatrix}
I_n \\
0 \\
\vdots \\
0
\end{pmatrix}
\]

and \(L_0(BA^{-1}) = A^{-1}\) is the matrix of IRFs upon impact.

As in Uhlig (2005) and Caldara et al. (2016), the set of all possible IRFs is characterized by a \(n \times n\) orthonormal matrix \(S \in \zeta(n)\), where \(\zeta(n)\) is the universe of all orthonormal \(n \times n\) matrices. Note that for any orthonormal matrix \(S\), \(\sim A^{-1} = TS\) is also a decomposition that satisfies \([\sim A\sim A']' = \Omega\), where \(T\) is a Cholesky factorization of \(\Omega\). Identification therefore amounts to appropriate restrictions on \(S\).

As in Caldara et al. (2016), we only identify a subset \(\theta < n\) of shocks, represented by \(s_j = Se_j\), for \(j = 1, \ldots, \theta\), where \(e_j\) is the \(j\)th column of \(I_n\). For example, let \(\{A, B\}\) be any draw of the structural parameters and consider a case where the identification of the \(j\)th structural shock restricts the IRFs of a set of variables indexed by \(I_j^+ \subset \{0, 1, \ldots, n\}\) to be positive and those of a set of variables indexed by \(I_j^- \subset \{0, 1, \ldots, n\}\) to be negative. Also suppose that the restrictions on variable \(i\) are enforced for \(H \geq 0\) periods. Then identification of \(s_j\) is achieved by solving the following optimization problem

\[
s_j^* = \arg \min_{s_j} \Psi(s_j)
\]

subject to

\[
e_i' L_h(T^{-1}, \Phi T^{-1}) s_j > 0, \quad i \in I_j^+ \quad \text{and} \quad h = 0, \ldots, H \tag{2}
\]

\[
e_i' L_h(T^{-1}, \Phi T^{-1}) s_j < 0, \quad i \in I_j^- \quad \text{and} \quad h = 0, \ldots, H \tag{3}
\]

\[
S_{j-1} s_j = 0
\]
where
\[ \Psi(s_j) = \sum_{i \in I_j^+} \sum_{h=0}^{H} \left( -e_i' L_h \left( T^{-1}, \Phi T^{-1} \right) s_j \omega_i \right) + \sum_{i \in I_j^-} \sum_{h=0}^{H} \left( e_i' L_h \left( T^{-1}, \Phi T^{-1} \right) s_j \omega_i \right) \] (4)
and \( \omega_i \) is the standard deviation of variable \( i \), and \( S_{j-1}^* = [s_{j-1}^*, ..., s_j^*] \), for \( j = 1, \ldots, n \).

As posited by Caldara et al. (2016), the penalty function approach differs from the traditional pure sign restrictions approach, since the IRFs corresponding to each draw of the structural parameters are computed using the rotation matrix \( S^* \) that minimizes the criterion function (4). Importantly, the constraints in (2) and (3) do not identify the model, they only provide a set of admissible rotation matrices from which \( S^* \) is chosen.

In implementing the penalty function approach, we order uncertainty, \( U_t \), first, followed by the federal funds rate, \( R_t \), then leverage, \( l_t \), with the money, \( \mu_t \), real GDP, \( y_t \), and inflation rate, \( \pi_t \), being the fourth, fifth and sixth variables, respectively. We also include and order real gross private investment, \( i_t \), personal consumption expenditure, \( c_t \), employment, \( e_t \), and the unemployment rate, \( u_t \), respectively in the seventh to the tenth position. That is, \( Z_t \) in equation (1) is
\[ Z_t = \begin{bmatrix} U_t & R_t & l_t & \mu_t & y_t & \pi_t & i_t & c_t & e_t & u_t \end{bmatrix}. \]
All the variables are in annualized growth rates except for the federal funds rate. Also, all variables are seasonally adjusted except for the federal funds rate and the uncertainty measures. It is worth noting that the penalty function approach is invariant with respect to the ordering of the variables.

Identification is sequential when using the penalty function approach. In our case, it means that we will have to identify shock 1 first and conditional on being orthogonal to shock 1 and satisfying the inequality constraints, shock 2 is identified. Lastly, shock 3 is identified given that it is orthogonal to shocks 1 and 2 and the restrictions on the impulse response functions of the target variable. Since identification is sequential, in our baseline identification scheme, we first identify the uncertainty shock, then a monetary policy shock, and lastly a leverage shock. With this ordering of the shocks, we are essentially assuming that the uncertainty shock is the most exogenous of the three shocks. Since we identify three shocks, there are six possible orderings of the shocks, as shown in Table 4. To check the sensitivity of our findings to the sequence in which the shocks are identified, we present the results of all the other alternative ordering of the shocks in our robustness section.

In the case of our baseline identification scheme, we proceed in the following three steps. In the first step, we identify the uncertainty shock as an innovation that produces the largest increase in the measure of uncertainty with a concurrent decrease in the real GDP growth rate for one quarter. These restrictions are inspired by the findings in the empirical literature
regarding uncertainty shocks. See for example Bloom (2009), Mumtaz, and Zanetti (2013), Jurado et al. (2015), Fernandez-Villaverde et al. (2015), Bloom et al. (2018), Davis (2019), and Caldara et al. (2016, 2020), all of which find that uncertainty shocks usually lead to an increase in uncertainty and decline in output, among others. The resulting penalty function of this shock is

$$\Psi (s_1) = \sum_{h=0}^{1} \left( - e_1^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_1 \right) + \sum_{h=0}^{1} \left( e_5^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_5 \right)$$

where

$$e_1^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_1 > 0, \text{ for } h = 0, 1$$

$$e_5^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_5 < 0, \text{ for } h = 0, 1$$

and

$$j = 1$$ because we identify the first shock and

$$i = \{1, 5\}$$ because the uncertainty measure and real GDP growth rate are the first and fifth variable, respectively, in the VAR.

In the next step, the monetary policy shock is identified as an innovation that generates the largest increase in the federal funds rate with a concurrent decrease in real GDP growth rate and inflation rate for one quarter and is orthogonal to the shock identified in the first step. Apart from Uhlig (2005), most researchers find that monetary contractions raise the federal funds rate, lower prices, and reduce real GDP. Thus, we narrow the set of admissible rotation matrices from which $$S^*$$ is chosen using this conventional wisdom. The corresponding penalty function is given by

$$\Psi (s_2) = \sum_{h=0}^{1} \left( - e_2^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_2 \right) + \sum_{\gamma=5}^{6} \sum_{h=0}^{1} \left( e_5^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_\gamma \right)$$

with

$$e_2^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_2 > 0, \text{ for } h = 0, 1$$

$$e_5^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_2 < 0, \text{ for } h = 0, 1$$

$$e_6^\prime L_h \left( T^{-1}, \Phi T^{-1} \right) s_2 < 0, \text{ for } h = 0, 1$$

$$S^*_1 s_2 = 0$$

where

$$j = 2$$ because we identify the second shock, and

$$i = \{2, 5, 6\}$$ because the federal funds rate, real GDP growth rate, and inflation are the second, fifth, and sixth variables in the VAR, respectively. Therefore, the admissible set of rotation matrices from which a

\[4\]We add an additional restriction on money growth in the ordering where the monetary policy shock is identified before the uncertainty shock.
contractionary monetary policy shock is chosen is that for which there is an increase in the impulse response of the federal funds rate with a concurrent decrease in output and the inflation rate for at least one quarter.

