ESSAYS ON THE ASYMMETRIC EFFECTS OF MONETARY POLICY

by

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A DISSERTATION

Presented to the Department of Economics
and the Division of Graduate Studies of the University of Oregon
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy

June 2021

DISSERTATION APPROVAL PAGE

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Title: Essays on the Asymmetric Effects of Monetary Policy

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Degree awarded June 2021

DISSERTATION ABSTRACT

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Doctor of Philosophy

Department of Economics

June 2021

Title: Essays on the Asymmetric Effects of Monetary Policy

The asymmetric effects of monetary policy is the idea that monetary policy actions have asymmetric effects on output and inflation across different states of the world or across different characteristics of the monetary policy action. In the existing literature, there are three types of asymmetry discussed. Monetary policy actions can have different effects depending on the direction of the action, the size of the action, and the phase of the business cycle that the action took place in. This is a topic that is of interest to policy makers around the world as they try to assess the impacts that their proposed policies will have on output and inflation.

The asymmetric effects of monetary policy across the three dimensions listed above is the dominant theme of my dissertation. In Chapter 2, I study the asymmetric effects of monetary policy on output over the business cycle using a local projections model. In Chapter 3, I expand the model to include all three types of asymmetry. In Chapter 4, I use a simulation-based study to determine whether the differences specification or the levels specification with a time trend is the correct specification to run in the local projections models from Chapter 2 and Chapter 3.

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ACKNOWLEDGMENTS

I thank Professors Evans, Evans, and Wu for their guidance throughout the preparation of this manuscript. Special thanks are due to Professor Jeremy Piger, whose vision and mentorship was invaluable during my time here at the University of Oregon. I also thank Professor Abdullah Dewan for motivating me to pursue my Ph.D. in the first place.

To Kelly and Adeline

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CHAPTER I

INTRODUCTION

The asymmetric effects of monetary policy is the idea that monetary policy actions have asymmetric effects on output and inflation across different states of the world or across different characteristics of the monetary policy action. In the existing literature, there are three types of asymmetry discussed. Monetary policy actions can have different effects depending on the direction of the action, the size of the action, and the phase of the business cycle that the action took place in. This is a topic that is of interest to policy makers around the world as they try to assess the impacts that their proposed policies will have on output and inflation.

The asymmetric effects of monetary policy across the three dimensions listed above is the dominant theme of my dissertation. In Chapter II, I study the asymmetric effects of monetary policy on output over the business cycle. In doing so, I help reconcile an existing literature that documents conflicting evidence on asymmetry related to the business cycle. In Chapter III, I expand my model to include all three types of asymmetry in the same model. This allows me to drop the restrictive assumption inherent in any model with only one type of asymmetry that the differential effects of one type of asymmetry on output are not being driven by the other two types of asymmetry. In Chapter IV, I take the local projection model used in Chapter II and Chapter III and use a simulation-based study to determine if the differences specification or the levels specification with a time trend is the correct specification to run.

Chapter II investigates whether there are significant differences in the response of US output to monetary policy in expansions and recessions. While much of the existing literature has found that monetary policy is more effective in recessions, a recent influential paper, Tenreyro and Thwaites (2016), that found the opposite has left the literature with a lack of consensus. A contribution of this influential paper was their use of local projections to calculate impulse response functions. Developed in Jordá (2005), local projections are an attractive way to estimate impulse responses since they directly estimate impulse responses over future horizons rather than having to rely on extrapolation of short-run dynamics as in a VAR model. They are also simple to estimate, more robust to misspecification than VAR models,and can more easily accommodate non-linear specifications in multivariate specifications than VAR models. I follow Tenreyro and Thwaites (2016) in their use of local projections to study the asymmetric effects of output over the business cycle.

The results of my baseline model agree with the result that monetary policy is more effective in expansions. I explore the robustness of this result across three dimensions. I find that this result is not robust to the frequency of data and measure of output used, the way that stochastic trends in the data are handled, and outliers in the monetary policy shock measure. When all three of these specifications are considered simultaneously, I find that monetary policy is more effective in recessions.

Inside of any model with only one type of asymmetry is an assumption that the results are not being driven by the other two types of asymmetry. By including all three types of asymmetry, this assumption can be dropped. Chapter III drops this assumption and investigates whether the response of U.S. output to a monetary policy shock is symmetric over all three dimensions simultaneously. Theory suggests that looking at individual asymmetries may not tell the whole story and that interactions between the asymmetries may be important. Therefore, my local projection model includes interactions between the three types of asymmetry in the model.

My results in Chapter III show that business cycle and directional asymmetry are important while the size of the shock is not. In addition, the directional asymmetry results are being driven by monetary policy stimulus in recession having little effect on output. In addition, the impulse responses generated from this local projection model show that monetary policy stimulus has a small negative effect on output during recessions and expansions. This is a profound result as this calls into question the ability of traditional monetary policy to combat recessions. If traditional monetary policy has either no effect or a negative effect on output, then non-traditional monetary policy may have a larger role as we move into the future.

Throughout Chapter II and Chapter III, I make extensive use of local projections to calculate impulse response functions. In the empirical macroeconomics literature, there has been much discussion about the correct specification of data to use in these models. Many papers choose to run the local projections regression using levels and a time trend while other papers choose to difference the data in the regression. This is partially responsible for the differing results in the business cycle asymmetry literature as I demonstrate in Chapter II. In Chapter IV, I use a simulation based study to determine which specification should be used in a local projections model.

Simulations are run on a variety of univariate models including AR(1) models, ARMA(1,1) models, unobserved components models, and VAR models. The results suggest that no matter the level of persistence in the model, the differences specification appears to be the better option. The differences specification is less biased than the levels specification, it has a better model fit than the levels specification, and it is more likely to contain the true impulse response function inside its confidence interval. This result suggests that the differences specification is the safer option when using local projections.

CHAPTER II

THE ASYMMETRIC EFFECTS OF MONETARY POLICY OVER THE BUSINESS CYCLE

II.1 Introduction

There is substantial interest in whether the effects of monetary policy are symmetric across multiple dimensions. The literature has focused on three manifestations of asymmetry: asymmetry related to the direction of the shock, asymmetry related to the size of the shock, and asymmetry related to the phase of the business cycle. The asymmetry literature began with Cover (1992) who was interested in directional asymmetry. Since then, a large literature has explored all three types of asymmetry with varying results. This paper will contribute to the business cycle asymmetry literature by attempting to reconcile these varying results. While this literature has focused on many countries including the United States, I study asymmetry using US data.

Most papers, such as Thoma (1994), Peersman and Smets (2002), Kaufmann (2002), Garcia and Schaller (2002), and Lo and Piger (2005) find that monetary policy has a larger impact on output during recessions than expansions. However, more recent evidence from Tenreyro and Thwaites (2016) finds that the output effects of monetary policy shocks are much larger in expansions than recessions. This paper has been influential and has left the literature with a lack of consensus. Reaching a consensus in this literature is important given the reliance of many nations on monetary policy to control inflation and output. If traditional monetary policy is not very effective at impacting output during recessions then fiscal policy and non-traditional monetary policy might have more of a place moving forward. The goal of this paper is to address why the literature comes to different conclusions about monetary policy and the business cycle.

Many of the papers in the business cycle asymmetry literature use a regime switching framework. This paper will follow this methodology by allowing effects of monetary policy on output to switch between expansions and recessions. I use monetary policy shock constructed as in Romer and Romer (2004) as the measure of monetary policy. Impulse response functions are generated using the method of local projections, developed in Jordá (2005). This approach allows for ease in the generation of impulse responses in non-linear models.

My analysis finds that there are three main reasons for the discrepancies in the asymmetry literature. First, outliers have a major impact on the impulse response functions. This finding is consistent with other papers in the asymmetry literature that have pointed out the influential impact of outliers. For example, Ravn and Sola (2004) found that the asymmetry results of Cover (1992) were not robust to a large outlier in the first quarter of 1983 in the money supply equation. Thoma (1994) found that the money-income relationship was stronger over periods where real output declines, being the strongest over the periods 1969-1973 and 1978-1982. Both cases feature data points during the Volcker chairmanship of the Federal Reserve. I also find that the early years of the Volcker chairmanship are very influential in generating business cycle asymmetry in the effects of monetary policy. Specifically, measured monetary policy shocks, including the Romer and Romer (2004) shocks used in this paper, display large outliers during the 1979-1982 period. When these outliers are controlled for, monetary policy flips from being more effective in expansions to being more effective in recessions.

Second, data frequency and the measure of output has an impact on the results. Papers in the asymmetry literature favor quarterly measures of output such as GDP, although there are papers that utilize monthly measures such as industrial production as their output measure. I find that while monetary policy was more effective in expansions in the quarterly real GDP specification, when monthly industrial production is used the effects in expansions versus recessions are approximately the same. This could be due to the higher sensitivity of industrial production to interest rate changes or the differences in how recessions are defined on quarterly and monthly frameworks. Either way, asymmetry results are impacted by the frequency of data chosen.

Finally, the way that trends are modeled when specifying the local projection regression is important. Most early papers in the asymmetry literature assume a stochastic trend and use models estimating the growth rate of the response variable. More recent papers, especially those using the local projections framework for estimating impulse responses (see Tenreyro and Thwaites (2016) and Ramey and Zubairy (2018)) run variables in log level form with a deterministic trend added to the equation. I explore the results using both the log level with trend specification and growth rate specification. I find that while the expansion effect was greater than the recession effect in the log level with trend specification, this disappears when output is expressed as growth rates.

The rest of the analysis proceeds as follows: section II.2 lays out the existing literature on the subject and my contribution to this literature. Section II.3 lays out the model to be estimated. Section II.4 lays out the results of the analysis. Section II.5 concludes.

II.2 Literature Review

Monetary policy asymmetry is the idea that monetary policy may have different effects on output or prices depending on what phase of the business cycle of the economy, the size of the monetary shock, or the direction of the monetary shock. This question is important for central banks, who should be interested if policies they take during recessions can increase output or control inflation during expansions. There is a sizable literature investigating the topic of monetary policy asymmetry, with most of these papers investigating a single type of asymmetry. This paper will focus on the asymmetry of policy effects relating to the phase of the business cycle. However, the remainder of this literature review will summarize the existing literature on all three types of asymmetry.

Business cycle asymmetry can be explained by three main theories. First, models with price rigidities, specifically prices that are more rigid downward than upward can generate asymmetry relating to the direction of the shock. This manifests itself as a convex short-run aggregate supply curve. Positive shocks to aggregate demand will have more of an affect on prices and less on output than a negative shock. This convex supply curve argument can also be used to explain business cycle asymmetry; the same shock to an equilibrium left of the long-run aggregate supply curve (a recession) would have a much different effect on output and prices than an equilibrium to the right of long-run aggregate supply. This model predicts that monetary policy would be more effective on output in recessions than expansions. Second, menu cost models can be used to explain asymmetry regarding the size of the shock. This model predicts that only small shocks will have large effects, since firms would only find it optimal to pay the menu costs if the shock was large enough. Finally, there is the credit channel explanation explored by Bernanke and Gertler (1995) that can explain asymmetry in different phases of the business cycle. This explanation runs through the balance sheet channel and finds that monetary policy is more powerful during recessions than expansions since firms are more likely to use internal financing during expansions but rely on external financing during recessions when internal funds dry up.

There have been many empirical investigations into asymmetry. The earliest paper in this field was Cover (1992). This paper employed a two step procedure to estimate the monetary shocks. First specify the money supply process and then obtain the residuals from the regression of that process. Second, these residuals are used as the monetary shock series upon which output can be regressed. He studied the difference between positive and negative monetary shocks, measured by shocks to the money supply. By regressing output growth on positive and negative money supply shocks, he found that positive shocks to money had no effect on output, but negative shocks decreased output. In addition to this paper, there were a few others that studied the asymmetry of positive versus negative shocks. Kandil (1995) and Karras (1996) found similar results to Cover (1992) while employing a similar method. Karras (1996) looked at a panel of 38 different countries and found evidence supporting international asymmetry. Kandil (1995) found that prices and wages tend to respond more to positive monetary shocks than negative ones. A more recent paper, Angrist et al. (2018) used propensity score matching on the policy variable and found that monetary tightening had an effect on yield curves and macroeconomic variables but monetary accommodation had less profound effects.

Many papers use a regime-switching framework to study asymmetry, allowing the models to differentiate between different phases of the business cycle or different types of shocks. Peersman and Smets (2002) allow for regime switching between high and low growth rate periods. They measure monetary policy as a shock to the short-term interest rate from a simple VAR model, finding that monetary policy in the Euro-area had significantly larger effects on output in recessions than expansions. Garcia and Schaller (2002) model regime switching as the economy switching from expansion and recession states. They use movements in the Federal Funds rate and innovations from a VAR as their monetary policy measures and find that US monetary policy has larger effects on output during recessions than expansions. Kaufmann (2002) allows for switching between above average and below average growth periods. Kaufmann uses the first difference of the Austrian 3-month interest rate as the policy variable and finds a significant negative effect of monetary policy on output during below average growth periods and insignificant effects during normal and above average growth periods.

Lo and Piger (2005) and Ravn and Sola (2004) also employ a regime switching framework and both papers study multiple manifestations of asymmetry in the same model. Ravn and Sola (2004) tie the regime switching to the mean and variance of the monetary shock, allowing them to study large versus small shocks in addition to positive and negative ones. Using US data, they find that large shocks are neutral while smaller shocks have real effects on output and less support of asymmetry between positive and negative shocks. Lo and Piger (2005) use this framework to study all three types of asymmetry. They use a time-varying transition probability model that allowed the switching process to be a function of the sign and size of the shock, as well as the phase of the business cycle. The shocks were identified from a monetary VAR model. Using US data, they found that policy actions taken during a recession had larger effects on output than actions taken during expansions, but less evidence of the other two types of asymmetry.

Weise (1999) is another paper that considers all three types of asymmetry at once. Money based indicators of monetary policy are used, which come from ordering money last in a VAR model. The innovation of this paper was to show that these asymmetries could be modeled by applying a smooth-transition technique (see Anderson and Teräsvirta (1992)), to a VAR model. Weise did not find evidence of asymmetry regarding the direction of the shock but did regarding the phase of the business cycle and the size of the shock. Shocks during low growth periods were found to have larger effects on output than shocks during high growth periods and large shocks were found to have disproportionately larger effect than smaller shocks.

The smooth-transition technique was also a highlight of Tenreyro and Thwaites (2016), following Granger and Teräsvirta (1993). This was also the paper that had the most influence on the methodology of this paper. They were interested in asymmetry dealing with the phase of the business cycle. Tenreyro and Thwaites (2016) innovated in two dimensions over the existing literature. First, they made use of the Romer and Romer monetary shocks from Romer and Romer (2004). Second, they employed local projections, developed in Jordá (2005), to generate impulse responses. Following these two methodologies they found that the response of output and prices to monetary policy shocks were more powerful in expansions than recessions.

The results of Tenreyro and Thwaites (2016) has been an influential and has left the business cycle asymmetry literature without a consensus. The primary objective of this paper is to reconcile the differences in this literature. As discussed above, there are differences in the way these various authors have identified monetary policy shocks and estimated the state-dependent response of the economy to these shocks. There are two additional key differences in this literature. The first is the measurement of the response variable, particularly the way that trends are removed from the data. The second is the treatment of outlier observations.

It is well known that how a researcher deals with stationarity is important for measuring the effects of policy innovations. One way this can be dealt with is by differencing the data and rendering it stationary. This is the strategy that most papers in the asymmetry literature deal with de-trending their data. Another strategy for de-trending the data is to add a time trend into the regression model. Papers in the more recent literature such as Tenreyro and Thwaites (2016) use this approach. Their use of levels data stems from other papers that use the local projection methodology, as other papers employing local projections also use levels data. For example, Ramey and Zubairy (2018) use levels data with a quartic trend. Regressions in levels are consistent even if there is a unit root (Sims et al. (1990)). However, Kilian and Kim (2011) find that there is a significant bias in IRF estimates when the process is persistent. Thus, while regressions in levels may seem safe since they are agnostic about the integration properties of the data, may give severely biased estimates. As I show in my paper, the de-trending strategy that the researcher uses can have a major impact on the asymmetry results.

The asymmetry literature generally measures monetary policy by using residuals from a simple monetary VAR or by using the Romer and Romer residuals, as discussed in section II.3.2. In both cases, there are outliers in the measured shocks that happen during the 1979-1982 time period, corresponding to the Volcker chairmanship at the Federal Reserve. There have been some papers in the asymmetry literature that have highlighted the importance of the Paul Volcker chairmanship period, which lasted from 1979-1987. Prior to and during his chairmanship was a period characterized by high inflation rates, making the Feds primary goal during this time to reign in inflation. Volcker also oversaw the transition of the Fed from targeting the money supply to the Federal Funds rate as its primary policy tool. This paper finds that the results of asymmetry vary depending on how the residuals in this period are treated, much like other papers in this literature.

Morgan (1993) showed that changes in the Federal funds rate showed some asymmetry in output when looked at over the full sample 1963:2-1992:3, finding that increases in the funds rate had more of an effect than a decrease. There is less evidence for this result when the period 1979:4-1982:4 was excluded from the sample, the period when the Fed deemphasized the Federal funds rate. Thoma (1994) studied asymmetry and instability in the money-income causality. He used a rolling regression approach to show that the p-value of the money-income causality test is highly correlated with the level of real economic activity. There were two periods in his sample that this relationship was the strongest, 1969-1973 and 1978-1982. Ravn and Sola (2004) were also concerned about this period, their regime switching model allowing them to control for the Volcker period since the change in policy that happened then produced some large negative outliers that needed to be controlled for. Specifically they found that a large outlier in the money supply equation appeared in the first quarter of 1983. They found that the results of Cover (1992) were not robust to this outlier. Even Romer and Romer (2004) find outliers during this time period and find that there are many problems with measuring shocks during this time. The baseline specification in this paper follows Romer and Romer (2004) by generating residuals from an estimation of the Feds reaction function. Analyzing the data for this period, one will find that the residuals generated will typically be the largest during the 1979-1982 period, suggesting that some of the varying results observed in the asymmetry literature might be driven by how papers dealt with this time period. The results are similar to Ravn and Sola (2004) in that asymmetry disappears when I control for this time period.

II.3 Econometric Method

In this section, I lay out the econometric method used in the paper. This section begins with a discussion of the local projection methodology for computing impulse responses and how inference is conducted in this framework. Second, the Romer and Romer (2004) monetary policy shock measure is discussed. Third, a brief description of the data used for this paper is discussed. Finally, this section concludes with a discussion of how asymmetry is tested for in this paper.

II.3.1 Local Projections

I follow Tenreyro and Thwaites (2016) in the use of the local projection model for estimating impulse responses, developed in Jordá (2005). The local projection approach has a few advantages over a VAR model. First, it is simple to estimate and draw inference from, requiring only running OLS over increasing time horizons. Second, this model is robust to misspecification of the data generating process. Finally, it can more easily accommodate non-linear specifications in multivariate contexts. For the purpose of studying business cycle asymmetry in the response of output to monetary policy, local projections proceeds by estimating equations of the form:

$$y_{t+h} = F_t(\beta_r^h \varepsilon_t + \gamma_r' x_t) + (1 - F_t)(\beta_e^h \varepsilon_t + \gamma_e' x_t) + u_t \tag{II.1}$$

where y_{t+h} is output measured in log levels at time horizon h, F_t is an indicator variable indicating if the US economy is in a recession or an expansion, ε_t is the monetary policy shock, and x_t is a control vector. The coefficients of interest are β_r^h indicating the response of output at horizon h to monetary policy shocks in recessions, and β_e^h being the response at horizon h during expansions.

Equation II.1 is estimated using log levels of the output variable. One might be interested in instead working with first differences of the logged output variable, such as in the case where the log level of output is thought to have a unit root. To do so, consider first the local projection of the first difference of the log level of output on the monetary policy shock:

$$\Delta y_{t+h} = F_t(\beta_{r,D}^h \varepsilon_t + \gamma_r' x_t) + (1 - F_t)(\beta_{e,D}^h \varepsilon_t + \gamma_e' x_t) + u_{t+h}^D$$

where $\beta_{r,D}^h$ and $\beta_{e,D}^h$ are the responses of the growth rate of output to a monetary shock in recessions and expansions respectively. Note that the sum of growth rate responses gives the level responses. We can estimate this level response directly in the growth rate specification using the transformation suggested in Stock and Watson (2018). Summing the growth rates over h gives:

$$\sum_{i=0}^{h} \Delta y_{t+i} = F_t(\sum_{i=0}^{h} \beta_{r,D}^{i} \varepsilon_t + \gamma_r' x_t) + (1 - F_t)(\sum_{i=0}^{h} \beta_{e,D}^{i} \varepsilon_t + \gamma_e' x_t) + \sum_{i=0}^{h} u_{t+i}^{D}.$$

This can be simplified:

$$\sum_{i=0}^{h} \Delta y_{t+i} = F_t(\beta_r^h \varepsilon_t + \gamma_r' x_t) + (1 - F_t)(\beta_e^h \varepsilon_t + \gamma_e' x_t) + \sum_{i=0}^{h} u_{t+i}^{D}$$

where β_r^h and β_e^h are the responses of the log level of output to a monetary shock in recessions and expansions respectively. These responses, β_r^h and β_e^h, are equal to the sum of the growth rate responses up to horizon h, $\sum_{i=0}^{h} \beta_{r,D}^{i}$ and $\sum_{i=0}^{h} \beta_{e,D}^{i}$. The terms inside the summation $\sum_{i=0}^{h} \Delta y_{t+h}$ cancel out, until this equation is left:

$$y_{t+h} - y_{t-1} = F_t(\beta_r^h \varepsilon_t + \gamma_r' x_t) + (1 - F_t)(\beta_e^h \varepsilon_t + \gamma_e' x_t) + \sum_{i=0}^{h} u_{t+i}^{D}. \tag{II.2}$$

The impulse response for the logged first difference of output in recessions is β_r^h and β_e^h in expansions. The standard errors are calculated from the estimation of equation II.2. This specification will be helpful because it will allow us to directly compare the impulse responses from the log level form of output to the logged first difference form.

Following Tenreyro and Thwaites (2016), the control vector will contain one lag each of output and the Federal funds rate. Impulse responses will be calculated out to twenty quarters, $H = 20$ (or 60 months in the monthly specification). The shocks developed in Romer and Romer (2004) will be used as the measure of the monetary policy shock (see section II.3.2) and real GDP will be the main dependent variable.

I run specifications in both levels and growth rates. A linear time trend is added to any model estimated in level form.

