Assessing U.S. Aggregate Fluctuations Across Time and Frequencies*

Thomas A. Lubik, Federal Reserve Bank of Richmond[†]
Christian Matthes, Indiana University[‡]
Fabio Verona, Bank of Finland[§]

May 2020

Abstract

We study the behavior of key macroeconomic variables and their response to monetary policy in the time and frequency domain. For this purpose, we decompose U.S. time series into various frequency components using a wavelet filter. We use these jointly in a structural VAR where we identify monetary policy shocks using a sign restriction approach. We find that monetary policy shocks affect these key variables in a broadly similar manner across all frequency bands. However, we find evidence of a Fisher effect in the long run that is not present in short-term components. Finally, we assess the ability of a standard DSGE model to replicate these findings. While the model generally captures low-frequency movements via stochastic trends and business cycle fluctuations through various frictions it does less well at capturing the medium-term cycle.

JEL Classification: C32, C51, E32

Key Words: Wavelets, SVAR, sign restrictions, DSGE model

*We wish to thank the editor Olivier Coibion and four anonymous referees for comments and suggestions that greatly improved the paper. We also want to thank Marco del Negro, Bob King, Annika Lindblad, and Denis Tkachenko for useful comments. We are grateful to participants at the 2018 CEF Conference in Milan, the University of Adelaide, Carleton University, the 2019 Meeting of the Finnish Economic Association and the Bank of Finland. James Geary provided exceptional research assistance. The views expressed in this paper are those of the authors and should not be interpreted as those of the Federal Reserve Bank of Richmond, the Federal Reserve System, or the Bank of Finland.

†Research Department, P.O. Box 27622, Richmond, VA 23261. Email: thomas.lubik@rich.frb.org.

‡Wylie Hall, 100 South Woodlawn Avenue, Bloomington, IN 47405. Email: matthesc@iu.edu.

§Monetary Policy and Research Department. Snellmaninaukio, PO Box 160, 00101 Helsinki. Email: fabio.verona@bof.fi.

1 Introduction

Economists have often found it useful to separate long-run trends from business cycle fluctuations, typically those that occur with a cycle length of between two and eight years. From a statistical perspective, this approach is probably best characterized by the idea of a trend-cycle decomposition as in Beveridge and Nelson (1981), where the trend is associated with permanent movements in a time series as opposed to a business cycle being driven by transitory shocks. Conceptually, this idea is also inherent in filtering methods such as the Hodrick-Prescott (HP) filter, which has been the dominant approach in business cycle modeling for extracting a trend from aggregate times. Such decompositions are convenient since they align with the idea of economic fluctuations as being driven by either permanent or temporary shocks that do not necessarily interact.

However, there is a growing awareness in the macroeconomics literature that this common view of economic fluctuations is no longer adequate to characterize the behavior of economic activity over time. For instance, Comin and Gertler (2006) argue that a substantial part of economic fluctuations is located in what they label a 'medium-term cycle', that is, fluctuations beyond a length of eight years, but falling short of a trend. Importantly, these medium-term fluctuations should not be thought of in isolation of other frequency bands. Using a theoretical model, Comin and Gertler (2006) show that business cycles and medium-term cycles are intimately connected since they are driven by the same underlying temporary shocks. Specifically, a temporary innovation to productivity or the monetary policy rate can reverberate throughout several frequency bands as they get propagated over time.[1]

In this paper, we study the effects of monetary policy shocks across different frequency bands to assess the plausibility of medium-term and long-term cycles as being generated by transitory shocks. We thus aim to provide a somewhat more encompassing view of cyclical behavior across all frequencies. Furthermore, we investigate whether a standard dynamic stochastic general equilibrium (DSGE) model used in monetary policy analysis can replicate the effects of a monetary policy shock across different frequency bands and the volatility of different cycles of each macroeconomic variable under consideration. We do so by using a wavelet-based filtering approach to compute decompositions of key macroeconomic time series. That is, we decompose a time series into several time series components, each of them

[1] Cogley (2001) makes a similar point for trend specifications where he shows the effects of trend specification errors are not confined to low frequencies, but are spread across the entire frequency domain. Researchers therefore need to have a clear understanding of the inter-relatedness of frequency bands.

fluctuating within a specific frequency band, and use these series as inputs for the further analysis.

We establish two key findings. First, using identified structural VARs with sign restrictions we find that across frequency bands the results from an aggregate VAR generally carry over to individual components and short-term, business-cycle, medium-term and long-term components. In a baseline specification that includes only the overall data series, a contractionary policy shock, that is, an increase in the federal funds rate (FFR), lowers inflation, and decreases real GDP. When adding individual frequency components, we find a similar patterns across most frequency bands, but as we increase the cycle length, the peak response moves further out, while precision of the impulse response estimates worsens and their quantitative importance declines. We take this as tentative evidence that monetary policy has an impact across all frequency bands and that a mechanism in line with interaction of endogenous growth and cycles as in Comin and Gertler (2006) is at play. In addition, we find that in the long run the relationship between the nominal interest rate and the inflation rate is positive, whereas in the short run an interest-rate increase lowers inflation. This relationship weakens or is non-existent over the medium term, which arguably reflects a contrast between a demand effect in the short run and the Fisher effect in the long term.

Our second finding demonstrates that a standard DSGE model is in principle capable of replicating the behavior of macroeconomic variables in different frequency bands, both in terms of unconditional variance decompositions and conditional on the responses to a monetary shock. It does fall short, however, along a few key dimensions. We simulate artificial time series from the canonical and widely-used DSGE model of Del Negro et al. (2015) and apply a wavelet decomposition to the artificial data. Generally, the model performs well for business-cycle frequencies and for long-term fluctuations. In a sense, this is perhaps not surprising in that DSGE models are built as business-cycle models around the idea that such fluctuations are the outcome of stochastic shocks and endogenous propagation. To that effect, such models include elements such as habit formation, investment adjustment costs, and wage and price indexation to impart persistence on the variables which helps match behavior at business-cycle frequencies.[2]

Long-run behavior in DSGE models is typically captured by stochastic trends and time-varying inflation targets, which helps in matching low-frequency components unconditionally. We show, however, that conditional on monetary policy shocks the model predicts a much

[2]Tkachenko and Qu (2012) and Sala (2015) estimate medium-size DSGE models in the frequency domain with a focus on business-cycle frequencies. They report similar findings as to the ability of such models to replicate observed behavior over the cycle.

too quick return to trend for these components. Similarly, we find that the model does less well in capturing behavior at medium-term frequencies. We regard this finding as a challenge for modelers to develop frameworks capable of capturing medium-term cycles and the long-term effects of transitory shocks.

This paper touches upon various literatures in macroeconomics and time series analysis. It contributes to the growing number of papers that study aspects of monetary policy and the transmission of shocks across different frequencies. Recent examples include Aguiar-Conraria et al. (2018) who estimate a Taylor rule using wavelet-based decompositions and Aguiar-Conraria et al. (2020) who study Okun's law, a key concept in the transmission and effectiveness of monetary policy, across different frequency bands obtained by wavelet filtering. We expand on this literature by studying the effects of identified monetary policy shocks in a VAR where individual frequency components have explanatory power for aggregate dynamics, while being affected in different ways.[3]

Our paper also speaks to a wider literature on whether a frequency-based view of economic fluctuations is useful for analyzing and understanding monetary policy. Watson (1993) has argued that policy analysis at different frequencies is not relevant for policymakers and that the close relationship between a time series representation of a variable and its counterpart in the frequency domain invalidates the need for a separate analysis of frequency-specific considerations. In contrast, Onatski and Williams (2003) show that when uncertainty enters a policymaker's decision problem at different frequencies it may have substantially different effects on outcomes. In addition, Brock et al. (2007, 2013) analyze the differential effects of various policy rules on outcomes across frequencies and show the existence of a frequency-based monetary policy trade-off. Our paper informs this debate in showing empirically the contributions of different frequency bands to the overall volatility of key macroeconomic variables and how they are impacted by monetary policy shocks.