Lastly, in the third step, we identify the leverage shock as an innovation that leads to the largest decrease in commercial bank leverage for one quarter and is orthogonal to the uncertainty and monetary policy shocks. The penalty function is thus given by

$$\Psi(s_3) = \sum_{h=0}^{1} \left( e_3' L_h \left( T^{-1}, \Phi T^{-1} \right) s_3 \right)$$

with

$$e_3' L_h \left( T^{-1}, \Phi T^{-1} \right) s_3 < 0, \text{ for } h = 0, 1$$
$$S_1^x s_3 = 0$$
$$S_2^x s_3 = 0$$

with $i = 3$, because leverage is the third variable in the VAR. Therefore our set of admissible rotations for a negative leverage shock is at least a one quarter reduction in the leverage measure.

We worry that there might be a close relationship between changes in uncertainty and changes in the federal funds rate which may be argued to confound our results. Hence in the robustness section, we provide evidence and attempts to validate that we indeed identify the monetary policy shock. By construction, our monetary policy shock should not be correlated with for instance our uncertainty shock, and we thus check the correlation between our uncertainty shock and the monetary policy shock in all six orderings of the shocks as well as present evidence of association between our monetary policy shock and the monetary policy shocks of Romer and Romer (2004) and Rogers et al. (2018).

As argued by Caldara et al. (2016), only persistent changes in the target variable(s) are identified are shocks under the penalty function approach. Compared to for instance a method where the forecast error variance is maximized as in Barsky and Sims (2011) and Kurmann and Otrok (2013), the penalty function approach has the advantage of ensuring that one off spikes in the target variable(s) are not identified as shocks. For instance to qualify as a contractionary monetary policy shock, with the penalty function approach, we need a persistent and prolonged increase in the federal funds rate and a concurrent decrease in the inflation rate and the real GDP. Following Caldara et al. (2016), we rely on Bayesian estimation, imposing a Minnesota prior on the reduced-form VAR parameters using dummy observations. See Del Negro and Schorfheide (2011) for details. We use two years of data to train the model and obtain the hyper-parameters which govern the prior distributions and VAR lag length $p$ by maximizing the marginal data density. The maximizing is done with the Hansen et al. (2003) CMA-ES evolutionary algorithm. Finally, all results are based on
1,000,000 draws from the posterior distribution of the structural parameters with the first
200,000 as burn-in.

5 Empirical Evidence

We begin by looking at the dynamic response of the economy to the three identified shocks
using our baseline identification scheme. For each response, the shaded areas in Figures 6-9
show the 68% credibility region while the dashed lines show the 95% confidence band of the
median response. For each shock, we present the responses of all ten variables to the shock.
Throughout this section, uncertainty is measured by the Jurado et al. (2015) macroeconomic
uncertainty index, leverage is measured by commercial bank leverage, and we use the Divisia
M3 monetary aggregate as the money variable.

Figure 6 shows the response of each variable to the uncertainty shock. Consistent with our
identification strategy, there is a persistent and statistically significant increase in uncertainty
and decrease in real GDP. Following the uncertainty shock, we observe a general contraction
of the economy. This is shown by the statistically significant decrease in the growth rate
of real GDP, investment, consumption, and employment. There is also significant increase
in unemployment and deflation. The growth rate of real GDP declines by almost 0.8%
and continues to decline until it bottoms out at about 1.3%. Although real GDP starts
to recover from the third quarter onward, it takes almost six quarters for the negative
effect to statistically disappear. The effect on inflation is persistent for almost 3 years
while the effect of this uncertainty shock on investment, consumption, employment, and
unemployment typically persists for at least a year. We also find that there is a significant
and persistent reduction in the federal funds rate, perhaps because of the attempt by the
central bank to revert the economic contraction. Moreover, higher uncertainty appears to
increase the growth rate of commercial bank leverage and the money supply, even though
these are relatively short-lived. The impulse responses of each variable to a monetary policy
shock are presented in Figure 7. We find that a contractionary monetary policy shock
reduces uncertainty, investment, consumption, employment, and increases unemployment;
all of which are consistent with our expectation. The responses of real GDP and inflation to
this contractionary monetary policy shock are also consistent with theory and many empirical
studies — see, for example, Sims (1992), Leeper et al. (1996), Bagliano and Favero (1998),
Christiano et al. (1999), Kim (1999), Ireland (2004), Zanetti (2012), Belongia and Ireland
(2015, 2016), and Arias et al. (2019). We find that both the growth rate of real GDP and
inflation decline by approximately 0.3% on impact. The persistent effect of a monetary policy
shock on real GDP is relatively shorter compared to that on inflation. Comparing uncertainty
and monetary policy shocks, both have relatively more persistence in terms of their effect
on inflation compared to their effect on real GDP, investment, consumption, employment,
and unemployment. Also, the effect of uncertainty shocks on these real variables appears
to last longer than the effect of monetary policy shocks. The monetary policy shock has a relatively persistent effect on inflation and a less prolonged effect on output contraction. In Figure 8, a negative leverage shock turn to produce short-lived effects most of which are not statistically significant.

In Figure 9, we present forecast error variance decompositions of real GDP, inflation, investment, consumption, employment, and unemployment to uncertainty, monetary policy, and leverage shocks. Uncertainty shocks explain about 60% of the variation in real GDP on impact. This gradually increases to peak at about 71% by the third quarter and there after declines to about 53% by the end of our forecast horizon. Even though not directly comparable, it is worth noting that the proportion of variation in industrial production that is explained by the uncertainty shock according to Caldara et al. (2016) generally ranges from 20% to almost 60% by the end of their three-year forecast horizon. Also, Dery and Serletis (2020a) using monthly data identified monetary policy, uncertainty and financial shocks. Even thought their information set is different, they found uncertainty shocks account for on average 30% of the variation in industrial production. Thus, our results here are in that general direction of uncertainty shocks being an important source of output variation. Uncertainty shocks, however, explain a negligible fraction of the variation in inflation on impact. By the end of the three-year forecast horizon, uncertainty accounts for almost a quarter of the total variation in inflation. We find that monetary policy shocks explain about 8% of the variation in real GDP on impact, gradually decreasing to about 5% by the end of our forecast horizon. Also, monetary policy shocks account for more than 40% of the contemporaneous variation in inflation and an average of about 27% over the 3 year forecast horizon that we consider. This is consistent with Faust (1998), Christiano et al. (2005), and Dery and Serletis (2020b, 2021), who all argue that monetary policy shocks account for a non-trivial proportion of the variation in inflation. With regards to variations in investment, consumption, employment, and unemployment, an overwhelming proportion of the variation in these variables is ascribed to uncertainty shocks explaining on average 54%, 38%, 43%, and 50%, respectively, compared to monetary policy shocks that typically account for an average of mostly 10% or less of these variables. Finally, we find that leverage shocks explain on average of less than 5% of the variables under consideration.

