1 Are the Effects of Monetary Policy Asymmetric in China?

1.1 Introduction

Since 2000, China's economic growth has been very strong. The reported GDP growth rate surpassed 8 percent for a decade after 2000, reaching a local peak of 14 percent in 2007. This growth has led to China becoming an increasingly important part of the world economy. It is now the second largest economic engine in the world measured by nominal GDP, and the world's largest economy by purchasing power parity, contributing 27 percent of global GDP in 2018.

Despite this importance, there has been relatively little work done on understanding the effects of Chinese monetary policy. One reason for the small amount of research is the poor quality of Chinese macroeconomic data (Wallace (2014), Rawski (2001), Maier (2011), Holz (2014)). Researchers like Mehrotra & Paakkonen (2011), Fernald, Hsu, & Spiegel (2015), and Clark, Pinkovskiy, & Sala-i-Martin (2017) find that officially reported data has become more informative in recent decades. Meanwhile, China has experienced rapid institutional and structural changes, which may lead to changes in the Chinese monetary policy mechanism post 2000 (He, Leung, & Chong (2013), Fernald, Spiegel, & Swason (2014), Chen, Higgins, Waggoner, & Zha (2016)).

In other countries, especially Western market economies, substantial attention has been paid to state-dependence, or asymmetry, in the effects of policy over the business cycle. Most papers find that monetary policy is more powerful in affecting output during recessions than during expansions (Thoma (1994), Garcia & Schaller (2002), Lo & Piger (2005), Weise (1999), Kaufmann (2002), Peersman & Smets (2001)). However, in a recent influential paper, Tenreyro & Thwaites (2016) find an opposite result.

I investigate how monetary policy instruments affect output growth and inflation, and whether this effect is asymmetric across different states of output growth. Following Fernald et al. (2014), I measure economic activity and inflation as dynamic factors from a large number of Chinese economic indicators. To measure monetary policy, I estimate a factor-augmented vector autoregression (FAVAR) and extract monetary policy shocks using a Cholesky causal ordering with the policy variable ordered last. As in Tenreyro & Thwaites (2016), I use a smooth transition logistic function to measure high- and low-growth states in Chinese economic activity. Finally, to estimate the response of economic activity and inflation to monetary policy shocks in different growth states, I use the method of local projections first introduced by Jorda (2005).

I find evidence that the effects of measured monetary policy shocks on the Chinese economy are different between high-growth periods vs. low-growth periods. Monetary policy shocks have larger impacts on output growth in low-growth states. This is consistent with the majority of the literature studying the asymmetric effects of monetary policy shocks in Western economies. Additionally, I find that monetary policy shocks have larger effects on inflation in high-growth states. Overall, this evidence is consistent with a convex aggregate supply curve.

The remainder of this paper is structured as follows: Section I reviews the literature. Section II describes the dataset. Section III explains the empirical methods. Section IV sets out the main results. Section V concludes with some thoughts for future research.

1.2 Literature Review

According to Lo & Piger (2005), the literature has focused on three types of asymmetry: (1) asymmetry related to the direction of the monetary policy action, (2) asymmetry related to the existing business cycle phase, and (3) asymmetry related to the size of the policy action. I focus on the second type of asymmetry.

As one of the earliest papers in this area, Thoma (1994) defines the business cycle, or the state of the economy, as deviations of the growth rate of output from trend. Another method to identify the unobserved state of the economy is to use a Markov regime switching model, as in Peersman & Smets (2001), Garcia & Schaller (2002), Kaufmann (2002) and Lo & Piger (2005). These papers define transition probabilities from the state of expansion to the state of recession as time-varying functions of the changes of the observed monetary policy actions. In this paper, I use a smooth transition logistic function to exploit variation in the degree of the economic activity factor of being in a regime. This Smooth transition method has been used in a number of papers to study the asymmetric effect of fiscal or monetary policy on output across expansions and recessions, such as Weise (1999), Auerbach & Gorodnichenko (2012), and Tenreyro & Thwaites (2016).[1]

Early papers measure monetary policy shocks using the first difference of a monetary policy instrument (Thoma (1994) and Peersman & Smets (2001)). Tenreyro & Thwaites (2016) estimate monetary policy shocks as residuals from a nonlinear analogue of the Romer & Romer (2004) regression. The majority of the literature has measured the monetary shock using Choleski innovations identified from the contemporaneous relationships of the variables in a standard structural VAR model, with the monetary policy tool ordered last (Weise (1999), Peersman & Smets (2001), Garcia & Schaller (2002), Lo & Piger (2005), He et al. (2013), and Fernald et al. (2014)). This is the method I adopt.

Much of the recent literature has measured the effects of macroeconomic shocks, and possible asymmetry in these effects, using Jorda's (2005) method of local projections. For example, Auerbach & Gorodnichenko (2012) and Ramey & Zubairy (2014) measure the asymmetric effects of fiscal policy over the business cycle, and Tenreyro & Thwaites (2016) measure the asymmetric effects of monetary policy over the business cycle. In this paper I will also use the method of local projections to measure asymmetric effects of monetary policy in China.

Most papers that study asymmetric effects of monetary policy on output in Western market economies find that monetary policy is more powerful in affecting output during recessions than during expansions (Thoma (1994), Garcia & Schaller (2002), Lo & Piger (2005), Weise (1999), Kaufmann (2002), Peersman & Smets (2001)). However, Tenreyro & Thwaites (2016) find an opposite result. I find evidence that Chinese monetary policy shocks have larger impacts on output growth in low-growth states, which is consistent with the majority of the literature in other countries.

For the literature that focus on Western market economies, output is measured by industrial production and GDP volume, or the logarithm and the growth rate of these indicators (Thoma (1994), Weise (1999), Peersman & Smets (2001), Garcia & Schaller (2002), Kaufmann (2002), Tenreyro & Thwaites (2016)). I focus on asymmetric effects of monetary policy on output in China, where output cannot be measured directly with industrial production or GDP, due to the poor quality of

[1] I have used multiple two-state Markov regime switching models to capture the latent states. However, this family of models only fit two periods where growth rate is very fast and the single period where growth rate is very slow.

the officially published Chinese economic data (Rawski (2001), Maier (2011), Wallace (2014), Holz (2014)).