Finally, our findings also highlight the importance of joint theoretical modelling of economic behavior across all frequency bands and especially the medium term as an important component of economic fluctuations. While the importance of the medium run has been on economists' minds for a long time (e.g., Blanchard, 1997), there has been a flurry of recent research recent in the wake of Comin and Gertler's (2006) contribution that study the origin and effects of medium-term cycles (e.g., Beaudry et al., 2020; Cao and Huillier, 2018). In addition, this aspect also connects with the literature on hysteresis, namely whether

[3]Another issue that has been studied through the lens of frequency-domain methods is the Great Moderation, for instance by see Ahmed et al. (2004) and Pancrazi (2015).

transitory shocks can have highly persistent, even permanent effects. Jorda et al. (2020) provide recent evidence in favor of hysteresis, which is consistent with our findings. Using an approach based on frequency bands helps teasing out hysteresis effects that would otherwise disappear in aggregate data.

The remainder of the paper is structured as follows. In the next section, we discuss and use wavelet methodology to produce a decomposition of key aggregate data series. The core of our results is in section 3, where we use this decomposition to assess the effects and importance of monetary policy shocks across different frequency bands in a structural VAR framework. Section 4 considers the question whether existing DSGE models are able to capture these regularities. Section 5 concludes.

2 A Time-Frequency Decomposition of Aggregate Time Series

In studying the effects of monetary policy shocks across frequency bands we proceed in two steps. First, we use wavelet methodology to decompose standard U.S. macroeconomic time series into different components that we can associate with different frequencies of the underlying cycles. The resulting time-frequency decomposition, that is, a decomposition of a variable into components in the time domain with precise counterparts in the frequency domain, is an informative alternative to more standard trend-cycle decompositions. In the next section, we then assess the effects of monetary policy shocks on individual frequency bands by using the frequency components as explanatory variables in a structural VAR. Given a plausible identification of policy shocks, we study the impulse responses to these shocks for the various decompositions.

We briefly discuss the methodology and data used in our empirical exercise, followed by a presentation of our baseline decomposition. Our analysis is based on a time-frequency decomposition of economic time series using wavelets. This methodology is becoming more widely used in economics as it offers some distinct advantages over more traditional methods. Crowley (2007) is a comprehensive survey of this approach, while Yogo (2008) and Rua (2010) offer early applications. We discuss wavelets in more detail in the online appendix.

We decompose a time series into individual components that can be associated with fluctuations at different frequencies or different lengths of a cycle, but that have a representation in the time domain. For this purpose, we employ wavelet multiresolution analysis (MRA) which produces such decompositions in a manner similar to a traditional time series trend-cycle decomposition approach (e.g., Beveridge and Nelson, 1981; Watson, 1986) or other filtering methods like the Hodrick and Prescott (1997) or the Baxter and King (1999) band-pass filter. However, a wavelet approach aims at a more fine-grained understanding of the different components of a time series that make up what is considered a 'cycle' as opposed to a 'trend'.

To fix ideas and terminology, consider the following example. The wavelet MRA with the one-sided Haar filter allows to decompose any time series X_t into a scale component $S_{J,t}$ and J detail components $D_{j,t}$:

$$X_t = \sum_{j=1}^{J} D_{j,t} + S_{J,t}, \tag{1}$$

where the coefficients are functions of weighted averages of lagged values of the underlying time series. These coefficients are given by:

$$D_{j,t} = \frac{1}{2^j}\left(\sum_{i=0}^{2^{j-1}-1} X_{t-i} - \sum_{i=2^{j-1}}^{2^j-1} X_{t-i}\right), \tag{2}$$

$$S_{J,t} = \frac{1}{2^J}\sum_{i=0}^{2^J-1} X_{t-i}. \tag{3}$$

Intuitively, the wavelet filter separates the original series X_t, which is defined in the time domain, into different time series components. These represent the fluctuations of X_t in a specific frequency band, that is, a range of frequencies, or length of cycles, that are grouped together.[4]

The key parameter for the economic interpretation of the wavelet decomposition is the scale parameter J, which determines how fine-grained or detailed the decomposition is. For J large enough, the scale component $S_{J,t}$ approximates the true underlying trend of the series. If J is small, then the scale component includes fluctuations of shorter duration, which one may not normally associate with a trend. The bands are associated with different details j such that for small j, the wavelet component $D_{j,t}$ captures the higher-frequency characteristics of the time series, that is, its short-term fluctuations. As j increases, the components represent lower frequency movements of the series. The smooth component $S_{J,t}$ captures the lowest frequency dynamics.[5]

An advantage of the wavelet decomposition is that the choice of the scale allows the

[4]The individual components, or *wave-lets*, thus make up the overall *wave* in a specific manner.

[5]As in the Beveridge and Nelson (1981) decomposition of a time series into stochastic trends and transitory components, the wavelet coefficients $D_{j,t}$ can be viewed as components with different levels of calendar-time persistence operating at different frequencies, whereas the scaling component $S_{J,t}$ can be seen as the low-frequency trend of the time series under analysis.

researcher to hone in on and isolate specific frequency bands that are objects of interest. In that, wavelet methods are similar to filtering by a set of band-pass filters to capture the fluctuations of a time series in different frequency bands, e.g., Christiano and Fitzgerald (2003). The band-pass filter is a combination of a Fourier decomposition in the frequency domain with a moving average in the time domain. It applies optimal Fourier filtering to a sliding window in the time domain with constant length regardless of the frequency being isolated. Wavelet filtering, in contrast, provides better resolution in the time domain as wavelets allow the importance of a given frequency band to change over time: in the terminology of the wavelets literature, the wavelet basis functions are both time-localized and frequency-localized.

For our decomposition used in the VAR analysis we use a one-sided Haar filter. In a sense, the different scale components are generated regressors. We therefore do not want to impart information onto econometricians running the VAR that they could not possibly possess; that is, knowledge of the data at the end of sample should not be used to produce a decomposition for periods in the middle.[6] We employ the filter to decompose each time series into seven individual series, labeled D_1, ..., D_6 for the detail components and S_6 for the scale component, that is, we choose $J = 6$. The individual components are such that they add up to the underlying series. Given the scale of the decomposition as powers of two we can associate the components with individual frequency bands. Specifically, D_1 captures fluctuations up to four quarters, D_2 between four and eight quarters, and up to D_6, which covers the band between 64 and 128 quarters. The scale component S_6 is associated with movements above 128 quarters.

For purposes of exposition, we find it convenient to group the seven series further into four categories which we label 'Short Term' (D_1, D_2), 'Business Cycle' (D_3, D_4), 'Medium Term' (D_5, D_6), and 'Long Term' (S_6). The short-term category captures high-frequency fluctuations under two years. The business-cycle category covers fluctuations at frequencies between 8 and 32 quarters (2-8 years), which most macroeconomic research on the sources of aggregate movements focuses on. Components D_5 and D_6 are grouped under 'Medium Term' fluctuations and cover frequencies up to 128 quarters (32 years). Finally, we associate S_6 with the 'Long Term' or, loosely speaking, the trend.

We collect quarterly data on US macroeconomic aggregates, interest rates, and prices. Specifically, we report results for log real GDP per capita, the inflation rate for the overall

[6]In the extended working paper version, Lubik et al. (2019), we report on robustness checks that use two-sided (smoothed) wavelet filters, alternative kernels, and alternative filters, such as the HP and the Christiano-Fitzgerald bandpass filters.

personal consumption price index (PCE) (quarter over quarter), and the federal funds rate.[7] To offer a more complete picture of variables that policymakers closely monitor, we also report results for the quarter-over-quarter growth rate of real per-capita GDP.[8] The data are described in more detail in the online appendix. The full range of our sample covers the period from 1964Q1 to 2015Q3.

