Frequency-Dependent Real-Time Effects of Uncertainty in the United States: Evidence from Daily Data

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Abstract

In this paper, we analyze the impact of uncertainty shocks at the daily-frequency on key macroeconomic variables for the United States. In doing so, we use a vector autoregressive (VAR) model, including the inflation rate, a real-time measure of economic activity and a measure of monetary policy as endogenous variables and decompose uncertainty effects into short, medium and long-term based on a discrete-time Fourier transformation. Aggregate results (prior to decomposition) show that an increase in economic uncertainty has a significant expansionary impact on monetary policy. However, when we decompose uncertainty into its short-, medium- and long-run components, we find that economic activity is affected negatively in a statistically significant manner to shocks in low-frequency uncertainty, while, statistically significant monetary expansion is observed under shocks to relatively high frequencies of uncertainty.

JEL Codes: C32, E31, E32, E52
Keywords: Uncertainty, Frequency-Dependence, Daily Data; Vector Autoregressive Model, United States

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1. Introduction

A stylized fact in macroeconomics is that uncertainty has a negative effect on the macroeconomy, populated in a theoretical manner by the works of Bernanke (1983), Dixit and Pindyck (1994), and recently Bloom (2009). However, in the wake of the "Great Recession", the focus to quantifying uncertainty (an otherwise latent variable) has shifted towards structural (Dynamic Stochastic General Equilibrium (DSGE)) and atheoretical (Vector Autoregressive (VAR)) models (see Castelnuovo et al., (2017), and Gupta et al., (2018, forthcoming) for detailed literature reviews in this regard). Given that the measure of economic activity in these papers is either industrial production, unemployment rate or Gross Domestic Product (GDP), all existing studies are based on low-frequency monthly or quarterly data. Nevertheless, economic agents and especially the financial market participants need to make decisions in real-time and on higher frequencies. In this manner, they would want to have a timely estimate of the impact of uncertainty on the current state of economic activity before this is reflected in the official lower-frequency official announcements. In this regard, low-data frequency analyses are not likely to be very useful (Aruoba et al., 2009).

Against this backdrop, the objective of this study is to extend the above line of research by analysing the impact of uncertainty on economic activity in real-time (besides inflation and interest rates) at the highest possible daily frequency over the period of 19/09/2008 to 31/07/2015 for the United States. Also, given that there is some concern as to whether the various measurements of uncertainty are purely exogenous or not (Ludvigson et al., 2015), and hence the correct identification of uncertainty shocks, it is believed that using high frequency data allows us to address the issue of endogeneity in a clean-manner (Nakamura and Steinsson, forthcoming). Finally, as pointed out in Balcilar et al. (2016), economic uncertainty is considered to be a leading indicator of economic activity. Utilized at the highest possible frequency one could predict the future path of low-frequency variables, such as industrial production, GDP, and unemployment rate before the official announcements of the estimates about the macroeconomic variables.

Note that, recently, Barrero et al., (2017) and Antonakakis et al., (2018) indicated that economic decisions and economic variables are likely to react differently to short-, medium-, and long-run movements of uncertainties. Given this, we supplement our main analysis, by disaggregating uncertainty into its various components (high, medium, and low) using a discrete-time Fourier transform and then analysing the impact of frequency-based measures of uncertainty on daily movements of economic activity. To the best of our knowledge, this is the first attempt to analyze the impact of overall and decomposed measures of news-based economic policy uncertainty (EPU, as developed by Baker et al., (2016)) on daily real business conditions (as measured by the Aruoba, Diebold and Scotti (ADS) index proposed in Aruoba et al., (2016)), for the United States. The remainder of the paper is organized as follows: Section 2 briefly discusses the methodology, while Section 3 presents the data and results, with Section 4 concluding the paper.

2. Methodology

We start with the workhorse in macroeconomics, the typical VAR model:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \mu_t \tag{1}$$

where y_t is *kx1* vector of endogenous variables; A_0 is a *kx1* vector of constant terms, A_0 is a *kxk* matrix of the coefficients of the model associated with the *p* lags of the endogenous variables, which in our case chosen by the Akaike information criterion (AIC), and μ_t represents the *kx1* matrix of the reduced-form errors, with $\mu_t \sim N(0, \sigma^2)$.