The NBER indicator, that will be used as F_t in equation II.1, is a monthly variable published by the National Bureau of Economic Research indicating if the US economy is in a recession or expansion. To convert this monthly measure to a quarterly measure I count a quarter as in recession when at least two of the three months in that quarter are counted as a recession by the monthly NBER indicator. This indicator is denoted the NBER majority rule indicator. The use of this indicator is in contrast to other papers which use a logistic function in the regime switching framework. Granger and Teräsvirta (1993) and more recently Tenreyro and Thwaites (2016) both use a logistic function in their smooth transition models. I prefer the NBER specification as it offers a more clear definition about which quarter is in a recession state versus an expansion state.[1]

I employ the Newey-West methodology to calculate asymptotic standard errors. As Jordá (2005) shows, the disturbance term in the local projection equation is serially correlated and has a moving average (MA) process. I use these standard errors to calculate 90% confidence intervals around the impulse response of output in recessions and expansions from Equations II.1 and II.2 depending on the specification of output. The maximum autocorrelation lag is set to be H+1 following Jordá (2005).

II.3.2 Non-Linear Romer and Romer (2004) Monetary Policy Shocks

I make use of the monetary policy shocks developed in Romer and Romer (2004). One must be mindful of the endogenous or anticipatory movements that plague monetary policy measures such as the money supply or the Federal funds rate. Romer and Romer (2004) developed a two-step process to derive a measure of monetary policy

[1]The results of this paper are robust to the smooth transition model.

that is free from these problems. First, the intended Federal Funds rate for a given Federal Open Market Committee (FOMC) meeting is found by reading the narrative record of each FOMC meeting. Second, the intended funds rate series is regressed around the forecast dates of the Fed's Greenbook forecasts. The Greenbook forecast is produced prior to each FOMC meeting by the research staff of the Board of Governors. The forecasts contain projections of many macroeconomic variables of output, prices, employment, and investment. By regressing the intended funds rate on these forecasts, the residuals from this regression are now free of anticipatory movements. These residuals are the series of interest.

I follow Tenreyro and Thwaites (2016) in the use of non-linear Romer and Romer (2004) shocks. Given that the premise of this study is to estimate non-linearities in the response of monetary policy, subjecting the reaction function of the Federal Reserve to be linear may add some state dependent measurement error, causing asymmetry to show up where there is none. The original Romer and Romer (2004) regression is written as follows:

$$\begin{aligned}\Delta ff_m = \alpha + \beta ffb_m + \sum_{i=-1}^{2} \gamma_i \widetilde{\Delta y}_{m,i} + \sum_{i=-1}^{2} \lambda_i (\widetilde{\Delta y}_{m,i} - \widetilde{\Delta y}_{m-1,i}) \\ + \sum_{i=-1}^{2} \phi_i \widetilde{\pi}_{m,i} + \sum_{i=-1}^{2} \theta_i (\widetilde{\pi}_{m,i} - \widetilde{\pi}_{m-1,i}) + \rho \widetilde{u}_{m,0} + \varepsilon_m\end{aligned}$$

where Δff_m is the change in the intended funds rate around FOMC meeting m, ffb_m is the level of the intended funds rate before any changes were made at the associated FOMC meeting, $\widetilde{\Delta y}$ is the forecast of real output growth, $\widetilde{\pi}$ is the forecast of inflation, and $\widetilde{u}$ is the forecast of the unemployment rate. Define X_m as:

$$X_m = \alpha + \beta ffb_m + \sum_{i=-1}^{2} \gamma_i \widetilde{\Delta y}_{m,i} + \sum_{i=-1}^{2} \lambda_i (\widetilde{\Delta y}_{m,i} - \widetilde{\Delta y}_{m-1,i})$$
$$+ \sum_{i=-1}^{2} \phi_i \widetilde{\pi}_{m,i} + \sum_{i=-1}^{2} \theta_i (\widetilde{\pi}_{m,i} - \widetilde{\pi}_{m-1,i}) + \rho \widetilde{u}_{m,0}$$

then we can express the original Romer and Romer (2004) regression as follows:

$$\Delta ff_m = \beta' X_m + \varepsilon_m$$

where X contains the control variables from the Greenbook forecasts and the residuals ε_m are the linearly identified monetary policy shocks. The state-dependent reaction function is then:

$$\Delta ff_m = NBER * \beta' X_m + (1 - NBER) * \beta' X_m + \varepsilon_{m,nl} \qquad \text{(II.3)}$$

where NBER is an indicator variable for recession or expansion. In this framework $\varepsilon_{m,nl}$ represents the non-linear monetary policy shocks.

II.3.3 Data

The data used in this study was taken from a variety of sources. Real GDP, industrial production, personal consumption expenditure, and federal funds rate data was taken from the St. Louis Federal Reserve's FRED database. The NBER indicator data was taken from the National Bureau of Economic Research recession indicators. Finally, the data used to generate the Romer and Romer (2004) monetary policy shocks was collected from the Philadelphia Federal Reserve's Greenbook data set. The main sample period for the quarterly frequency runs from 1969:Q1-2008:Q4. Since H=20, the last 20 quarters of this sample are reserved for the calculation of impulse responses by local projections. For monthly, the sample period runs from 1969:03-2008:12. For consistency with the quarterly analysis, the last 5 years of this sample will be reserved for impulse response calculation by local projections. In both cases the sample period cuts off prior to the onset of the Great Recession, since the interest rate was near the zero lower bound for most of the duration and aftermath of the recession.

II.3.4 Asymmetry Test

To test for asymmetry, Equation II.1 is rewritten as follows:

$$y_{t+h} = \beta_r^h \varepsilon_t + \gamma_r' x_t + (1 - F_t) * (\theta_e^h \varepsilon_t + \gamma_e' x_t) + u_t. \tag{II.4}$$

In this specification, the coefficient θ_e^h has the interpretation of being the response of output in expansions minus the response of output during recessions. Similarly for growth rate specifications, Equation II.2 can be rewritten as follows:

$$y_{t+h} - y_{t-1} = \beta_r^h \varepsilon_t + \gamma_r' x_t + (1 - F_t)(\theta_e^h \varepsilon_t + \gamma_e' x_t) + \sum_{i=0}^{h} u_{t+h}^D. \tag{II.5}$$

where θ_e^h has the same interpretation as in Equation II.4. The standard error for θ_e^h is calculated using the Newey-West methodology and a t-test is performed on the coefficient θ_e^h. There is evidence for asymmetry if the corresponding p-value is low enough to reject the null hypothesis of no asymmetry at the 10% significance level.

II.4 Results

In this section, I present the results of the estimation of the model laid out in section II.3. I then consider various variants of this model in an attempt to reconcile the differences in the existing literature.

II.4.1 Baseline Results

I begin with the baseline specification that mirrors the specification Tenreyro and Thwaites (2016) used in their analysis. In Tenreyro and Thwaites (2016) they ran a local projection model using a smooth-transition logistic function to switch between expansion and recession regimes. They found a significant difference between the impulse responses of output between expansions and recessions. The impulse response of output in expansions reached its peak about ten periods from the time of the shock while the recession response stayed closer to zero for the duration of the horizon. They conducted inference using both a bootstrap method and asymptotic standard errors. The results from the asymptotic standard errors showed a significant difference between the response of output in expansions and recessions to a monetary shock while the bootstrap test was inconclusive.

Figure II.1 shows the impulse response of real GDP to a positive Romer and Romer (2004) monetary shock and shows the results of the asymmetry test for this variable. These results very closely mirror the Tenreyro and Thwaites (2016) result. The impulse responses are generated using Equation II.1. In Figure II.1a-II.1c, red lines indicate the response of output in a recession and blue lines show the response in an expansion. Variables in the equation are in log levels and a linear time trend is included in the model. The key interest in Figure II.1a is the difference between the two impulse response lines. Aside from a brief period at the beginning of the horizon, the expansion line is lower than the recession line for the remainder of the horizon, reaching its peak difference around ten quarters from the time of the shock. For most of the duration of the horizon, the recession response stays close to zero.

Figures II.1b and II.1c give us evidence that the responses in expansions and recessions are both significantly different from zero. The expansion response of output is significant from zero from approximately horizon 7-18, and its peak response is -

0.017. The recession response of output is only significantly different from zero in the early part of the horizon and its peak response is approximately -0.007. The point estimates suggest that asymmetry exists between the response of output in expansions and recessions.

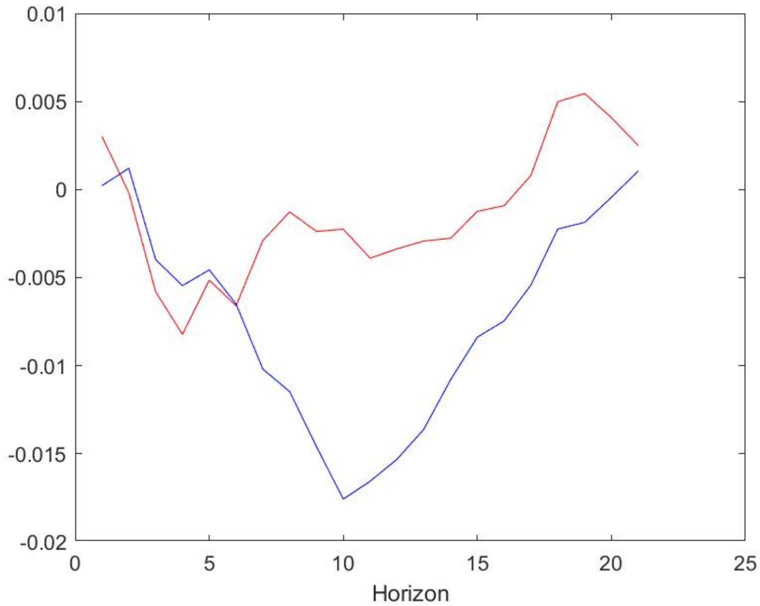
To confirm that these differences are significant from each other, a t-test is performed on the sign of $\beta_e^h - \beta_r^h$ following Equation II.4. Figure II.1d shows the p-value of the t-test using Newey-West standard errors. Referencing back to Figure II.1a, the largest differences happen between horizons 9-15, corresponding to the horizons that the t-test find a significant difference. Given the evidence from the point estimates and the t-test, Figure II.1 largely mirrors the findings of Tenreyro and Thwaites (2016) that the response of output to a monetary shock in expansions is larger than during recessions. The remainder of this section will explore how robust this result is to different specifications of the model.

II.4.2 Robustness to Measure of Output and Data Frequency

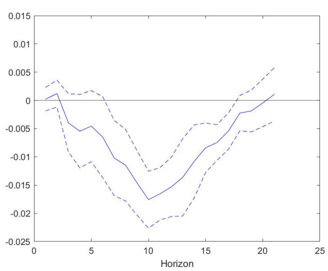
Many papers in the asymmetry literature have used Industrial Production as the measure of output. Weise (1999), Peersman and Smets (2002), Garcia and Schaller (2002), and Lo and Piger (2005) all used industrial production in their baseline specifications. Romer and Romer (2004) also used industrial production to evaluate their monetary shock measure. Kaufmann (2002), Ravn and Sola (2004), and Tenreyro and Thwaites (2016) use measures of GDP as their measures of output. Industrial production is a narrower measure of output than GDP that is also more sensitive to interest rates. This section explores the robustness of the results in section II.4.1 to the measure of output.

Figure II.2 shows the impulse response of quarterly industrial production to a monetary shock in expansions and recessions. The model is run in log levels with a linear time trend added to the model. The expansion response tells a similar story

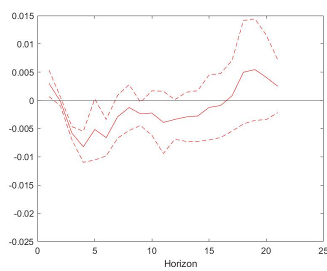
Figure II.1
Impulse Response of Quarterly real GDP in Levels



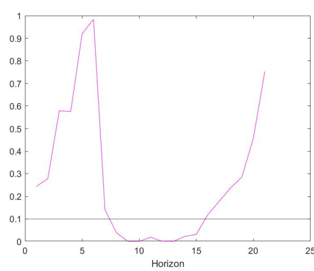
(a) Point Estimates



(b) Expansion



(c) Recession



(d) t-test p-value

Notes: This Figure shows the impulse response of real GDP in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of real GDP to the shock. Variables are in log levels and a linear time trend is added to the model. The sample is quarterly from 1969:Q1-2008:Q4. Figure (a) shows the impulse response point estimates for expansions and recessions. Figure (b) and (c) show the impulse responses with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the response in expansions and recessions with the line in the figure corresponding to the 90% significance level.

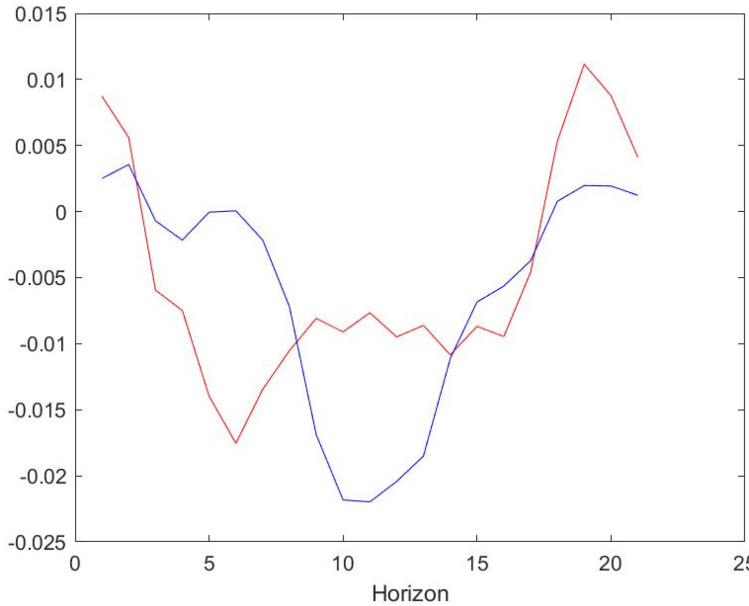
to the response in Figure II.1. The main difference between Figure II.2a and Figure II.1a is the peak response of industrial production in expansions and recessions. In expansions, the peak response is between -0.02 and -0.025 using industrial production compared to -0.017 in the baseline case, showing more sensitivity to interest rates than the baseline case. The recession response to a monetary shock also shows more sensitivity as the peak response in Figure II.1 was -0.007 versus -0.017 when industrial production is used. The recession response of industrial production also stays around -0.010 from horizon 8-17 before it heads back up to zero. This is in contrast to Figure II.1a, where the response went right back to zero after reaching its peak.

Figures II.2b and II.2c allow us to identify if the point estimates from Figure II.2a are significantly different from zero at the 10% level. A comparison of the expansion responses for real GDP and industrial production is very similar in terms of significance. Around horizon 10, which corresponds to the peak point estimate in absolute value, the impulse response for expansion shows a significant difference from zero. The response during recessions has two periods of significance. The first occurs around horizon 6, corresponding to the peak response in absolute value, and the other from horizon 12-16.

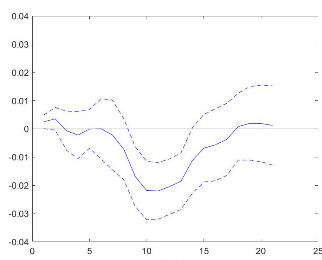
The evidence thus far suggests that when industrial production is used in place of real GDP, that the recession response closes the gap but still does not pass the response in expansions. However, the results of the t-test for asymmetry gives inconclusive results. The t-test says that there is a significant difference between expansions and recessions at horizon zero but this difference is not useful for asymmetry. At all other horizons, the t-test does not find any significant differences.

The results for industrial production are less clear that that of real GDP. The peak response for expansions is still larger than it is during recessions although there were no significant differences found from the asymmetry tests. Given that there is weak evidence that industrial production is more responsive to a monetary shock in expansions, changing the measure of output does not overturn the results from section II.4.1.

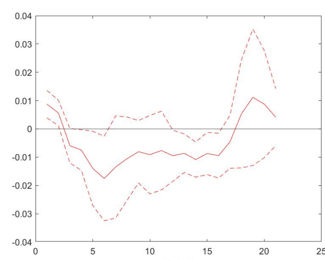
Figure II.2
Impulse Response of Quarterly Industrial Production in Levels



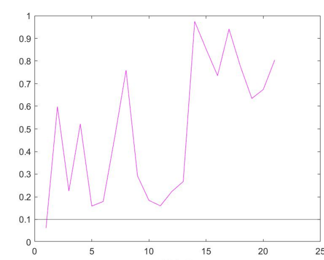
(a) Point Estimates



(b) Expansion



(c) Recession



(d) t-test p-value

Notes: This Figure shows the impulse response of Industrial Production in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of Industrial Production to the shock. Variables are in log levels and a linear time trend is added to the model. The sample is quarterly from 1969:Q1-2008:Q4. Figure (a) shows the impulse response point estimates for expansions and recessions. Figure (b) and (c) show the impulse responses with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the response in expansions and recessions with the line in the figure corresponding to the 90% significance level.

In addition to variability in the measure of output used, there has also been some variability in the data frequency used in the asymmetry literature. Most papers tend to favor quarterly measures since GDP is measured in quarterly frequency. Given the nature of quarterly measures, there may be some difficultly defining recessions in this time frequency. For example, the quarterly NBER indicator that I use requires that two of the three months in a quarter be in a recession in order for that quarter to be counted as a recession. There are certain quarters where only one month was in a recession but this would not be counted as such in the NBER definition used. This happens in 1973:Q4, since only December of 1973 was counted as a recession by the NBER. As higher frequency data specifications are used, recessions become more clearly defined since this lowers the chance that one period of time can be counted as a recession in the monthly measure but an expansion in the quarterly measure. In this section, I explore how robust the baseline result is to the frequency of the data.

Figure II.3 shows the impulse response of Industrial Production to a positive monetary policy shock. There are two main differences between the regression used to obtain these results and the baseline quarterly results. First, the Romer and Romer shocks are measured monthly rather than quarterly. Romer and Romer (2004) construct monthly shocks originally and then aggregate these to quarterly, so there is no measurement problem here. Second, the measure of output is industrial production versus real GDP in the baseline quarterly case. The impulse response runs out to time 60, which is five years and consistent with the quarterly case.

Figure II.3 shows that the results are similar to Figure II.2. Comparing Figure II.3a to Figure II.2a, there is still a timing difference visible between the response in expansions and recessions. The difference is that the peak recession response has now increased to the point of surpassing the peak expansion response. Therefore, while the baseline results were weakened by the use of quarterly industrial production, this weakness is accentuated by switching from quarterly to monthly industrial production. It is important to note that when monthly industrial production is used that there are horizons where both camps of the literature are correct. From horizons 5-25 the recession response is stronger and from 25-40 the expansion effect is stronger.

The confidence interval around the point estimate for the expansion response is consistent with the impulse responses of quarterly real GDP and industrial production. For the periods around horizon 30, the peak expansion response, there are significant differences from zero. Switching to monthly now has the recession response exhibiting similar behavior to the expansion response. It is significantly different from zero in many places along the horizon, including horizon 5-20 (which contains the peak response in recessions) and intermittent intervals over the rest of the horizon.

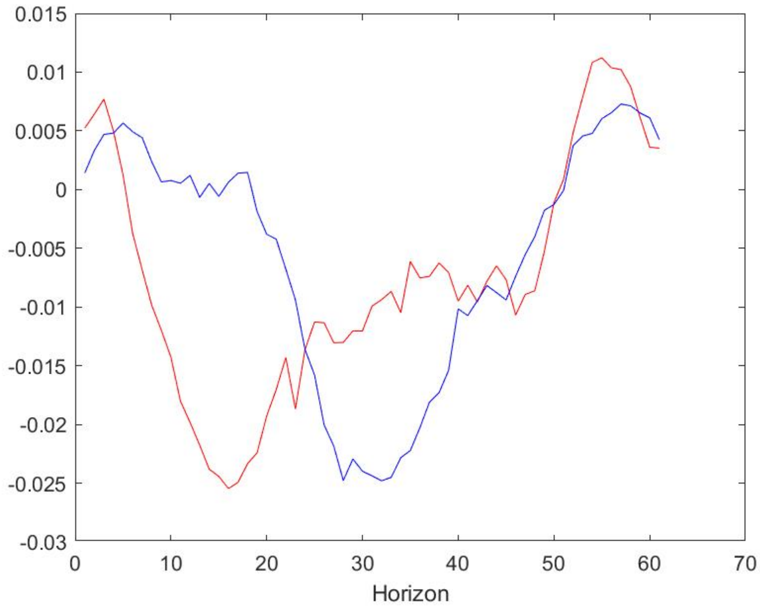
The asymmetry test for monthly industrial production is in Figure II.3d. There are two places that exhibit significant differences in the responses between expansions and recessions. The recession response is significantly larger between horizons 6-9 and around horizon 15. The expansion response is significantly larger around horizon 33.

Given the results in Figure II.3, the frequency of the data used can have a major effect on asymmetry results. As stated above, this result is likely due to recessions being defined more clearly in the monthly specification rather than quarterly. Given the results of this section, it appears that the measure of output used has a major impact on the asymmetry results, with the frequency of data used accentuating this result.

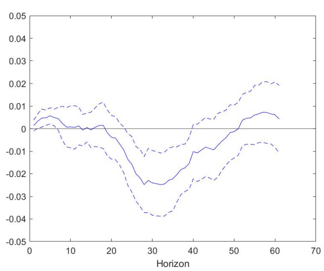
II.4.3 Robustness to Treatment of Stochastic Trends

There is some variability in the asymmetry literature with the way that trends in the data are dealt with. Most early papers in the literature assume a unit root in output and specify their empirical models in terms of the growth rates of output measures. More recent papers, especially those using local projections for impulse responses, use the level of the data augmented with a time trend to the model. In this section, I demonstrate that the asymmetry results are not robust to the choice of estimating the model in levels versus growth rates.

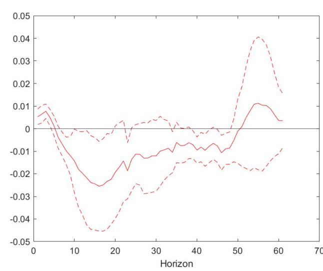
Figure II.3
Impulse Response of Monthly Industrial Production in Levels



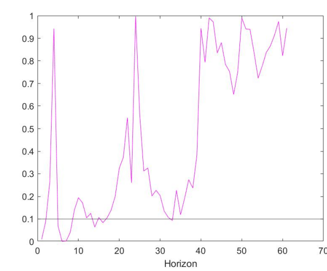
(a) Point Estimates



(b) Expansion



(c) Recession



(d) t-test p-value

Notes: This Figure shows the impulse response of Industrial Production in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of Industrial Production to the shock. Variables are in log levels and a linear time trend is added to the model. The sample is monthly from 1969:03-2008:12. Figure (a) shows the impulse response point estimates for expansions and recessions. Figure (b) and (c) show the impulse responses with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the response in expansions and recessions with the line in the figure corresponding to the 90% significance level.