In the empirical literature that studies macroeconomics in China, there are mainly two methods to deal with the quality issue of Chinese data. The first method is to choose data that is not subject to government manipulation. Nakamura, Steinsson, & Liu (2014) take a microeconomic perspective and use Chinese urban household survey data, which is subject to less intervention from government compared with the headline macroeconomic data. Based on the survey, the authors estimate Engle curves, and “back out” the estimate of Chinese growth and inflation. Fernald et al. (2015) use quarterly trading-partner export to China data, which is an independent measurement. They find that economic activity factors extracted from electricity consumption, rail freight, retail sales, an index of raw material supply are more informative than the officially reported GDP alone. They also find that the information content of Chinese GDP improves after 2008. Clark et al. (2017) use annual satellite nighttime lights data as an independent benchmark of Chinese economy growth. They find that the growth rate of electricity production, railroad freight, and bank loans with modified weights computed by nighttime lights data does a good job at predicting the true unobserved Chinese economy growth. Their predictor of Chinese growth shows that the rate of Chinese growth is higher than is reported in the official statistics.

The second method to evaluate Chinese economy when data is suspected to be inaccurate is to extract latent factors from a large panel of underlying time series. Mehrotra & Paakkonen (2011) use principal component analysis to evaluate China’s growth from 1997 to 2009. Their estimated factor matches closely the reported GDP dynamics, especially since 2002. He et al. (2013) treat output and inflation as observed variables, measured by industrial production and consumer price index respectively. The authors extract the monetary policy factor from 15 policy variables and apply a factor-augmented vector autoregression model to study the monetary transmission mechanism in China over the period from January 1998 to February 2010. Fernald et al. (2014) also use a factor-augmented vector autoregression to estimate the effects of monetary policies on Chinese economy, over the period from January 2000 to September 2013. They treat Chinese output and inflation as unobserved latent variables, and extract an economic activity factor and an inflation factor. Their factors capture well the slowdown in China during the U.S. Great Recession and the following recovery. Dynamic factors extracted from a large number of underlying variables convey more information regarding Chinese economic activity than the reported GDP data alone. Another advantage of this method is that no prior knowledge is needed when determining which variables to include in the model, and data will speak in terms of the goodness of fit. Therefore, this is the method I use.

To my knowledge, Chen et al. (2016) is the only paper that studies asymmetric effects of monetary policy on Chinese economy. According to Chen et al. (2016), the main function of Chinese monetary policy is to control the growth rate of money supply M2 and provide support to achieve the GDP growth rate target set by the State Council, the chief administrative authority of China. In contrast to my paper, which focuses on asymmetric effects of monetary policy across high-growth and low-growth states, Chen et al. (2016) focus on the normal state when actual GDP growth meets the GDP growth rate target, and the shortfall state when actual GDP fails to meet the GDP growth rate target. Chen et al. (2016) measure monetary policy shocks as the difference between actual M2 growth and the systematic component of M2 growth, and adopts the official GDP and CPI data in their analysis. The structural VAR approach suggests that when actual GDP growth fails to meet the GDP growth target set by the government, monetary policy is more powerful in influencing the economy. Their paper presents significant evidence of the existence of asymmetric effects of Chinese monetary policy on the economy during "above the target" periods and "below the target" periods of the economy.

1.3 Data

Table 1 lists all the variables included in this paper. All data are downloaded from the CEIC China Premium Database. As in Fernald et al. (2014), data series are divided into three groups. The first group includes fundamental series that correlate with output, from which the economic activity factor is extracted. The second group includes four price indexes, from which the inflation factor is extracted. The third group comprises the measure of monetary policy. This group has just one variable, interest rates on loans to financial institutions for less than 20 days, which is the central bank benchmark interest rate.

The release of monthly data series is affected by the two-week lunar calendar New Year holiday, of which the first day begins between late January and late February. For some indicators, the sum of January and February data is reported.[2] To get monthly values of these indicators, I redistribute values for January and February so that the growth rate from December to January equals the growth rate from January to February. Then I obtain monthly values from March to December by taking first differences.

After removing effects of the Chinese New Year, I use the Census X-12 ARIMA package to adjust for seasonality. Then I take monthly growth rates of each series, except for benchmark interest rates and price indexes.[3] Outliers of each series are identified as those data points that lie outside 10 times the interquartile range from the median. Outliers are treated as missing values and imputed as described below.

In addition to outliers, other sources of missing data include: (1) missing January and February data, which systematically stem from the lunar calendar New Year holiday;[4] (2) missing data exists at the beginning of the sample for indicators collected later than January 2000; (3) in-sample missing data; (4) missing data exists at the end of the sample for data that are no longer being released or not released in synchronicity. I adopt an iterative expectation-maximization (EM) algorithm develoepd by McCracken & Ng (2015) to handle missing values. This EM algorithm is initialized by filling in missing data for each series with unconditional mean; then I extract factors from the demeaned and standardized dataset; then I update missing values using factors, and repeat this iterative procedure until factors converge.

After all missing values are imputed, the monthly dataset contains 224 months. I standardize the dataset to have zero mean and unit variance. Following Stock & Watson (2012), I remove a local mean from each series using a biweight kernel with a bandwidth of 100 months. The biweight kernel

[2] These indicators include electricity consumption, fixed assets investment, fixed assets investment in equipment purchase, fixed assets investment in new construction, real estate investment for residential buildings, and floor space started for commodity buildings.

[3] Price indexes are measured in units where the previous month's price level is fixed at 100.