To decompose EPU, we use the Ashley and Verbrugge (2008) approach, that applies a discrete-time Fourier transform on moving windows in order to disintegrate a time series into its frequency (persistence) components. This transformation is embodied in the *MxM* orthonormal matrix *A,* where *M* is the length of the moving window. In the present application, *M=60* days and matrix *A* is defined as:

$$a_{s,j} = \begin{cases} \left(\frac{1}{60}\right)^{\frac{1}{2}}, for\ q = 1 \\ \left(\frac{2}{60}\right)^{\frac{1}{2}} cos\left(\frac{\pi q(j-1)}{60}\right), for\ q = 2,4,6, \ldots 58 \\ \left(\frac{2}{60}\right)^{\frac{1}{2}} sin\left(\frac{\pi (q-1)(j-1)}{60}\right), for\ q = 3,5,7 \ldots 59 \\ \left(\frac{1}{60}\right)^{\frac{1}{2}} (-1)^{j+1}, for\ q = 60 \end{cases} \tag{2}$$

The decomposition yields 11 frequency (persistence) components that add up, by construction, to the original EPU time series. Based on their variability, we aggregate the first 5 components to form the high-frequency component, aggregate the next three (6th, 7th, and 8th) for the medium-frequency component, and the last three components (9th, 10th, and 11th) for the low-frequency component. Furthermore, the three frequencies of uncertainty were standardised to have a variance of one, in order to make their impact comparable.

3. Data and Results

We used the Aruoba-Diebold-Scotti (ADS) business conditions index as our measure of economic activity (OUTPUT) as developed by Aruoba et al., (2009). In essence the ADS business conditions index is designed to track real business conditions at high frequency. Its underlying (seasonally adjusted) economic indicators (weekly initial jobless claims; monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales; and quarterly real GDP) blend high- and low-frequency information and stock and flow data in order to get a view of the overall level of economic activity.[1] Daily data on year-on-year Consumer Price Index (CPI) inflation (INFLATION), based on prices collected from hundreds of online retailers, and hence considered to be a more accurate measure of inflation than the official data published by national agencies (Cavallo and Rigobon, 2016), is derived from the Billion Prices Project at MIT.[2] The availability of the daily inflation rates over the period of 19/09/2008 to 31/07/2015 determines the data-sample of our study. Given that this period corresponds to the zero lower bound (ZLB) scenario of the monetary policy in the interest rates, we use the Shadow Short Rate (SSR), developed by Krippner (2013), as the primary summary measure of the stance of monetary policy for the Unites States,[3] instead of the Federal Funds Rate. The SSR is the nominal interest rate that would prevail in the absence of its effective lower bound, with it derived by modelling the term structure of the yield curve.[4] Note that, baring the SSR (which had a downward trend capturing continuous unconventional monetary policy expansions during the ZLB), the other three variables (ADS, daily inflation rate and EPU) were all found to be stationary based on standard unit root tests. Given this, the SSR was first-differenced to ensure that it is a I(0) process.[5]

We analyze the impact of uncertainty on the macroeconomic variables using impulse response functions (IRFs) over a 100-day period from the imposition of the shock. To identify the uncertainty shocks, we follow the Choleski structural decomposition, whereby the overall EPU is

[1] The data is available for download from: https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.

[2] The data is downloadable from: http://www.thebillionpricesproject.com/.

[3] We also replaced the SSR with the Expected Time to Zero (ETZ), and the Effective Monetary Stimulus (EMS), as alternative measures of monetary policy developed also by Krippner (2013). However, our main results were qualitatively similar, and complete details are available upon request from the authors.