What emerges from the wavelet decompositions is a multifaceted picture of macroeconomic fluctuations. Table 1 reports the variance decompositions of each variable by frequency to give a sense of the importance of different components. We briefly summarize these facts, which are established in the wavelet literature (see, for instance, Crowley, 2007), in the following paragraph and otherwise refer to our working paper Lubik et al. (2019) for extended discussion.

Fluctuations in inflation are roughly evenly attributed to movements in the D_1 - D_5 components, of around 8-10% each. As the bands incorporate lower frequencies above 16 years, these components become more important, in particular, the scale S_6, which captures almost 40% of inflation. This pattern is broadly similar for the FFR, with a smaller contribution of high-frequency short-run components and a much higher contribution of the long-run series. In other words, inflation and interest rates have sizeable long-term components, which could be interpreted as "trends"and natural or potential rates. Their behavior arguably conforms to conventional wisdom, that is, much of inflation is slow-moving and trend, driven by the Federal Reserve's inflation target.

As is well known, the behavior of (the logarithm of) real GDP is essentially all trend, and neither short-run nor business-cycle components matter much, with only a small contribution of the medium-term component. Looking ahead, this finding is relevant for the analysis of DSGE models since they tend to match the level path of GDP by using stochastic, but exogenous trends. At the same time, 55% of real GDP growth is captured by high frequency components (cycles of less than 2 years), while the business-cycle components D_3 - D_4, that is, cycles between two and eight years, explain about one third of overall fluctuations. Essentially, much of quarterly GDP growth movements occur at high frequencies. This presents a tension inherent in DSGE modeling practice, where the exogenous long-run

[7]We use the log level of GDP to avoid unnecessary data transformations. We look at the inflation rate because policymakers are generally more interested in the rate of price changes and less in the level of prices. Moreover, both theoretical models, like the one we consider below, and empirical models, such as in the VAR literature, are often specified in terms of the level of GDP and the inflation rate. To maintain consistency with the literature we follow this convention

[8]A more detailed study of real GDP growth can be found in the earlier working paper version, Lubik et al. (2019).

behavior is decoupled from the business cycle.

Against this background, we now study whether empirical and theoretical models that are being used to describe and analyze monetary policy are consistent with the heterogeneity in fluctuations. In the following section we investigate whether identified monetary policy shocks have differential effects on key variables for different frequencies, while in section 4 we study whether some standard DSGE models are capable of replicating the wavelet-based facts reported in this section and the frequency-specific effects of monetary policy shocks reported in Section 3.

3 The Frequency-Specific Effects of Monetary Policy Shocks

We now study whether and to what extent monetary policy shocks affect key aggregate variables across different frequencies. It is well known from the literature, and confirmed by the analysis in the previous section, that the behavior of macroeconomic variables differs in terms of the contribution of various frequency bands to overall volatility. The overwhelming majority of fluctuations in the level path of GDP is driven by its trend component, while GDP growth appears largely dominated by highest frequency movements. In turn, most of the movements in nominal variables, such as the inflation rate and interest rates, are captured by low-frequency components, which we might associate with an inflation target. We thus raise the question whether identified, non-systematic behavior of monetary policy affects these variable at frequencies that are the main drivers of their overall volatility.

3.1 Frequency Bands in a Structural VAR

We assess the effects of monetary policy shocks on individual frequency bands by using the filtered series as explanatory variables in a structural VAR (SVAR). Given a plausible identification of policy shocks, we then compute impulse response functions to these shocks for the various decompositions. We first investigate the plausibility of our preferred identification scheme in a typical VAR used in the analysis of monetary policy. To this end, we estimate a three-variable VAR in real GDP, inflation, and the FFR. We identify a structural monetary policy shock using a sign restriction approach, where we impose impact restrictions only. Specifically, we assume that a contractionary monetary policy shock, namely an shock that raises the FFR on impact, lowers output and reduces inflation.

In the specification and estimation of our SVAR we follow Arias et al. (2018), specifically in the procedure to identify the effects of a structural shock. We estimate an SVAR of the following form:

$$y_t' A_0 = c + \sum_{l=1}^{L} y_{t-l}' A_l + \varepsilon_t'. \tag{4}$$

y_t is a column vector that collects the observable variables, while ε_t collects the structural innovations; c is a vector of constants and L is the number of lags in the VAR.

Our goal is to determine the elements of the structural impact matrix A_0. Since we do not assume overidentifying restrictions, we can estimate the reduced-form VAR and impose our identification restrictions after estimation. To do so, we post-multiply the previous equation by A_0^{-1} to arrive at:

$$y_t' = x_t' B + u_t', \tag{5}$$

where x_t also contains the intercept term. We use conjugate Normal-inverse Wishart priors of the form used in Arias et al. (2018). We assume 4 lags and a loose, but proper, prior throughout. We use a Minnesota-type prior with large prior variances. The prior is centered around stationary, but persistent AR(1)-processes (with an AR coefficient of 0.9) for all variables except the log level of real GDP, which we center at a random walk. In our later robustness checks we also use the Romer and Romer (2004) monetary shocks in our VAR. We center the prior for that variable at an i.i.d. process. Our data spans the sample period 1980Q1-2007Q4.[9] Once we have parameter estimates for B and for the covariance matrix of u_t we apply the algorithm outlined in Rubio-Ramirez et al. (2010) to impose sign restrictions on impact.

Figure 1 reports impulse responses to an identified policy shock from this baseline VAR in the first column. It shows the median response and a 68% posterior band. In this specification, an identified policy shock raises the FFR by 32bp, which lowers the level of GDP and inflation by 32bp and 60bp, respectively. While inflation returns to its pre-shock level over the projection horizon, it appears that the level of GDP does not, although this is far from a robust conclusion given the width of the uncertainty region. However, this provides tentative support for the notion that monetary policy shocks can have highly persistent, even permanent effects, as argued by Jorda et al. (2020).

In the next step, we add the frequency components to the baseline VAR model. We consider two alternative specifications. First, we add the seven frequency bands, D_1-D_6 and S_6, of each variable included in the VAR one by one. This results in a six-variable VAR, three aggregate variables and a respective wavelet component for each, estimated separately

[9]We used a longer sample in the earlier working paper version Lubik et al. (2019) and found qualitatively similar results. We focus here on the shorter sample since it presents one stable monetary regime.

for each band. Importantly, we identify the policy shock only from the aggregate series and do not separately impose any restriction on the behavior of the wavelet components. We report selected impulse responses in Figure 1 where columns 2, 3, and 4 show the impulse responses for the D_2, D_4, and S_6 components from separately estimated VARs.

The first specification in Figure 1 for the high-frequency component D_2 shows that the respective responses to the policy shock are in line with the aggregate results and go in the direction that we would expect from economic theory. That is, a monetary contraction reduces the short-term components of GDP and inflation. Notably, all responses return to their pre-shock levels over the projection horizon. However, the responses are economically small and zero is within the error bands. To some extent, this is an artifact of the sample size, the number of variables in the VAR, and the use of sign restrictions for identification.

The responses of the business-cycle components D_4 in Figure 1 are quantitatively small, with error bands that include zero for any of the three variables on impact and also further out, although the confidence regions shrinks. While the direction of the responses is consistent with the identification scheme imposed on the overall series, lack of statistical and economic significance suggests that policy shocks do not induce substantial, if any, behavior of GDP, inflation and the federal funds rate at business-cycle frequencies.[10]

Finally, we report the impulse responses for the specification with the long-term components S_6 in the last columns of Figure 1. Overall, as might be expected, the responses are drawn out and not significant over the business cycle horizon. Specifically, the long run responses to a policy shock are negative in case of the federal funds rate and inflation, albeit small, as it is for level GDP. That is, contractionary policy not only has a small negative effect on GDP at higher frequencies, but also a considerably stronger effect on the trend component. While not conclusive, this finding provides support for the idea that monetary policy shocks can have long-lasting, even permanent effects.[11]

Another observation that we can draw from this exercise is that the federal funds rate and inflation comove positively over the response horizon, in contrast to the specifications in the panels to the left.[12] In other words, at longer horizons and cycles, the Fisher effect, namely that interest rates and inflation rates are positively correlated, is apparent from the

[10] In the working paper Lubik et al. (2019), we report results for the same exercise but with real GDP growth. Responses are quite similar to the point that policy shocks appear to have no effect at business cycle frequencies

[11] This finding is consistent with the recent evidence provided by Jorda et al., 2020, using a different methodology with a different identification strategy

[12] Note that the error bands for both variables do not include 0 for the longest horizons we consider in these graphs.

impulse responses, conditional on the monetary policy shock. At higher frequencies, this correlation moves in the opposite direction as the demand-constricting effect of higher rates reduces inflation. It appears obvious from these findings that in the transition between high-frequency and low-frequency movements the comovement patterns for these two variables switch.