Figure II.4 shows the impulse response of real GDP growth to a monetary shock. The impulse responses for the growth rate specification are generated from estimating

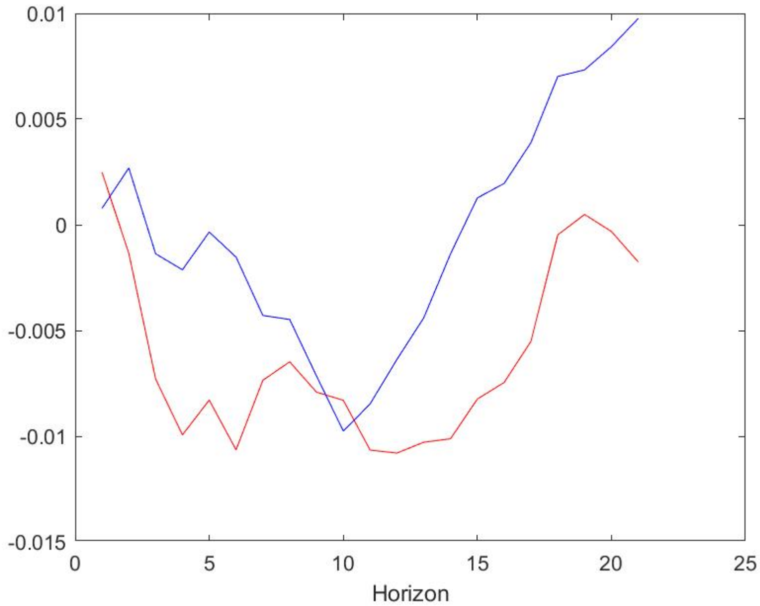
Equation II.2. Figure II.4a shows the cumulative sum of the growth rate response making it comparable to the log level responses from the previous sections. Figure II.4b and Figure II.4c shows the impulse responses for the cumulative sum of the growth rates in expansions and recessions and the t-test for asymmetry in Figure II.4d tests for the differences between the cumulative sum of the growth rates in expansions and recessions.

Figure II.1a suggested that output was more responsive to monetary policy in expansions than recessions. The point estimates in Figure II.4a appear to wash out the result in the baseline specification. Here the peak response in expansions and recessions are about equal, -0.010 and -0.012 respectively. The response in the recession regime reaches its peak response more quickly and stays there for longer than the expansion regime. From horizons 1-9 and 11-20 the response of output in recessions is much lower than the response during expansions, suggesting that monetary policy is more effective in recessions than expansions. This result is in contrast to Tenreyro and Thwaites (2016) but in agreement with much of the rest of the asymmetry literature.

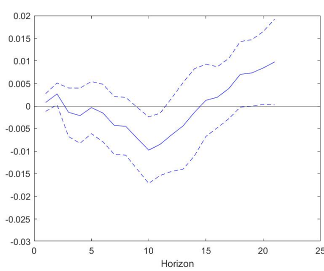
Figures II.4b and II.4c show the response of the cumulative sum of the growth rates of real GDP to a monetary shock. There are a couple of periods of interest in these two graphs. One, the recession response is significantly different from zero in the early part of the horizon, between horizons 3 and 6. The expansion response is significantly different from zero in the middle of the horizon, around horizon 9-12.

Figure II.4d shows the p-values of the t-test for asymmetry between the cumulative sum of the growth rates between expansions and recessions. The p-value shows evidence that there is asymmetry between expansions and recessions, with the response in recessions being larger. During horizons 2-6 and 15-20, the response in recessions is larger than expansions. The t-test finds a significant difference between the responses early in the horizon.

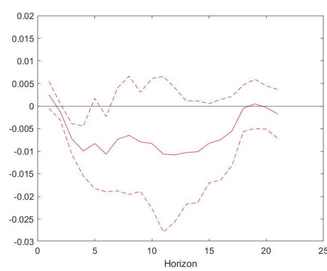
Figure II.4
Impulse Response of Quarterly real GDP in Growth Rates



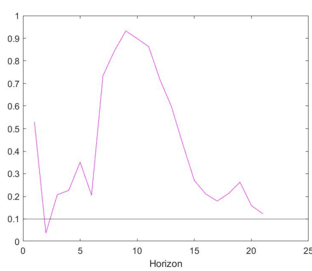
(a) Point Estimates



(b) Expansion



(c) Recession



(d) t-test p-value

Notes: This Figure shows the impulse response of real GDP growth in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of real GDP growth to the shock. Variables are in logged first difference. The sample is quarterly from 1969:Q1-2008:Q4. Figure (a) shows the impulse response point estimates for expansions and recessions where the point estimate is the cumulative sum of the growth rate. Figure (b) and (c) show the impulse responses of the growth rate of real GDP with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the growth rates of real GDP in expansions and recessions with the line in the figure corresponding to the 90% significance level.

Given the results of Figure II.4, there is weak evidence that monetary policy is more effective in recessions when real GDP is expressed in terms of growth rates. I have shown that the measure of output and the frequency of the output variable had an effect on the asymmetry results based on levels regressions. Figure II.5 combines these results showing the impulse response of monthly industrial production growth to a positive monetary shock. This specification is identical to the one in Figure II.4 with monthly industrial production growth replacing quarterly real GDP growth.

Comparing the point estimates in Figure II.5 to the monthly specification in Figure II.3 gives further evidence that the switch to growth rates flips the baseline result. In Figure II.3 the story was one of timing. Expansions and recessions had approximately the same peak response but the peak happened earlier in recessions. In Figure II.5, the response in recession still reaches its peak well before the response in expansions but it strictly dominates in terms of response size over the entire horizon. The recession response quickly reaches -0.025 and stays there while only reaching -0.015 for a brief period in the expansion response.

Figure II.5b and Figure II.5c show that there are a few periods where the cumulative response of the growth rate of industrial production are significantly different from zero. The recession response has some significance between horizons 6-18 and 45-50. The expansion response is only significantly different from zero in the early portion of the horizon. The remainder of the horizon is insignificant, even where it reaches its peak response.

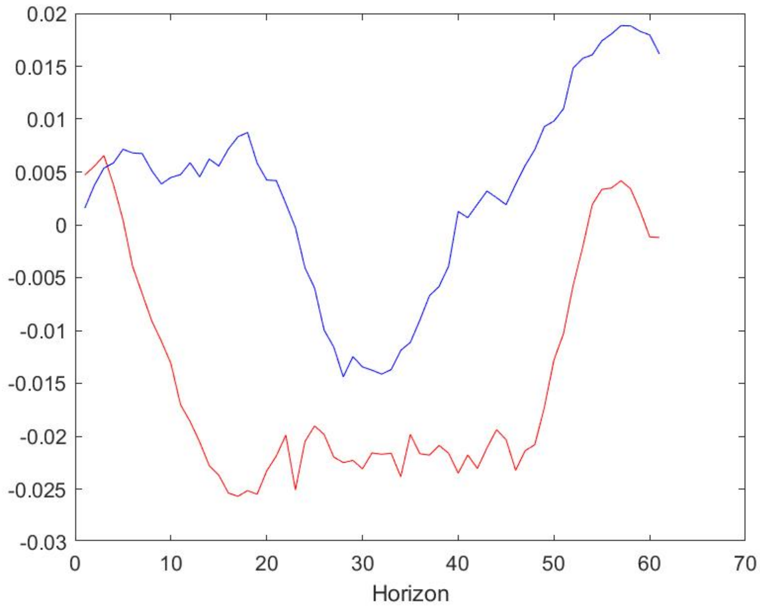
The results of the asymmetry test of the cumulative growth rates in Figure II.5d is similar to the result of using quarterly real GDP growth. In the t-test you will find significant differences between the responses in expansions and recessions in the early portion of the horizon, between horizons 6-18. This period corresponds to the response in recessions reaching its peak rapidly while the expansion response stays close to zero. Even though there is no other horizon that shows evidence of asymmetry, this does give more evidence that monetary policy is more effective in expansions than recessions.

Given the results from Figures II.4 and II.5, there is evidence that estimating the model in levels versus growth rates has has a major impact on the asymmetry results. Which specification should be trusted? On the one hand, if there is no unit root, the differences specification over-differences the data, introducing a non-invertible moving average component into the regression disturbance. This danger of over-differencing for the purposes of impulse response estimation is discussed in Gospodinov et al. (2013) for IRF analysis using VARs. However, if there is a unit root, the differenced specification should be more efficient, and the levels specification, while consistent, will be severely biased in finite samples (Kilian and Kim (2011)). Also, typical inference methods employed in the literature using local projections, such as Newey-West standard errors, are not robust to the presence of a unit root.

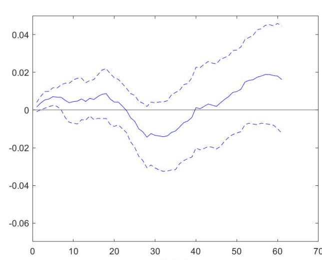
In an attempt to provide evidence on the correct specification, I run unit root test on the quarterly real GDP series from 1959:Q1-2018:Q2. The tests run include the augmented Dickey-Fuller test (ADF), the Elliot, Rothemberg, and Stock test (DF-GLS), the Zivot-Andrews test (ZA), and the KPSS stationarity test. The results of these tests are presented in Table II.1.

The evidence from these tests points to there being a unit root present in the quarterly real GDP series. The ADF and DF-GLS tests both have a null hypothesis that the series has a unit root while the alternative is a trend stationary series. The tests statistics for these two tests are -2.2335 and -0.7539, neither being significant at any conventional level. The null hypothesis of the Zivot-Andrews test is that the series has a unit root while the alternative is a trend stationary series with a break at an unknown point in either the intercept, the linear trend, or in both. The test statistic is -4.4729 and I fail to reject the null at any conventional significance level. The final test is the KPSS test where the null is a trend stationary series and the

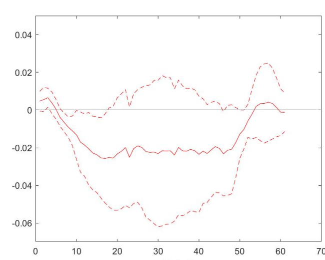
Figure II.5
Impulse Response of Monthly Industrial Production in Growth Rates



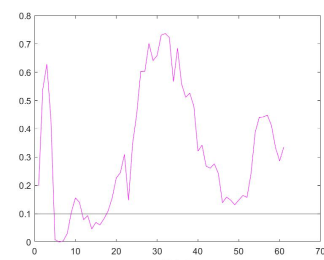
(a) Point Estimates



(b) Expansion



(c) Recession



(d) t-test p-value

Notes: This Figure shows the impulse response of industrial production growth in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of industrial production growth to the shock. Variables are in logged first difference. The sample is monthly from 1969:03-2008:12. Figure (a) shows the impulse response point estimates for expansions and recessions where the point estimate is the cumulative sum of the growth rate. Figure (b) and (c) show the impulse responses of the growth rate of industrial production with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the growth rates of industrial production in expansions and recessions with the line in the figure corresponding to the 90% significance level.

alternative is that the series has a unit root. The test statistic for this test is 0.8888, which is significant at the 10% level.

The evidence from these tests does suggest that the real GDP series has a unit root. This result is supported by both unit root and stationarity tests, suggesting the result is not driven by a lack of power. In addition, this result was robust to shortening the sample period to 1959:Q1-2008:Q4 and to the use of monthly industrial production as the output measure. Given these results, it is not unreasonable to conclude that the results from the differences specifications are more credible.

Table II.1
Unit Root Tests of Quarterly real GDP

Sample Period	ADF	DF-GLS	Zivot-Andrews	KPSS
1959:Q1-2018:Q3	-2.2335	-0.7539	-4.4729	0.8888*
1959:Q1-2008:Q4	-3.1341	-1.1755	-3.8401	0.3907*

Notes: The results of various unit root tests over the time horizons 1959:Q1-2018:Q3 and 1959:Q1-2008:Q4. A * indicates significance at the 10% level. The first test is an Augmented Dickey Fuller test where the null hypothesis is that the series has a unit root and the alternative is trend stationary. The second is an Elliot, Rothemberg, and Stock "DF-GLS" test where the null hypothesis is that the series has a unit root and the alternative is trend stationary. The third is a Zivot-Andrews test where the null hypothesis is that the series has a unit root and the alternative is trend stationary where the trend has a break in it. The fourth test is the KPSS stationarity test where the null is the series is trend stationary and the alternative is that the series has a unit root.

II.4.4 Robustness to Outliers

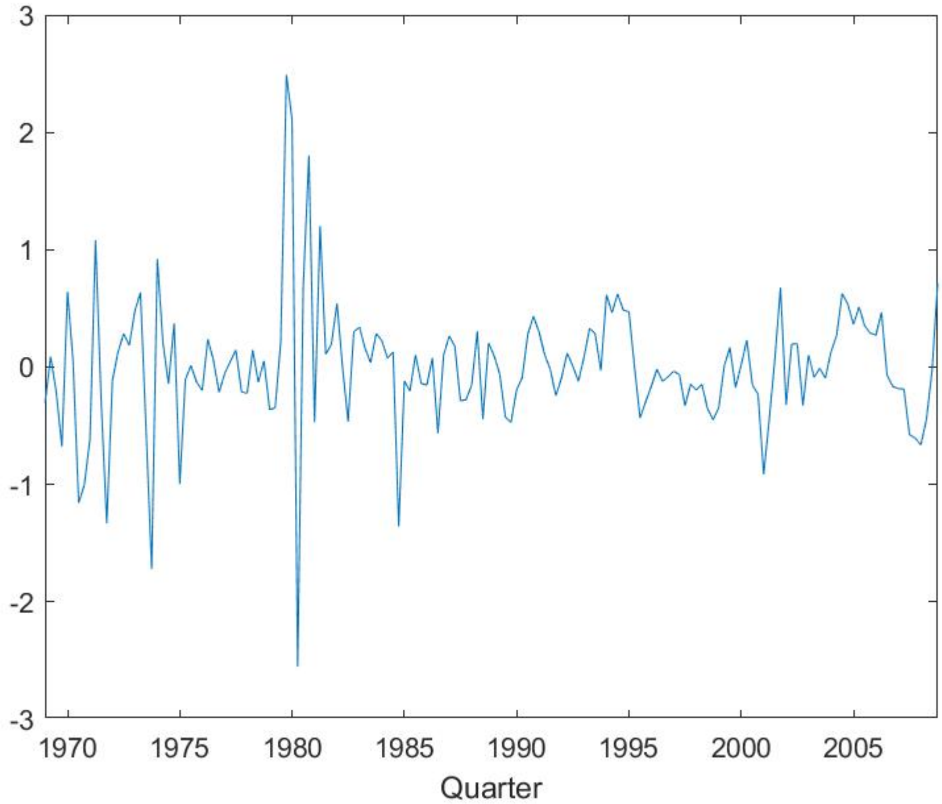
As was discussed in sections II.1 and II.2, the Volcker chairmanship of the Federal Reserve was a period of change in the conduct of monetary policy. There was significant emphasis placed on reducing the high inflation rates that persisted during the 70's and the Fed also switched from money supply to interest rate targeting. Many asymmetry papers have used measures of interest rates or money supply as their measure of monetary policy in the past. The Volcker period makes it unclear which one measure is the correct one to use given that the target switched during this time period. I use Romer and Romer (2004) monetary shocks to measure monetary policy which allows us to circumvent this measurement problem during the Volcker period. Romer and Romer (2004) discuss in their paper that even when the FOMC was not explicitly targeting the Federal Funds rate, they were concerned about this key interest rate and the implications that policy actions would have on the funds rate. Because of this it is natural to construct a shock series using the intended Federal Funds rate for the duration of the sample period.

That being said, there are still potential problems with using the Romer and Romer (2004) monetary shocks over this period as there are large outliers in these shocks during the Volcker period. A few of the papers in the asymmetry literature have explored how this period impacted the results of asymmetry such as Morgan (1993) and Thoma (1994). In this section, I demonstrate how the baseline results change depending on how the researcher deals with this period.

Figure II.6 plots the updated non-linear Romer and Romer shocks following Equation II.3. Table II.2 contains the values of the ten largest Romer and Romer shocks in absolute value. The largest data points in absolute value happen during the Volcker chairmanship at the Fed, where three of the quarters from 1980 being in the top 4 largest values. This was a feature of the shocks produced in the original Romer and Romer (2004) paper as well. It is also important to note that the first three quarters of 1980 were recessions by the NBER majority rule metric. This is problematic since of the 160 quarters in our sample, only 27 quarters are counted as recessions in the NBER majority rule metric. Since there are so few data points, they are highly susceptible to the influence of outliers.

Figure II.7 shows the impulse response of the first difference of real GDP with a dummy variable for 1979:Q4-1982:Q4 added into Equation II.1. In this case, the re-

Figure II.6
Quarterly Non-Linear Romer and Romer Shocks



Notes: This Figure plots the non-linear Romer and Romer shocks updated to include the sample 1969:Q1-2008:Q4. A feature of these shocks are the large outliers during the Volcker period of the Federal Reserve with the largest coming mostly between the years 1979-1982.

cession response is always below the expansion response, indicating that the response of output during recessions is larger than the response during expansions. In contrast with Figure II.4, controlling for these outliers moved the conclusion from inconclusive to monetary policy being more effective in recessions. The peak response in recessions is measured to be about three times larger when I control for the Volcker period. Also, the expansion results in the baseline case appear to be driven by the Volcker period, since the response in expansions went from significant in Figure II.4 to zero in Figure II.7. If I compare this to the baseline results by controlling for both stochastic trends

Table II.2
Quarterly Non-Linear Romer and Romer Shocks Ranked

Quarter	**Value**	$NBER_{mr}$
1980:Q2	-2.6377	1
1979:Q4	2.6151	0
1980:Q1	2.1771	1
1980:Q4	1.9366	0
1973:Q4	-1.6411	0
1981:Q2	1.3189	0
1971:Q4	-1.2106	0
1970:Q3	-1.1734	1
1984:Q4	-1.1583	0
1975:Q1	-1.1531	1

Notes: This Table contains the values of the ten largest shocks (in absolute value) of the Romer and Romer shock series. The column $NBER_{mr}$ is 1 if the quarter was in a recession and 0 if the quarter was in an expansion.

in the data and the Volcker period, this completely flips the result of monetary policy being more effective during expansions.

Figures II.7b and II.7c explore if the cumulated growth rates in expansions and recessions are significantly different from zero. The response of output in expansions is not significantly different from zero anywhere of interest. The recession growth rate is significant for a large portion of the horizon, from horizons 2-17. Given that the recession response is always larger and significant, there are already signs that asymmetry exists in this specification.

The results of the t-test for asymmetry in the cumulative response between expansions and recessions is presented in Figure II.7d. This Figure shows that the differences that appeared in the other three graphs are indeed significant. Horizons 2-17 all show p-vlues that are significant at any conventional level, indicating that asymmetry does exist and the response of real GDP to a monetary shock is larger in recessions.

The evidence for quarterly real GDP growth with a Volcker dummy does strongly suggest that monetary policy is more effective in recessions. Monthly industrial production growth tells a similar story. Figure II.8a is identical to Figure II.7a in that the response during recessions is always larger than the response during expansions. Comparing Figure II.8a to Figure II.5a, does not change the conclusion but does accentuate the difference between the expansion and recession response. The expansion response in Figure II.5a while smaller than the recession response is still large. Any expansion response there was vanishes when the Volcker period is controlled for, again suggesting that the Volcker period is driving the expansion results in Figure II.5a. Consistent with the quarterly GDP case, the peak response of industrial production in Figure II.8a is much larger than in Figure II.5a, by a factor of between three and four.

The results from the asymmetry test largely support the result that when industrial production growth and a Volcker period dummy are used, that output responds more to the monetary shock in recessions. The asymmetry t-test has numerous periods where there is a significant difference between the expansion and recession responses and is again significant for a large portion of the horizon, from approximately horizon 5-52. This result is supported by Figures II.8b and II.8c. The expansion response is not significant at any point over the horizon except for a significant positive response around horizon 8. The recession response is significant from horizon 10-50.

To summarize the results so far, it appears that moving to monthly specifications and industrial production data erases the result that output responds to monetary policy more in expansions than recessions. The peak responses are similar, but there is a timing difference between the expansion and recession responses. Moving to growth rate specifications of output reverses the result for both real GDP and industrial production, while accounting for outliers further accentuates this result. In section II.4.5, I explore how these results are impacted by various robustness checks.

II.4.5 Additional Robustness Checks

Figure II.9 explores the robustness of my results to different shock types. I use shocks generated from a non-linear monetary VAR containing real GDP growth, PCE inflation growth, and the Federal Funds rate. The Federal Funds rate is ordered last in the model. The shocks from this VAR were added in place of the Romer and Romer shocks in equation II.2. Figure II.9 shows the impulse responses and asymmetry tests of real GDP growth to a VAR shock. Figure II.10 shows the impulse responses and asymmetry tests of real GDP growth over the same sample period with the Volcker period dummied out as in section II.4.4.

Analysis of these two Figures gives the same result as in section II.4.4. In Figure II.9a, I see inconclusive evidence of which phase of the business cycle has more effective policy. Over the first half of the horizon the effect in expansions dominates while recessions dominate over the later half of the horizon, with both of these being significant. It should be noted that the peak effect of monetary policy is larger in recessions than expansions. Dummying out the Volcker period again causes the response in recessions to increase in size while the response in expansion stays relatively the same between the two graphs. The t-tests do find some significant differences in the cumulative sum of the growth rates between expansions and recessions, finding that the response in recessions is larger at horizons 8 and 20. Overall, the response in recessions is larger than that of expansions for most of the horizon, suggesting that the results shown thus far are robust to the type of shock used.

Figure II.11 explores how robust the results are to other measures of economic activity. In this Figure, I use real personal consumption expenditure as the measure of economic activity. Figure II.11 shows the impulse responses and asymmetry tests of monthly real PCE over the sample 1969:03-2008:12. Figure II.12 does the same analysis but dummies out the Volcker period. In Figure II.11a, there are very small to no differences in the response of real PCE to monetary policy in expansions versus recessions. Both responses feature the same peak response that happens slightly earlier in expansions. When I control for the Volcker period, I see a change similar to the one in Figure II.10. The expansion response is virtually unchanged while the peak response during recessions increases to approximately four times its original size. The t-test shows that there are now significant differences between the responses in expansions and recessions. Again, controlling for the Volcker period suggests that monetary policy is more effective in recessions than expansions because the impulse response for recessions is always larger than that of expansions over the horizon.