[4] These indicators include retail sales of consumer goods, crude steel production, real estate climate index, electricity consumption, electricity production, natural gas production

Table 1: Data Summary

Time Series	Sample Period
ECONOMIC ACTIVITY FACTOR	
Gross Industrial Output	2003m1 - 2012m5
Electricity Consumption	2003m1 - 2018m9
Energy Production: Electricity	2000m1 - 2018m9
Natural Gas Production	2000m1 - 2018m9
Steel: Production: Crude Steel	2001m1 - 2018m8
Real Estate Inv: Residential Building	2000m1 - 2018m9
Floor Space Started: Commodity Bldg	2000m1 - 2018m9
Real Estate Climate Index	2004m1 - 2016m12
Consumer Confidence Index	2000m1 - 2018m9
Consumer Expectation Index	2000m1 - 2018m9
Fixed Asset Investment	2000m1 - 2018m9
FAI: Equipment Purchase	2004m1 - 2017m12
FAI: New Construction	2000m1 - 2017m12
Purchasing Managers' Index: Mfg	2005m1 - 2018m9
PMI: Mfg: New Export Order	2005m1 - 2018m9
PMI: Non Mfg: Business Activity	2007m1 - 2018m9
No of Employee: Industrial Enterprise	2000m12 - 2018m8
Retail Sales of Consumer Goods	2000m1 - 2018m9
Railway: Freight Traffic	2000m1 - 2018m9
Automobile Sales: Truck	2005m1 - 2018m9
Index: CSI 300 Index	2005m4 - 2018m9
Index: Shanghai Stock Exchange: Composite	2000m1 - 2018m9
Index: Shenzhen Stock Exchange: Composite	2000m1 - 2018m9
PE Ratio: Shanghai SE: All Share	2000m1 - 2018m9
PE Ratio: Shenzhen SE: All Share	2000m1 - 2018m9
FX Rate: RMB to USD	2000m1 - 2018m9
Export FOB	2000m1 - 2018m9
Import SITC: MF: Petroleum, Petroleum Pdt and Related Material	2000m1 - 2018m8
Trade Balance	2000m1 - 2018m9
Foreign Reserves	2000m1 - 2018m9
INFLATION FACTOR	
CPI: Core (excl. Food and Energy)	2006m1 - 2018m9
CPI: Food, Tobacco and Liquor	2000m1 - 2018m9
Consumer Price Index: 36 City	2002m1 - 2018m9
Consumer Price Index	2000m1 - 2018m9
POLICY VARIABLES	
Central Bank Benchmark Interest Rate: Loan to FI Less Than 20 days	2000m1 - 2018m9

smoothes the series.

1.4 Methodology

1.4.1 Extracting Factors

Estimates of economic activity and inflation are measured with the first principal component of the series that measure output and price respectively. I follow Stock & Watson (2016) to set up the dynamic factor model.

$$X_t = \lambda(L)f_t + e_t$$

$$f_t = \Psi(L)f_{t-1} + \eta_t$$

An $n \times 1$ vector of X_t contains observable underlying variables. f_t is a $k \times 1$ vector of latent common factors. The number of the observables n is assumed to be much larger than the number of factors k. I let $k = 1$ to extract one factor from series that correlate with output, and one factor from price indexes. f_t is allowed to follow an AR process. $\lambda(L)$ and $\Psi(L)$ are polynomials in the lag operator. λ is a $n \times k$ matrix and $\Psi(L)$ is a $k \times k$ matrix. $\lambda_i(L)$ is the loading of X_{it} on f_t, and $\lambda_i(L)f_t$ is the common component of the ith variable X_i. η_t is assumed to be a mean-zero $k \times 1$ vector of serially uncorrelated error term to the factors. The idiosyncratic term e_t is a $n \times 1$ vector and assumed to be uncorrelated with η_t at all leads and lags.

The principal component method is computationally simple. In addition, as long as the correlation is not too big, e_t can be assumed to be correlated across series and across observations. The standard strict factor model assumes e_t to be serially uncorrelated, while the approximate factor model relaxes this assumption. The principal component method is appropriate to find an approximate factor structure, according to Chamberlain & Rothschild (1983) and Stock & Watson (2002).

The left panel of Figure 1 presents the economic activity factor extracted with the principal component method from variables that relate to the broad macroeconomic movement in China. The right panel presents the inflation factor extracted with the principal component method from four price indexes. Both series have been smoothed by taking the 12-month moving average and standardized to have zero mean and unit variance. In the figure, it can be seen that there are clear periods of sustained below-average growth and above-average growth. The persistent decline in the economic activity growth and inflation during the late 2008 is aligned with the U.S. Great recession and the global financial crisis.

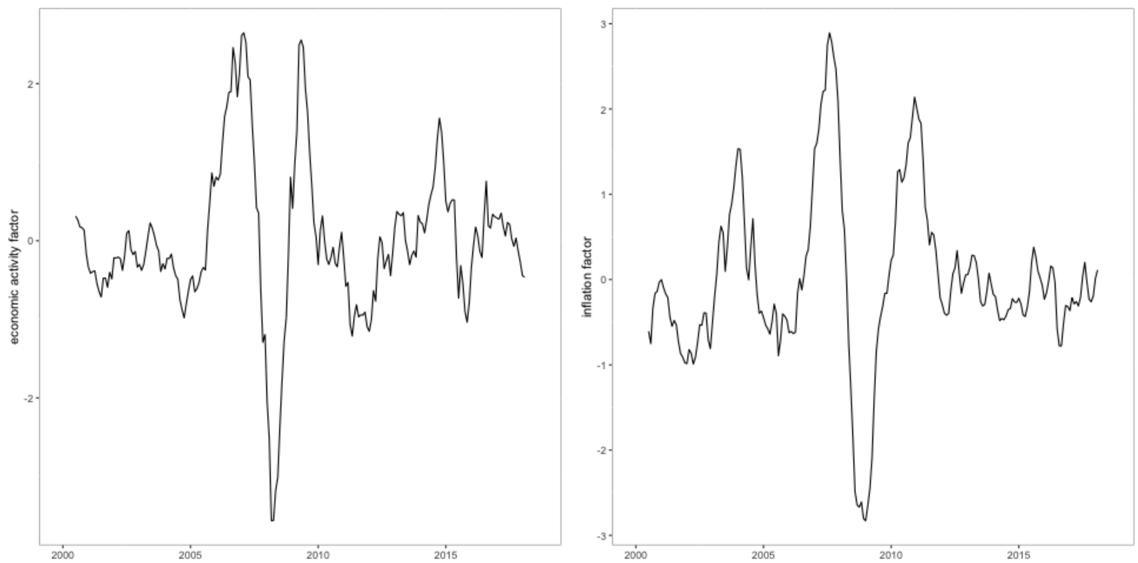

Figure 1: Economic Activity and Inflation Factors

A recession in the United States is defined by the National Bureau of Economic Research as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales". In contrast to the literature that studies the asymmetric effects of monetary policy during recessions and expansions, I will avoid labeling the periods of persistent below-average growth "recessions" for the purpose of my paper. Instead, I will call those periods "low-growth states", and periods of above-average growth "high-growth states". Note that output does not necessarily decline during "low-growth states", because the trend of economic growth of China is high over these periods.