In Figure 10, we provide a summary of the responses of real GDP, inflation, investment, consumption, employment, and unemployment to each of the three shocks while the corresponding comparison for the forecast error variance decomposition is shown in Figure 11. As can be seen in Figure 11, except for inflation, the response of any variable to uncertainty shocks is more severe than the effects of monetary policy and leverage shocks. Regarding inflation, monetary policy shocks have a more pronounced and immediate deflationary effect compared to uncertainty shocks whose effect on inflation is gradual. There is no much difference between the response of inflation to uncertainty and monetary policy shocks after four quarters. In terms of variance decomposition, we observe similar patterns that uncertainty shocks account for an overwhelming proportion of the variation in all real variables except for
inflation (see Figure 11). Thus, with regards to the importance of these shocks being sources of macroeconomic fluctuations, we show in Figure 10 and 11 that the most important source of variations in real GDP, investment, consumption, employment, and unemployment is uncertainty shocks, followed by monetary policy shocks. Leverage shocks appears to account for a relatively trivial source of variation in these variables. When it comes to variation in inflation, the most important shock is the monetary policy shock.

In Figure 12, we present the historical variance decomposition for each variable. The solid black line is the actual data deviation of each variable from its mean. For each year, we show the relative contribution of each shock by its height in the stack column bar. Most of the historical variations in uncertainty are due to uncertainty shocks with occasional increases in uncertainty emanating from monetary policy and leverage shocks. Leverage shocks are the main drivers of the deviations of leverage from its mean with uncertainty shocks occasionally contributing relatively small variation to changes in leverage. Monetary policy almost never accounts for historical changes in leverage. An overwhelming proportion of the historical variation in real GDP is driven by uncertainty shocks, particularly during the 2007-2009 global financial crisis. The importance of uncertainty shock in explaining the historical variation in investment, consumption, employment, and unemployment also dominates the significance of monetary policy and leverage shock particularly during the 2007-2009 global financial crisis. This supports the assertion in Stock and Watson (2012, p. 119) that “the main contributions to the decline in output and employment during the recession are estimated to come from financial and uncertainty shocks.”

In an online Appendix, we rerun this baseline model limiting the sample to the pre-financial crisis period to understand if the financial crisis and its aftermath had an impact on the relative importance of uncertainty, monetary policy, and leverage shocks. The (online) Appendix Figures A1, A2, and A3 show that the impulse responses are identical to those in Figure 6, 7, and 8, respectively. Also, (online) Appendix Figure A4 shows similar variance decompositions as the ones already reported in Figure 9. Thus, the role of uncertainty, monetary policy, and leverage shocks in explaining macroeconomic variations did not significantly change in the pre-financial crisis data.

We conclude that uncertainty shocks are relatively more important source of variations in the real sector of the economy than traditional monetary policy shocks. However, monetary policy shocks still outperform uncertainty shocks in explaining inflation fluctuations. Even though leverage is important in other regards, it does not seem to be an important source of macroeconomic fluctuations relative to uncertainty and monetary policy shocks.

6 Robustness

In this section, we perform a number of robustness checks to assess the sensitivity of our findings. We find that our main results are quite robust in several dimensions.
Before discussing the robustness results, we first check if our recovered monetary policy shocks are correlated with more traditional measures that incorporate more information about monetary policy — see Miranda-Agrippino and Ricco (2018) and Caldara and Herbst (2019). We provide evidence of significant correlation between our model's generated shocks and two externally identified monetary policy shocks. In particular, we use the original Romer and Romer (2004) identified monetary policy shock from 1975:q1 to 1996:q4, and two extensions to 2008:q4 and 2012:q4. We also use the Rogers et al. (2018) monetary policy shocks from 1994:q1 to 2015:q4. In Table 5, we show the correlations between these two externally identified monetary policy shocks. As can be seen, the correlations are all positive and range from 0.46 to 0.59. The correlations between the Romer and Romer (2004) extended versions of the shocks and the Rogers et al. (2018) shocks are all statistically significant. However, the correlations between the original Romer and Romer (2004) shock and the Rogers et al. (2018) shocks are not statistically significant, which could be due to the fact that these correlations are based on a relatively shorter sample (only 12 quarters).

In Table 6, we present correlations between our recovered monetary policy shocks and these externally identified monetary policy shocks. Each column of Table 6 shows one of the six possible identification schemes (see Table 4) with which we can identify monetary policy shocks. In Panel A of Table 6, we show the correlations between our recovered monetary policy shocks and the two other shocks we identified (uncertainty and leverage shocks). By construction, these should not be correlated, which is indeed the case. In panel B of Table 6, we show that our recovered monetary policy shocks are significantly correlated with the Romer and Romer (2004) monetary policy shocks. The correlations ranges from 0.52 to 0.60. Panel C of Table 6 shows that our monetary policy shocks are also significantly correlated with the Rogers et al. (2018) monetary policy shocks. Finally, in Tables 7 and 8, we show that our uncertainty and leverage shocks which should not be correlated with the Romer and Romer (2004) and Rogers et al. (2018) monetary policy shocks, are indeed not significantly correlated. Each column of Tables 7 and 8 shows one of the six possible identification schemes (see Table 4) with which we identify uncertainty and leverage shocks in our model. We conclude that we indeed identify monetary policy shocks as intended.

As noted earlier, the evidence based on the penalty function approach is invariant with respect to the ordering of the variables. It is, however, sensitive to the ordering of the shocks, since it identifies shocks sequentially. We therefore check sensitivity of our main findings in the previous section to all the possible orderings of the shocks. As before, uncertainty is measured by the macroeconomic uncertainty index, money by the Divisia M3 aggregate, and leverage is commercial bank leverage. Figures 13 and 14 present the impulse responses and variance decompositions, respectively, of real GDP, inflation, investment, consumption, employment, and unemployment to uncertainty, monetary policy, and leverage shocks for

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5See https://eecon.uibk.ac.at/ breitenlechner/research.html.

6See https://econ.jhu.edu/directory/jonathan-wright/
each of the six identification schemes. As can be seen in Figures 13 and 14, impulse responses and variance decompositions are identical across schemes. Thus, we conclude that our findings are not sensitive to the order in which the shocks are identified. Also, our results are robust to the use of different broad Divisia monetary aggregates (see Figures 15 and 16). Finally, in Figures 17 and 18, we check if different leverage measures matter for our overall conclusion. Even though the impulse responses (in Figure 17) and variance decompositions (in Figure 18) turn to be more pronounced for the shadow banks measure of leverage, our conclusions are robust across different measures of leverage.

So far we have used the Jurado et al. (2015) macroeconomic uncertainty index as the relevant measure of uncertainty. To examine the sensitivity of our results to alternative uncertainty measures, we use our baseline identification scheme, with commercial banks leverage, and the Divisia M3 monetary aggregate, to investigate robustness of the main results to the use of the six other proxies of risk and uncertainty. We find that changing the risk and uncertainty measure does not significantly change our main conclusions regarding the dynamic behavior of the variables we consider. In terms of variance decomposition, our conclusions remains unchanged with all measures of risk and uncertainty except trade policy uncertainty. In the case of trade policy uncertainty, monetary policy shocks become more important than uncertainty shocks in explaining variations in consumption, employment, and unemployment (see Figures 19 and 20).