II.5 Conclusion

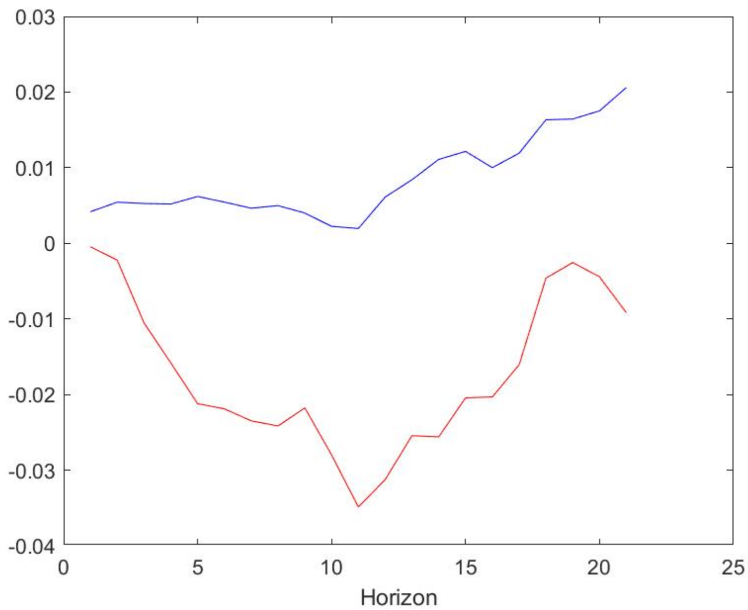
There is substantial evidence in the literature that the effects of monetary policy on output might have different effects in recessions and expansions. Much of the earlier literature on this topic found that monetary policy was more effective in recessions while recent studies have found the opposite to be true. My baseline specification agreed with these recent studies, finding monetary policy to be more effective in expansions. In this paper, I explored some reasons that discrepancies might arise in the literature. This can be narrowed down to three main reasons, which also impacted my baseline result.

First, the frequency of the data and measure of output had an effect on the results. The driving factor behind this is that focusing on interest rate sensitive sectors, such as industrial production, and using monthly recession dates provides a cleaner identification of the effects of monetary policy in expansions and recessions. Switching from quarterly to monthly based measures of output changed the results dramatically. In the quarterly baseline specifications, I found evidence that monetary policy was more effective in expansions than recessions. This result was not robust to switching the measure of output or frequency of data used and the story became one of timing rather than which regime experienced a larger effect. The point estimate in expansions and recessions was largely the same with the estimate in recessions reaching its peak much earlier.

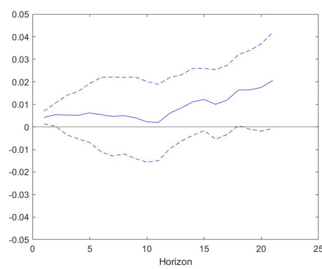
Second, the way that stochastic trends in the data are dealt with also had an effect. Papers earlier in the asymmetry literature favored using growth rates while running levels data has become a more recent trend when using the local projections approach. When I switched the model from running the level of real GDP with a trend to the logged first difference, the asymmetry result from the baseline case disappeared. Instead of the response in expansions being larger, the response in recessions became the same size as during expansions. This leaves us with inconclusive evidence about which regime experienced a larger effect. Both specifications using levels with a trend and logged first difference are correct since they are not inconsistent with a unit root. The unit root tests performed are consistent with a unit root, and if there is one, the differences specification should be more efficient.

Finally, outliers appear to have a major effect on asymmetry. This was a major driving force behind the results since the recession quarters 1980:01-1980:03 featured among the largest shocks in absolute value in the updated Romer and Romer shock series. When a dummy variable is added to the model to control for these outliers, the response during recessions increased in size and the response in expansions disappeared, completely flipping the result from the baseline case. This suggests that the recession outliers were working against finding an effect in the earlier specifications and that a large part of the expansion response in the earlier specifications was being driven by this time period. Recent papers have moved away from recognizing the importance of this time period but the shocks from this period should not be blindly trusted, no matter which type of shock is being used. Given the results of this paper, when the frequency of data and measure of output, stochastic trends, and outliers are considered simultaneously, I find than monetary policy is more effective in recessions than expansions.

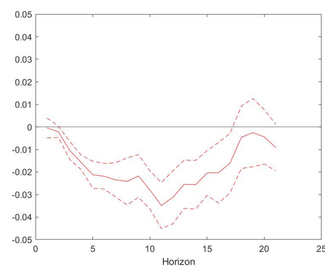
Figure II.7
Impulse Response of Quarterly real GDP in Growth Rates
Volcker Results



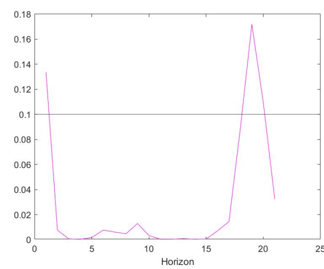
(a) Point Estimates



(b) Expansion



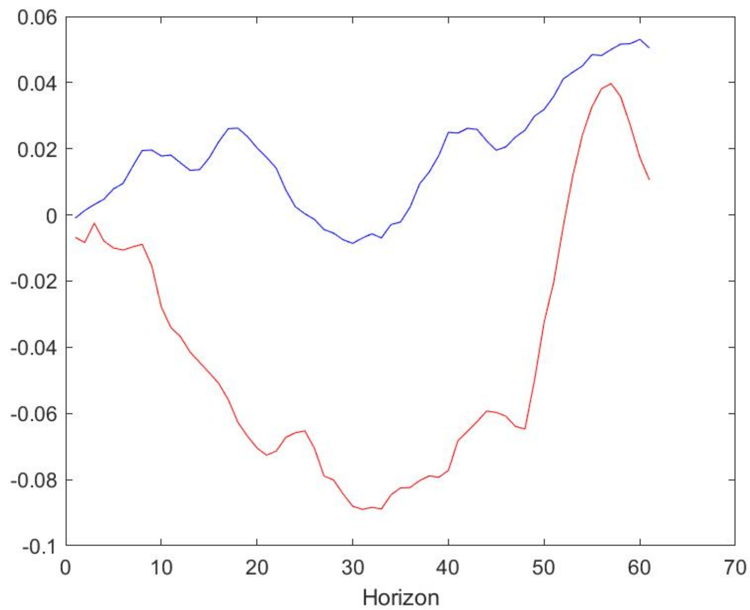
(c) Recession



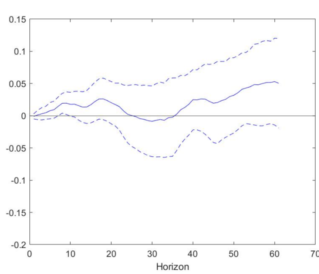
(d) t-test p-value

Notes: This Figure shows the impulse response of real GDP growth in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of real GDP growth to the shock. Variables are in logged first difference. The sample is quarterly from 1969:Q1-2008:Q4 with the years 1979:Q4-1982:Q4 dummied out. Figure (a) shows the impulse response point estimates for expansions and recessions where the point estimate is the cumulative sum of the growth rate. Figure (b) and (c) show the impulse responses of the growth rate of real GDP with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the growth rates of real GDP in expansions and recessions with the line in the figure corresponding to the 90% significance level.

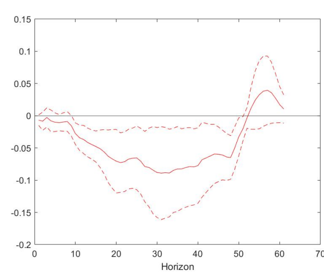
Figure II.8
Impulse Response of Monthly Industrial Production in Growth Rates
Volcker Results



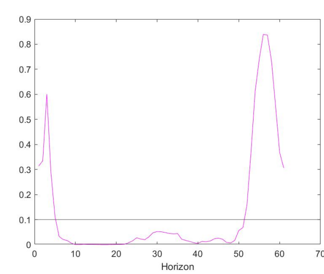
(a) Point Estimates



(b) Expansion



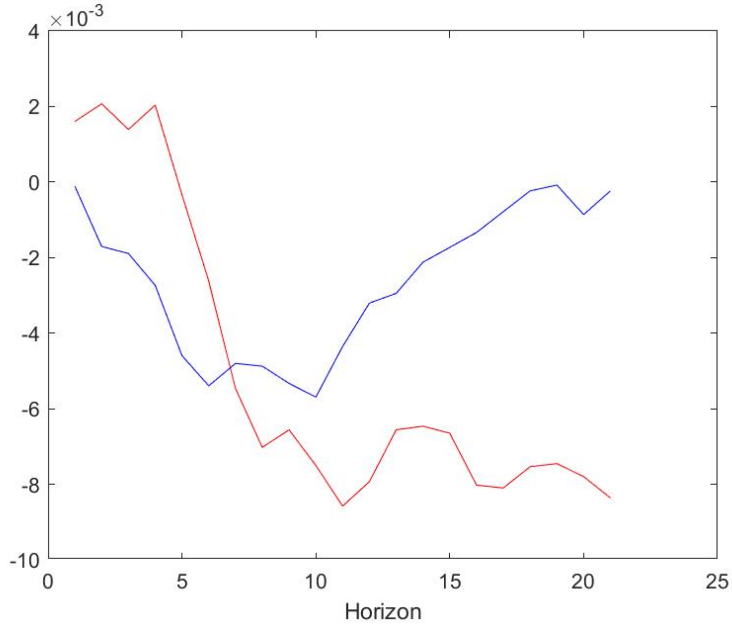
(c) Recession



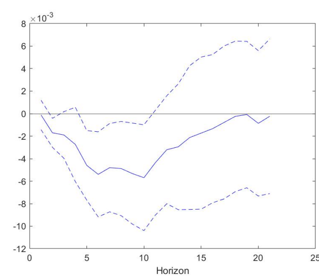
(d) t-test p-value

Notes: This Figure shows the impulse response of industrial production growth in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of industrial production growth to the shock. Variables are in logged first difference. The sample is monthly from 1969:03-2008:12 with the years 1979:10-1982:12 dummied out. Figure (a) shows the impulse response point estimates for expansions and recessions where the point estimate is the cumulative sum of the growth rate. Figure (b) and (c) show the impulse responses of the growth rate of industrial production with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the growth rates of industrial production in expansions and recessions with the line in the figure corresponding to the 90% significance level.

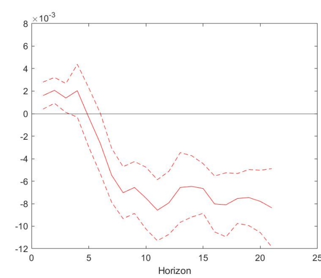
Figure II.9
Impulse Response of Quarterly real GDP in Growth Rates
VAR Shock



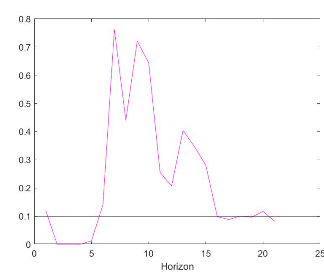
(a) Point Estimates



(b) Expansion



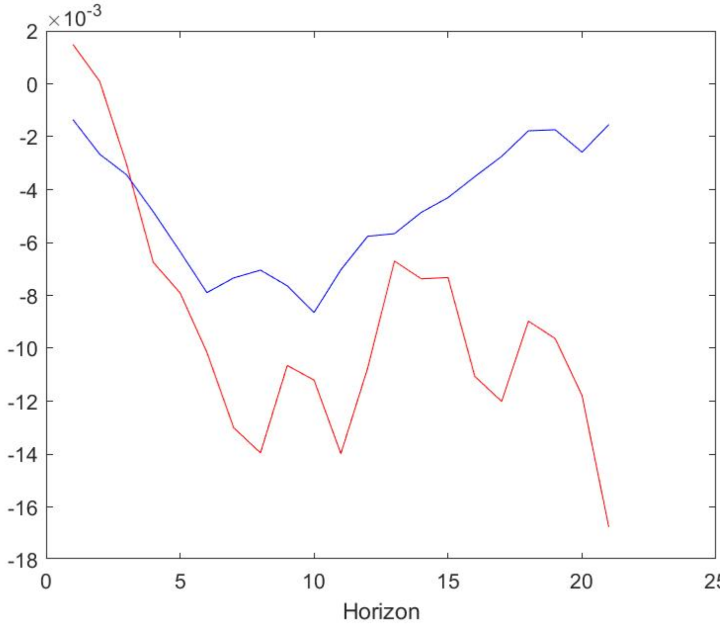
(c) Recession



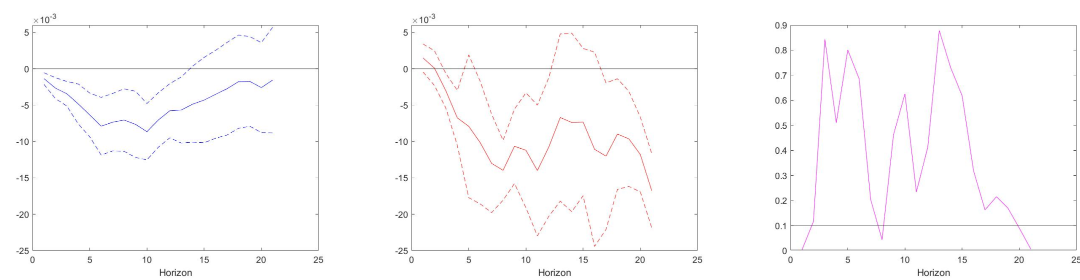
(d) t-test p-value

Notes: This Figure shows the impulse response of real GDP growth in recessions (red) versus expansions (blue) to a one standard deviation positive VAR shock generated from a VAR model containing real GDP, PCE inflation, and the Federal Funds rate. The response multiplied by 100 gives the percent change of real GDP growth to the shock. Variables are in logged first difference. The sample is quarterly from 1969:Q1-2008:Q4. Figure (a) shows the impulse response point estimates for expansions and recessions where the point estimate is the cumulative sum of the growth rate. Figure (b) and (c) show the impulse responses of the growth rate of real GDP with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the growth rates of real GDP in expansions and recessions with the line in the figure corresponding to the 90% significance level.

Figure II.10
Impulse Response of Quarterly real GDP in Growth Rates
VAR Shock with a Volcker Period Dummy



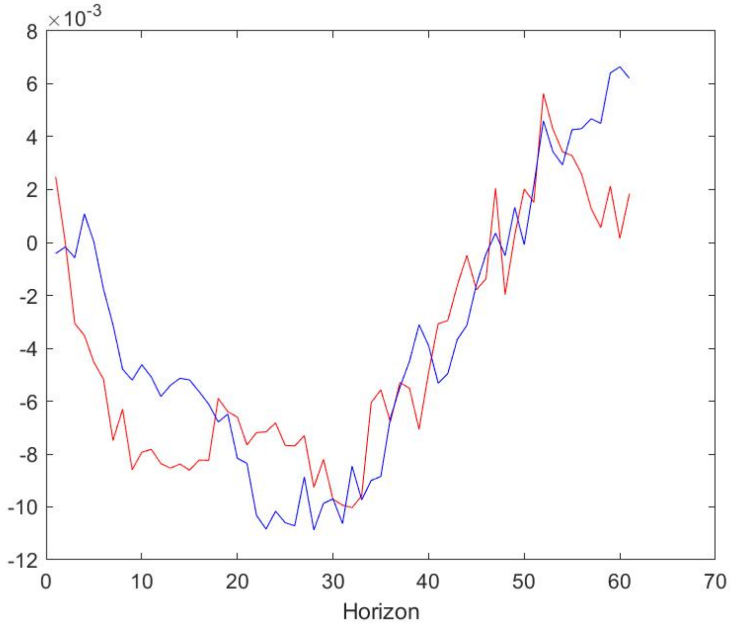
(a) Point Estimates



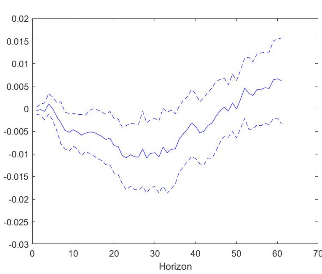
(b) Expansion **(c) Recession** **(d) t-test p-value**

Notes: This Figure shows the impulse response of real GDP growth in recessions (red) versus expansions (blue) to a one standard deviation positive VAR shock generated from a VAR model containing real GDP, PCE inflation, and the Federal Funds rate. The response multiplied by 100 gives the percent change of real GDP growth to the shock. Variables are in logged first difference. The sample is quarterly from 1969:Q1-2008:Q4 with the years 1979:Q4-1982:Q4 dummied out. Figure (a) shows the impulse response point estimates for expansions and recessions where the point estimate is the cumulative sum of the growth rate. Figure (b) and (c) show the impulse responses of the growth rate of real GDP with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the growth rates of real GDP in expansions and recessions with the line in the figure corresponding to the 90% significance level.

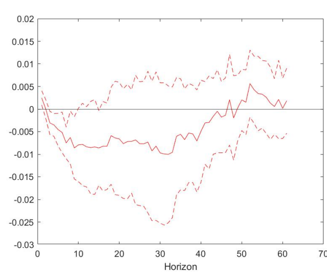
Figure II.11
Impulse Response of Monthly real PCE in Growth Rates



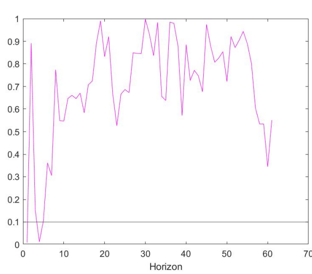
(a) Point Estimates



(b) Expansion



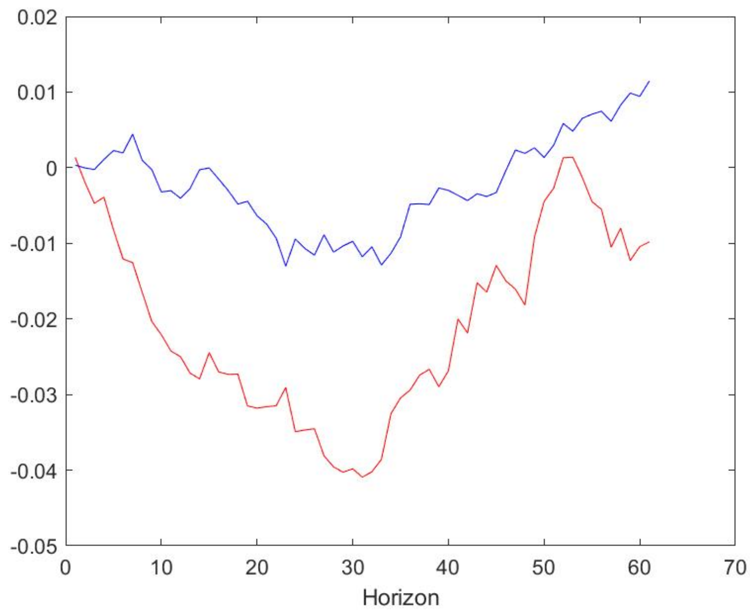
(c) Recession



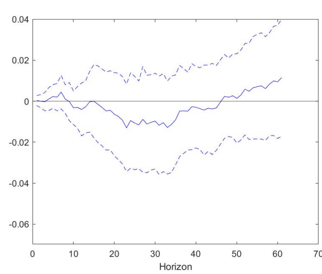
(d) t-test p-value

Notes: This Figure shows the impulse response of real personal consumption expenditure growth in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of real PCE growth to the shock. Variables are in logged first difference. The sample is monthly from 1969:03-2008:12. Figure (a) shows the impulse response point estimates for expansions and recessions where the point estimate is the cumulative sum of the growth rate. Figure (b) and (c) show the impulse responses of the growth rate of industrial production with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the growth rates of industrial production in expansions and recessions with the line in the figure corresponding to the 90% significance level.

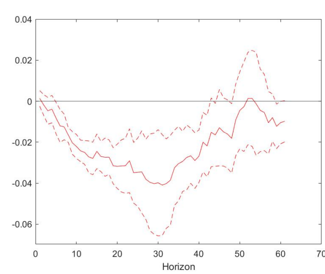
Figure II.12
Impulse Response of Monthly real PCE in Growth Rates
Volcker Results



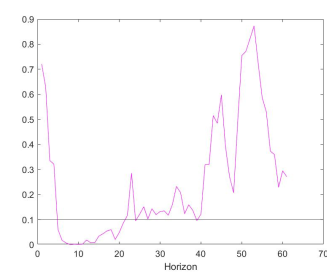
(a) Point Estimates



(b) Expansion



(c) Recession



(d) t-test p-value

Notes: This Figure shows the impulse response of real personal consumption expenditure growth in recessions (red) versus expansions (blue) to a one standard deviation positive Romer and Romer shock where the response multiplied by 100 gives the percent change of real PCE growth to the shock. Variables are in logged first difference. The sample is monthly from 1969:03-2008:12 with the years 1979:10-1982:12 dummied out. Figure (a) shows the impulse response point estimates for expansions and recessions where the point estimate is the cumulative sum of the growth rate. Figure (b) and (c) show the impulse responses of the growth rate of industrial production with the Newey-West 90% confidence intervals for expansion and recession respectively. Figure (d) shows the p-value of the t-test for the difference between the growth rates of industrial production in expansions and recessions with the line in the figure corresponding to the 90% significance level.

CHAPTER III
MONETARY POLICY STIMULUS DURING RECESSIONS DOES NOT AFFECT OUTPUT

III.1 Introduction

There is a large literature focusing on whether the effects of monetary policy shocks are asymmetric across multiple dimensions. The literature has focused mainly on three dimensions: asymmetry related to the direction of the shock, the size of the shocks, and the phase of the business cycle within which the shock took place. The asymmetry literature began with Cover (1992) who was interested in studying directional asymmetry. Since then, a large literature has explored all three types of asymmetry with varying results. This paper will contribute to the asymmetry literature by studying all three manifestations of asymmetry simultaneously. While this literature has focused on many countries including the United States, I study the asymmetric effects of monetary policy using U.S. data.

Most papers study one particular type of asymmetry at a time as in Cover (1992), Morgan (1993), Thoma (1994), Kandil (1995), Karras (1996), Peersman and Smets (2002), Garcia and Schaller (2002), Kaufmann (2002), Tenreyro and Thwaites (2016), and Angrist et al. (2018). A small group of papers attempt to study multiple manifestations of asymmetry simultaneously, including Weise (1999), Ravn and Sola (2004), and Lo and Piger (2005). It is important to consider the asymmetry types simultaneously since inherent in any model with only one type of asymmetry is an assumption that the results are not being driven by the other two types of asymmetry. By including all three types of asymmetry, this assumption can be dropped.

Most papers in the business cycle asymmetry literature, such as Thoma (1994), Weise (1999), Peersman and Smets (2002), Kaufmann (2002), Garcia and Schaller (2002), and Lo and Piger (2005) find that monetary policy has a larger impact on output during recessions than expansions. However, more recent evidence from Tenreyro and Thwaites (2016) finds that the output effects of monetary policy shocks are much larger in expansions than recessions. In the directional asymmetry literature, most of the early papers found that contractionary monetary policy shocks had more of an effect on output than accommodative monetary policy. Cover (1992) found that negative money supply shocks have a negative effect on output while positive money supply shocks have little effect on output. Kandil (1995) and Karras (1996) agree with the result that negative money supply shocks have larger effects on output than positive money supply shocks. Morgan (1993) used the federal funds rate as his policy measure and found that contractionary monetary policy reduces output while accommodative policy has insignificant effects.

