Asymmetric Effects of Monetary Policy Shocks: Evidence from China*

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Abstract

Monetary authorities use contractionary monetary policy to rein in inflation pressure and expansionary monetary policy to stimulate economic growth. However, economists had noticed that the responses to these two types of policy shocks might not be equal. In this paper, we use local projection methods proposed by Jorda to compute the impulse responses of monetary policy shocks in China under different regimes of output growth and inflation rates. The results show that: i) Conventional monetary policy effectively controls inflation and stimulates output growth in a high inflation regime. However, merely increasing money supply in a low inflation regime not only fails to stimulate output growth in the short run but also causes persistent stagflation; ii) As the economy of China edged down to a new period by slowing its output growth – namely "The New Normal," simply increasing monetary supply causes not only adverse effects to economic growth in the short run but also a lagged deflation. This phenomenon is identified as the "Price Puzzle" in China by us. This paper provides evidence for the asymmetric effects of monetary policy shocks in China and provides insights on improving the pertinence and flexibility of monetary policy-making in China.

JEL Classification: E52, E58, E61
Keywords: monetary policy, asymmetry, local projection, impulse responses, China

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1 Introduction

Since Sims (1980) proposed the vector autoregression model (VAR) in response to the rigid assumptions used in macroeconomic analysis, it has been a workhorse and standard in macroeconomics. Scholars tend to use VAR as the tool even if the underlying data do not follow a linear data generating process. In fact, when Sims proposed the VAR model, there were several assumptions: 1) Symmetric effects assumption. Sims assumed that a positive shock and a negative shock produce equal effects with different signs; 2) Effects of different magnitudes of shocks are proportional. Inevitably, some model defects follow: a linear data generating process may fail to capture the actual process. Further, impulse responses are high-dimensional functions of the parameters' estimates, therefore, forecast errors are quite large when forecast horizons are long.

A growing body of literature has noticed the asymmetric effects of monetary policy. A contractionary monetary policy might effectively control inflation, but attempting to stimulate the economy with expansionary monetary policy during a downturn might not be very useful. Some economists use a metaphor to describe this phenomenon: imagine a string with monetary policy at one end and the economy at the other. Employing contractionary policy during a boom is like pulling on the string to keep the economy in check, but attempting to stimulate the economy with loose policy during a downturn is like trying to push on the string to move the economy – not very effective (Barnichon et al., 2017).

To address the problem of nonlinearities and asymmetric effects, many variants of the VAR model have been proposed. For example, Weise uses the LSTVAR, and Assenmacher-Wesche uses the Markov-Switching VAR model (Weise, 1996; Assenmacher-Wesche, 2006). In this paper, we will introduce local projection methods proposed by Jorda and conduct an empirical analysis based on data from China. The advantages of local projection methods are numerous. First, they can be estimated by simple least-square; Second, they do not have a specific specification, thus are robust to misspecification of the data generating process; Third, since local projections can be estimated by univariate equation methods, they can be easily calculated with available regression packages and thus become a natural alternative to estimating impulse responses from VARs (Jorda, 2005).

There is also a reason why we use local projection method in this paper. The properties of the data from China are usually not satisfying. Measurement errors exist. Besides, China adopts a somewhat different monetary policy from the United States: despite China started its financial regulatory reform in 2015 to shift from "quantity-based" regulation to "price-based" regulation, the People's Bank of China still puts heavy weight on regulating with respect to the total money supply.[1] Many scholars have studied it and sought ways to find a good proxy for China's monetary policy, such as mixing quantity, price, and forward guidance (Sun, 2015). However, no consensus has been formed yet on which exact proxy should be used to measure China's monetary policy. Due to this reason, we still use the total money supply as the proxy for China's monetary policy in this paper. Given how China's monetary authority determines its monetary policy, one may naturally doubt that the data follow a linear data generating process. In light of this, choosing local projection as the analytic tool is a better choice.

2 Local Projection

2.1 A Recap of VAR and Impulse Response

A structural VAR (SVAR) can be concisely written as

$$\boldsymbol{B_0 Y_t} = \boldsymbol{\alpha_t} + \boldsymbol{B(L)Y_t} + \boldsymbol{\epsilon_t}$$

where the residuals $\boldsymbol{\epsilon_t}$ are assumed to be white noise with zero mean.

In reduced form, it is

$$\boldsymbol{Y_t} = \boldsymbol{\tilde{\alpha}_t} + \boldsymbol{\tilde{B}(L)Y_t} + \boldsymbol{u_t}$$

where $\boldsymbol{\tilde{\alpha}_t} = \boldsymbol{B_0^{-1}\alpha_t}, \ \boldsymbol{\tilde{B}(L)} = \boldsymbol{B_0^{-1}B(L)}$.

We notice that the reduced form residuals $\boldsymbol{u_t}$ are contemporaneously correlated, which impedes an unbiased economic interpretation. One must impose $\frac{n(n-1)}{2}$ assumptions to identify the structural form. The most general approach is to separate the residuals into orthogonal shocks by calculating a Cholesky decomposition. The result thus depends on ordering. By Wold theorem we can express the estimated VAR(p) coefficients recursively to the infinite-order vector moving-average coefficients. Then we can estimate the impulse response functions iteratively by rewriting the VAR(p) into its companion form:

$$\widehat{IR}(j) = \boldsymbol{\Phi^j B_0^{-1}}, \ j \in \{0, 1, 2, ...\}$$

where the matrix $\boldsymbol{\Phi}$ contains the coefficients of the companion form of VAR(1).