In the second VAR specification considered, we add the filtered series in groups that represent broader frequency bands. Since the wavelet decomposition is fully additive we cannot include all individual series. Therefore, we focus on a specification that looks at the business-cycle components ($D_3 + D_4$), the medium-term cycles ($D_5 + D_6$), and the long term (S_6). This results in a twelve-variable VAR, where we identify the policy shock by imposing sign restrictions on impact on the aggregate variables only, that is, the response of the wavelet components is entirely unrestricted.

We report the resulting impulse responses in Figure 2. The first column contains the aggregate responses, followed by the short-term, medium-term, and long-term components in separate columns. Results are generally similar to those obtained using the first specification. Since we use many more variables jointly in this VAR, the error bands tend to be wider than in the previous specification. A contractionary monetary policy shock has a negative impact on real activity in each frequency band with the possible exception of the medium term. The responses of the business-cycle and medium-term components return to zero relatively quickly. The median response of the long-term component on the other hand remains negative over the full horizon of 10 years. This again indicates that monetary policy shocks can have long-lasting effects on real GDP.[13]

The behavior of the business-cycle and medium-term components in response to the contractionary policy shock is similar, with the latter being more drawn out. The policy shock raises the FFR and lowers inflation on impact , with both returning to their long-run levels. As in the exercise with individual decompositions, we find evidence of the presence of a Fisher effect in the long term. Conditional on a policy shock, both inflation and the FFR turn persistently negative and comove positively. This is not the case at business-cycle frequencies, and also, but a lesser extent over the medium run. It seems clear from this exercise that a monetary policy shock induces behavior that is different across frequency bands for inflation and the FFR. We return to this issue when we confront the empirical findings with a DSGE model.

[13] In the working paper version Lubik et al. (2019), we find a similar pattern for the unemployment rate, with oscillating behavior of the higher-frequency components and a more drawn out response of the trend.

3.2 Robustness

We now assess whether the findings from the baseline VAR are robust to alternative identification schemes. The literature has developed a variety of approaches for teasing out independent monetary policy shocks. Our benchmark specification relies on sign restrictions that directly impose behavior derived from theoretical considerations on the impact of the policy shock. This often comes at the price of imprecise inference and large confidence regions as the algorithm that implements the identification assumption generally has to rule out a large number of potential candidate identifications. At the same time, other approaches such as the Romer and Romer shocks used in conjunction with local projections (e.g. Jorda et al, 2020) rely on strong exogeneity assumptions as well as auxiliary assumptions (such as the specific form of the regression in Romer and Romer, 2004), while recursive schemes, such as the standard Cholesky decomposition, lead to implausible behavior in some of the responses, such as the price puzzle.

In our robustness analysis, we deviate from our baseline identification in two directions. First, we identify monetary policy shocks not from the FFR series but use instead the series constructed by Romer and Romer (2004), which is based on quantitative and narrative evidence. Second, we use a recursive identification scheme inspired by Bu et al. (2020). In this specification, we include additional variables, namely FOMC Greenbook forecasts, a commodity price index, the Romer and Romer series, in addition to the other variables already present in our benchmark specification. We then identify a monetary policy shock as the shock associated with the Romer and Romer series in a recursive identification scheme.

Plagborg-Moller and Wolf (2020) show that this identification scheme is asymptotically equivalent (as the number of lags goes to infinity) to using local projections with the Romer and Romer shock as a measure of the monetary policy shock. As highlighted by Bu et al. (2020), using such a local projection approach can lead to implausible results, however. We therefore implement their specification and control for one- and two-quarter-ahead Greenbook forecasts of CPI inflation and GDP growth by ordering them ahead of the Romer and Romer shock in the VAR. We also control for commodity price inflation as is commonly done in standard recursive identification schemes for monetary policy shocks.

We report selected estimated impulse responses to a such identified monetary policy shock in Figures 3 and 4. These parallel the figures reported for the baseline identification. Figure 3 shows the responses for the aggregate series in the left column.[14] A contractionary

[14]As discussed before, we identify the policy shock from the series constructed by Romer and Romer (2004). The response of the FFR is therefore not to its own innovation but to the identified shock

policy shock raises the FFR and lowers the level of GDP significantly and for a prolonged period. The price puzzle is still apparent on impact, but inflation quickly reverts course and declines below its pre-shock level.

Next, we add the wavelet components for the FFR, the level of GDP, and the inflation rate to the robustness specification individually, that is, one set for each frequency band. In Figure 3 we report the responses of the decomposition for the three variables by their frequency band D_2, D_4 and S_6. For the high-frequency component D_2, the responses are quantitatively similar, in that a contractionary policy shock raises the federal funds rate, lowers GDP on impact, with the price puzzle still present. The responses are quantitatively small, however, and insignificant beginning from a few periods out. The third column in Figure 3 shows the responses of the business cycle components D_4. The responses are qualitatively consistent with the baseline, with the exception of inflation, where the price puzzle is present. The responses of the long-term component S_6 in the last column of Figure 3 show the same qualitative response as those in Figure 1, whereby the persistent effects of the shocks and the presence of the Fisher effect are clearly visible.

Finally, we report the impulse responses for the grouped decompositions added jointly in the VAR in Figure 4. Results are again broadly similar to the first specification (where the various frequency-specific variables enter different VARs), but also very similar to the baseline responses in Figure 2. Notably, there is again evidence for the presence of a Fisher effect in inflation and the FFR.

We can therefore conclude that an identified monetary policy shock in a structural VAR has robust effects on impulse response functions for key aggregate variables. In the short term, at business cycle frequencies, and over the medium run, a contractionary policy shock lowers the respective wavelet components of GDP, of inflation (subject to the presence of the price puzzle in some identification schemes) and increases the FFR components. Over the long term, monetary policy shocks have highly persistent, even permanent effects on these components. This effect is not necessarily visible in the aggregate data since it it co-mingled with the movements at other frequency bands, but it is discernible in the scale component S_6. This finding thus provides new evidence for the long-term effects of monetary policy, whereby wavelet methodology is a central component.

4 Assessing DSGE Models in the Time-Frequency Domain

We now investigate whether a marquee DSGE model can replicate the behavior identified in the previous sections, both in terms of the unconditional variance decomposition and the impulse responses to a monetary shock. DSGE models are widely used in the analysis of monetary policy, both by academic researchers and policymakers. Such models are intended to replicate aggregate economic behavior over the business cycle and over the long run.[15] This naturally raises the question whether they can, in fact, capture behavior along all frequency bands identified by our wavelet decomposition, or more specifically, the behavior conditional on identified monetary policy shocks.

In a preview of the results, we find that the DSGE model can generally replicate the behavior at business-cycle frequencies and in the long term as these are frequency bands which the model *is* designed to capture.[16] We show that including stochastic trends in inflation is central for the latter, while various adjustment costs are key to the former. However, the model generally does not do as well in capturing behavior at medium-term frequencies. In addition, the model captures the responses of nominal variables to an identified policy shock to a remarkable degree, but struggles with replicating the conditional behavior of GDP, especially over the medium and the long run. In addition, the model fails to capture the Fisher effect.