Weise (1999), Ravn and Sola (2004), and Lo and Piger (2005) all find little evidence of directional asymmetry in their models that simultaneously estimated multiple asymmetries. There is much less evidence regarding size asymmetry than exists for the other two types of asymmetry. Evidence for this type of asymmetry comes from Weise (1999) and Ravn and Sola (2004). Weise (1999) found that large shocks had disproportionately larger effect than small shocks while Ravn and Sola (2004) found that large shocks were neutral and small shocks had real effects on output. Lo and Piger (2005) also studied size asymmetry but found no evidence for this type of asymmetry.

The theme that exists between each of the asymmetry types is that there is conflicting evidence about the direction of the asymmetry or which types of asymmetry are important. Reaching a consensus in this literature is important given the importance of monetary policy to control inflation during expansions and boost output during recessions. If traditional monetary policy is not very effective at impacting output during recessions then fiscal policy and non-traditional monetary policy might have more of a place moving forward. Knowing about size asymmetry is important as well. If small shocks are found to have disproportionately larger effects on output than larger shocks then central bankers can respond to recessions by taking smaller policy actions rather than resorting to large scale changes.

My analysis will focus on investigating multiple manifestations of asymmetry in the same model. This paper will use a similar methodology as Tenreyro and Thwaites (2016) by using the local projection framework developed in Jordá (2005), but will study multiple manifestations of asymmetry at the same time and the possible interactions between them. The few papers that look at multiple types of asymmetry do not consider the interactions between them, making this a novel contribution to the literature. In addition to this contribution, the use of local projections will provide me with a simple framework to investigate multiple types of asymmetry. The existing literature has made use of non-linear VAR models when studying the asymmetric effects of monetary policy. In VAR models, restrictive assumptions must be made about the short-run dynamics of the model in order to extrapolate forward and calculate the impulse responses. This becomes even more complicated when a non-linear VAR or a VAR model with regime switching is used since the state over the horizon must be considered when interpreting the impulse responses. Local projection models bypass this problem by directly calculating the impulse responses over the horizon based on the state of the model at time t. This will make the impulse responses generated from this model easier to interpret than impulse responses from a VAR model.

My analysis finds that business cycle asymmetry and directional asymmetry are important for explaining changes in output while size asymmetry is less so. The interaction between business cycle and directional asymmetry is also found to be an important factor for explaining output. Monetary policy shocks are found to affect output more in recessions than expansions. Contractionary monetary policy shocks are found to affect output in both recessions and expansions while accommodative monetary policy shocks have little effect on output in recessions and a *negative* effect on output during expansions. This result shows the value added of including multiple types of asymmetry in the same model. A model containing only business cycle asymmetry might incorrectly conclude that accommodative monetary policy is effective during recessions when in fact the business cycle results are being driven by policy contractions.

The rest of the analysis proceeds as follows: Section III.2 lays out the existing literature and my contribution to this literature. Section III.3 describes the model to be estimated. Section III.4 lays out the results of the analysis. Section III.5 concludes.

III.2 Literature Review and Motivation

There is a sizable literature investigating whether monetary policy shocks have asymmetric effects on output or prices depending on the phase of the business cycle, the size of the policy shock, or the direction of the shock. Most papers in this literature focus on a single type of asymmetry. In this paper I will focus on asymmetric effects of monetary policy shocks on measures of output, and will consider all three types of asymmetry simultaneously. The remainder of this literature review will summarize the existing literature on all three types of asymmetry.

There are three main theoretical arguments that can be used to explain the asymmetric effects of monetary policy on output. The first theoretical model that features monetary policy asymmetry are rigid price models. Prices in these models are more rigid in the downward direction and this manifests itself as a convex short-run aggregate supply curve. This can be used to explain all three types of asymmetry with respect to output. Directional asymmetry is present since accommodative monetary policy will have more of an effect on output than contractionary monetary policy through its effects on the aggregate demand curve. Business cycle asymmetry is present since a recession means that the intersection between the aggregate demand curve and short-run aggregate supply happens to the left of potential GDP on the flat portion of the short-run aggregate supply curve. At this point, a shock in either direction will affect output more than a shock during an expansion, where the intersection of aggregate demand and the short-run aggregate supply curve is on the vertical portion of the short-run supply curve. Size asymmetry will also show up depending on where the short-run equilibrium occurs on the short-run supply curve. For example, on the flat portion of the curve, small monetary policy shocks will disproportionately affect output more than large shocks.

The second theoretical argument is the credit channel theory laid out in Bernanke and Gertler (1995). This channel works through the balance sheet channel of firms and the decision by these firms to use external finance through banks and other financial institutions. During business cycle expansions, firms have a surplus of internal funds that can be used so they will be less likely to use external finance to fund their operations. During business cycle recessions, the internal sources of funds dry up, meaning firms will more heavily rely on external financing. Since monetary policy affects the macroeconomy through financial institutions and external finance, monetary policy actions will have more of an effect on output during recessions when external finance is being more widely used.

The third theoretical argument can be used to explain size asymmetry. Menu cost models are models where firms face costs, known as menu costs, to adjust their prices. If the prices of a firms inputs only change by a small amount then the increase in profits from adjusting prices may be smaller than the cost associated with changing prices, so the firm will decide to not change its prices. Only when this price change gets large enough will firms undergo price changes. In this case, only small shocks will have real effects on output since firms will adjust their prices proportionally to the shock when the shock is large.

The empirical monetary policy asymmetry literature began with Cover (1992), who studied asymmetry between accommodative and contractionary monetary policy. Money supply shocks were used as the measure of monetary policy. This paper employed a two-step procedure to estimate monetary policy shocks. The first step involved specifying the money supply process and obtaining the residuals from the regression of that process. The second step involved using these residuals as the monetary policy shock series upon which output, measured as real gross national product, could be regressed. By regressing output growth on positive and negative money supply shocks, he found that contractionary monetary policy shocks had no effect on output but accommodative monetary policy shocks decreased output.

There have been a few other papers that studied directional asymmetry. Kandil (1995) and Karras (1996) found similar results to Cover (1992) while also employing a similar method. Kandil (1995) used real industrial production and the consumer price index from nineteen industrialized countries and found that prices and wages tend to respond more to contractionary monetary policy than to accommodative monetary policy. Karras (1996) used real GDP in a panel of 38 different countries and found evidence supporting international asymmetry between accommodative and contractionary monetary policy. A more recent paper, Angrist et al. (2018), used propensity score matching on the policy variable and found that contractionary monetary policy had an effect on yield curves and macroeconomic variables, industrial production and consumer price index among them, but monetary accommodation had less profound effects.

Regime switching frameworks are popular tools used to study the other two types of asymmetry. One can allow the states of the model to be recessions or expansions in the case of business cycle asymmetry or large and small shock regimes by tying the switching to the variance or size of the shocks. Peersman and Smets (2002) allow for regime switching between high and low growth rate periods. They measure monetary policy as a shock to the short-term interest rate from a simple VAR model, finding that monetary policy in the Euro-area had significantly larger effects on output, measured as industrial production, in recessions than expansions. Garcia and Schaller (2002) model regime switching as the economy switching from expansion and recession states. They use movements in the Federal Funds rate and innovations from a VAR as their monetary policy measures and find that US monetary policy has larger effects on output, measured using industrial production, during recessions than expansions. Kaufmann (2002) allows for switching between above average and below average growth periods. Kaufmann uses the first difference of the Austrian 3-month interest rate as the policy variable and using Bayesian methods, finds a significant negative effect of monetary policy on real GDP during below average growth periods and insignificant effects during normal and above average growth periods.

Tenreyro and Thwaites (2016) used the smooth-transition technique, developed in Granger and Teräsvirta (1993), to study business cycle asymmetry. Tenreyro and Thwaites (2016) innovated in two dimensions over the existing literature. First, they made use of the Romer and Romer monetary policy shocks from Romer and Romer (2004). Second, they employed local projections, developed in Jordá (2005), to generate impulse responses. Following these two methodologies they found that the response of output and prices to monetary policy shocks were more powerful in expansions than recessions. In this paper, I will use methodology similar to The Tenreyro and Thwaites (2016), specifically the combination of Romer and Romer (2004) monetary policy shocks and local projection methods.

An analysis of the theories behind the asymmetric effects of monetary policy on output suggest that a model containing a single type of asymmetry may not be enough to explain the movements in output. All three types of asymmetry can be partially explained by the convex aggregate supply curve theory, suggesting that there may be some interactions between the different types of asymmetry. In fact, the Aggregate Demand-Aggregate Supply model supports the idea that there may be interactions between the three types of asymmetry if the short-run aggregate supply curve is convex. If the short-run equilibrium takes place below potential GDP as it does during a recession, then small shocks will disproportionately affect output more than larger shocks and accommodative monetary policy will affect output more than contractionary monetary policy. Both of these asymmetries interact with business cycle asymmetry since these effects on output will be larger than they would be in a business cycle expansion. There have been a few papers that explored multiple manifestations of asymmetry within the same model, namely Weise (1999), Ravn and Sola (2004), and Lo and Piger (2005).

Weise (1999) considers all three types of asymmetry at once. Money based indicators of monetary policy are used, which come from ordering money last in a VAR model. The innovation of this paper was to show that these asymmetries could be modeled by applying a smooth-transition technique, developed in Anderson and Teräsvirta (1992), to a VAR model. Asymmetry is determined through the use of impulse response functions, calculated using forecasts generated by drawing shocks from the residuals of the model. By repeating this numerous times and averaging over initial values, you can get impulse responses for different subsamples of the data, such as low output growth versus high output growth periods. Weise did not find evidence of asymmetry regarding the direction of the shock but did regarding the phase of the business cycle and the size of the shock. Shocks during low growth periods were found to have larger effects on industrial production than shocks during high growth periods and large shocks were found to have disproportionately larger effect than smaller shocks. The size of shocks were measured based on their standard deviation, with the large versus small shock comparison based on a two versus a one-standard error shock. The size of shock asymmetry was particularly pronounced in negative, low growth rate periods suggesting that there are interactions between the types of asymmetry.

Ravn and Sola (2004) used unanticipated money supply shocks as their measure of monetary policy while revisiting the Cover (1992) (the seminal asymmetry paper) two equation model. They tie the regime switching to the mean and variance of the monetary policy shock, allowing them to study large versus small shocks in addition to the direction of the shock. They distinguish between four different types of shocks: large positive, large negative, small positive, and small negative. Large versus small shocks are defined by multiplying the residuals (unexpected money supply shocks) at time t by the probability of being in a small shock or large shock state at time t-1. Using US data, they find that large shocks are neutral while smaller shocks have real effects on real GNP and less support of directional asymmetry.

Lo and Piger (2005) use a regime switching framework to study all three types of asymmetry simultaneously as well as some interactions between the types of asymmetry. They use a time-varying transition probability model that allowed the switching process to be a function of the sign and size of the shock, as well as the phase of the business cycle. The shocks were identified from a monetary VAR model. Using US data, they found that policy actions taken during a recession had larger effects on industrial production than actions taken during expansions, but less evidence of the other two types of asymmetry.

To summarize the previous three papers, Weise (1999), Ravn and Sola (2004), and Lo and Piger (2005) use non-linear VARs or regime switching frameworks to generate impulse response functions. Their frameworks make it difficult to directly incorporate multiple types of asymmetry in a straightforward way and lead to impulse response functions with complicated interpretations. In this paper, I make use of the local projection methodology to generate impulse response functions. This will allow me to easily incorporate all three types of asymmetry into one model and directly calculate the impulse responses for each of these different states of asymmetry. In addition, my local projection model will allow me to easily incorporate interaction terms between the types of asymmetry, something these papers did not have in their models.

The use of local projections in the asymmetry literature was popularized by Tenreyro and Thwaites (2016). They used this model to study business cycle asymmetry and found that the response of GDP and prices to monetary policy shocks were more powerful in expansions than recessions. Developed by Jordá (2005), local projection models directly calculate the impulse response functions over increasing horizons without having to rely on extrapolation of short-run dynamics as in a VAR model. Local projections offer a few other advantages over VAR models. One, they are simple to estimate and draw inference from since they rely on running OLS over increasing time horizons. Two, local projections are more robust to misspecification of the data generating process than VAR models. Finally, local projections can more easily accommodate non-linear specifications in multivariate contexts.

The asymmetry literature generally measures monetary policy by using residuals from a simple monetary VAR or by using the Romer and Romer residuals, as discussed in Section III.3.2. In both cases, there are outliers in the measured shocks that happen during the 1979-1982 time period, corresponding to the Volcker chairmanship at the Federal Reserve. There have been some papers in the asymmetry literature that have highlighted the importance of the Paul Volcker chairmanship period, which lasted from 1979-1987. Prior to and during his chairmanship was a period characterized by high inflation rates, making the Feds primary goal during this time to reign in inflation. Volcker also oversaw the transition of the Fed from targeting the money supply to the Federal Funds rate as its primary policy tool. This paper finds that the results of asymmetry vary depending on how the residuals in this period are treated, much like other papers in this literature.

Morgan (1993) showed that changes in the Federal funds rate showed some asymmetry in output when looked at over the full sample 1963:2-1992:3, finding that increases in the funds rate had more of an effect than a decrease. There is less evidence for this result when the period 1979:4-1982:4 was excluded from the sample, the period when the Fed deemphasized the Federal funds rate. Thoma (1994) studied asymmetry and instability in the money-income causality. He used a rolling regression approach to show that the p-value of the money-income causality test is highly correlated with the level of real economic activity. There were two periods in his sample that this relationship was the strongest, 1969-1973 and 1978-1982. Ravn and Sola (2004) were also concerned about this period, their regime switching model allowing them to control for the Volcker period since the change in policy that happened then produced some large negative outliers that needed to be controlled for. Specifically they found that a large outlier in the money supply equation appeared in the first quarter of 1983. They found that the results of Cover (1992) were not robust to this outlier. Even Romer and Romer (2004) find outliers during this time period and find that there are many problems with measuring shocks during this time. The baseline specification in this paper follows Romer and Romer (2004) by generating residuals from an estimation of the Feds reaction function. Analyzing the data for this period, one will find that the residuals generated will typically be the largest during the 1979-1982 period, suggesting that some of the varying results observed in the asymmetry literature might be driven by how papers dealt with this time period. Given the effect that this period can have on the results of monetary policy asymmetry, my baseline model will include a dummy variable for the Volcker period.

III.3 Empirical Strategy

In this section, I lay out the econometric model and methods used in the paper. This section begins with a discussion of the local projection methodology for computing impulse responses and how inference is conducted in this framework. Second, the Romer and Romer (2004) monetary policy shock measure is presented. Finally, a brief description of the data used for this paper is discussed.

III.3.1 Local Projection Model

I follow Tenreyro and Thwaites (2016) in the use of the local projection model, developed in Jordá (2005), for estimating impulse responses. The local projection approach has a few advantages over a VAR model. First, it is simple to estimate and draw inference from, requiring only running OLS over increasing time horizons. Second, this model is robust to misspecification of the data generating process. Finally, it can more easily accommodate non-linear specifications in multivariate contexts. Tenreyro and Thwaites (2016) used their local projection model to study the asymmetric effects of monetary policy on output and prices in regards to business cycle asymmetry. I modify their approach to include all three types of asymmetry in one model, estimating equations of this form:

$$y_{t+h} = c + \gamma' x_t + \beta_h \varepsilon_t + \beta_h^{rec} \varepsilon_t rec_t + \beta_h^{small} \varepsilon_t small_t + \beta_h^{neg} \varepsilon_t neg_t + u_t \qquad \text{(III.1)}$$

where y_{t+h} is output measured in log levels at time horizon h, ε_t is the monetary policy shock, x_t is a control vector, rec_t is a dummy variable that is one if the shock ε_t takes place in a quarter t that is in a recession and zero otherwise, $small_t$ is a dummy variable that is one if the shock ε_t is small (defined below) in quarter t and zero otherwise, and neg_t is a dummy variable that is one if the shock ε_t is negative (accommodative monetary policy) in quarter t and zero otherwise.

Equation III.1 is estimated using log levels of the output variable. I will instead work with first differences of the logged output variable, given the strong evidence of a stochastic trend in the log level of measures of output in the United States. To accomplish this, consider first the local projection of the first difference of the log level of output on the monetary policy shock:

$$\Delta y_{t+h} = c + \gamma^{'} x_t + \beta_{h,D}\varepsilon_t + \beta^{rec}_{h,D}\varepsilon_t rec_t + \beta^{small}_{h,D}\varepsilon_t small_t + \beta^{neg}_{h,D}\varepsilon_t neg_t + u^D_{t+h}$$

where $\beta_{h,D}$, $\beta^{rec}_{h,D}$, $\beta^{small}_{h,D}$, and $\beta^{neg}_{h,D}$ are the responses of the growth rate of output to a monetary policy shock under the different types of asymmetry. Note that the sum of growth rate responses gives the level responses. We can estimate this level response directly in the growth rate specification using the transformation suggested in Stock and Watson (2018). Summing the growth rates over h gives:

$$\sum_{i=0}^{h} \Delta y_{t+i} = \sum_{i=0}^{h} (c + \gamma^{'} x_t + \beta_{i,D}\varepsilon_t + \beta^{rec}_{i,D}\varepsilon_t rec_t + \beta^{small}_{i,D}\varepsilon_t small_t + \beta^{neg}_{i,D}\varepsilon_t neg_t) + \sum_{i=0}^{h} u^D_{t+i}$$

This can be simplified:

$$\sum_{i=0}^{h} \Delta y_{t+i} = c + \gamma^{'} x_t + \beta_h\varepsilon_t + \beta^{rec}_{h}\varepsilon_t rec_t + \beta^{small}_{h}\varepsilon_t small_t + \beta^{neg}_{h}\varepsilon_t neg_t + \sum_{i=0}^{h} u^D_{t+i}$$

where $\beta_{h,D}$, $\beta^{rec}_{h,D}$, $\beta^{small}_{h,D}$, and $\beta^{neg}_{h,D}$ are the responses of the log level of output to a monetary policy shock under the different types of asymmetry. These log level responses are equal to the sum of the growth rate responses up to horizon h. The terms inside the summation $\sum_{i=0}^{h} \Delta y_{t+h}$ cancel out, until this equation is left:

$$y_{t+h} - y_{t-1} = c + \gamma' x_t + \beta_h \varepsilon_t + \beta_h^{rec} \varepsilon_t rec_t + \beta_h^{small} \varepsilon_t small_t + \beta_h^{neg} \varepsilon_t neg_t + \sum_{i=0}^{h} u_{t+i}^{D} \quad \text{(III.2)}$$

The impulse response for the logged first difference of output for the different types of asymmetry are $\beta_{h,D}$, $\beta_{h,D}^{rec}$, $\beta_{h,D}^{small}$, and $\beta_{h,D}^{neg}$. The standard errors are calculated from the estimation of equation III.2. This specification will be helpful because it will allow for all impulse responses to be reported in log level form rather than in logged first difference form, making it easier to draw conclusions.

Following Tenreyro and Thwaites (2016), the control vector will contain one lag each of output and the Federal funds rate. Impulse responses will be calculated out to twenty quarters, $H = 20$. The shocks developed in Romer and Romer (2004) will be used as the measure of the monetary policy shock (see Section III.3.2) and real GDP will be used as the measure of output to construct the dependent variable.

The dummy variable rec_t is defined as one if the Romer and Romer (2004) shock takes place in a quarter t that is in a recession and zero otherwise. The NBER indicator is a monthly variable published by the National Bureau of Economic Research indicating if the U.S. economy is in a recession or expansion. To convert this measure to a quarterly measure I count a quarter as in a recession when one of the months in the quarter are counted as a recession by the monthly NBER indicator. The dummy variable $small_t$ is defined as one if the Romer and Romer (2004) shock is small in quarter t and zero otherwise. I follow Lo and Piger (2005) and define a small shock as any shock within one standard deviation of its historical mean and large shocks are anything larger than one standard deviation of its historical mean[1]. The dummy variable neg_t is defined as one if the Romer and Romer (2004) shock is negative in

[1]The Romer and Romer residuals will be the main shock measure used. Since they are constructed as residuals from a regression they are mean zero by construction.

quarter t and zero if the Romer and Romer (2004) shock is positive. Negative shocks represent accommodative monetary policy while positive shocks represent contractionary monetary policy. When it comes to the shock measures in this paper, it is important to note that they represent different things. The business cycle shock measure represents the Fed responding to some outside variable, whether the economy is currently in a recession or expansion. The other two measures, size and directional shocks, represents how the Fed responds with monetary policy. That is, when the Fed conducts monetary policy, it must decide to raise or lower the policy variable and by how much.

There are a few tests that can be run using Equation III.2. One, we can test the null hypothesis that the effects of a monetary policy shock do not depend on whether the economy is in an expansion or recession by testing if $\beta_h^{rec} = 0$. Two, we can test the null hypothesis that the effects of a monetary policy shock do not depend on whether the shock is small or large by testing if $\beta_h^{small} = 0$. Third, we can test the null hypothesis that the effects of a monetary policy shock do not depend on whether the shock is positive or negative by testing if $\beta_h^{neg} = 0$.

There are several implicit assumptions that were made in Equation III.2. One, the differential effects of a monetary policy shock that are due to the shock occurring when the economy is in an expansion or recession do not depend on whether the shock is a large versus small shock or whether the shock is a positive versus negative shock. Two, the differential effects of a monetary policy shock that are due to the shock being a small versus large shock do not depend on whether the shock is positive versus negative or whether the economy is in a recession or expansion. Three, the differential effects of a monetary policy shock that are due to the shock being a positive versus negative shock do not depend on whether the shock is large versus small or whether the economy is in a recession or expansion. My baseline model drops these assumptions by introducing three new interaction variables into Equation III.2:

- $rec_t * small_t * \varepsilon_t$
- $rec_t * neg_t * \varepsilon_t$
- $neg_t * small_t * \varepsilon_t$

$$y_{t+h} - y_{t-1} = \alpha_h + \gamma_h^{'} x_t + \beta_h \varepsilon_t + \beta_h^{rec} rec_t \varepsilon_t + \beta_h^{small} small_t \varepsilon_t + \beta_h^{neg} neg_t \varepsilon_t$$
$$+ \beta_h^{recsmall} rec_t small_t \varepsilon_t + \beta_h^{recneg} rec_t neg_t \varepsilon_t + \beta_h^{negsmall} neg_t small_t \varepsilon_t + \sum_{i=0}^{h} u_{t+i}^{D} \quad \text{(III.3)}$$

I employ the Newey-West methodology to calculate asymptotic standard errors. As Jordá (2005) shows, the disturbance term in the local projection equation is serially correlated and has a moving average (MA) process. I use these standard errors to calculate 95% confidence intervals around the impulse response of output in recessions and expansions from Equations III.2 and III.3 depending on the specification of output. The maximum autocorrelation lag is set to be H+1 following Jordá (2005).