7 Conclusion

We use two proxies for risk — geopolitical risk and the Chicago financial conditions risk — and six proxies for uncertainty — financial uncertainty, macroeconomic uncertainty, real uncertainty, economic policy uncertainty, trade policy uncertainty, and the CBOE S&;P 100 volatility index — and assess their information content in predicting real economic activities (we use 11 different measures of real economic activity). In the context of Granger causality tests and forecasting regressions, we find that the set of risk and uncertainty proxies that have a stronger predictive relationship with economic activities are the Jurado et al. (2015) macroeconomic uncertainty, financial uncertainty, real economic uncertainty, and the Chicago Fed national financial conditions risk index. We conclude that the most informative risk and uncertainty measures for predicting economic activities are macroeconomic uncertainty and the Chicago Fed national financial conditions risk index.

We use a Bayesian monetary structural VAR, augmented with a risk/uncertainty variable and a measure of financial leverage, to assess the dynamic effects and relative importance of uncertainty, monetary policy, and leverage shocks in explaining several real variables including real GDP, investment, consumption, employment, unemployment, and inflation. We follow Caldara et al. (2016) and use the penalty function approach to identify multiple shocks, thus avoiding the Fry and Pagan (2011) criticism of the pure sign restrictions iden-
tification approach. We find that uncertainty shocks are a relatively more important source of variations in the real sector of the economy than traditional monetary policy shocks. In particular, a positive uncertainty shock results in a general contraction of the economy — that is, there are significant declines in the growth rate of real GDP, investment, consumption, and employment and increases in the unemployment rate. The contraction in the real economy from an adverse uncertainty shock is more pronounced and persistent than a contractionary monetary policy shock. For example, the contemporaneous decline in the growth rate of real GDP associated with uncertainty and monetary policy shocks is about 0.8% and 0.3%, respectively. The finding that an increase in uncertainty leads to economic contraction is consistent with the evidence in Bloom et al. (2018) who find that uncertainty shocks generate declines in GDP of 2.5%. Caldara et al. (2020) also find that uncertainty shocks lead to a fall in GDP, inflation, and interest rates.

In terms of forecast error variance decomposition, we find that uncertainty shocks account for an overwhelming proportion of the variation of all real variables that we consider, ranging from 38% to 61% over a 3 year average, depending on the variable, while the corresponding proportion for monetary policy shocks ranges from 3% to 10%. However, monetary policy shocks outperform uncertainty shocks in explaining inflation fluctuations. On average, 27% of the variation in inflation is attributable to monetary policy while the corresponding proportion for uncertainty shocks is approximately 18%. The average over the three year horizon for leverage shocks ranges from 1% to 3% of the forecast error variance decomposition depending on the variable. From a historical variance decomposition perspective, our model ascribes most of the historical variation in uncertainty to uncertainty shocks with occasional increases in uncertainty emanating from monetary policy and leverage shocks. An overwhelming proportion of the historical variation in real GDP is driven by uncertainty shocks, particularly during the 2007-2009 global financial crisis. The importance of uncertainty shock in explaining the historical variation in investment, consumption, employment, and unemployment also dominates the significance of monetary policy and leverage shock particularly during the 2007-2009 global financial crisis. Our findings are robust to six alternative proxies of risk and uncertainty, three broad Divisia monetary aggregates, as well as four measures of leverage.

The paper contributes to the literature in several ways. We provide a comprehensive analysis of the information content and predictive abilities of various risk and uncertainty measures thereby complementing the strand of the literature that studies the relationship between real economic activity and risk and uncertainty measures. In this regard, we provide corroborating evidence to Caldara et al. (2016), Meinen and Rohe (2017), and Shinohara et al. (2020) in projecting the information content of macroeconomic uncertainty. Our paper also connects with the literature that investigates the economic effects of risk and uncertainty. This branch of the literature typically finds uncertainty to cause economic contractions, with pronounced declines in GDP, employment, investment, inflation, and interest rates. See, for example, Bloom (2009), Bloom et al. (2018), Jurado et al. (2015), and Caldara et al. (2016,
The paper also relates to the interaction between uncertainty and the conduct of monetary policy. In this regard, Bekaert et al. (2013) show that expansionary monetary policy leads to a decrease in uncertainty while Aastveit et al. (2013), treating uncertainty as an exogenous interaction variable, show that higher deciles of uncertainty render monetary policy ineffective. With the relative increase in the frequency of uncertainty related disturbances, it is important to understand the general impact of these uncertainty shocks on key macroeconomic variables relative to more traditional shocks such as monetary policy shocks. We show that increased uncertainty in principle is akin to severe and prolonged contractionary monetary policy shocks. In this regard, monetary authorities should embark on significant expansionary monetary policies with the onset of positive uncertainty shocks.

In this paper we have focused on the interaction of monetary policy and leverage shocks with uncertainty. As noted earlier, in recent years most economists believe that monetary shocks are not the principal cause of business fluctuations. In fact, following the Lucas (1976) critique, the modern core of macroeconomics consists of the real business cycle model and the new Keynesian model. The former, developed by Kydland and Prescott (1982), is a stochastic formalization of the neoclassical growth model, represents the latest development of the classical approach to business cycles, and argues that mainly real shocks (shocks to long-run aggregate supply, such as shocks to productivity or the willingness of workers to work) cause economic fluctuations. The opposing new Keynesian model, on the other hand, argues that aggregate demand shocks are the most important source of fluctuations in economic activity. Evaluating the importance of uncertainty shocks as drivers of business cycles, by simultaneously evaluating the effects of technology shocks, fiscal shocks (government spending shocks and tax shocks), and other shocks (for example, oil shocks), is an area for potentially productive future research.
References


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Figure 1: Risk indices. Shaded vertical bars are NBER recession dates.
Figure 2: Uncertainty indices. Shaded vertical bars are NBER recession dates.
Figure 3: Broad Divisia monetary aggregates in log levels and growth rates. Shaded vertical bars are NBER recession dates.
Figure 4: Leverage series. Shaded vertical bars are NBER recession dates.