1.4.2 Measuring Monetary Policy Shocks

As in Fernald et al. (2014), I measure structural shocks of monetary policy using a Factor-Augmented Vector Autoregression (FAVAR) model.

$$\begin{bmatrix} f_t^e \\ f_t^p \\ y_t \end{bmatrix} = A(L) \begin{bmatrix} f_{t-1}^e \\ f_{t-1}^p \\ y_{t-1} \end{bmatrix} + u_t$$

$$u_t \overset{iid}{\sim} N(0, \Sigma)$$

Here, f_t^e denotes the standardized economic activity factor and f_t^p denotes the standardized inflation factor. y_t is the benchmark interest rate. $A(L)$ denotes polynomials in the lag operator, and I set its order to be 2. In future work, I plan to evaluate alternative lag orders using Akaike Information Criterion (BIC) or Bayesian Information Criterion (AIC).

I use u_t to denote the reduced-form idiosyncratic term that is assumed to be independent and identically distributed with zero mean. I identify the structural shock through a Cholesky decomposition of Σ. This identification strategy assumes that the monetary policy variable can respond to changes in the economic activity factor and inflation factor contemporaneously, but the economic activity factor and inflation factor responds to changes in monetary policy with a lag of one month or more. This is implemented by recursively ordering the economic activity factor f_t^e and inflation factor f_t^p first, and the policy variable y_t last. Monetary policy shocks measured with the central bank benchmark interest rate are shown in Figure 2.

1.4.3 Identifying High and Low Growth Phases

As in Tenreyro & Thwaites (2016), probabilities of the unobservable states of the economy, "high-growth" states and "low-growth" states, are defined as a smooth increasing function.

$$F(z_t) = \frac{exp(\theta \frac{z_t - c}{\sigma_z})}{1 + exp(\theta \frac{z_t - c}{\sigma_z})}$$

Here, z_t is an indicator of the state of the economy, measured with 6-month one-sided moving average of the standardized economic activity factor. $F(z_t)$ measures the probability of the economy being in the high growth state. $F(z_t)$ increases as z_t increases; therefore, the economy is growing at

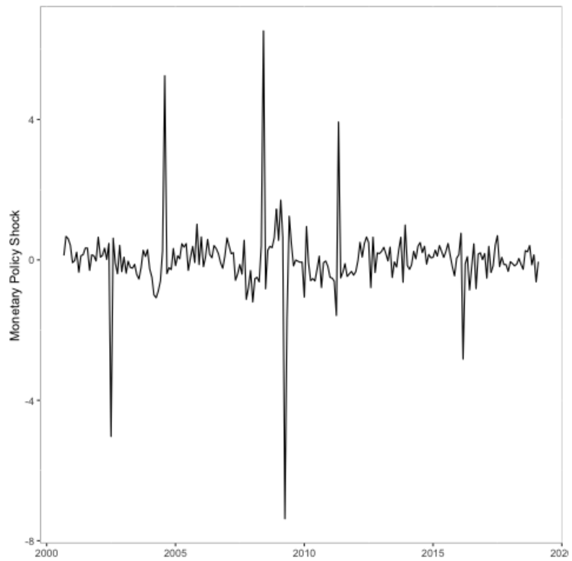

Figure 2: Monetary Policy Shocks

a fast rate when $F(z_t) \approx 1$, and economy is growing at a slow rate when $F(z_t) \approx 0$. The probability that the economy is in the "high-growth" state is shown in Figure 3. The probability that the economy is in the "low-growth" state is $1 - F(z_t)$.

c is a parameter that controls the proportion of the sample the economy spend in the "slow-growth" state. The baseline specification sets $c = 0$, which indicates that the unconditional probability of the economy being in the "slow-growth" state to be equal to that in the "high-growth" state, when $z_t = 0$. σ_z is the standard deviation of z_t. θ is the parameter that controls how sharply the economy switches from "high-growth" state to "low-growth" state as z_t changes. As in Tenreyro & Thwaites (2016), this parameter is calibrated to 3 in the baseline specification, indicating an intermediate degree of intensity to the regime switching. The robustness of results to each of these choices is investigated below.

1.4.4 Estimating Impulse Response Functions using Local Projections

As in Tenreyro & Thwaites (2016), the baseline model specifies the impulse response of the standardized economic activity factor f_t^e and the standardized inflation factor f_t^p at horizon $g \in [0, G]$ in state $j \in \{h, l\}$ to a shock u_t as the coefficient β_g^j. $j = h$ indicates the state of high growth, and $j = l$ indicates the state of slow growth. τ denotes a linear trend. α_g^j is a constant. The lag of

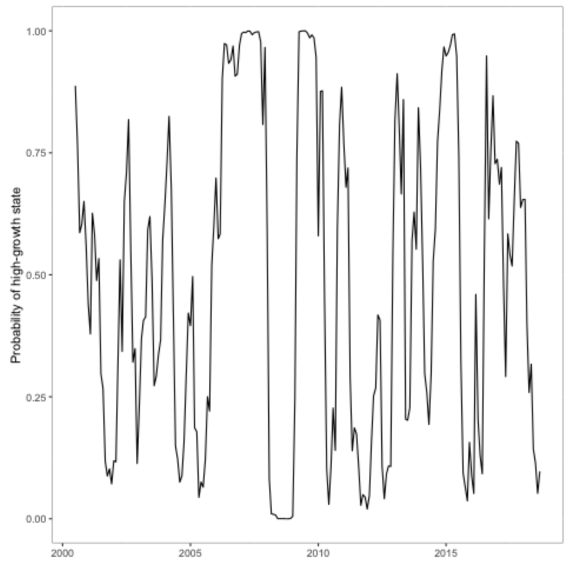

Figure 3: Probability of High-growth State

dependent variable f^e_{t-1} and benchmark interest rate b_{t-1} are included as control variables.