We focus our analysis on the model developed by Del Negro et al. (2015) as an extension of the canonical Smets and Wouters (2007) model. The model is a prototypical large-scale, optimization-based model designed to jointly capture the evolution of output, inflation and the monetary policy process. To this end, the model contains a variety of shocks and frictions that are central to understanding aggregate fluctuations. The basic setup involves a representative household that makes consumption choices and supplies labor to a competitive labor market. On the production side there are monopolistically competitive firms that employ labor and capital to generate output, make investment decisions and set prices. The third type of agent in this model is a policymaker, who sets interest rates based on a given

[15] This is, of course, well understood in the DSGE literature. See, for instance, the programmatic papers by Christiano et al. (2005) and Christiano et al. (2010), but also the seminal DSGE models by Smets and Wouters (2003, 2007). Modeling devices such as habits in consumption, investment adjustment costs, and highly persistent shock processes are useful in matching persistence in the data. At the same time, stochastic trends have proved to be a flexible modeling component to capture drifting behavior over time. We focus on whether these modeling elements are useful across all frequencies and specifically conditional on a monetary policy shock.

[16] Our findings are in line with recent research that shows that DSGE models perform well within both the time and frequency domain, for instance, Tkachenko and Qu (2012), Sala (2015), Caraiani (2015), or Gallegati et al. (2019).

feedback rule.

The model features nominal price stickiness and sticky wages with backward inflation indexation to capture slow-moving aspects of these variables. On the real side, there is habit formation in consumption and investment adjustment costs designed to create hump-shaped responses of these aggregate demand components. The model is driven by seven structural shocks including a monetary policy disturbance. Moreover, it includes a time-varying target inflation rate and incorporates financial frictions in the vein of Christiano et al. (2014). Del Negro et al. (2015) demonstrates that the model is compatible with Great Recession outcomes in that it successfully predicts a sharp contraction in economic activity along with a drawn-out but modest decline in inflation.

Our quantitative procedure is as follows. The DSGE model is estimated using Bayesian methods with data from 1964Q1-2015Q3. We take the posterior median estimates and simulate the model 10,000 periods, but keep only the same number of observations that is used in the estimation. This is repeated 100 times. We then compute wavelet decompositions in the same manner as described in section 2. For exposition, we group the individual decompositions into the categories 'Short Term' (D_1-D_2), 'Business Cycle' (D_3-D_4), 'Medium Term' (D_5-D_6), and 'Long Term' (S_6). As a first check on model performance and the importance of individual components we report the variance decomposition in Table 2.[17]

Overall, the full benchmark version of del Negro et al. (2015) does remarkably well in matching frequency-specific fluctuations that we identified in the data. Generally speaking, the volatility of real GDP growth and inflation at business cycle frequencies, but also in the long term are on the mark, while the model overpredicts fluctuations in the FFR over the business cycle and underpredicts long-term behavior. Where the model misses is in the medium-term frequencies relative to the data, although the discrepancies are arguably not large.[18]

Table 2 also reports variance decompositions for selected versions of the model, where we shut down one feature at a time from the benchmark model. The differences between the various specifications are not that large overall, but the analysis shows that several modeling elements are clearly necessary for matching specific aspects of the data. For instance, habits in consumption, financial frictions, and investment adjustment costs are important for matching GDP growth numbers across several frequency bands. Capital

[17]For the full list of specifications, see the online appendix. We report only a subset in Table 2.

[18]The extended working paper version Lubik et al. (2019) reports simulation results for a wider range of DSGE models from the literature. Similar patterns appear, namely that the models can capture business cycle and trend behavior, but fall short at medium-term frequencies

utilization costs, on the other hand, do not seem to matter. The behavior of inflation and the FFR are impacted less when shutting down these channels.

Fluctuations in nominal variables, on the other hand, are very much influenced by the behavior of monetary policy. In fact, a time-varying inflation target is crucial to get the inflation and FFR numbers in the long term correct. In other words, the trend component in nominal variables is a product of an exogenous component in the policy rule, which raises questions what the role of policy in DSGE models is. We can derive some additional insight by changing coefficients in the policy rule. Setting the response coefficients for real variables in the rule to zero makes inflation and the policy rate more volatile as does the move to a more aggressive policy focused on inflation only.

We now turn to our main exercise. We simulate 100 datasets of the same length used for our estimation from 14 different versions of the del Negro et al. (2015) model. Given a wavelet decomposition from each dataset, we estimate structural VARs as in section 3. We then compute impulse response functions to an identified monetary policy shock. In the following figures, we show the responses from the actual data (with error bands as shaded regions) and the average median responses across the 100 simulated datasets from each version of the DSGE model. The impulse responses are normalized so that on impact the nominal interest rate response from the DSGE model coincides with the median response in the actual data.

Figure 5 contains the key finding. The baseline specification of the DSGE model performs perform remarkably well in terms of the nominal variables in response to a policy shock, especially for the aggregate series and at higher frequencies, but to a lesser degree for the long-term component. In a sense, this parallels the findings from the variance decomposition above in that the long-term behavior is determined by exogenous trend inflation, whereas the S_6 component in the VAR is an endogenous variable that is allowed to change in response to an innovation. This presents a challenge for nominal DSGE models to capture trend inflation without relying on exogenous behavior. More pithily, explaining the inflation process through an exogenous process is not explaining it all.

At the same time, the model tends to miss the responses for the level of GDP across all frequency bands, perhaps with the exception of the short-term component. This is especially notable for the aggregate response and the business-cycle component D_4, which revert too quickly after the contractionary shock or show exaggerated hump-shaped behavior. In addition the response of the long-run component is far too optimistic. We can find a similar pattern in Figure 6, where we group the individual wavelet components into frequency bands. Specifically, the DSGE model does extremely well for the aggregate FFR and inflation series as well as their components. However, the behavior of level GDP does not line up with the VAR evidence across essentially all frequency bands.

One model version that does not have this problem is the specification with higher interest rate smoothing. In general, changing the monetary policy rule, either by increasing the degree of interest rate smoothing or focusing on the inflation response only, helps align the GDP responses. Figure 7 demonstrates that a more aggressive policy stance in terms of higher interest smoothing can replicate the behavior of GDP in the DSGE model conditional on a monetary policy shock, without hurting the performance of the other variables much. Removing features such as financial frictions, habits, investment adjustment costs, capital utilization costs, and price indexation does not help as much. This aspect highlights tension between matching the behavior of a variable conditional on a shock, for instance, the identified monetary policy shock in our setting, and capturing the overall behavior of a model when multiple sources of variation are present.

Finally, we observe across all variants of the DSGE model that the long-run behavior of inflation and the FFR are not consistent with the Fisher effect. The respective components either comove negatively, see Figure 5 and 6 for the baseline specification of the DSGE model; or they mildly comove, but the responses are insignificant. On the other hand, at higher frequencies the differential response of inflation and the FFR are present across any specification. This leaves us to conclude that the New Keynesian framework inherent to del Negro et al. (2015) is designed to capture this behavior via, for instance, nominal rigidities, but that it does not impose strong restriction to enforce the long-run behavior. This finding is consistent with the observation in Uribe (2018), which presents a challenge to DSGE modeling of this stylized fact.

What we can conclude from this is that the model is reasonably successful when it comes to reduced-form statistics, but less so when it comes to impulse responses across frequencies. More specifically, the model variants that change the policy rule coefficient generally do worse than the benchmark model when it comes to the reduced form statistics. This point highlights a tension between fit in terms of first and second moments (as the DSGE model is linearized and the shocks are assumed to be Gaussian) and conclusions about the effects of structural shocks.