Figure 5: Annualized leverage growth rates. Shaded vertical bars are NBER recession dates.
Table 1. Granger causality tests from uncertainty measures to economic variables

<table>
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<tr>
<th>Risk/uncertainty variable</th>
<th>$Y_1$</th>
<th>$Y_2$</th>
<th>$Y_3$</th>
<th>$Y_4$</th>
<th>$Y_5$</th>
<th>$Y_6$</th>
<th>$Y_7$</th>
<th>$Y_8$</th>
<th>$Y_9$</th>
<th>$Y_{10}$</th>
<th>$Y_{11}$</th>
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</thead>
<tbody>
<tr>
<td>Economic activity variables</td>
<td>$Y_1 = \text{Real GDP}$</td>
<td>$Y_2 = \text{Industrial production}$</td>
<td>$Y_3 = \text{Capacity utilization}$</td>
<td>$Y_4 = \text{Real private gross investment}$</td>
<td>$Y_5 = \text{Employment rate}$</td>
<td>$Y_6 = \text{Unemployment rate}$</td>
<td>$Y_7 = \text{Housing starts}$</td>
<td>$Y_8 = \text{Real per capita personal disposable income}$</td>
<td>$Y_9 = \text{Real personal disposable income}$</td>
<td>$Y_{10} = \text{Personal consumption expenditure}$</td>
<td>$Y_{11} = \text{Consumption expenditure for durable goods}$</td>
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<td>Panel A. Risk measures</td>
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<td></td>
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<td>Geopolitical Risk</td>
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<td>0.252</td>
<td>0.216</td>
<td>0.044</td>
<td>0.087</td>
<td>0.434</td>
<td>0.935</td>
<td>0.212</td>
<td>0.277</td>
<td>0.276</td>
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<td>0.000</td>
<td>0.000</td>
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<td>Panel B. Uncertainty measures</td>
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<td>0.961</td>
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<td>0.000</td>
<td>0.529</td>
<td>0.029</td>
<td>0.023</td>
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<tr>
<td>CBOE S&amp;P 100 Volatility Index</td>
<td>0.157</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
<td>0.302</td>
<td>0.286</td>
<td>0.232</td>
<td>0.010</td>
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</table>

Notes: Numbers are marginal significance levels. Bold numbers indicate significance at the 5% level. CBOE S&P 100 volatility index data starts from 1986q1.
Table 2: Risk, uncertainty and economic activity (1 quarter forecast horizon)

<table>
<thead>
<tr>
<th>Economic activity variables</th>
<th>Y_1 = Real GDP</th>
<th>Y_2 = Industrial production</th>
<th>Y_3 = Capacity utilization</th>
<th>Y_4 = Real private gross investment</th>
<th>Y_5 = Employment rate</th>
<th>Y_6 = Unemployment rate</th>
<th>Y_7</th>
<th>Y_8 = Real per capita personal disposable income</th>
<th>Y_9 = Real personal disposable income</th>
<th>Y_10 = Personal consumption expenditure</th>
<th>Y_11 = Consumption expenditure for durable goods</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Risk/uncertainty variable</th>
<th>Y_1</th>
<th>Y_2</th>
<th>Y_3</th>
<th>Y_4</th>
<th>Y_5</th>
<th>Y_6</th>
<th>Y_7</th>
<th>Y_8</th>
<th>Y_9</th>
<th>Y_10</th>
<th>Y_11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A. Risk measures</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Geopolitical risk</td>
<td>-0.181</td>
<td>-0.191</td>
<td>-0.111</td>
<td>-0.148</td>
<td>-0.188</td>
<td>0.183</td>
<td>-0.009</td>
<td>0.104</td>
<td>0.077</td>
<td>-0.167</td>
<td>-0.069</td>
</tr>
<tr>
<td>(0.148)</td>
<td>(0.041)</td>
<td>(0.210)</td>
<td>(0.066)</td>
<td>(0.235)</td>
<td>(0.198)</td>
<td>(0.903)</td>
<td>(0.348)</td>
<td>(0.478)</td>
<td>(0.117)</td>
<td>(0.333)</td>
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</tr>
<tr>
<td>Chicago financial conditions risk</td>
<td>-0.315</td>
<td>-0.340</td>
<td>-0.386</td>
<td>-0.409</td>
<td>-0.188</td>
<td>0.292</td>
<td>-0.382</td>
<td>-0.221</td>
<td>-0.218</td>
<td>-0.004</td>
<td>-0.202</td>
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<tr>
<td>(0.000)</td>
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<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.963)</td>
<td>(0.013)</td>
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<td>Panel B. Uncertainty measures</td>
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<tr>
<td>Financial uncertainty</td>
<td>-0.338</td>
<td>-0.378</td>
<td>-0.397</td>
<td>-0.381</td>
<td>-0.353</td>
<td>0.437</td>
<td>-0.244</td>
<td>-0.024</td>
<td>-0.030</td>
<td>-0.161</td>
<td>-0.231</td>
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<tr>
<td>(0.006)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.012)</td>
<td>(0.007)</td>
<td>(0.653)</td>
<td>(0.841)</td>
<td>(0.810)</td>
<td>(0.161)</td>
<td>(0.604)</td>
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<tr>
<td>Macroeconomic uncertainty</td>
<td>-0.447</td>
<td>-0.508</td>
<td>-0.494</td>
<td>-0.340</td>
<td>-0.346</td>
<td>0.467</td>
<td>-0.302</td>
<td>-0.200</td>
<td>-0.204</td>
<td>-0.088</td>
<td>-0.226</td>
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<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.021)</td>
<td>(0.017)</td>
<td>(0.013)</td>
<td>(0.413)</td>
<td>(0.027)</td>
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</tr>
<tr>
<td>Real uncertainty</td>
<td>-0.420</td>
<td>-0.465</td>
<td>-0.428</td>
<td>-0.432</td>
<td>-0.347</td>
<td>0.466</td>
<td>-0.157</td>
<td>-0.084</td>
<td>-0.092</td>
<td>-0.086</td>
<td>-0.126</td>
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<tr>
<td>(0.004)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.036)</td>
<td>(0.016)</td>
<td>(0.213)</td>
<td>(0.516)</td>
<td>(0.462)</td>
<td>(0.543)</td>
<td>(0.247)</td>
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</tr>
<tr>
<td>Economic policy uncertainty</td>
<td>-0.241</td>
<td>-0.243</td>
<td>-0.194</td>
<td>-0.262</td>
<td>-0.252</td>
<td>0.272</td>
<td>-0.007</td>
<td>-0.055</td>
<td>-0.065</td>
<td>-0.114</td>
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<tr>
<td>(0.054)</td>
<td>(0.011)</td>
<td>(0.038)</td>
<td>(0.015)</td>
<td>(0.126)</td>
<td>(0.000)</td>
<td>(0.938)</td>
<td>(0.651)</td>
<td>(0.590)</td>
<td>(0.327)</td>
<td>(0.658)</td>
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</tr>
<tr>
<td>Trade policy uncertainty</td>
<td>-0.111</td>
<td>-0.057</td>
<td>-0.047</td>
<td>-0.072</td>
<td>-0.109</td>
<td>0.072</td>
<td>0.039</td>
<td>0.114</td>
<td>0.084</td>
<td>-0.131</td>
<td>-0.059</td>
</tr>
<tr>
<td>(0.210)</td>
<td>(0.429)</td>
<td>(0.505)</td>
<td>(0.161)</td>
<td>(0.370)</td>
<td>(0.532)</td>
<td>(0.472)</td>
<td>(0.201)</td>
<td>(0.341)</td>
<td>(0.137)</td>
<td>(0.209)</td>
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</tr>
<tr>
<td>CBOE S&amp;P 100 volatility index</td>
<td>-0.248</td>
<td>-0.278</td>
<td>-0.289</td>
<td>-0.368</td>
<td>-0.296</td>
<td>0.329</td>
<td>-0.284</td>
<td>0.061</td>
<td>0.067</td>
<td>-0.230</td>
<td>-0.233</td>
</tr>
<tr>
<td>(0.072)</td>
<td>(0.010)</td>
<td>(0.013)</td>
<td>(0.007)</td>
<td>(0.063)</td>
<td>(0.027)</td>
<td>(0.641)</td>
<td>(0.592)</td>
<td>(0.555)</td>
<td>(0.085)</td>
<td>(0.028)</td>
<td></td>
</tr>
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</table>