$$f^e_{t+g} = \tau t + F(z_t)(\alpha^h_g + \beta^h_g u_t + \gamma^h_{1,g} f^e_{t-1} + \gamma^h_{2,g} b_{t-1})$$

$$+(1 - F(z_t))(\alpha^l_g + \beta^l_g u_t + \gamma^l_{3,g} f^e_{t-1} + \gamma^l_{4,g} b_{t-1}) + \nu_{t+g}$$

$$f^p_{t+g} = \tau t + F(z_t)(\alpha^h_g + \beta^h_g u_t + \gamma^h_{1,g} f^p_{t-1} + \gamma^h_{2,g} b_{t-1})$$

$$+(1 - F(z_t))(\alpha^l_g + \beta^l_g u_t + \gamma^l_{3,g} f^p_{t-1} + \gamma^l_{4,g} b_{t-1}) + \nu_{t+g}$$

I compute impulse response functions by a local projection method: response at period h is measured by regressing the dependent variables from period h+1 to the end on right-hand-side variables from period 1 to h period from the end. According to Jorda (2005), computing impulse responses by local projections does not assume specific structure on specification and the unknown true multivariate dynamic system as required by a VAR model. With a VAR model, the impulse response function is measured by extrapolating the one-period ahead forecast, while local projections measure the impulse response function with direct multi-step forecasting.

An advantage of local projections is that it is easy to identify state-dependent asymmetry by allowing the coefficients on u_t to differ across two states, associated with the probability of being in a particular state. Hence, the impact of policy shocks on the economy in one state is separated from that in another state.

1.4.5 Inference

In order to construct confidence intervals for the impulse response functions estimated via local projections, I follow the suggestion of Jorda (2005) and construct standard errors for each local projection regression using Newey-West standard errors. The Newey-West correction is necessary as the v_{t+g} disturbance term in the local projection regression has a moving average structure. In constructing the Newey-West standard errors I follow Jorda (2005) and set the maximum lag equal to $g+1$.

The null and alternative hypothesis of no asymmetry are given by the following parametric restrictions:

$$H_0 : \beta_g^h - \beta_g^l = 0$$

$$H_1 : \beta_g^h - \beta_g^l \neq 0$$

In order to test the null hypothesis of no asymmetry, I follow Tenreyro & Thwaites (2016) to bootstrap the sign of $\beta_g^h - \beta_g^l$ using a block bootstrap approach.[5] I construct 10,000 bootstrap datasets by drawing with replacement from the dataset. The block length used in generating the replicate time series is fixed at $G = 20$.

Specifically, I first generate a random date and then select from that date the next 20 observations from the original dataset, which is called the first block. I then randomly draw a new time point, select the next 20 observations as a new block, and add it to the first block. The process is repeated until the time series is equal to the length of the original time series. This is called one bootstrap dataset. In total, I have constructed 10,000 bootstrap datasets.

For each bootstrap dataset, I first randomly assign values of $F(z_t)$ with replacement such that

[5] Under the null hypothesis, coefficients of monetary policy shocks for "high-growth" periods and "low-growth" periods are the same, but coefficients of constant and control variables are different.

the null hypothesis of no asymmetry is satisfied in population. By doing this, the actual $F(z_t)$ is randomly distributed across the data points so that there shouldn't be any relationship between $F(z_t)$ and the response of the economy at $t+h$ to shocks at time t. Then I calculate the the impulse response β_g^h and β_g^l using the local projection method. The p-value of the test is then calculated as the fraction of 10,000 cases in which the bootstrapped $\beta_g^h - \beta_g^l$ is larger than the value of $\beta_g^h - \beta_g^l$ estimated in the baseline model.

1.5 Results

1.5.1 Baseline Results

Figure 4 presents the impulse response function of the economic activity factor and inflation factor to a one percentage point increase in the identified monetary policy shock. Horizon g is on the x-axis, and β_g^h and β_g^l are on the y-axis. The dashed curve on the left panel represents how an initial one percentage point increase in the benchmark interest rate impacts the economic activity factor over the next 20 periods during the low-growth period, and the solid curve represents how an initial one percent increase in the benchmark interest rate impacts the economic activity factor during the high-growth period. The counterpart curves on the right panel show the response of the inflation factor to an initial one percent increase in the benchmark interest rate during high-growth and low-growth periods respectively.

The economic activity factor is extracted from a large number of growth rates of the underlying series. The negative economic activity factor during the first two months represents a decline in the level of economic activity following the monetary policy shock. Responses of economic activity during high-growth states and low-growth states are negative for the initial two months. The results are consistent with the standard theory that a tightening monetary policy leads to economic slowdown. Starting from the third month, responses of economic activity during high-growth states become positive and fluctuate around zero for the rest of the horizon, while responses of economic activity during low-growth states are negative for seven consecutive months, and then dies out over time for the rest of the periods. The evidence shows that monetary policy is more powerful in impacting

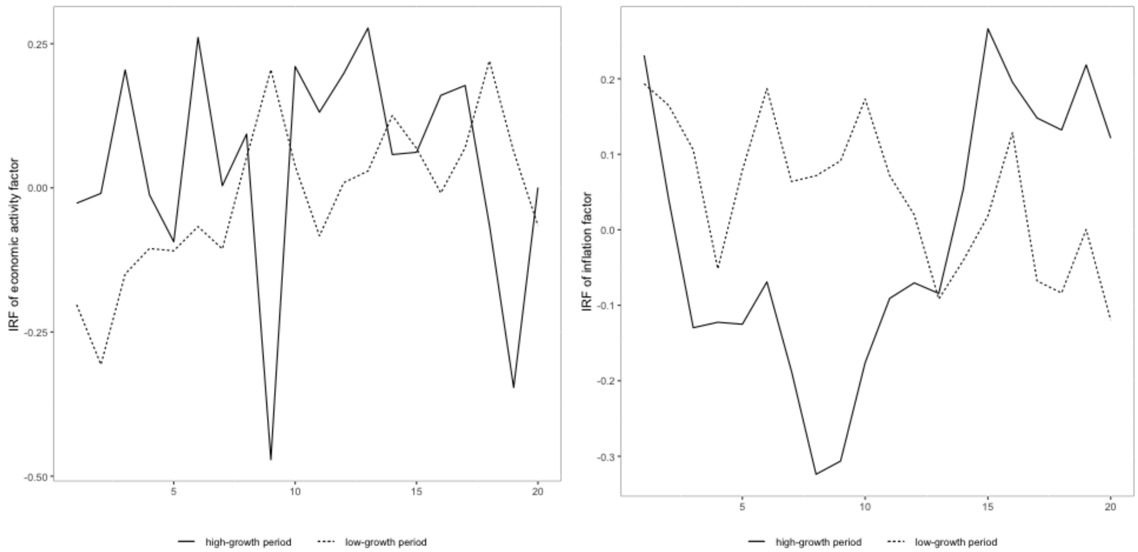

Figure 4: Impulse Response Functions

economic activity during low-growth states.