5 Conclusion

This paper offers two main findings. First, we show in a structural VAR that monetary policy shocks have similar effects across all frequency bands computed from a wavelet decomposition of aggregate time series. Contractionary policy leads to a decline in the business-cycle component of GDP, but it also has negative effects over the medium term and in the longer run. This finding is relevant for the conduct of monetary policymakers as stabilization policy may have undesirable effects on the behavior of macroeconomic variables at different frequencies. An exception to this pattern is the relationship between short-term interest rates and inflation. In response to policy shocks the short-term components of these variables move in opposite directions as standard macroeconomic models would predict. In the long run, however, the Fisher effect prevails, namely positive comovement.

The second finding shows that a standard DSGE model with many of the modeling features, which are relevant in capturing policy trade-offs and achieving good fit in estimation, can replicate behavior at business-cycle frequencies that we identified in the data. However, the model needs to include stochastic trends or time-varying inflation targets to account for long-term behavior in inflation or GDP. It is less well adapted in capturing behavior at medium-term cycles of between 8 and 32 years. In addition, the model struggles with replicating the movements of GDP across several frequency bands conditional on a policy shock. This can be remedied by adapting monetary policy behavior, but comes at the cost of overall worse fit.

Our paper contributes to a growing area of research that suggests that the notion of a cycle relevant for stabilization policy should be extended to include at least the medium term. Specifically, our analysis indicates that temporary shocks can have long-lasting effects, both in the medium term but especially over the longer run, an aspect that traditional business cycle modelling largely abstracts from. Future work could therefore study time-frequency decompositions in models with such a transmission mechanism as in, for instance, Comin and Gertler (2006).

These findings also suggest an alternative approach to monetary policy. Typical analyses of optimal monetary policy focus on weighted averages of the unconditional variances of policy targets. It is common to compare policies by considering, for example, a weighted average of the unconditional variances of inflation and the output gap. However, such computations mask the effects of policies on the variance of fluctuations at different frequencies. Frequency-based optimal policy in the vein of Brock et al. (2013) would thus be an interesting extension based on the analysis in this paper.

Finally, our paper raises questions as to how the monetary transmission mechanism is modelled in standard macroeconomic framework. We find a disconnect between the conditional comovement of inflation and short-term interest rates at high frequency and at low frequencies. At some medium-term time frame the Fisher effect overcomes the price-constricting effect of interest rate increases, which typical New Keynesian models have difficulty matching as shown by Uribe (2018).[19] Linking the short run to the long run in a manner that captures both, but is also consistent with this transition in the medium-term frequency band is a key challenge for future research.

[19]In his model, a regular monetary policy shock has the same effects as in our DSGE framework. In order to produce the Fisher effect, a second shock needs to be introduced.

References

[1] Ahmed, Shaghil, Andrew Levin, and Beth Anee Wilson (2004): "Recent U.S. Macroeconomic Stability: Good Policies, Good Practices, or Good Luck?". *The Review of Economics and Statistics,*, 86(3), pp. 824-832.

[2] Aguiar-Conraria, Luis, Manuel M.F. Martins, and Maria Joana Soares (2018): "Estimating the Taylor rule in the Time-Frequency Domain". *Journal of Macroeconomics*, 57, pp. 122-137.

[3] Aguiar-Conraria, Luis, Manuel M.F. Martins, and Maria Joana Soares (2020): "Okun's Law Across Time and Frequencies". Forthcoming, *Journal of Economic Dynamics and Control*.

[4] Arias, Jonas E., Juan F. Rubio-Ramirez, and Daniel F. Waggoner (2018): "Inference Based on Structural Vector Autoregressions Identified With Sign and Zero Restrictions: Theory and Applications". *Econometrica*, vol. 86(2), pp. 685-720.

[5] Baxter, Marianne, and Robert G. King (1999): "Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series". *The Review of Economics and Statistics*, 81(4), pp. 575-593.

[6] Beaudry, Paul, Dana Galizia, and Franck Portier (2017): "Putting the Cycle Back into Business Cycle Analysis". *American Economic Review*, 110(1), pp. 1-47.

[7] Beveridge, Stephen, and Charles R. Nelson (1981): "A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the 'Business Cycle' ". *Journal of Monetary Economics*, 7(2), pp. 151-174.

[8] Blanchard, Olivier J. (1997): "The Medium Run". *Brookings Papers on Economic Activity*, 2, pp. 89-158.

[9] Brock, William A., James Nason, and Giacomo Rondina (2007): "Simple versus Optimal Rules as Guides to Policy". *Journal of Monetary Economics*, 54(5), pp. 1372-1396.

[10] Brock, William A., Steven N. Durlauf, and Giacomo Rondina (2013): "Design Limits and Dynamic Policy Analysis". *Journal of Economic Dynamics and Control*, 37, pp. 2710-2728.

[11] Bu, Chunya, John H. Rogers, and Wenbin Wu (2020): "Forward-Looking Monetary Policy and the Transmission of Conventional Monetary Policy Shocks". Finance and Economics Discussion Series 2020-014. Washington: Board of Governors of the Federal Reserve System.

[12] Cao, Dan, and Jean-Paul L'Huillier (2018): "Technological Revolutions and the Three Great Slumps: A Medium-run Analysis". *Journal of Monetary Economics*, 96, pp. 93-108.

[13] Caraiani, Petre (2015): "Estimating DSGE Models Across Time and Frequency". *Journal of Macroeconomics*, 44, pp. 33-49.

[14] Christiano, Lawrence J., and Terry J. Fitzgerald (2003): "The Band Pass Filter". *International Economic Review*, 44(2), pp. 435-465.

[15] Christiano, Lawrence J., Martin S. Eichenbaum, and Charles L. Evans (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy". *Journal of Political Economy*, 113(1), pp. 1-45.

[16] Christiano, Lawrence J., Mathias Trabandt, and Karl Walentin (2010): "DSGE Models for Monetary Policy Analysis". In: Benjamin M. Friedman and Michael Woodford (eds.): *Handbook of Monetary Economics*, Volume 3a, Chapter 7, pp. 285-367.

[17] Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno (2014): "Risk Shocks". *American Economic Review*, 104(1), pp. 27-65.

[18] Cogley, Timothy (2001): "Estimating and Testing Rational Expectations Models When the Trend Specification is Uncertain". *Journal of Economic Dynamics and Control*, 25, pp. 1485-1525.

[19] Comin, Diego, and Mark Gertler (2006): "Medium-Term Business Cycles". *American Economic Review*, 96(3), pp. 523-551.

[20] Crowley, Patrick M. (2007): "A Guide to Wavelets for Economists".*Journal of Economic Surveys*, 21(2), pp. 207-267.

[21] Del Negro, Marco, Marc P. Giannoni, and Frank Schorfheide (2015): "Inflation in the Great Recession and New Keynesian Models". *American Economic Journal: Macroeconomics*, 7(1), pp. 168-96.

[22] Gallegati, Marco, Federico Giri, and Antonio Pelestrini (2019): "DSGE Model with Financial Frictions over Subsets of Business Cycle Frequencies". *Journal of Economic Dynamics and Control*, 100, pp. 152-163.

[23] Hodrick, Robert, and Edward C. Prescott (1997): "Postwar U.S. Business Cycles: An Empirical Investigation". *Journal of Money, Credit, and Banking*, 29(1), pp. 1-16.

[24] Jorda, Oscar, Sanjay R. Singh, and Alan M. Taylor (2020): "The Long Run Effects of Monetary Policy". NBER Working Paper 26666.

[25] Lubik, Thomas A., Christian Matthes, and Fabio Verona (2019): "Assessing U.S. Aggregate Fluctuations Across Time and Frequencies". Federal Reserve Bank of Richmond Working Paper No. 19-06.

[26] Onatski, Alexei, and Noah Williams (2003): "Modeling Model Uncertainty". *Journal of the European Economic Association*, 1(5), pp. 1087-1122.

[27] Pancrazi, Roberto (2015): "The Heterogeneous Great Moderation". *European Economic Review*, 74(C), pp. 207-228.

[28] Plagborg-Moller, Mikkel, and Christian K. Wolf (2020): "Local Projections and VARs Estimate the Same Impulse Responses".