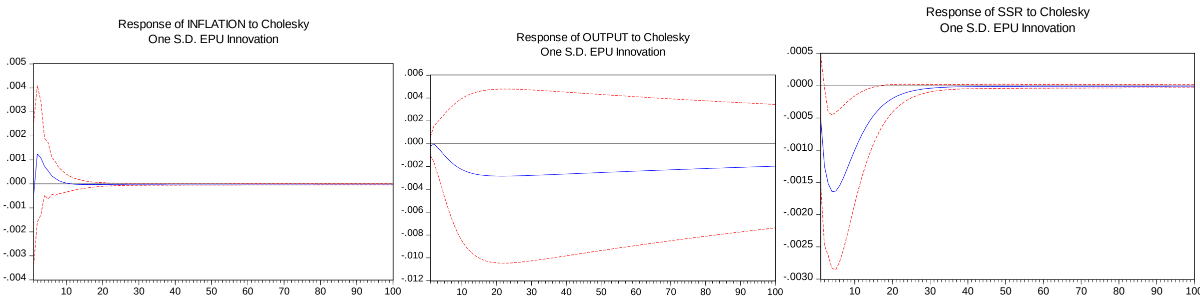
[4] The SSR is available for download from: https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy.

[5] Complete details of the unit root tests are available upon request from the authors.

ordered first (to capture its exogeneity), followed by the inflation rate, the ADS and the SSR. When we use the disaggregated EPU, the undecomposed EPU is replaced by the high-frequency (HIGHFREQ_EPU), medium-frequency (MEDFREQ_EPU), and low-frequency (LOWFREQ_EPU) EPUs in the VAR model, again understandably, capturing the degree of exogeneity in descending order.[6]

In Figure 1, we present the impulses responses on a shock on the aggregated EPU series. Apart from the response of SSR, the effects of a shock on EPU is statistically insignificant for economic activity and inflation The impulse response of the growth rate of SSR is negative and statistically significant for the first 20 days, denoting an increase in the adjusting speed of interest rates as a results of an increase in economic uncertainty. Thus, the uncertainty shock seems to be identified as an aggregate demand shock as reported widely in the literature (Gupta et al., 2018).

Figure 1: Impulse Responses following Aggregate EPU Shock



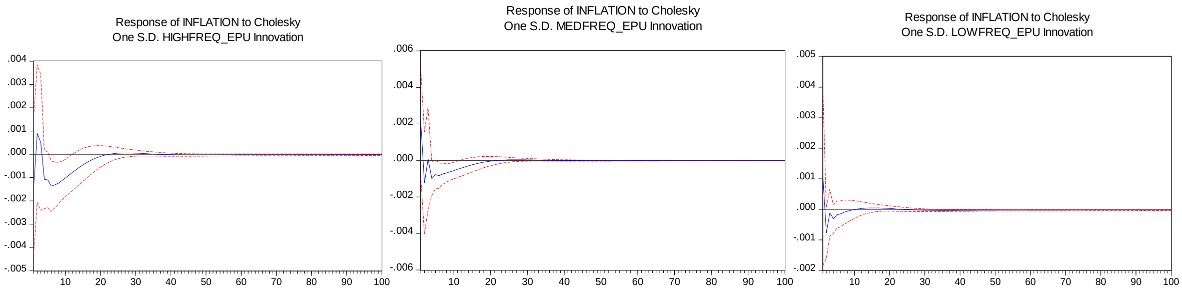
In Figure 2 (a)-2(c), we report the impact of the same-sized shock from HIGHFREQ_EPU, MEDFREQ_EPU and LOWFREQ_EPU on the inflation rate, the ADS and the SSR, respectively. While the impact of the high- and medium-frequency EPUs on OUTPUT is statistically insignificant, the effect of long-run uncertainty (LOWFREQ_EPU) is negative and statistically significant over the entire 100-day horizon analysed. Impact on inflation, as with the aggregate EPU continues to be short-lived and insignificant, but with a clear negative impact in general. The weak effect on inflation is possibly an indication of inflation not being a cause of major concern during- and post- the "Great Recession", which is essentially what the sample period of our study covers. The SSR reacts negatively, but only significantly following shocks to the HIGHFREQ_EPU and MEDFREQ_EPU. Our results suggest that, economic activity reacts negatively to low-frequency (relatively more persistent) movements in uncertainty, which is possibly due to the fact that, long-term uncertainty is known to affect investment decisions

[6] Alternative ordering, whereby the overall EPU or the decomposed versions of the same were ordered last as in Colombo (2013), did not qualitatively affect our results (of course barring the first period), complete details of which are available upon request from the authors.