The inflation factor is extracted from growth rates of price indexes. Initial responses of the inflation factor to the monetary policy shock are positive for both states. This is similar to the "price puzzle" found in the effects of a policy tightening on inflation in studies of the effects of U.S. monetary policy on prices. Starting from the third month, responses of the inflation factor during high-growth states becomes negative and remains so for 13 months. This is the effect standard theory would predict - a monetary policy tightening leads to an overall reduction in the price level. Responses of the inflation factor during low-growth states fluctuate around zero for the rest of the horizon. This evidence shows that monetary policy is more powerful in impacting inflation during high-growth states.

The evidence that monetary policy shocks have larger impacts on output growth during low-growth states and larger impacts on inflation during high-growth states is consistent with a convex aggregate supply curve. As Figure 5 shows, in such a model, during high-growth periods when the economy is more likely to be on the steep part of the aggregate supply curve, aggregate demand shifts should primarily affect prices. In contrast, during low-growth periods, when the economy is on the flat part of the aggregate supply curve, aggregate demand shifts should primarily affect output.

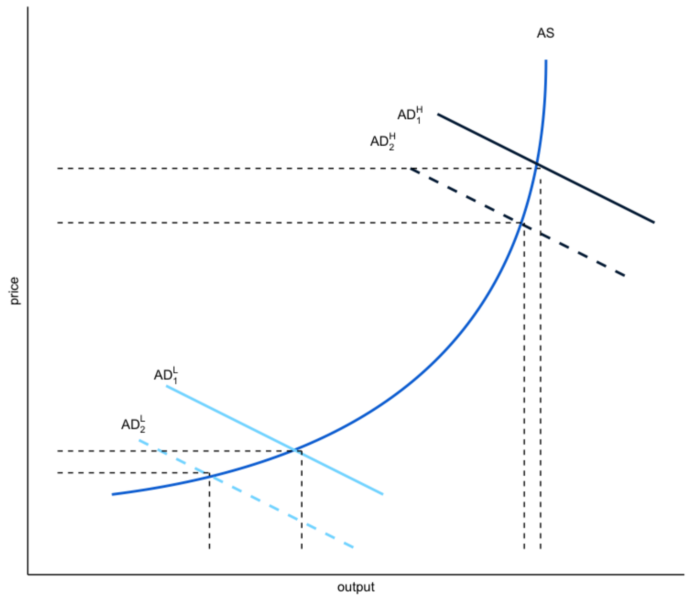

Figure 5: AS-AD Analysis

1.5.2 Inference

Figure 6 shows impulse response functions with 90 percent confidence intervals. The confidence intervals are calculated with the Newey-West standard errors. There is substantial uncertainty in the impulse response function estimates. This is not surprising, as impulse response function estimates are often imprecise, and this is compounded by the short time series and noisy nature of the Chinese data. However, despite this uncertainty, there are a number of horizons for which these impulse response function estimates are significantly different from zero, suggesting that monetary policy has statistically significant effects on the Chinese economy. Note that the response functions are for growth rates of the factor, so that a single significant growth rate response means that there is a significant level response.

Figure 7 shows the p-value for the null hypothesis that $\beta_g^h - \beta_g^l = 0$, using a 10 percent significance level. If the p-value is smaller than 10 percent, then the null hypothesis can be rejected. In both panels, there are a few horizons for which p-values are smaller than 0.1. At these horizons, the response of economic activity factor and inflation factor during high-growth periods is significantly different from that during low-growth periods, indicating asymmetry in the effects of monetary

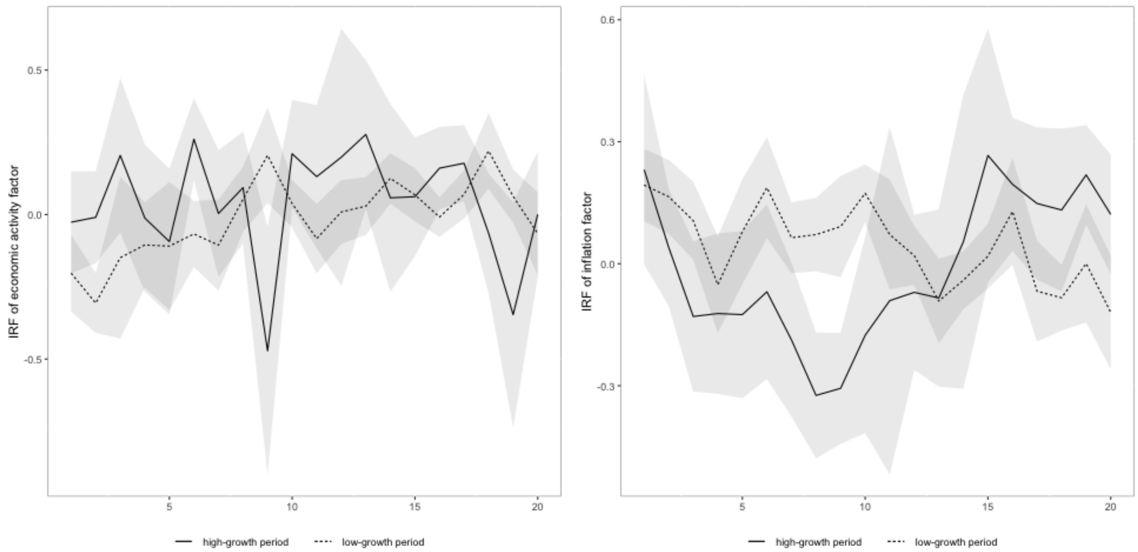

Figure 6: Impulse Response Functions with 90 percent Confidence Interval

policy.[6]