[29] Romer, Christina D., and David H. Romer (2004): "A New Measure of Monetary Shocks: Derivation and Implication". *American Economic Review*, 94(4), pp. 1055-1084.

[30] Rua, Antonio (2010): "Measuring Comovement in the Time-Frequency Space".*Journal of Macroeconomics*, 32(2), pp. 685-691.

[31] Rubio-Ramírez, Juan F., Daniel F. Waggoner, and Tao Zha (2010): "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference". *Review of Economic Studies*, 77(2), pp. 665-696.

[32] Sala, Luca (2015): "DSGE Models in the Frequency Domain". *Journal of Applied Econometrics*, 30, pp. 219-240.

[33] Smets, Frank, and Raf Wouters (2003): "An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area". *Journal of the European Economic Association*, 1(5), pp. 1123-1175.

[34] Smets, Frank, and Raf Wouters (2007): "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach". *American Economic Review*, 97(3), pp. 586-606.

[35] Tkachenko, Denis, and Zhongjun Qu (2012): "Frequency Domain Analysis of Medium Scale DSGE Models with Application to Smets and Wouters (2007)". *Advances in Econometrics : DSGE Models in Macroeconomics – Estimation, Evaluation and New Developments*, Volume 28, pp. 319-385.

[36] Uribe, Martin (2018): "The Neo-Fisher Effect: Econometric Evidence from Empirical and Optimizing Models". NBER Working Paper 25089.

[37] Watson, Mark W. (1986): "Univariate Detrending Methods with Stochastic Trends". *Journal of Monetary Economics*, 18, pp. 49-75.

[38] Watson, Mark W. (1993): "Measures of Fit for Calibrated Models". *Journal of Political Economy*, 101(6), pp. 1011-1041.

[39] Yogo, Motohiro (2008): "Measuring Business Cycles: A Wavelet Analysis of Economic Series". *Economics Letters*, 100(2), pp. 2008-2012.

Table 1: Variance Decomposition across Frequencies for US Data

Periods (years)	0.5-1y	1-2y	2-4y	4-8y	8-16y	16-32y	>32y
Periods (quarters)	2-4q	4-8q	8-16q	16-32q	32-64q	64-128q	>128q
Label	D1	D2	D3	D4	D5	D6	S6
Description	Short run		Business cycle		Medium run		Long run
Inflation	8.5	7.7	8.1	10.4	10.2	16.3	38.8
Fed funds rate	1.6	3.1	6.3	11.6	11.8	13.1	52.5
log(real GDP per capita)	0.0	0.1	0.2	0.6	1.9	6.0	91.1
real GDP per capita growth rate (qoq)	34.2	21.0	17.8	13.8	7.1	3.0	3.2

Table 2: Variance Decomposition: Data vs. Models

	Short Term	Business Cycle	Medium Term	Long Term
Log Per Capita Real GDP				
Data	0	1	8	91
Benchmark	0	2	12	87
Fixed Inflation Target	0	2	11	87
Higher Interest Rate Smoothing	0	1	11	88
Inflation				
Data	16	18	26	39
Benchmark	17	18	23	43
Fixed Inflation Target	32	28	22	18
Higher Interest Rate Smoothing	11	14	28	47
Federal Funds Rate				
Data	5	18	25	53
Benchmark	8	24	35	32
Fixed Inflation Target	11	31	41	17
Higher Interest Rate Smoothing	4	15	35	46
Per-Capita Real GDP Growth Rate				
Data	55	32	10	3
Benchmark	47	31	18	4
Fixed Inflation Target	48	31	18	3
Higher Interest Rate Smoothing	54	31	12	3

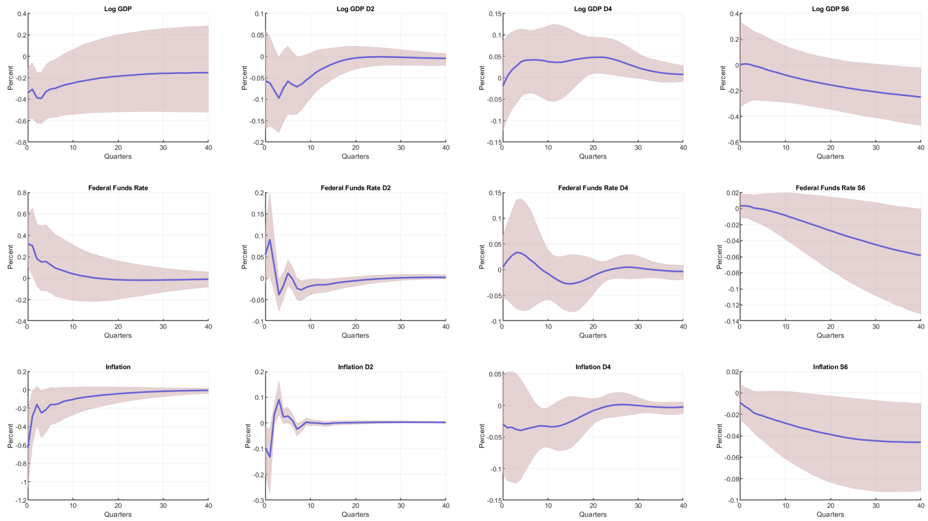

Figure 1: Results with sign restrictions, one frequency band at a time. 68 percent posterior bands are in red, posterior median in blue.

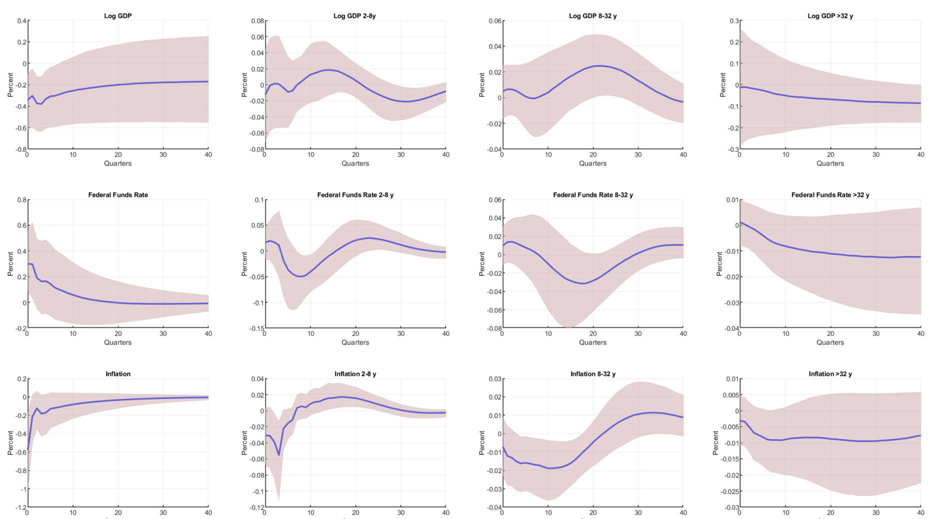

Figure 2: Results with sign restrictions, multiple frequency bands in the same VAR. 68 percent posterior bands are in red, posterior median in blue.

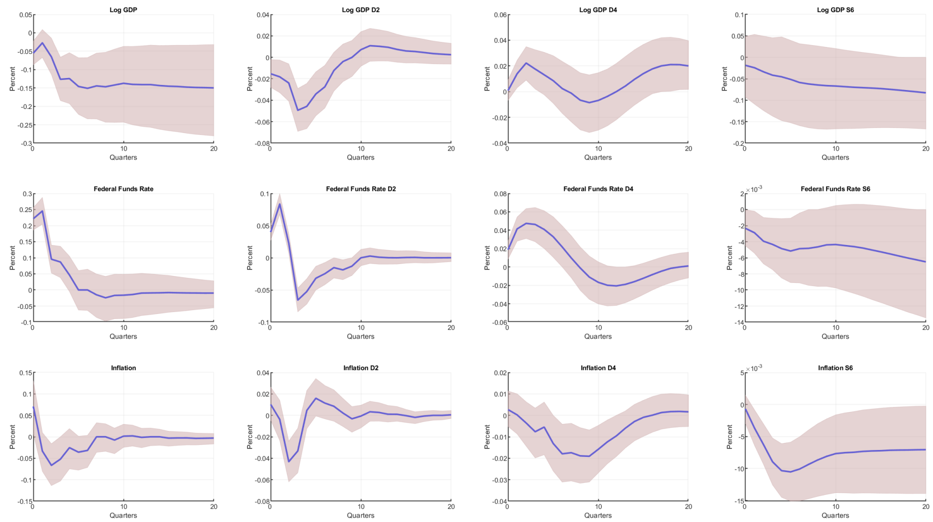

Figure 3: Results, one frequency band at a time. Romer & Romer robustness check. 68 percent posterior bands are in red, posterior median in blue.