Notes: Numbers are standardized estimates of the OLS coefficients. Numbers in parenthesis are p-values. CBOE S&P 100 volatility index data starts from 1986q1.
Table 3: Risk, uncertainty and economic activity (4 quarters forecast horizon)

<table>
<thead>
<tr>
<th>Economic activity variables</th>
<th>Y&lt;sub&gt;1&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;2&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;3&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;4&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;5&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;6&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;7&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;8&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;9&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;10&lt;/sub&gt;</th>
<th>Y&lt;sub&gt;11&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y&lt;sub&gt;1&lt;/sub&gt; = Real GDP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y&lt;sub&gt;2&lt;/sub&gt; = Industrial production</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y&lt;sub&gt;3&lt;/sub&gt; = Capacity utilization</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y&lt;sub&gt;4&lt;/sub&gt; = Real private gross investment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y&lt;sub&gt;5&lt;/sub&gt; = Employment rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y&lt;sub&gt;6&lt;/sub&gt; = Unemployment rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Panel A. Risk measures**

| Geopolitical risk | -0.096 (0.288) | -0.201 (0.005) | -0.037 (0.573) | -0.119 (0.115) | -0.121 (0.141) | 0.059 (0.425) | 0.144 (0.058) | 0.056 (0.468) | 0.064 (0.576) | -0.021 (0.653) | 0.017 (0.797) |
| Chicago financial conditions risk | -0.330 (0.000) | -0.460 (0.000) | -0.464 (0.000) | -0.458 (0.000) | -0.279 (0.000) | 0.408 (0.000) | -0.095 (0.000) | -0.278 (0.000) | -0.185 (0.000) | 0.037 (0.594) | 0.032 (0.688) |

**Panel B. Uncertainty measures**

| Financial uncertainty | -0.225 (0.002) | -0.328 (0.000) | -0.370 (0.000) | -0.353 (0.000) | -0.312 (0.000) | 0.403 (0.000) | 0.036 (0.673) | -0.119 (0.138) | 0.010 (0.934) | 0.010 (0.876) | 0.016 (0.822) |
| Macroeconomic uncertainty | -0.426 (0.000) | -0.564 (0.000) | -0.479 (0.000) | -0.543 (0.000) | -0.322 (0.000) | 0.478 (0.000) | -0.173 (0.000) | -0.370 (0.000) | -0.203 (0.000) | -0.024 (0.737) | 0.017 (0.840) |
| Real uncertainty | -0.260 (0.004) | -0.370 (0.000) | -0.349 (0.000) | -0.337 (0.000) | -0.162 (0.000) | 0.302 (0.000) | 0.009 (0.935) | -0.294 (0.000) | -0.112 (0.385) | 0.077 (0.246) | 0.160 (0.096) |
| Economic policy uncertainty | -0.049 (0.446) | -0.068 (0.268) | 0.026 (0.653) | -0.012 (0.860) | -0.074 (0.230) | 0.062 (0.406) | 0.241 (0.001) | -0.249 (0.001) | -0.055 (0.662) | 0.066 (0.186) | 0.211 (0.002) |
| Trade policy uncertainty | -0.132 (0.329) | -0.064 (0.513) | -0.036 (0.716) | -0.060 (0.384) | -0.170 (0.358) | 0.082 (0.639) | 0.047 (0.321) | 0.176 (0.154) | 0.074 (0.404) | -0.088 (0.228) | -0.015 (0.741) |
| CBOE S&amp;P 100 volatility index | -0.059 (0.536) | -0.160 (0.027) | -0.201 (0.031) | -0.197 (0.038) | -0.211 (0.024) | 0.205 (0.005) | 0.086 (0.340) | -0.101 (0.302) | 0.071 (0.539) | -0.027 (0.796) | -0.075 (0.345) |

Notes: Numbers are standardized estimates of the OLS coefficients. Numbers in parenthesis are p-values. CBOE S&amp;P 100 volatility index data starts from 1986q1.
Figure 6: Impulse responses to a macroeconomic uncertainty shock.
Figure 7: Impulse responses to a monetary policy shock.
Figure 8: Impulse responses to a commercial bank leverage shock.
Figure 9: Variance decomposition to uncertainty, monetary policy, and leverage shocks.
Figure 10: Comparison of impulse responses to uncertainty, monetary policy, and leverage shocks.
Figure 11: Comparison of variance decomposition to uncertainty, monetary policy, and leverage shocks.
Figure 12: Historical variance decomposition.
Table 4: Possible orderings of uncertainty, monetary policy, and leverage shocks

<table>
<thead>
<tr>
<th>Identification scheme</th>
<th>First shock</th>
<th>Second shock</th>
<th>Third shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification 1</td>
<td>Uncertainty shock</td>
<td>Monetary policy shock</td>
<td>Leverage shock</td>
</tr>
<tr>
<td>Identification 2</td>
<td>Uncertainty shock</td>
<td>Leverage shock</td>
<td>Monetary policy shock</td>
</tr>
<tr>
<td>Identification 3</td>
<td>Monetary policy shock</td>
<td>Uncertainty shock</td>
<td>Leverage shock</td>
</tr>
<tr>
<td>Identification 4</td>
<td>Monetary policy shock</td>
<td>Leverage shock</td>
<td>Uncertainty shock</td>
</tr>
<tr>
<td>Identification 5</td>
<td>Leverage shock</td>
<td>Uncertainty shock</td>
<td>Monetary policy shock</td>
</tr>
<tr>
<td>Identification 6</td>
<td>Leverage shock</td>
<td>Monetary policy shock</td>
<td>Uncertainty shock</td>
</tr>
</tbody>
</table>

Note: Identification 1 is our baseline identification.
Table 5: Correlations between Romer and Romer (2004) and the Rogers et al. (2018) monetary policy shocks

<table>
<thead>
<tr>
<th></th>
<th>Rogers et al. (2018) MPS</th>
<th>Rogers et al. (2018) MPS2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Romer and Romer (2004) MPS</td>
<td>0.53</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>(0.738)</td>
<td>(0.738)</td>
</tr>
<tr>
<td>Romer and Romer (2004) MPS extended to 2008</td>
<td>0.59</td>
<td>0.59</td>
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<tr>
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<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Romer and Romer (2004) MPS extended to 2012</td>
<td>0.46</td>
<td>0.46</td>
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<tr>
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<td>(0.000)</td>
<td>(0.000)</td>
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</table>

Table 6: Correlations between our identified shocks and the Romer and Romer (2004) and Rogers et al. (2018) monetary policy shocks