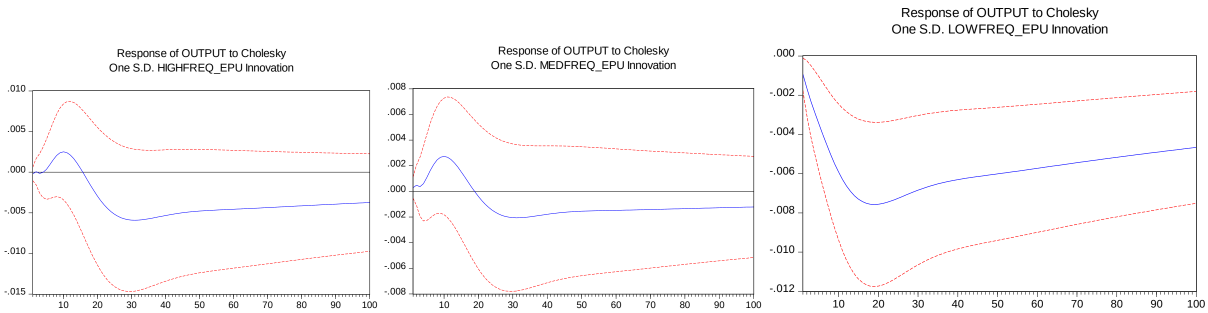
(Barrero et al., 2017). At the same time, the monetary authority tends to react strongly to relatively high frequency movements of uncertainty, possibly in an effort to negate the long-term effects of uncertainty on the real economy.

Figure 2. Impulse Responses to Frequency-Dependent EPU Shock

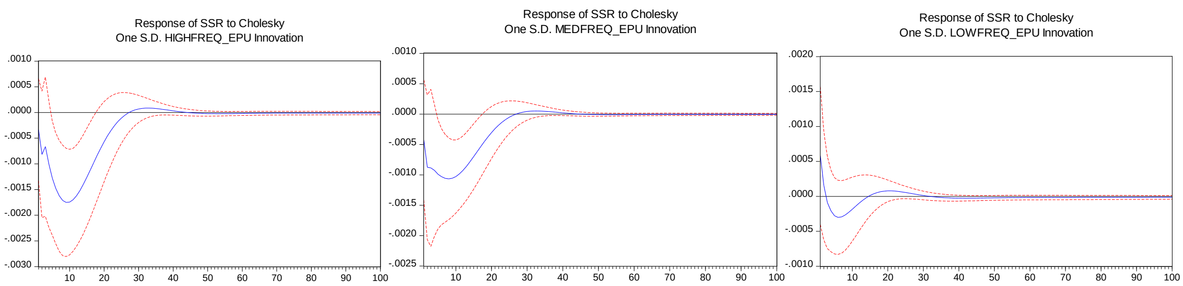
2(a): Impact on the Inflation Rate:



2(b): Impact on the ADS Index:



2(c): Impact on the Interest Rate:



4. Conclusion

In this paper, we analyze the impact of uncertainty shocks on a real-time measure of economic activity, inflation rate and a measure of monetary policy at daily-frequency. In doing so, we train a VAR model and decompose our uncertainty on its short, medium and long-term components based on Fourier transformation. Our initial results indicate that an increase in economic uncertainty has only an expansionary effect on monetary policy. Unlike with overall uncertainty, the disaggregated uncertainty results indicate that real-time economic activity is affected negatively in a statistically significant manner to shocks in low-frequency uncertainty, with statistically significant monetary expansion observed under shocks to relatively high frequencies of uncertainty. In general, we highlight the importance of disaggregating uncertainty into its frequency components.

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