III.3.2 Romer and Romer (2004) Monetary Policy Shocks

I make use of the monetary policy shocks developed in Romer and Romer (2004). One must be mindful of the endogenous or anticipatory movements that plague monetary policy measures such as the money supply or the Federal funds rate. Romer and Romer (2004) developed a two-step process to derive a measure of monetary policy that is free from these problems. First, the intended Federal Funds rate for a given Federal Open Market Committee (FOMC) meeting is found by reading the narrative record of each FOMC meeting. Second, the intended funds rate series is regressed on the data from the Greenbook forecasts. The Greenbook forecast is produced prior to each FOMC meeting by the research staff of the Board of Governors. The forecasts contain projections of many macroeconomic variables of output, prices, employment, and investment. By regressing the intended funds rate on these forecasts, the residuals from this regression are now free of anticipatory movements. These residuals are the series of interest. The Romer and Romer (2004) regression is written as follows:

$$\Delta ff_m = \alpha + \beta ffb_m + \sum_{i=-1}^{2} \gamma_i \widetilde{\Delta y}_{m,i} + \sum_{i=-1}^{2} \lambda_i (\widetilde{\Delta y}_{m,i} - \widetilde{\Delta y}_{m-1,i}) + \sum_{i=-1}^{2} \phi_i \widetilde{\pi}_{m,i} + \sum_{i=-1}^{2} \theta_i (\widetilde{\pi}_{m,i} - \widetilde{\pi}_{m-1,i}) + \rho \widetilde{u}_{m,0} + \varepsilon_m$$

where Δff_m is the change in the intended funds rate around FOMC meeting m, ffb_m is the level of the intended funds rate before any changes were made at the associated FOMC meeting, $\widetilde{\Delta y}$ is the forecast of real output growth, $\widetilde{\pi}$ is the forecast of inflation, and $\widetilde{u}$ is the forecast of the unemployment rate. The series ε_m is the monetary policy shock series that will be used in this paper in meeting date space. I follow Tenreyro and Thwaites (2016) by summing the shocks that take place within a particular quarter to obtain a quarterly Romer and Romer (2004) shock measure.

III.3.3 Volcker Period Outliers

The Volcker period of the Federal Reserve was a period of change in the conduct of monetary policy. There was an emphasis placed on reducing the high inflation rates that persisted during the 1970s and the Fed also switched to targeting non-borrowed reserves rather than interest rates from 1979-1982. Many papers studying asymmetry have used measures of interest rates or money supply as their measure of monetary policy. The Volcker period makes it unclear which one measure is the correct one to use given that the target switched during this time period. I use Romer and Romer (2004) monetary policy shocks to measure monetary policy which allows us to circumvent this measurement problem during the Volcker period. Romer and

Romer (2004) note that even when the FOMC was not explicitly targeting the Federal Funds rate, they were concerned about this key interest rate and the implications that policy actions would have on the funds rate. Because of this, it is natural to construct a shock series using the intended Federal Funds rate for the duration of the sample period.

There are still some potential problems with using the Romer and Romer (2004) monetary policy shock series. Romer and Romer (2004) found large outliers in their monetary policy shock measure during this Volcker period of 1979-1982. Coibion (2012) found that when the rapid decrease in the federal funds rate in mid-1980 and the subsequent rise in late 1980 are dropped from the sample then the estimated effects that the Romer and Romer (2004) shocks have is significantly reduced. In addition to these papers, there have been numerous papers that have explored the robustness of asymmetry results to this period. Morgan (1993) found that the asymmetric effects of changes in the federal funds rate on output disappeared when 1979:Q4-1982:Q4 is excluded from the sample. Thoma (1994) found that the money-income relationship was strongest over the periods of 1969-1973 and 1978-1982. Ravn and Sola (2004) found that the asymmetry results found in Cover (1992) were not robust to a large outlier found in 1983:Q1.

The result from past research suggests that the Volcker period should be accounted for in the data. I accomplish this by adding dummy variables into Equation III.2 and Equation III.3 for the quarters 1979:Q4-1982:Q4. Given that the existing literature has found sensitivity of results to the inclusion of the Volcker period, my baseline specification will contain these Volcker period dummy variables.[2]

[2]However, my primary conclusions are robust to the exclusion of the Volcker period dummies.

III.3.4 Data

The data used in this study was taken from a variety of sources. Real GDP and federal funds rate data was taken from the St. Louis Federal Reserve's FRED database. The NBER indicator data was taken from the National Bureau of Economic Research recession indicators. Finally, the data used to generate the Romer and Romer (2004) monetary policy shocks was collected from the Philadelphia Federal Reserve's Greenbook data set. The main sample period for the quarterly frequency runs from 1969:Q1-2008:Q4. The sample period cuts off prior to the onset of the Great Recession, since the interest rate was near the zero lower bound for most of the duration and aftermath of the recession.

III.4 Results

This section contains the results of the analysis. Section III.4.1 begins with the baseline results of the interaction model in Equation III.3, while Section III.4.2 contains the results of the non-interaction model in Equation III.2. Finally, Section III.4.3 shows results from a model with only business cycle asymmetry, which serves to demonstrate the value added of a model that contains multiple types of asymmetry and their interactions.

III.4.1 Baseline Interaction Model Results

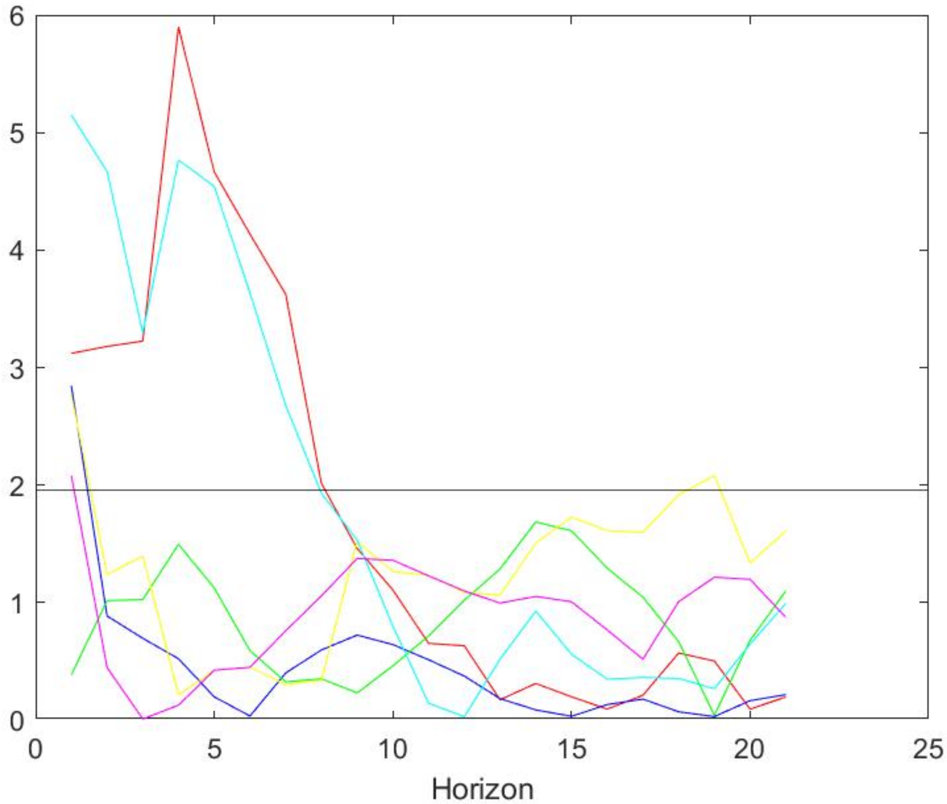
Using Equation III.3, I used a t-test to determine if there were asymmetric effects of monetary policy on output across the business cycle, the size of the shock, the direction of the shock, and any interactions between these asymmetries. The test was conducted over the sample period from 1969:Q1-2008:Q4. The sample ends right before the onset of the Great Recession when the federal funds rate was dropped to the zero lower bound and had no variation until 2015. Following Section III.3.3, dummy variables for the Volcker period of 1979:Q4-1982:Q4 are added into the model. Newey-West standard errors were used in the calculation of the test statistics. The t-test is calculated over the length of the horizon H for each type of asymmetry.

Figure III.1 contains the results of the t-test for the different types of asymmetry and interactions. In this Figure, the red line is the test statistic for business cycle asymmetry, the blue line is for size asymmetry, the green line is for directional asymmetry, the yellow line is for the interaction between business cycle and size asymmetry, the cyan line is for the interaction between business cycle and directional asymmetry, and the magenta line is for the interaction between directional and size asymmetry. The test statistics are reported in absolute value and the horizontal line shows the 5% significance level for a two-sided test.

In the interaction model test contained in Figure III.1, business cycle asymmetry and the interaction between business cycle and directional asymmetry are the only asymmetries that are strongly significant for more than one period. These two asymmetry types are significant for the first eight periods of the horizon. Other asymmetry types are also significant in this model but they are weakly significant. For this reason, when displaying impulse response functions below I will use a model that drops size asymmetry and its interactions. This will considerably simplify the presentation of impulse response functions.

The t-tests tell us which types of asymmetry exist but do not give us information regarding the nature of the asymmetry. This is explored by generating the impulse response functions of output to a monetary policy shock. Figure III.2 contains the impulse responses of output to a monetary shock when local projections is run on Equation III.2. Figure III.2a contains the response of output to a contractionary shock during a recession, Figure III.2b contains the response of output to an accommodative shock during a recession, Figure III.2c contains the response of output to

Figure III.1
Test Statistics for the Types of Asymmetry
Baseline Model



Notes: This Figure displays the t-statistics in absolute value for the different types of asymmetries and interactions when local projections are run on Equation III.3. The sample size is 1969:Q1-2008:Q4. The colors are as follows: rec = red, small = blue, neg = green, recsmall = yellow, recneg = cyan, negsmall = magenta. The horizontal bar represent the 5% significance level for a two sided test. Romer and Romer linear shocks are used in this equation.

a contractionary shock during an expansion, and Figure III.2d contains the response of output to an accommodative shock during an expansion.

Looking at Figure III.2, the results of the t-test become clear. Business cycle asymmetry can be observed by comparing Panel (a) to Panel (c) and comparing Panel (b) to Panel (d), particularly in horizons up to ten. In panel (a) there is a significant peak response of output to a contractionary shock in a recession of -0.0726 at horizon 5 while in Panel (c) the response of output to a contractionary shock in an expansion is -0.0227 at horizon 14. In the latter case, the peak response happens much later in the horizon and is not significant at any point along the horizon. In Panel (b), the estimated stimulative effect on output is 0.0228, although this is not significant. In comparison, Panel (d) estimates that there is only a negative response of output to an accommodative shock. It is important to note that the accommodative shocks in expansions and in the very short-run during recessions have the incorrect sign which I will discuss in more detail shortly. All this gives evidence that the response of output to either a contractionary or accommodative shock is larger during recessions, particularly within the first ten horizons from the time of the shock.

Directional asymmetry can be observed by comparing Panel (a) to Panel (b) and comparing Panel (c) to Panel (d). In the absence of directional asymmetry, these impulse responses should be mirror images of each other across zero. This is not the case in either recessions or expansions. The peak response of output to a contractionary shock during a recession is much larger and happens earlier in the horizon than the peak response of output to an accommodative shock in a recession. The response of output to a contractionary shocks is significantly less than zero from horizons 1-8 and the response of output to an accommodative shock is significantly less than zero from horizons 1-6 and horizons 19-21. Looking at shocks during expansions, the response of output to contractionary and expansionary shocks are not mirror images of each other. There is no significant difference from zero for the response of output to a contractionary shock during an expansion and the response of output to an accommodative shock is significantly less than zero only from horizons 14-15. The overall conclusion for directional asymmetry is that it is more prevalent during recessions and during the first 10 horizons, which is why the interaction between business cycle and directional asymmetry was significant in Figure III.1.

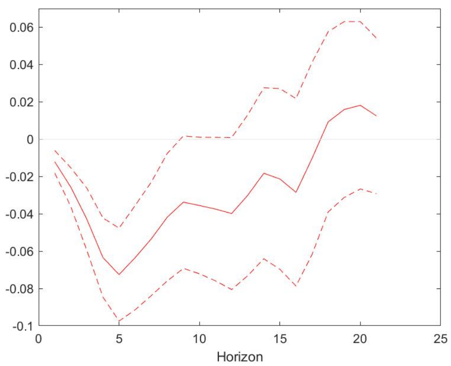
Figure III.2 reveals a striking result regarding the response of real GDP to accommodative shocks. The sign on the response of output is counter-intuitive to what theory says that it should be. This is true in both expansions and recessions. In recessions, there is a negative response of output to an accommodative shock during the first 6 horizons and during the last 3 horizons. While the response of output does have the correct sign during the middle portion of the horizon, this is not significant at any point. During expansions, the response to output is negative and significant from horizons 14-15, and it is negative and insignificant at every other horizon. If one had estimated an asymmetry model that did not included directional asymmetry, they would not find this result.

In summary, the results from the interaction model with Volcker period dummies give three main results. One, monetary policy has more of an effect on output during recessions than expansions. Two, directional asymmetry exists strongly during recessions and weakly during expansions, reinforcing the significance of the interaction term between business cycle and directional asymmetry in Figure III.1. Three, accommodative monetary policy is having a negative effect on output or at best no effect on output at all. This is true during expansions and recessions, but it is especially troublesome during the latter case. This leaves the door open for more non-traditional monetary policy or fiscal policy working in conjunction with monetary policy moving forward.

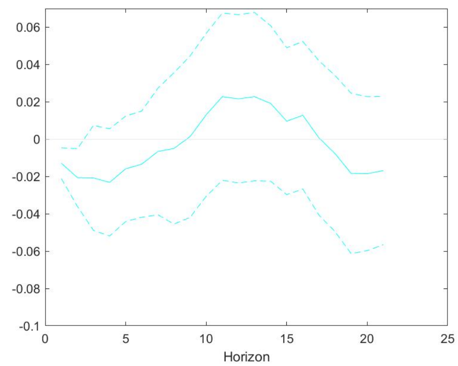
III.4.2 Non-Interaction Model Results

In this Section, I perform the t-test for asymmetry using the non-interaction model from Equation III.2. Figure III.3 contains the results of the t-test for the different types of asymmetric effects of monetary policy. The red line is the test statistic for business cycle asymmetry, the green line is the test statistic for directional asymmetry, and the blue line is the test statistic for size asymmetry. The test statistics are reported in absolute value and the horizontal line shows the 10% significance level for

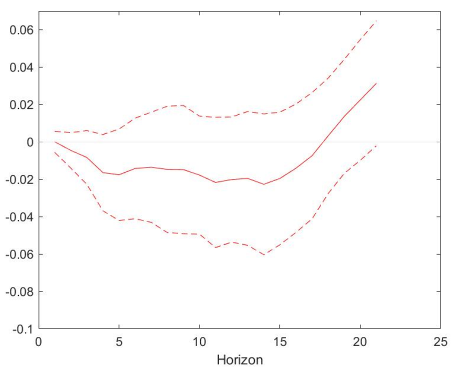
Figure III.2
Impulse Response of Output to a Monetary Policy Shock
Baseline Model



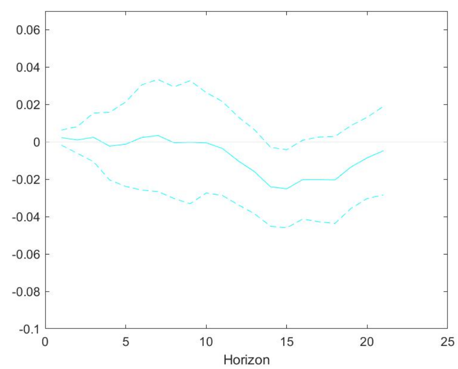
(a) Contractionary Recession Shock



(b) Accommodative Recession Shock



(c) Contractionary Expansion Shock



(d) Accommodative Expansion Shock

Notes: This Figure displays the impulse responses of output to a one standard deviation positive monetary policy shock when local projections are run on Equation III.2, size asymmetry is dropped from the model, and the Volcker period of 1979:Q4-1982:Q4 is dummied out. The response multiplied by 100 gives the percent change of output to the shock. Positive (contractionary) shocks will be in red and negative (accommodative) shocks will be in cyan for this Figure. Panel (a) shows the response of output to a contractionary shock in a recession. Panel (b) shows the response of output to an accommodative shock in a recession. Panel (c) shows the response of output to a contractionary shock in an expansion. Panel (d) shows the response of output to an accommodative shock in an expansion. The sample size is 1969:Q1-2008:Q4. Romer and Romer linear shocks are used in this equation.

a two-sided test.

This t-test picks up business cycle asymmetry the strongest. Business cycle asymmetry is important during the earliest horizons and again later in the horizon. Size asymmetry is briefly significant during the early stages of the horizon and directional asymmetry is not significant at any point along the horizon. The results of Figure III.3 show the value added of the interaction model of Section III.4.1. In both cases, business cycle asymmetry matters. However, directional asymmetry is also important but only manifests itself inside of recessions. This second point is impossible to pick up without the interaction terms. The impulse responses of the non-interaction model are not presented but are qualitatively similar to the impulse responses in Section III.4.1.

III.4.3 Results From a Model With Only Business Cycle Asymmetry

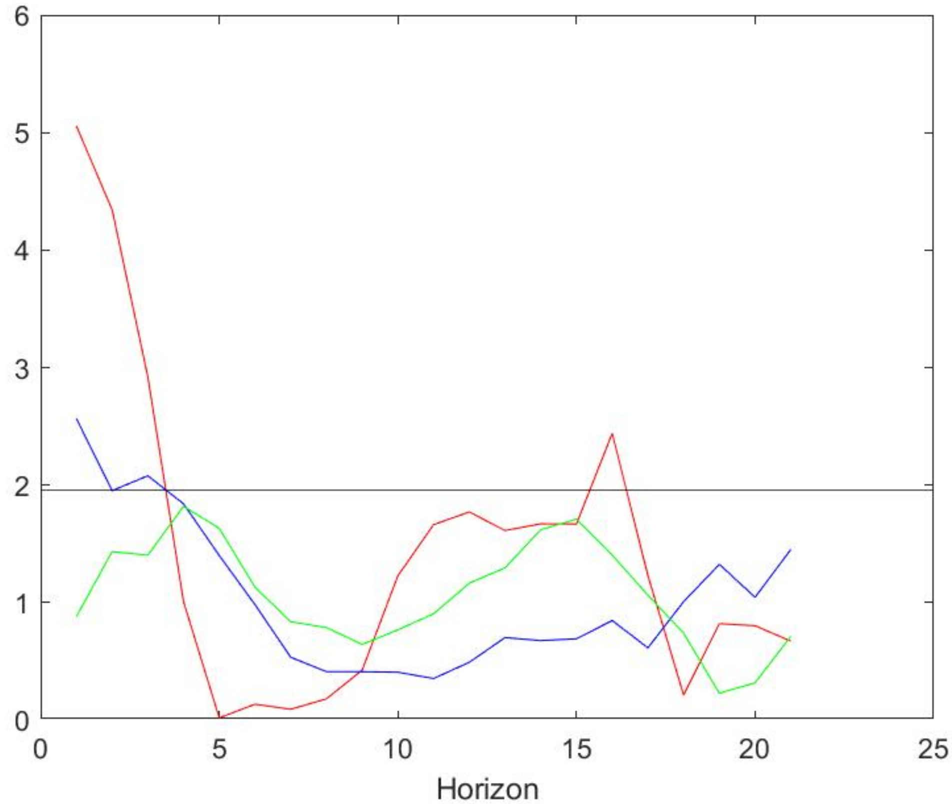
The results thus far have shown that business cycle asymmetry, directional asymmetry, and the interaction between the two are most important for explaining output. In this section, I provide further evidence demonstrating the value added of a model containing multiple types of asymmetry and their interactions. Specifically, I will show that models containing only business cycle asymmetry miss the important result that accommodative monetary policy shocks do not increase output.

I run the following local projection regression that contains only business cycle asymmetry.

$$y_{t+h} - y_{t-1} = c + \gamma^{'} x_t + \beta_h \varepsilon_t + \beta_h^{rec} \varepsilon_t rec_t + \sum_{i=0}^{h} u_{t+i}^{D} \tag{III.4}$$

Figure III.4a contains the response of output to a contractionary shock during a recession, Figure III.4b contains the response of output to an accommodative shock during a recession, Figure III.4c contains the response of output to a contractionary shock during an expansion, and Figure III.4d contains the response of output to

Figure III.3
Test Statistics for the Types of Asymmetry
Non-Interaction Model



Notes: This Figure displays the t-statistics in absolute value for the different types of asymmetries when local projections are run on Equation III.2. The sample size is 1969:Q1-2008:Q4. The colors are as follows: rec = red, small = blue, neg = green. The horizontal bars represent the 5% significance level for a two sided test. Romer and Romer linear shocks are used in this equation.

an accommodative shock during an expansion. The Volcker period has again been dummied out in this specification.

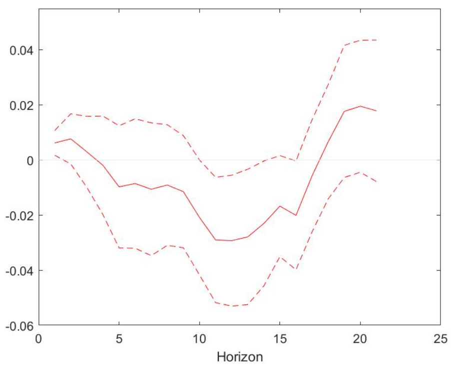
Figure III.4 shows that in a model containing only business cycle asymmetry, one would draw the conclusion that accommodative monetary policy shocks taken during recessions have very large stimulative effects, much larger than such shocks taken during expansions. This is exactly what economists would hope to be true, monetary policy stimulus is most effective during recessions when we would most want it to be. However, the results from the baseline model show that this is misleading. In fact, Figure III.2 shows that the large effect on output from monetary policy shocks is coming entirely from monetary policy tightening.

III.5 Conclusion

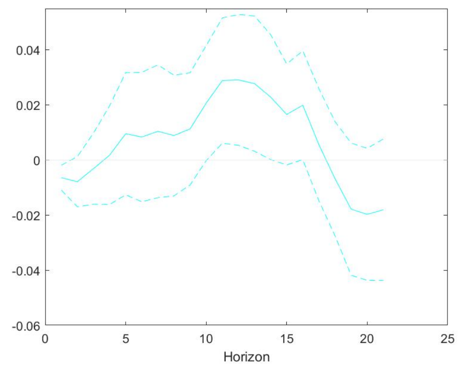
There is substantial evidence in the literature that the effects of monetary policy shocks on output might be asymmetric in three dimensions: shocks in different phases of the business cycle, shocks that differ in size, and shocks that differ in direction. In this paper, I explore these three types of asymmetry and potential interactions simultaneously using a local projection model. My results indicate that business cycle asymmetry, directional asymmetry, and the interaction between them are important for explaining how output reacts to a monetary policy shock. The results suggest that monetary policy shocks affect output more in recessions than expansions. In addition, no matter the phase of the business cycle, accommodative shocks appear to have little to no impact on output, with some impulse responses suggesting that accommodative shocks cause output to fall. These results suggest that models that only have one type of asymmetry in them are too simple to explain movements in output. This was demonstrated in Section III.4.3, where a model containing only business cycle asymmetry found that monetary policy shocks during recessions do have substantial positive effects on output.