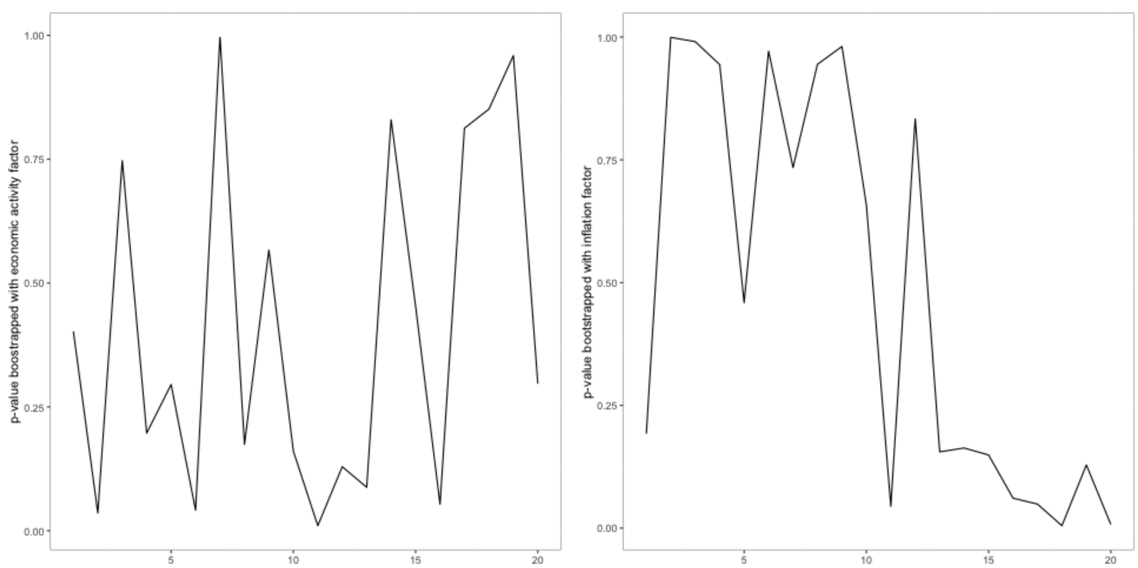

Figure 7: Boostrapped p-value

1.5.3 Robustness Checks

The baseline specification sets $c = 0$. This indicates that the probability of the economy being in the "slow-growth" state to be equal as that in the "high-growth" state, when $z_t = 0$ on average,

[6]As Figure 7 makes clear, the p-value falls below conventional significance levels for some, but not all, horizons. The number of horizons for which the asymmetry is significant is similar to that reported in Tenreyro & Thwaites (2016) for U.S. data.

because the factor is standardized to have zero mean. In the robustness checks section, c is set as -0.2, indicating the percentage of the time that $F(z_t)$ will place probability greater than fifty percent of being in the high growth regime. Figure 8 shows the impulse response function of the economic activity factor and inflation factor to a one percentage point increase in the identified monetary policy shock when c is set to be -0.2, keeping $\theta = 3$. Main results are robust to changing c to -0.2.

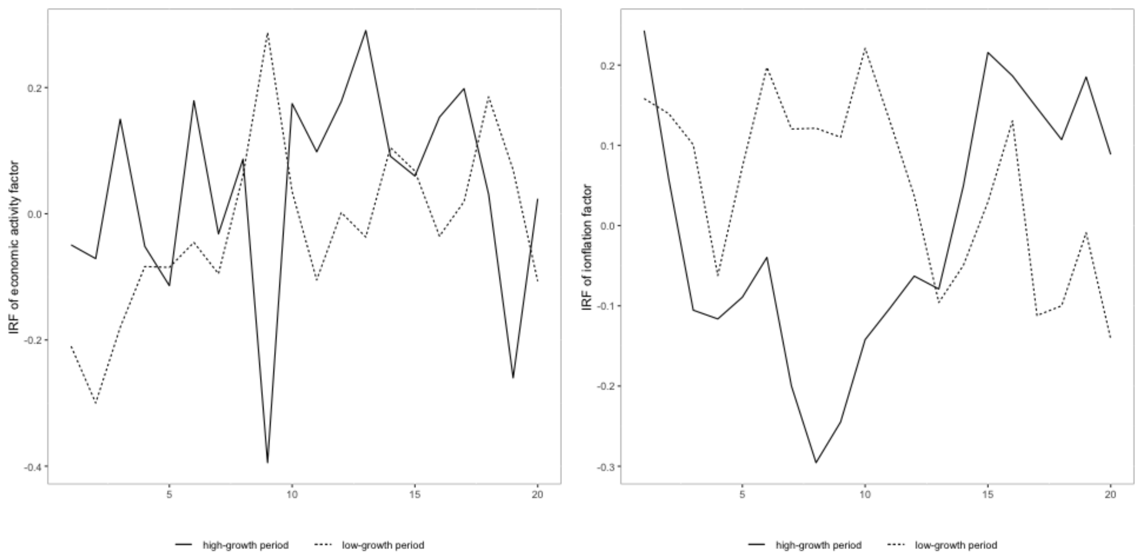

Figure 8: Impulse Response Functions with c=-0.2

The baseline specification sets $\theta = 3$. A lower θ indicates that the economy switches less sharply from "high-growth" states to "low-growth" states as z_t changes. Figure 9 shows the impulse response function of the economic activity factor and inflation factor to a one percentage point increase in the identified monetary policy shock when θ is set to be one, keeping $c = 0$. Figure 10 shows the results when θ is set to be five, keeping $c = 0$. The baseline result that monetary policy has asymmetric effects on Chinese economy across "slow-growth" states and "high-growth" states holds when θ is changed from one to five.