<table>
<thead>
<tr>
<th>Identification (see Table 4)</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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</thead>
<tbody>
<tr>
<td><strong>Panel A: Correlations between our monetary policy, uncertainty, and leverage shocks</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Uncertainty shock</td>
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<tr>
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<td>(0.495)</td>
<td>(0.984)</td>
<td>(0.471)</td>
<td>(0.227)</td>
<td>(0.429)</td>
<td>(0.339)</td>
</tr>
<tr>
<td>Leverage shock</td>
<td>-0.18</td>
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<td>-0.15</td>
<td>-0.14</td>
<td>-0.15</td>
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<tr>
<td></td>
<td>(0.093)</td>
<td>(0.610)</td>
<td>(0.172)</td>
<td>(0.223)</td>
<td>(0.262)</td>
<td>(0.181)</td>
</tr>
<tr>
<td><strong>Panel B: Correlations between our monetary policy shocks and the Romer and Romer (2004) monetary policy shocks</strong></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Romer and Romer (2004) MPS</td>
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<td>0.60</td>
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<td>0.58</td>
<td>0.55</td>
<td>0.58</td>
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<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Romer and Romer (2004) MPS extended to 2008</td>
<td>0.55</td>
<td>0.58</td>
<td>0.53</td>
<td>0.55</td>
<td>0.53</td>
<td>0.55</td>
</tr>
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<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
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<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Romer and Romer (2004) MPS extended to 2012</td>
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<td>0.54</td>
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<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td><strong>Panel C: Correlations between our monetary policy shocks and the Rogers et al. (2018) monetary policy shocks</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rogers et al. (2018) MPS</td>
<td>0.36</td>
<td>0.56</td>
<td>0.44</td>
<td>0.47</td>
<td>0.44</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Rogers et al. (2018) MPS2</td>
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<td>0.53</td>
<td>0.42</td>
<td>0.47</td>
<td>0.42</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
</tbody>
</table>

Note: Rogers et al. (2018) MPS2 uses a tight window of 15 minutes before the time of a Federal Open Market Committee (FOMC) or other monetary policy announcement to 15 minutes afterward while the Rogers et al. (2018) MPS uses a window of 15 minutes before the time of a Federal Open Market Committee (FOMC) or other monetary policy announcement to 1 hour 45 minutes afterward.
**Table 7**: Correlations between our uncertainty shocks and the Romer and Romer (2004) and Rogers et al. (2018) monetary policy shocks

<table>
<thead>
<tr>
<th>Identification (see Table 4)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Correlations between our uncertainty shocks and the Romer and Romer (2004) monetary policy shocks</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Romer and Romer (2004) MPS</td>
<td>-0.19</td>
<td>-0.03</td>
<td>-0.18</td>
<td>-0.23</td>
<td>-0.10</td>
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<tr>
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<td>-0.23</td>
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<td><strong>Panel B: Correlations between our uncertainty shocks and the Rogers et al. (2018) monetary policy shocks</strong></td>
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<td>Rogers et al. (2018) MPS</td>
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**Table 8**: Correlations between our leverage shocks and the Romer and Romer (2004) and Rogers et al. (2018) monetary policy shocks

<table>
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<th>Identification (see Table 4)</th>
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<td><strong>Panel A: Correlations between our leverage shocks and the Romer and Romer (2004) monetary policy shocks</strong></td>
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<td>-0.16</td>
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<td><strong>Panel B: Correlations between our leverage shocks and the Rogers et al. (2018) monetary policy shocks</strong></td>
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<tr>
<td>Rogers et al. (2018) MPS</td>
<td>-0.09</td>
<td>-0.15</td>
<td>-0.14</td>
<td>-0.17</td>
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<td>(1.000)</td>
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<td>(0.640)</td>
<td>(0.764)</td>
<td>(0.303)</td>
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<tr>
<td>Rogers et al. (2018) MPS2</td>
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<td>-0.14</td>
<td>-0.16</td>
<td>-0.16</td>
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<td>(1.000)</td>
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<td>(1.000)</td>
<td>(0.785)</td>
<td>(0.893)</td>
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Note: Rogers et al. (2018) MPS2 uses a tight window of 15 minutes before the time of a Federal Open Market Committee (FOMC) or other monetary policy announcement to 15 minutes afterward while the Rogers et al. (2018) MPS uses a window of 15 minutes before the time of a Federal Open Market Committee (FOMC) or other monetary policy announcement to 1 hour 45 minutes afterward.
Figure 13: Impulse responses to uncertainty, monetary policy, and leverage shocks under different orderings of the shocks.
Figure 14: Variance decomposition to uncertainty, monetary policy, and leverage shocks under different orderings of the shocks.
Figure 15: Impulse responses to uncertainty, monetary policy, and leverage shocks under different measures of Divisia money.
Figure 16: Variance decomposition to uncertainty, monetary policy, and leverage shocks under different measures of Divisia money.
Figure 17: Impulse responses to uncertainty, monetary policy, and leverage shocks under different measures of leverage.
Figure 18: Variance decomposition to uncertainty, monetary policy, and leverage shocks under different measures of leverage.
Figure 19: Impulse responses to uncertainty, monetary policy, and leverage shocks under different measures of uncertainty. MACRO = macroeconomic uncertainty, FIN = financial uncertainty, REAL = real uncertainty, GPR = geopolitical risk, NFCI = Chicago Fed national financial conditions risk, EPU = economic policy uncertainty, TPU = trade policy uncertainty.
Figure 20: Variance decomposition to uncertainty, monetary policy, and leverage shocks under different measures of uncertainty. MACRO = macroeconomic uncertainty, FIN = financial uncertainty, REAL = real uncertainty, GPR = geopolitical risk, NFCI = Chicago Fed national financial conditions risk, EPU = economic policy uncertainty, TPU = trade policy uncertainty.
Disentangling the Effects of Uncertainty, Monetary Policy, and Leverage Shocks on the Economy

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Department of Economics
University of Calgary
Calgary, AB T2N 1N4
Canada

Online Appendix
Forthcoming in: *Oxford Bulletin of Economics and Statistics*

March 9, 2021

*Corresponding author. Phone: (403) 220-4092; Fax: (403) 282-5262; E-mail: Serletis@ucalgary.ca; Web: http://econ.ucalgary.ca/profiles/162-33618
In this Appendix, we run

\[ Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j X_{t-j} + \sum_{k=1}^{r} \lambda_k P_{t-k} + e_t \]

without controlling for the price level as

\[ Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j X_{t-j} + e_t \]

where \( Y_t \) is a measure of real economic activity and \( X_t \) is a measure of risk or uncertainty. We test for Granger causality from uncertainty to the various real economic activity measures. We report the results in Table A1 (in the same fashion as those in Table 1). The results are robust to the exclusion of prices from the regression equation.