The fact that accommodative monetary policy shocks have no significant effects on output is concerning for those in favor of using monetary policy to combat recessions. If these results are believed, then there is a larger need to resort to non-traditional accommodative monetary policy or accommodative fiscal policy working in conjunction with monetary policy to successfully combat recessions. One of the lessons that can be taken away from the Great Recession is that lowering interest rates may not

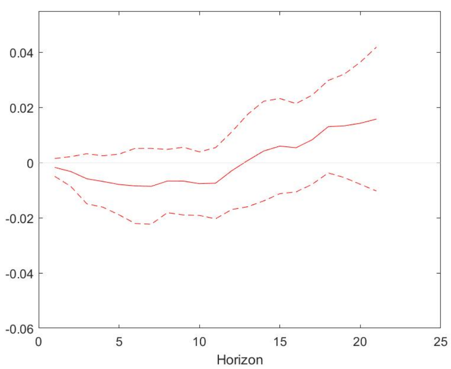
Figure III.4
Impulse Response of Output to a Monetary Policy Shock
Business Cycle Asymmetry Model



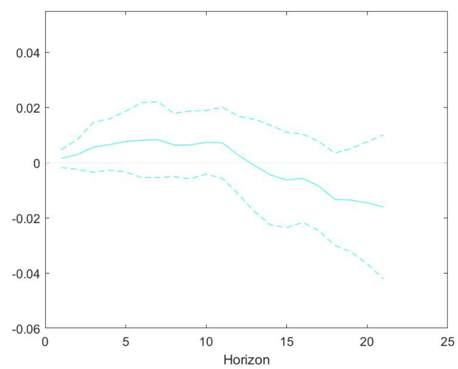
(a) Contractionary Recession Shock



(b) Accommodative Recession Shock



(c) Contractionary Expansion Shock



(d) Accommodative Expansion Shock

Notes: This Figure displays the impulse responses of output to a one standard deviation positive monetary policy shock when local projections are run on Equation III.4, a model containing only business cycle asymmetry, and the Volcker period of 1979:Q4-1982:Q4 is dummied out. The response multiplied by 100 gives the percent change of output to the shock. Positive (contractionary) shocks will be in red and negative (accommodative) shocks will be in cyan for this Figure. Panel (a) shows the response of output to a contractionary shock in a recession. Panel (b) shows the response of output to an accommodative shock in a recession. Panel (c) shows the response of output to a contractionary shock in an expansion. Panel (d) shows the response of output to an accommodative shock in an expansion. The sample size is 1969:Q1-2008:Q4. Romer and Romer linear shocks are used in this equation.

be enough to combat a recession, especially when the zero lower bound is reached. The results of this paper show that conventional monetary policy itself may not be enough even when the economy is not facing the zero lower bound.

There is one issue with the result that accommodative monetary policy shocks have no significant effects on output because there is a distinction between what a monetary policy shock is and how the Fed conducts monetary policy. In the asymmetry literature, economists use shocks that are generated from a VAR model or use Romer and Romer shocks in empirical models, which gives a policy measure that is orthogonal to output. In reality, the Fed does not conduct monetary policy in terms of "shocks", rather gathering all information about economic conditions before determining how to set the federal funds rate. While the result that accommodative recession shocks do not have a significant effect on output is alarming, actual policy actions taken by the Fed might have significant effects on output.

CHAPTER IV
SHOULD LOCAL PROJECTIONS BE ESTIMATED IN LEVELS OR DIFFERENCES? A MONTE CARLO STUDY

IV.1 Introduction

Following Jordá (2005), local projections have become a popular approach to estimate impulse response functions. In the empirical macroeconomics literature specifically, local projections are now widely viewed as a viable alternative to the usual impulse response functions generated by vector autoregressive (VAR) models. Local projections offer some well publicized potential advantages over VAR models. First, they are simple to estimate and draw inference on, since local projections can be implemented via univariate linear regressions. Second, since local projections place less structure on the assumed data generating process, they are in principle more robust to misspecification than VAR models. Third, local projections can more easily accommodate state-dependent and non-linear specifications, making them especially popular in these applications.[1] As local projections have increased in popularity, there has been a growing theoretical literature studying the asymptotic properties of local projections and their relation to VAR models.[2]

[1]See, e.g., Ramey and Zubairy (2018), Auerbach and Gorodnichenko (2013), and Tenreyro and Thwaites (2016).

[2]Examples include Plagbørg-Moller and Wolf (2021) and Olea and Plagbørg-Moller (2021)

It is well known that standard OLS estimates of VAR impulse response are biased and produce incorrect confidence intervals, particularly for persistent data (Kilian and Chang (2000)). There is a growing literature that shows local projections are not immune from this bias, particularly in the relatively small sample sizes used in the empirical macroeconomics literature. Using simulations, Kilian and Kim (2011) find asymptotic confidence intervals from local projections are less accurate than bias-adjusted VAR bootstrap confidence intervals. Herbst and Johannsen (2021) document that local projections are in practice often used with very small samples in the time dimension, and that point estimates of impulse response functions from local projections are severely biased on these sample sizes. This is especially true when the process under consideration is persistent, which is the case with most macroeconomic series of interest.

A growing literature also presents approaches for how to reduce bias in local projection regressions. Herbst and Johannsen (2021) use an approximate bias function to partially account for the bias in the local projections regression, while Olea and Plagbørg-Moller (2021) use lag-augmented local projections, which use lags of the regressors as controls. They show that local projections perform very well if the data is highly persistent and also in the estimation of impulse responses at longer horizons. To date, bootstrapping, which is popular as a bias correction device in the VAR literature, does not seem to be a viable method for estimating local projections. Kilian and Kim (2011) show that even in large samples where local projections and VARs had comparable accuracy, the average bootstrap confidence interval for the local projections was much wider than that of the VAR model.

In addition, it is common to find differences in the literature in the way the response variable is specified in local projection regressions. Many authors specify the local projection regression in levels, which has increasingly been considered the safer route to estimate impulse response functions in VARs when the true integration properties of the data is unknown (Ramey (2016)). The argument typically proceeds that while estimation in differences can provide a reduction in bias and improved efficiency if the system contains unit roots, if the process is instead stationary differencing will introduce non-invertibilities and hide long-run relationships that create issues for recovering structural shocks of interest. At the same time, estimation in levels retains long-run relationships and does not introduce non-invertible disturbances, while techniques have been developed for near-unit root or unit-root processes to provide appropriate inference (Gospodinov et al. (2013)). However, in the local projection literature, it is almost exclusively the case that standard estimation and inference techniques that assume stationarity are used, even when estimating in levels. Further, it is unclear that the lessons from the VAR literature regarding the relative merits of estimating in levels vs. differences apply to the local projections setting, especially in the common case where local projections are estimated with an externally identified shock of interest (Stock and Watson (2018)).

In this paper we attempt to fill a gap in this literature by conducting a simulation study to evaluate the finite sample performance of local projections conducted in levels vs. differences specifications. Consistent with Herbst and Johannsen (2021), we focus on the empirically relevant case where we have an identified shock in hand for which we wish to estimate the impulse response function via local projections. Using a wide variety of data generating processes for empirically relevant sample sizes, we show that the difference specifications can substantially reduce bias and improve inference over local projection regressions specified in levels for persistent processes, regardless of whether the true process contains a unit root. Further, even for data that is less persistent, the differences specification does not demonstrate any apparent disadvantages over the levels regression. Overall, the differences specification appears to be an effective approach to reduce bias and improve the accuracy of confidence intervals in local projection estimation of impulse response functions, regardless of the true integration properties of the data. As noted above, this stands in contrast to an existing literature using structural VARs with internally identified shocks, such as Gospodinov et al. (2013).

The rest of this paper proceeds as follows: Section IV.2 reviews the local projection approach to estimate impulse response functions with externally identified shocks and discusses standard inference techniques used in the literature. Section IV.3 lays out the details and results of the simulation excercise. Section IV.4 concludes.

IV.2 Local Projections

Suppose one has an observed shock of interest, labeled ε_t, and a response variable of interest, labeled y_t. We wish to measure the impulse response at horizon h, up to some maximum horizon H:

$$\beta_h = \frac{\partial y_{t+h}}{\partial \varepsilon_t}$$

A local projection to estimate β_h is simply a direct multi-step ahead prediction:

$$y_{t+h} = \beta^h \varepsilon_t + \rho_1^h y_{t-1} + \rho_2^h y_{t-2} + \cdots + \rho_p^h y_{t-p} + \gamma^h X_t + u_{t+h} \tag{IV.1}$$

In most applications of local projections, lagged values of the response variable appear as controls, and we have explicitly allowed for p lags of the response variable in equation (IV.1). Additional controls can appear in the vector X_t, and usually include deterministic terms, such as a constant or deterministic time trends. In some applications, lags of variables other than the response variable are also included. Since the left hand side is specified in the levels of the response variable, we refer to equation (IV.1) as the "levels" specification.[3]

[3]As discussed in SW, in most applications ε_t is likely better considered as an instrument for the true shock of interest rather than the shock itself. However, to stay consistent with a signifiant existing literature, here we follow the common specification of including ε_t in the local projection as the

The literature surrounding local proejctions assumes (trend) stationarity in the left hand side of equation (IV.1). If one is uncomfortable with this assumption, a local projection in the first difference of y_t might be performed:

$$\Delta y_{t+h} = \widetilde{\beta}^h \varepsilon_t + \widetilde{\rho}_1^h \Delta y_{t-1} + \widetilde{\rho}_2^h \Delta y_{t-2} + \cdots + \widetilde{\rho}_p^h \Delta y_{t-p} + \widetilde{\gamma}^h \widetilde{X}_t + \widetilde{u}_{t+h} \tag{IV.2}$$

where $\widetilde{\beta}^h$ is the impulse response of the first difference of y_{t+h} to the shock ε_t. We can then recover β^h as:

$$\beta^h = \sum_{i=0}^{h} \widetilde{\beta}^i$$

One could estimate β^h by first estimating equation (IV.2) and then forming this h-period sum. However, as pointed out by Stock and Watson (2018), we can instead first sum equation (IV.2), providing the following equation to estimate β^h directly:

$$y_{t+h} - y_{t-1} = \beta^h \varepsilon_t + \theta_1^h \Delta y_{t-1} + \theta_2^h \Delta y_{t-2} + \cdots + \theta_p^h \Delta y_{t-p} + \alpha X_t^D + v_{t+h} \tag{IV.3}$$

We refer to equation (IV.3) as the "differences" specification, though it should be recognized that the left hand side of this equation is in terms of the h-period difference of y_t, rather than the first difference.

While the impulse responses at alternative horizons could be estimated by treating the H equations as a seemingly unrelated regression and estimated jointly, it is common in the applied local projection literature to estimate via equation by equation OLS. Also, as discussed in Jordá (2005), the disturbance terms in the local projection equations in equations (IV.1) and (IV.2) are serially correlated and follow a moving

observed shock.

average (MA) process. Because of this, much of the literature makes use of robust standard errors to compute confidence intervals on the impulse response β_h, with the Newey-West methodology being a popular choice. The disturbance term in equation (IV.3) is potentially further complicated by the summation of errors from equation (IV.2). In the remainder of this paper we will evaluate the performance of equation by equation OLS estimation of the local projection in both the levels and differences specification, as well as the performance of the the Newey-West methodology for computing standard errors.

IV.3 Simulation Evidence

In this section, we perform a simulation study using a variety of different data generating processes (DGP) to evaluate the performance of the levels and differences local projections specifications. In each of the DGPs considered, we assume that the true DGP is not known, but ε_t is observed. We will consider both univariate and multivariate DGPs.

We set the control variables in equations (IV.1) and (IV.3) as follows: Both the levels and differences specification include p lags of the level of y_t in the levels specification and the first difference of y_t in the differences specification. For the levels specification, X_t includes a constant and linear time trend for univariate data generating processes, and additionally contains p lags of the level of additional endogenous variables beyond y_t for multivariate data generating processes. For the differences specification, X_t^D contains a constant for univariate DGPs, and additionally contains p lags of the first difference of additional endogenous variables beyond y_t for multivariate DGPs. When estimating the local projection models on the simulated data, we conduct data-based lag selection to select p via a test-down procedure. Specifically, a p_{max} is selected and then a test statistic is formed for the coefficient on the p_{max}

variable using Newey-West standard errors. If this test statistic is greater than two, then the number of lags is set to be p_{max}. Otherwise, p_{max} is lowered by one and the process is repeated. We set the initial value of p_max to equal 8.

For each DGP the results are based on 100 simulations, and the sample size for each simulation is set to $T = 160$, which corresponds to 40 years of quarterly data, a typical sample size in studies of U.S. macroeconomic data. We assess the accuracy of both the OLS point estimates and Newey-West coverage intervals for impulse responses at horizons up to and including a maximum horizon of $H = 20$. In constructing the Newey-West standard errors the maximum autocorrelation lag is set to be $H + 1$ following Jordá (2005).

IV.3.1 Autoregressive Models

We begin with a simple autoregressive model of order 1 (AR(1)) model:

$$y_t = \alpha + \phi y_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim \text{i.i.d. } N\left(0, 1\right).$$

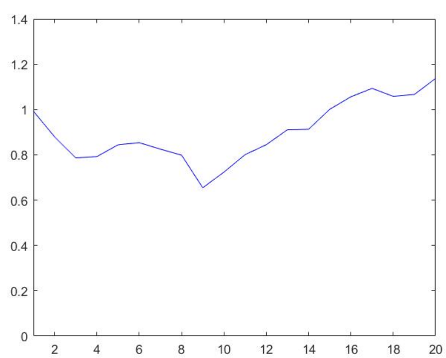
We explore three different calibrations for this model, which differ in their level of persistence. The first specification features a process that is persistent, but clearly stationary in that unit root tests will have very high power to detect the null of stationarity ($\phi = 0.70$), the second is a very persistent, though still stationary process ($\phi = 0.95$), while the third is a unit root process ($\phi = 1.00$). In all cases, we set the intercept $\alpha = 0$.

Figures IV.1, IV.2, and IV.3 show the results of level and differences specification applied to estimate the impulse response for data generated from the AR(1) model, where each figure corresponds to a different value for the autoregressive parameter. Each figure contains three sets of results. The top left panel of each figure contains the RMSE of the estimation of β^h using the differences specification relative to that estimated using the levels specification. The top right panel shows the true impulse response function (green) and the impulse response function estimated by both the differences (red) and levels (blue) specification. The bottom panel shows the proportion of simulations where the true value of β^h is contained inside of a 90% confidence interval constructed via the differences specification (red) and levels specification (blue).

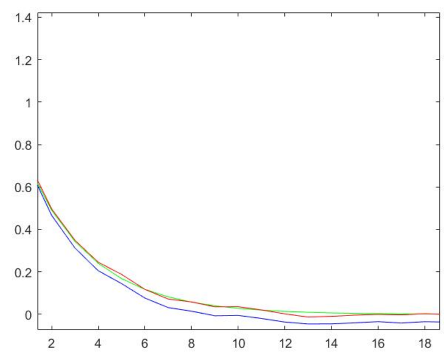
The figures provide a striking conclusion - for all three persistence levels for the AR(1) model, the differences specification has less bias, lower RMSE, and more accurate coverage intervals than the levels specification. As the persistence of the system increases, the better the performance of the differences specification becomes relative to the levels specification. Also, the relative improvement from the differences specification increases as the horizon of the impulse response function increases. It is worth emphasizing that the improvement in the differences specification is still visible even with a process that is clearly stationary.

With this general conclusion in place, we turn to the results in more detail. For the two stationary specifications, the differences specification is approximately unbiased and the coverage intervals have close to correct coverage at all horizons. The levels specification performs reasonably well in the $\phi = 0.7$ case, though it still displays more bias and less accurate coverage intervals than the differences specification. When $\phi = 0.95$, the performance of the levels specification deteriorates significantly, with estimates displaying very high levels of bias and coverage intervals that are far below their nominal levels. These inaccuracies become larger as the horizon of the impulse response increases. Finally, in the unit root case, there is some bias introduced in the differences specification, and coverage intervals fall below their nominal level. However, the differences specification vastly outperforms the levels specification in this case. Indeed, the levels specification in the unit root case has abysmal performance, with estimated impulse responses at the longest horizons that are less than half of their true value and with 90% Newey-West coverage intervals that are around 20%. Finally, the relative RMSE shows that for the $\phi = 0.95$ and $\phi = 1.0$ case, the levels specification has significantly higher RMSE than the differences specification at nearly all horizons. For the $\phi = 0.7$ case, the RMSE for the differences specification is lower for all but the longest horizons.

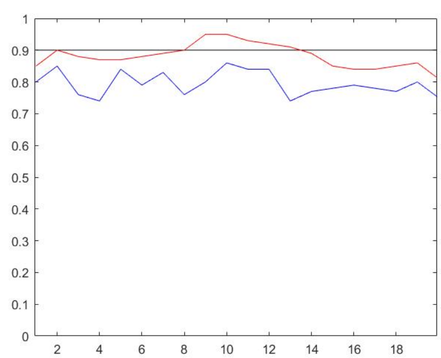
Figure IV.1
AR Model
$\phi = 0.70$



(a) RMSE



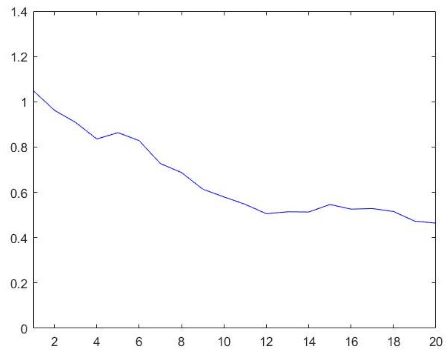
(b) True impulse response function vs Level vs Diff



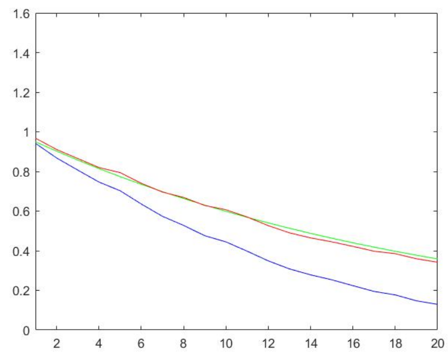
(c) 90% CI Coverage

Notes: This Figure displays the results of the simulation of an AR(1) model when $\phi = 0.70$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

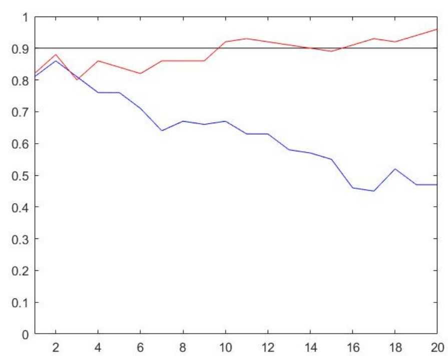
Figure IV.2
AR Model
$\phi = 0.95$



(a) RMSE



(b) True impulse response function vs Level vs Diff



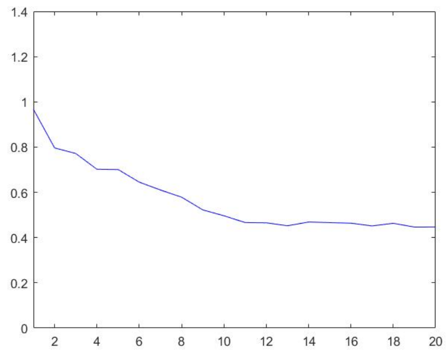
(c) 90% CI Coverage

Notes: This Figure displays the results of the simulation of an AR(1) model when $\phi = 0.95$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

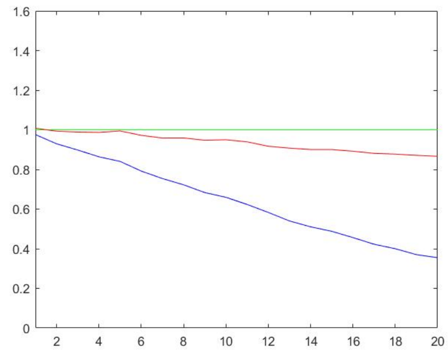
IV.3.2 Alternative Univariate Models

In this section, we explore the performance of the levels and differences specifications for DGPs beyond the simple AR(1) case. We begin by with an ARMA(1,1) model:

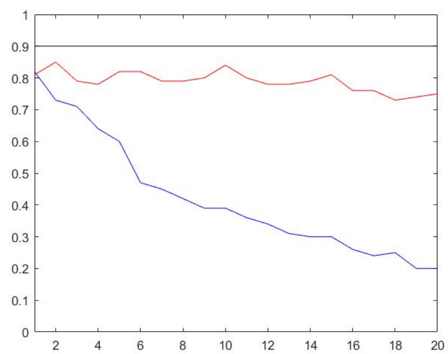
Figure IV.3
AR Model
$\phi = 1.00$



(a) RMSE



(b) True impulse response function vs Level vs Diff



(c) 90% CI Coverage

Notes: This Figure displays the results of the simulation of an AR(1) model when $\phi = 1.00$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

$$y_t = \alpha + \phi y_{t-1} + \theta \varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, 1)$$

We again explore three different calibrations for this model, a clearly stationary process ($\phi = 0.70$), a very persistent, but still stationary, process ($\phi = 0.95$), and a unit root process ($\phi = 1.0$).In all calibrations, $\alpha = 0$ and $\theta = 0.5$.

Figures IV.4, IV.5, and IV.6 show the results of the simulations for the ARMA(1,1) model, which are very similar to the AR(1) model. In particular, the levels specification displays significant estimation bias for the impulse response functions and very inaccurate coverage intervals, with the performance of the levels specification deteriorating as both the persistence of the process and the horizon of the impulse response increases. The differences specification performs much better than the levels specification at every level of persistence in the system, even in the relatively stationary case. In absolute terms, the differences specification is approximately unbiased and has close to correct coverage intervals at all horizons for the stationary calibrations. In the case of a unit root, the differences specification again displays some bias and coverage intervals that fall below their nominal level, but still displays large improvements over the levels specification in this case.