1.6 Conclusions

The literature that investigates asymmetries in the effects of China's monetary policy on economic activity and inflation is very limited. In this paper, I have investigated the asymmetric response of output growth and inflation to monetary policy actions during "high-growth" states and "low-growth"

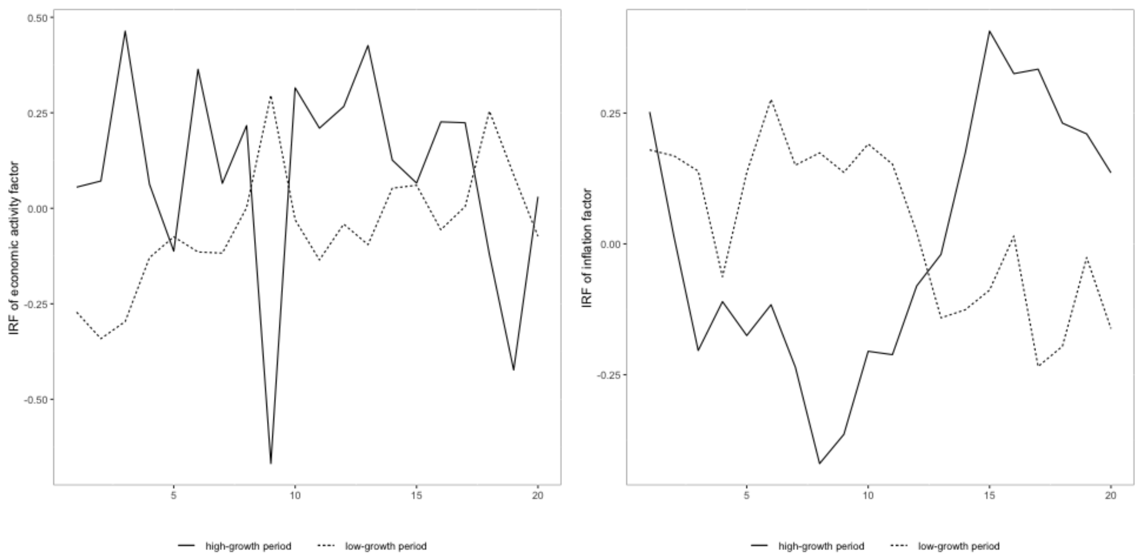

Figure 9: Impulse Response Functions with theta=1

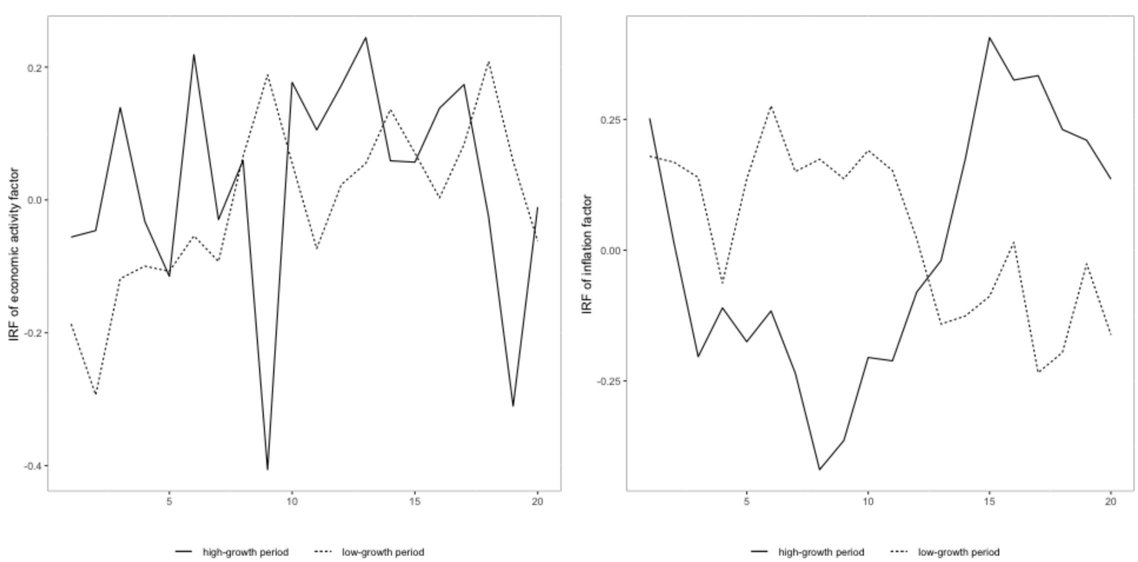

Figure 10: Impulse Response Functions with theta=5

states. The economic activity factor and inflation factor are extracted from a large panel of underlying macroeconomic series using the principal component method. Monetary policy shocks are identified with Choleski decomposition of residuals from a factor-augmented vector autoregression. Probabilities of high-growth and low-growth phases are measured using a smooth transition logistic function. Finally, I have used a local projection method to measure the response of real economy to the identified monetary policy shocks during "high-growth" states and "low-growth" states. The evidence is consistent with monetary policy shocks having larger impacts on output growth during low-growth states and monetary policy shocks have larger impacts on inflation during high-growth states. This result is consistent with a convex aggregate supply curve. There are periods during which the response of economic activity growth and inflation are positive following an increase in the benchmark interest rate. This indicates that economic activity and prices increase in response to a monetary policy tightening. This is counter-intuitive and may suggest potential issues with standard approaches to measure Chinese monetary policy shocks that have been used in the existing literature. According to Romer & Romer (2004), the likelihood of endogenous movements and anticipation movements can obscure the true effects of monetary policy. Romer & Romer (2004) address this problem and derive the indicator of monetary policy shocks by regressing the change in the intended policy interest rate around the Federal Reserve's internal forecast dates on these forecasts. The intended monetary policy shocks are derived using the narrative record, and the forecasts are publically available in the "Greenbook" before each meeting of the Federal Open Market Committee.

To my knowledge, the People's Bank of China does not publish its internal forecasts of inflation and real economic activity. Since 2009, the monetary policy committee of the PBC has been publishing reports of each of its quarterly meeting. Narrative analysis might be applicable to alleviate the endogeneity problem, which can be the focus of potential future research of this topic. Future research of this topic can also include the other two types of asymmetries: asymmetry related to the direction of the monetary policy action, and asymmetry related to the size of the policy action. This paper uses growth rates of factors to define phases of business cycle. Instead, future research can focus on the level of the factors relative to trend, and study the asymmetry of monetary policy over the cyclical component of the factors.

1.7 Future Directions

I have submitted a version of this chapter to China Economic Review. Although it was unfortunately rejected, I did receive some useful comments from an anonymous referee, and I plan to revise the paper along the lines of this referee's suggestions. These include:

- Price factors. This chapter has only included CPI series into the inflation factor. Policy makers are likely to reference various price information when making a decision. I plan to incorporate more prices indicators, such as PPI and house price, in empirical studies.

- Policy variable. This chapter has used central bank benchmark interest rate as the monetary policy instrument. After the financial crisis in 2008, People's Bank of China started to change its policy framework from the benchmark interest rate to the inflation-targeting interest rate. I plan to measure the monetary policy shock following Chen et al. (2016).

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