We also test for Granger causality from real economic activity measures to the various risk and uncertainty measures in the context of the following equation

\[ X_t = \alpha + \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{j=1}^{q} \theta_j Y_{t-j} + \sum_{k=1}^{r} \lambda_k P_{t-k} + e_t \]

where \( X_t \) is a measure of risk or uncertainty, \( Y_t \) is a measure of real economic activity, and \( P_t \) is the personal consumption expenditure deflator which acts as an adjustment variable to remove the effects of general prices from the estimates. We report the results in Table A2. Each entry in Table A2 shows the marginal significance level of the test statistic testing the null hypothesis that all lags of the real economic activity measure (the \( Y \) variable in the above regression equation) can be excluded from the regression; that is \( \theta_j = 0, \forall j \). Smaller \( p \)-values indicate a stronger role for that real economic activity measure. The evidence shows that most measures of real economic activity are not informative for predicting the various risk and uncertainty measures used in this study.

Finally, Figures A1 to A7 are produced from rerunning our baseline SVAR model, but restricting the sample to end before the 2007-2009 financial crisis. Specifically, we use data from 1973q1 to 2007q2 to produce Figures A1 to A7. Limiting the sample to the pre-financial crisis period allows us to understand if the financial crisis and its aftermath, as well as the current Covid-19 pandemic, had an impact on the relative importance of uncertainty, monetary policy, and leverage shocks. All the figures in this restricted sample are identical to their counterparts in the baseline analysis suggesting that the role of uncertainty, monetary policy, and leverage shocks in explaining macroeconomic variations did not significantly change in the post-financial crisis data.
Table A1. Granger causality tests from uncertainty measures to economic variables

<table>
<thead>
<tr>
<th>Economic activity variables</th>
<th>( Y_1 )</th>
<th>( Y_2 )</th>
<th>( Y_3 )</th>
<th>( Y_4 )</th>
<th>( Y_5 )</th>
<th>( Y_6 )</th>
<th>( Y_7 )</th>
<th>( Y_8 )</th>
<th>( Y_9 )</th>
<th>( Y_{10} )</th>
<th>( Y_{11} )</th>
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<tr>
<td>( Y_1 ) = Real GDP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>( Y_2 ) = Industrial production</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>( Y_3 ) = Capacity utilization</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>( Y_4 ) = Real private gross investment</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>( Y_5 ) = Employment rate</td>
<td></td>
<td></td>
<td></td>
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<td>( Y_6 ) = Unemployment rate</td>
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</table>

<table>
<thead>
<tr>
<th>Risk/uncertainty variable</th>
<th>( Y_1 )</th>
<th>( Y_2 )</th>
<th>( Y_3 )</th>
<th>( Y_4 )</th>
<th>( Y_5 )</th>
<th>( Y_6 )</th>
<th>( Y_7 )</th>
<th>( Y_8 )</th>
<th>( Y_9 )</th>
<th>( Y_{10} )</th>
<th>( Y_{11} )</th>
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<tr>
<td>Panel A. Risk measures</td>
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<td></td>
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<td>Geopolitical Risk</td>
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<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
<td><strong>0.013</strong></td>
<td>0.181</td>
<td><strong>0.000</strong></td>
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<td>0.052</td>
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<td>0.000</td>
<td>0.000</td>
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<td>0.000</td>
<td>0.000</td>
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<td>0.000</td>
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<td>0.051</td>
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<td>0.000</td>
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<td><strong>0.000</strong></td>
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<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
<td>0.324</td>
<td>0.323</td>
<td>0.200</td>
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Notes: Numbers are marginal significance levels. Bold numbers indicate significance at the 5% level. CBOE S&P 100 Volatility Index data starts from 1986:q1. We run \( Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j X_{t-j} \) where \( Y_t \) is a measure of real economic activity, \( X_t \) is a measure of risk or uncertainty and test for Granger causality from uncertainty to the various real economic activity measures.
Table A2. Granger causality tests real economic activity variables to risk and uncertainty measures

<table>
<thead>
<tr>
<th>Economic activity variables</th>
<th>Y₁ = Real GDP</th>
<th>Y₂ = Industrial production</th>
<th>Y₃ = Capacity utilization</th>
<th>Y₄ = Real private gross investment</th>
<th>Y₅ = Employment rate</th>
<th>Y₆ = Unemployment rate</th>
<th>Y₇ = Housing starts</th>
<th>Y₈ = Real per capita personal disposable income</th>
<th>Y₉ = Real personal disposable income</th>
<th>Y₁₀ = Personal consumption expenditure</th>
<th>Y₁₁ = Consumption expenditure for durable goods</th>
</tr>
</thead>
</table>

<table>
<thead>
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<th>Risk/uncertainty variable</th>
<th>Y₁</th>
<th>Y₂</th>
<th>Y₃</th>
<th>Y₄</th>
<th>Y₅</th>
<th>Y₆</th>
<th>Y₇</th>
<th>Y₈</th>
<th>Y₉</th>
<th>Y₁₀</th>
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<td>0.504</td>
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<td>0.538</td>
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<tr>
<td>Chicago financial conditions risk</td>
<td><strong>0.005</strong></td>
<td><strong>0.014</strong></td>
<td><strong>0.017</strong></td>
<td>0.107</td>
<td><strong>0.012</strong></td>
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<td><strong>0.003</strong></td>
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<td><strong>0.045</strong></td>
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<td>0.765</td>
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<td>0.958</td>
<td>0.920</td>
<td>0.543</td>
<td>0.588</td>
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<td>0.097</td>
<td>0.072</td>
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<td><strong>0.020</strong></td>
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<td><strong>0.020</strong></td>
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<td>0.913</td>
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<td>0.081</td>
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<td>CBOE S&amp;P 100 Volatility Index</td>
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<td>0.223</td>
<td>0.123</td>
<td>0.970</td>
<td>0.065</td>
<td>0.039</td>
<td>0.155</td>
<td><strong>0.024</strong></td>
</tr>
</tbody>
</table>

Notes: Numbers are marginal significance levels. Bold numbers indicate significance at the 5% level. CBOE S&P 100 Volatility Index data starts from 1986:q1. We regress \( X_t = \alpha + \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{j=1}^{q} \theta_j Y_{t-j} + \sum_{k=1}^{r} \lambda_k P_{t-k} + e_t \) where \( X_t \) is a measure of risk or uncertainty, \( Y_t \) is a measure of real economic activity and \( P_t \) is the personal consumption expenditure deflator which acts as an adjustment variable to remove the effects of general prices from the estimates. We then test for Granger causality from various real economic activity measures to the various risk or uncertainty measures.
Figure A1: Impulse responses to a macroeconomic uncertainty shock. Pre-financial crisis sample (1973-2007).
Figure A2: Impulse responses to a monetary policy shock. Pre-financial crisis sample (1973-2007).
Figure A3: Impulse responses to a commercial bank leverage shock. Pre-financial crisis sample (1973-2007).
Figure A4: Variance decomposition to uncertainty, monetary policy, and leverage shocks. Pre-financial crisis sample (1973-2007).
Figure A5: Comparison of impulse responses to uncertainty, monetary policy, and leverage shocks. Pre-financial crisis sample (1973-2007).
Figure A6: Comparison of variance decomposition to uncertainty, monetary policy, and leverage shocks. Pre-financial crisis sample (1973-2007).
Figure A7: Historical variance decomposition. Pre-financial crisis sample (1973-2007).