Next we consider a Trend-Stationary Unobserved Components model:

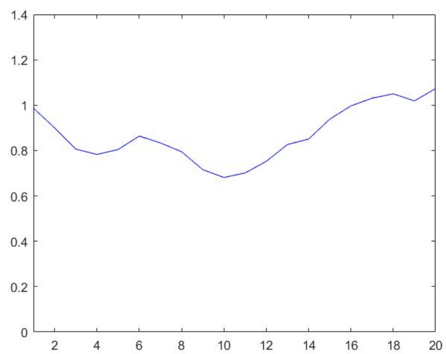
$$y_t = T_t + C_t$$
$$T_t = \mu + T_{t-1}$$
$$C_t = \phi_1 C_{t-1} + \phi_2 C_{t-2} + \varepsilon_t$$
$$\varepsilon_t \sim N\left(0, \sigma^2\right)$$

We calibrate the model based on maximum likelihood estimation of this trend-stationary UC model on log quarterly U.S. GDP, measured from 1969:Q1 to 2007:Q4. This estimation produced the following calibration:

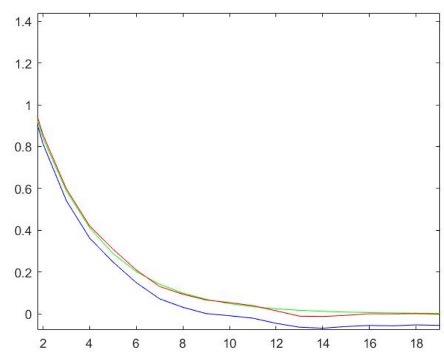
$$\mu = 0.77; \phi_1 = 1.22; \phi_2 = -0.3; \sigma = 0.76$$

Figure IV.7 contains the results of the simulations based on the trend stationary unobserved components model, and shows again that the differences specification outperforms the levels specification in all aspects considered. Figure IV.7b shows

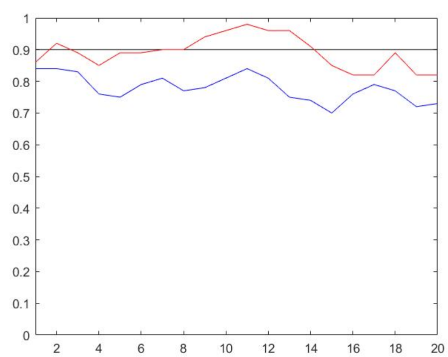
Figure IV.4
ARMA Model
$\phi = 0.70$



(a) RMSE



(b) True impulse response function vs Level vs Diff

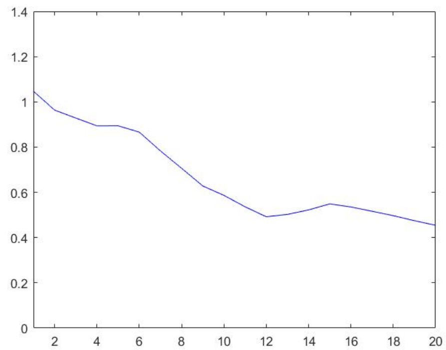


(c) 90% CI Coverage

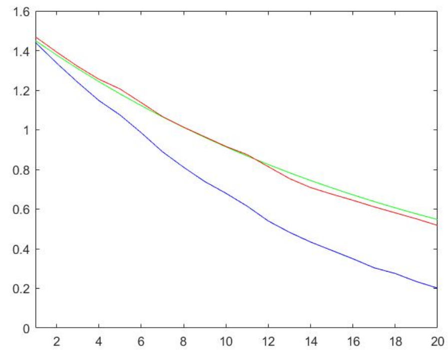
Notes: This Figure displays the results of the simulation of an ARMA(1,1) model when $\phi = 0.70$ and $\theta = 0.50$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

that the difference specification exhibits very little bias over the entire horizon while the levels specification has a large downward bias. If we look at the model fit as measured by the RMSE in Figure IV.7a, the RMSE becomes increasingly less than one as the horizon increases before stabilizing at around 0.60 for the last 8 periods. Figure IV.7c shows that the proportion of the time that the true impulse response

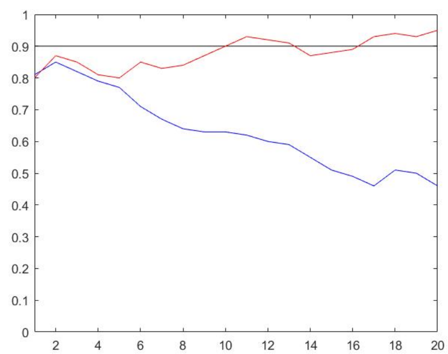
Figure IV.5
ARMA Model
$\phi = 0.95$



(a) RMSE



(b) True impulse response function vs Level vs Diff

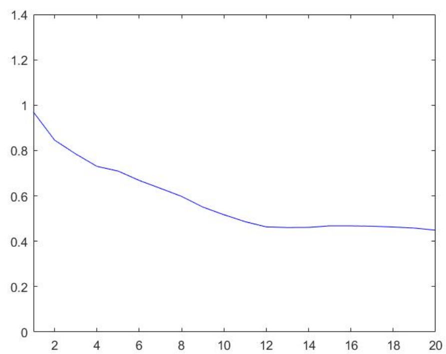


(c) 90% CI Coverage

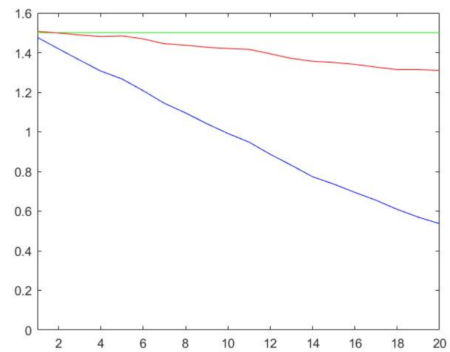
Notes: This Figure displays the results of the simulation of an ARMA(1,1) model when $\phi = 0.95$ and $\theta = 0.50$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

function is contained in the levels specification confidence interval decreases over the course of the horizon. By contrast, the differences specification confidence interval is close to its nominal value over the entire horizon. It is notable that the differences specification provides such large improvements despite the fact that the underlying process is stationary.

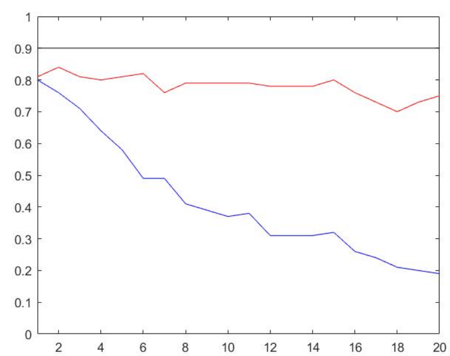
Figure IV.6
ARMA Model
$\phi = 1.00$



(a) RMSE



(b) True impulse response function vs Level vs Diff



(c) 90% CI Coverage

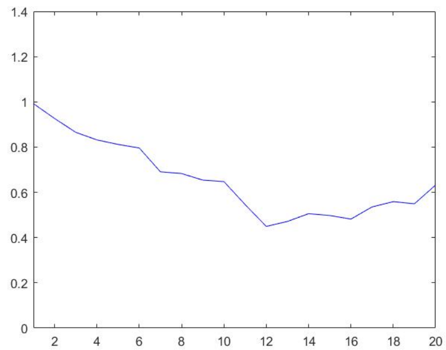
Notes: This Figure displays the results of the simulation of an ARMA(1,1) model when $\phi = 1.00$ and $\theta = 0.50$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

The final univariate model considered is the Stochastic Trend Unobserved Components Model listed below:

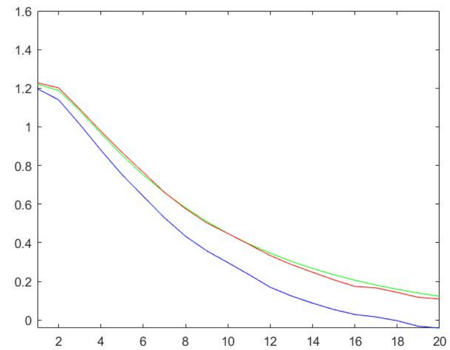
$$y_t = T_t + C_t$$

$$T_t = \mu + T_{t-1} + v_t$$

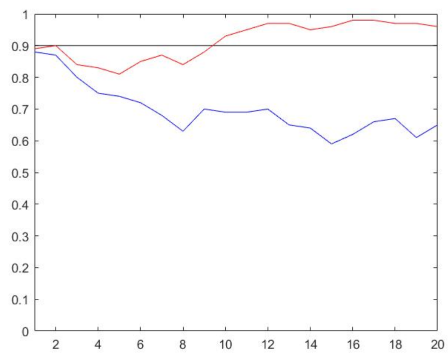
Figure IV.7
Trend Stationary UC Model



(a) RMSE



(b) True impulse response function vs Level vs Diff



(c) 90% CI Coverage

Notes: This Figure displays the results of the simulation of a Trend Stationary Unobserved Components model where $\mu = 0.77, \phi_1 = 1.22, \phi_2 = -0.3$, and $\sigma = 0.76$. These values were obtained by calibrating the model based on estimations of quarterly real GDP from 1969:Q1 to 2007:Q4. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

$$C_t = \phi_1 C_{t-1} + \phi_2 C_{t-2} + \varepsilon_t$$

$$v_t \sim WN\left(0, \gamma^2\right)$$

$$\varepsilon_t \sim N\left(0, \sigma^2\right)$$

We calibrate the model based on maximum likelihood estimation of this stochastic trend unobserved components model on log quarterly U.S. GDP, measured from 1969:Q1 to 2007:Q4. This estimation produced the following calibration:

$$\mu = 0.77; \phi_1 = 1.55; \phi_2 = -0.6; \gamma = 0.5783; \sigma = 0.443$$

Figure IV.8 contains the results of the simulations based on the stochastic trend unobserved components model. Again, the evidence from Figure IV.8 shows that the differences specification outperforms the levels specification. Figure IV.8b shows that the differences specification has very little bias compared to the levels specification over the course of the horizon. While the downward bias does increase for both specifications as the horizon increases, the bias in the levels specification increases at a much faster rate. Figure IV.8a shows that the RMSE is less than one for the majority horizons. Finally, Figure IV.8c shows that the levels specification confidence interval does not reach the 90% coverage rate of the true impulse response function except for briefly at the beginning of the horizon. The differences confidence interval reaches the 90% threshold numerous times across the horizon and almost universally contains the true impulse response function at a higher rate than the levels specification.

IV.3.3 VAR Models

In this section, we consider a DGP matching the bivariate VAR model considered in Kilian and Kim (2011):

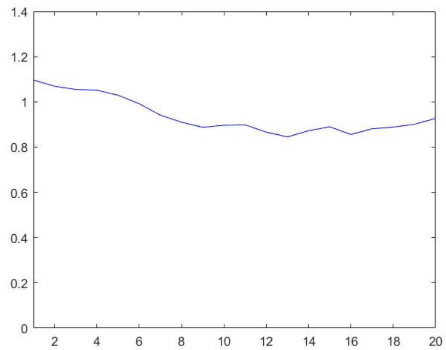
$$Y_t = (x_t, y_t)'$$

$$Y_t = \Phi_0 + \Phi_1 Y_{t-1} + W_t$$

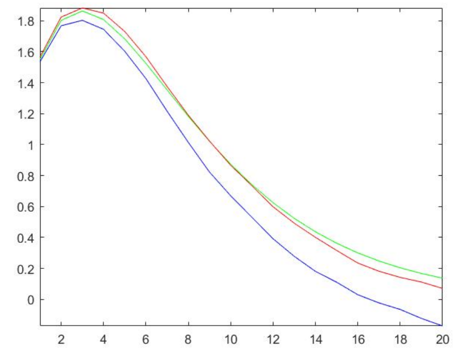
$$W_t \sim N(0, \Sigma)$$

where:

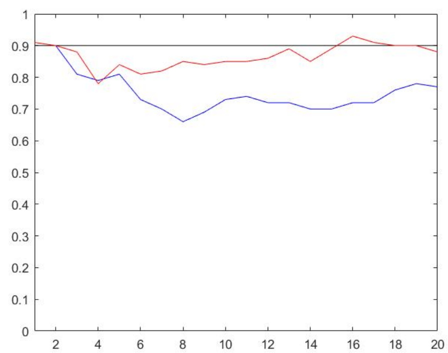
Figure IV.8
Stochastic Trend UC Model



(a) RMSE



(b) True impulse response function vs Level vs Diff



(c) 90% CI Coverage

Notes: This Figure displays the results of the simulation of a Stochastic Trend Unobserved Components model where $\mu = 0.77, \phi_1 = 1.55, \phi_2 = -0.6, \gamma = 0.5783$, and $\sigma = 0.443$. These values were obtained by calibrating the model based on estimations of quarterly real GDP from 1969:Q1 to 2007:Q4. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

$$\Phi_0 = \begin{bmatrix} \phi_1^0 \\ \phi_2^0 \end{bmatrix}, \quad \Phi_1 = \begin{bmatrix} \phi_{11}^1 & 0 \\ \phi_{12}^1 & \phi_{22}^1 \end{bmatrix}$$

and:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix},$$

The structural shocks are known and equal to:

$$U_t = Q * W_t$$

where Q is the inverse of the Cholesky factorization of Σ. Define the components of U_t as $U_t = (\varepsilon_t, u_t)$. Our interest is then on the response of the second variable to the first structural shock:

$$\beta^h = \frac{\partial y_{t+h}}{\partial \varepsilon_t}$$

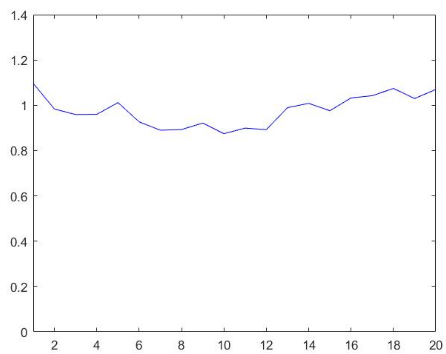
For all calibrations, we set: $\phi_1^0 = 0; \phi_2^0 = 0; \phi_{12}^1 = 0.5; \phi_{22}^1 = 0.5; \sigma_1^2 = 1, \sigma_{12} = 0.3, \sigma_2^2 = 1$.

We consider three different values for ϕ_{11}^1:

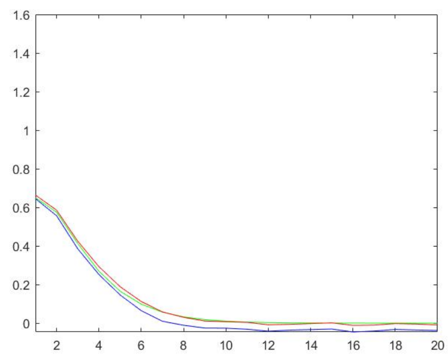
$$\phi_{11}^1 = 0.50$$
$$\phi_{11}^1 = 0.95$$
$$\phi_{11}^1 = 0.99$$

Figures IV.9, IV.10, and IV.11 show the results of the simulations for the VAR model, where each figure corresponds to a different value for ϕ_{11}^1. The results for the VAR DGP are very similar to the other univariate models that we have seen thus far. The levels specification has a small downward bias at the lowest calibration of ϕ_{11}^1, with the bias increasing as ϕ_{11}^1 increases and as the horizon increases. The differences specification has much less bias than the levels impulse response function in all three cases. The relative RMSE is close to one for the lowest value of ϕ_{11}^1, and falls far below one at most horizons as ϕ_{11}^1 increases. Finally, the confidence intervals have close to correct coverage for the differences specification for all values of ϕ_{11}^1, but are very undersized for the levels specification, particularly at larger values of ϕ_{11}^1.

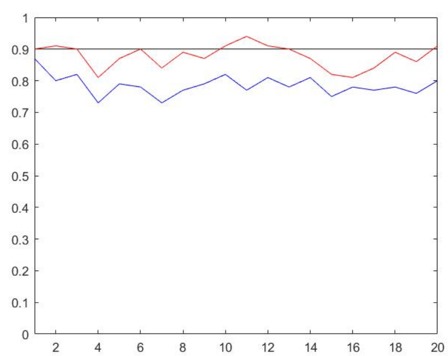
Figure IV.9
VAR Model
$\phi_{11}^1 = 0.50$



(a) RMSE



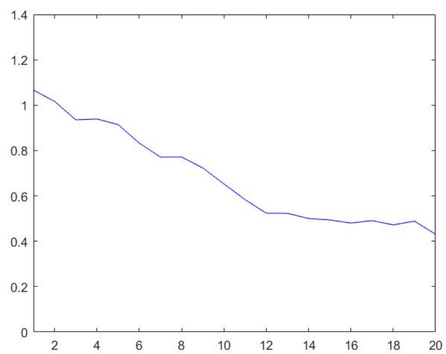
(b) True impulse response function vs Level vs Diff



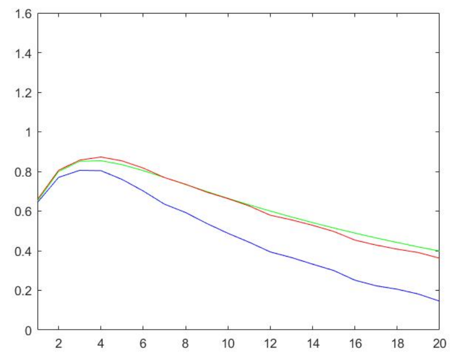
(c) 90% CI Coverage

Notes: This Figure displays the results of the simulation of a VAR model when $\phi_{11}^1 = 0.50$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

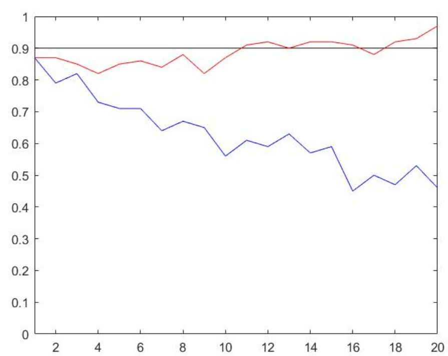
Figure IV.10
VAR Model
$\phi_{11}^{1} = 0.95$



(a) RMSE



(b) True impulse response function vs Level vs Diff



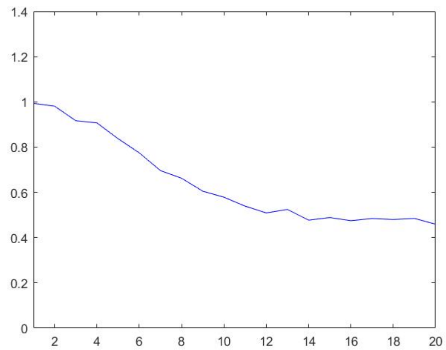
(c) 90% CI Coverage

Notes: This Figure displays the results of the simulation of a VAR model when $\phi_{11}^{1} = 0.95$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

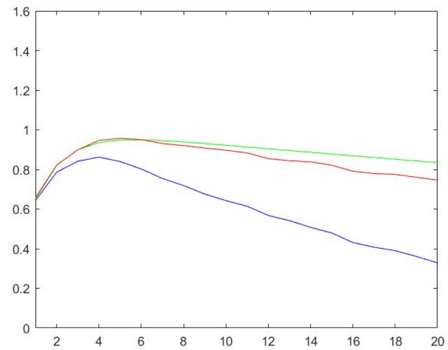
IV.4 Conclusion

The local projection methodology has become a popular alternative to VAR models for the calculation of impulse response functions. However, there is growing evidence that standard approaches to estimate local projections have significant bias

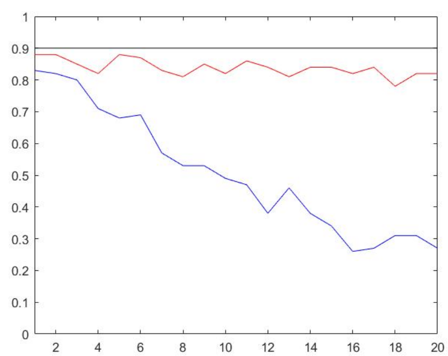
Figure IV.11
VAR Model
$\phi_{11}^1 = 0.99$



(a) RMSE



(b) True impulse response function vs Level vs Diff



(c) 90% CI Coverage

Notes: This Figure displays the results of the simulation of a VAR model when $\phi_{11}^1 = 0.99$. Panel (a) shows the RMSE of the differences specification relative to the levels specification. Panel (b) shows the impulse response function for the levels specification (blue) and differences specification (red) relative to the true model impulse response function. Panel (c) shows the 90% confidence interval coverage of the true impulse response function for the levels specification (blue) and differences specification (red).

in the sample sizes typically utilized for estimation of these models. There are also discrepancies in the literature with whether local projections are estimated in the log levels of response variables vs. differences, with a common assumption being that models estimated in levels are more reliable.

In this paper, we have used a simulation experiment to compare the performance of local projections estimated in levels vs. differences on a variety of different data generating processes including ARMA models, unobserved components models, and VAR models. We focus on the empirically relevant case where the econometrician has an externally identified shock of interest for which she wishes to compute impulse response functions. The simulations show the differences specification produces close to unbiased estimates and confidence intervals with close to correct coverage for all data generating processes and impulse response horizons considered. In contrast, the estimates from the levels specification are biased and have confidence intervals that are significantly undersized, with these deficiencies growing larger as both the persistence of the process and the horizon of the impulse response increases. Importantly, the differences specification provides improved inference even in cases where the data is relatively stationary. In other words, these results suggest that the preference for the differences specification should not hinge on the data containing a unit root.

CHAPTER V

DISSERTATION CONCLUSION

In this dissertation, I investigate the asymmetric effects of monetary policy on output throughout the business cycle, the direction of the monetary policy shock, and the size of the monetary policy shock. In Chapter II, I investigate business cycle asymmetry using a local projections model to generate impulse response functions. I show that monetary policy has more of an effect on output during recessions than expansions, a result that had no consensus in the existing literature. In addition to this result, I show that the differences in the literature can be attributed to the decision to use the levels versus the differences specification in the model, the frequency of the data used, and the treatment of outliers.

In Chapter III, I expand the local projection model to include all three types of asymmetry and their interactions in the same model. This allows me to drop the assumption that the differential effects of a monetary policy action on output due to one type of asymmetry are not being driven by the other two types of asymmetry. I find that directional asymmetry, business cycle asymmetry, and the interaction between the two are the most important types of asymmetry for explaining movements in output. In addition, my results suggest that accommodative monetary policy actions taken during recessions do not affect output. This is a concerning finding for those in favor of using monetary policy to alleviate the effects of a recession. Unconventional monetary policy and fiscal policy working together with monetary policy should have more of a place moving forward as was the case during the Great Recession.

In Chapter IV, I use a simulation-based study to determine if local projections should be run using the levels specification with a time trend or run using the differences specification. This is an important question in the asymmetry literature as this modeling decision accounted for one of the differences in the literature in Chapter II. I show that the differences specification provides a better model fit, has less bias, and is more likely to contain the true impulse response function in its confidence interval when compared to the levels specification.

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