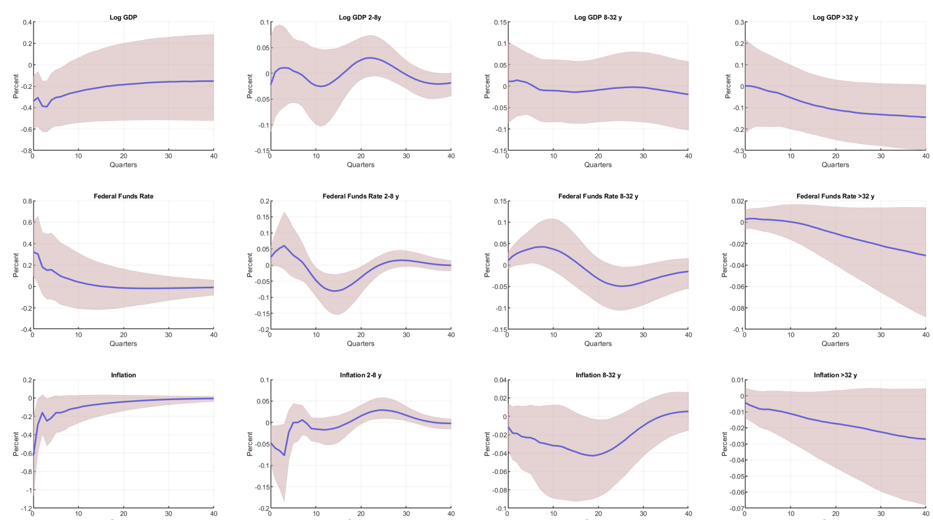

Figure 4: Results, multiple frequency bands in the same VAR. Romer & Romer robustness check. 68 percent posterior bands are in red, posterior median in blue.

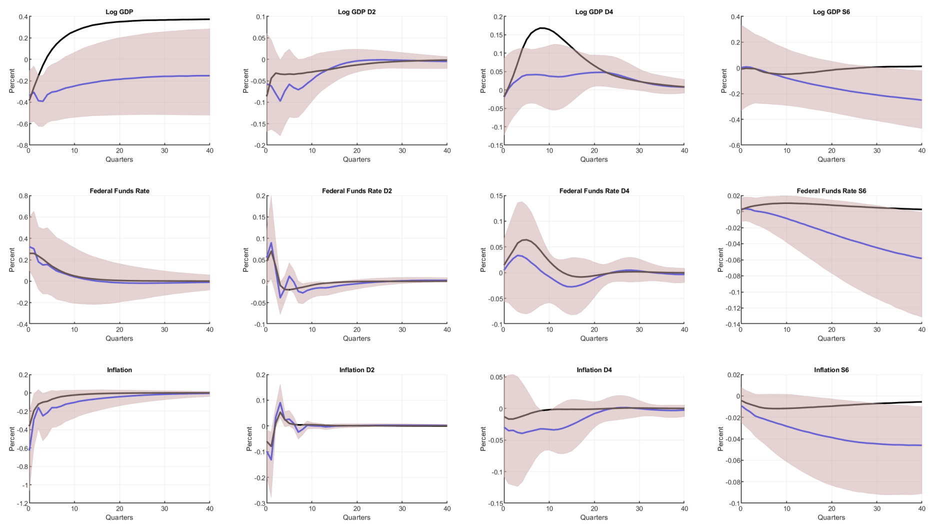

Figure 5: Results with sign restrictions, one frequency band at a time. Baseline DSGE model and data. 68 percent posterior bands are in red, posterior median in blue.

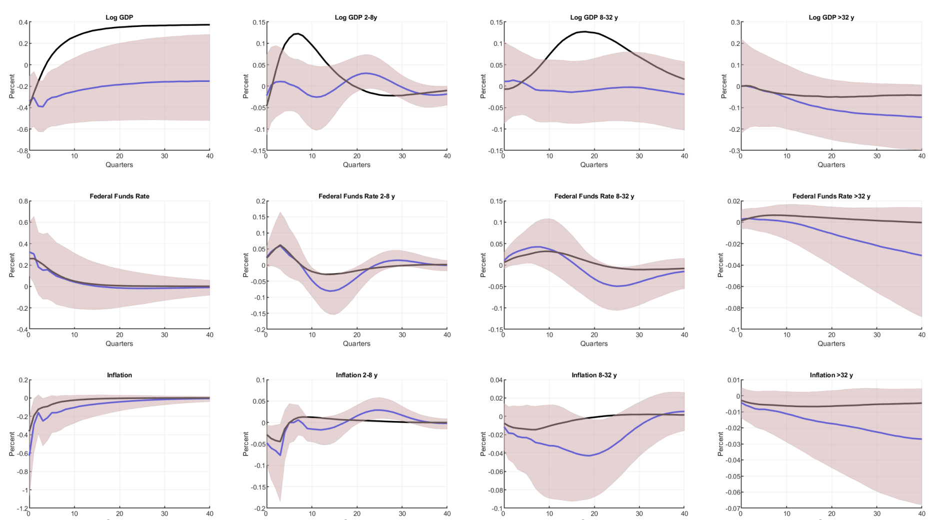

Figure 6: Results with sign restrictions, multiple frequency bands in the same VAR. Baseline DSGE model and data. 68 percent posterior bands are in red, posterior median in blue.

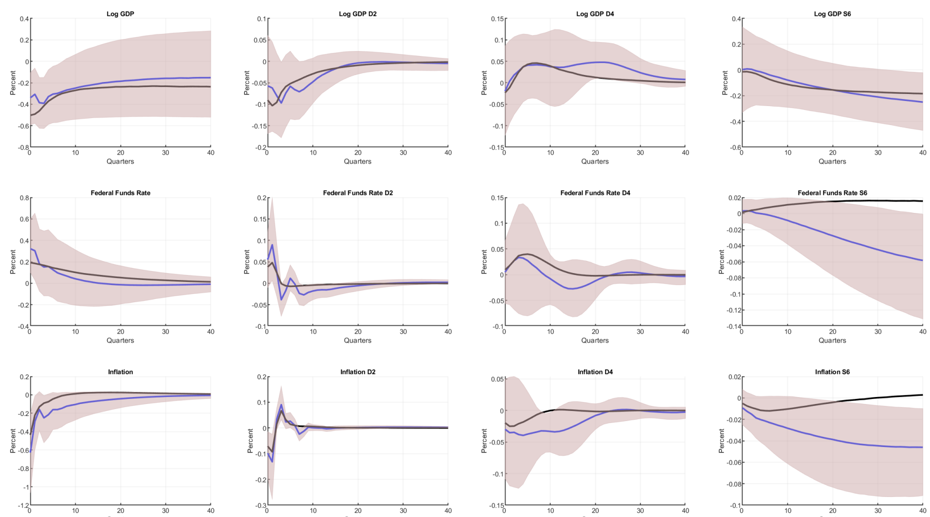

Figure 7: Results with sign restrictions, one frequency band at a time. DSGE model with more interest rate-smoothing in Taylor rule and data. 68 percent posterior bands are in red, posterior median in blue.