[1] To digress a little bit: though seemingly the Federal Reserve is using more quantity-based monetary policy tools such as quantitative easing while the People's Bank of China is using more price-based tools, the underlying logic is different. The People's Bank of China starts to put more weight on price-based tools because it wants to nurture a market-based financial regulatory system. However, The Federal Reserve has to employ quantity-based tools because it faces a liquidity trap where not much policy space is remaining for price-based tools.

2.2 Local Projection and Impulse Response

In his pioneering work, Jorda proposed an alternative approach to estimate impulse responses. His first step consists of ordinary least-square regressions for each forecast horizon:

$$\boldsymbol{y_{t+h}} = \boldsymbol{\alpha^h} + \boldsymbol{B_1^h y_{t-1}} + \boldsymbol{...} + \boldsymbol{B_p^h y_{t-p}} + \boldsymbol{u_{t+h}^h},\ h = 0, 1, 2, ..., H-1 \tag{1}$$

where $\boldsymbol{\alpha^h}$ is a vector of constants, and $\boldsymbol{B_i^h}$ are parameter matrices for lag p and forecast horizon h. The vector elements $\boldsymbol{u_{t+h}^h}$ are autocorrelated and/or heteroscedastic disturbances. The collection of all regressions of equation (1) are called local projections. Structural impulse responses are then estimated by the following:

$$\widehat{IR}(t, h, \boldsymbol{d_i}) = \boldsymbol{\hat{B}_1^h d_i}$$

where $\boldsymbol{d_i} = \boldsymbol{B_0^{-1}}$ must be identified from a linear VAR. Thus, the local projection method does not overcome the problem of identification.

A significant advantage of local projections is their easy extension to nonlinear frameworks. One may use dummy variables to separate data into two regimes, but it loses degrees of freedom. As a remedy, Auerbach and Gorodnichenko (2012) proposed a transition function to differentiate two regimes:

$$F(z_t) = \frac{e^{-\gamma z_t}}{1 + e^{-\gamma z_t}},\ \mathrm{Var}(z_t) = 1,\ \mathbb{E}(z_t) = 0 \tag{2}$$

the observations for the two regimes are the product of the transition function and the endogenous variables:

$$\begin{array}{lll} \text{Regime 1}: & y_{t-l} \cdot (1 - F(z_t)), & l = 1, ..., p \\ \text{Regime 2}: & y_{t-l} \cdot F(z_t), & l = 1, ..., p \end{array} \tag{3}$$

then estimate structural nonlinear impulse responses under two regimes.

3 Evidence from China

In the following analysis, we will start by introducing the data we use, then analyze the impulse responses from monetary policy shocks computed by VAR and local projection, respectively. We then compute impulse responses from local projection under different inflation regimes and different growth regimes. Specifically, the analysis under different growth regimes provides insights on how monetary policy should be made when the economy of

China edged down to "The New Normal" by slowing its growth rate.

3.1 Data

This paper selects China's quarterly GDP growth rate (y_t), CPI inflation rate (π_t), and money supply growth rate (m_t) data from the third quarter of 1993 to the third quarter of 2020.[2] The total number of observations is 108. We plot the data in the following figures. There are three periods worth special attention: 1) 1993-1997. During this period, former premier Rongji Zhu led the "soft-landing" process of the Chinese economy and stopped the high inflation. 2) 2008. The Financial Crisis. We can observe a sudden decrease in China's GDP growth rate and the following surge in the money supply. 3) 2020. The Global COVID-19 Outbreak. The huge drop in GDP growth rate in the first quarter of 2020 caused by the "lockdown" policy is obvious. The blue lines in the figures are corresponding threshold values determined later in the paper.

[Figure 1, 2, 3 about here.]

We present the descriptive statistics of the time series and report the unit root test results in Table 1. The results of unit root tests of the data suggest that they are stationary. However, it is worth pointing out that the results of the ADF test of GDP growth and money supply growth do not imply stationarity. Our argument is that in finite samples, it is hard to distinguish between a very persistent process (say, AR(1) process) and a random walk process. This is especially so when structural changes exist. We further perform the Phillips-Perron test and the results suggest that both time series are stationary.

[Table 1 about here.]

3.2 Impulse Response from VAR and LP

To set up the VAR(p) model, we need to select the lag order p. When setting maximum lags to be 4 and 8, AIC, BIC, and FPE all suggest $p = 2$; setting maximum lags to be 12, AIC and FPE suggest $p = 3$ while BIC suggest $p = 2$; setting maximum lags to be 16, AIC suggests $p = 13$, BIC suggests $p = 2$ and FPE suggests $p = 3$. When we allow more lags, AIC tends to use the largest lag, BIC always selects $p = 2$, while FPE always selects $p = 3$. Based on the results above, we choose $p = 3$.

[2]GDP growth and CPI inflation data from CSMAR. Money supply growth data from People's Bank of China and FRED.

This paper uses a standard Cholesky decomposition and the Wold order of y_t, π_t, m_t to compute the impulse responses to a unit shock from VAR and linear local projection. Note that as previously mentioned, the local projection method does not overcome the problem of identification. This is the reason why we estimate a structural VAR model first. The results are displayed in Figures 4-6 and 7.

[Figure 4, 5, 6, 7 about here.]

We can observe that the impulse responses from local projection are more sensitive than the impulse response from VAR. This is because local projection estimates impulse responses at each period and acquire different coefficients. The impulse responses measured by VAR suggest that a positive monetary shock has positive effects on GDP growth and the effects stabilize after four quarters. However, the impulse responses measured by the local projection method suggest that a positive monetary shock creates an increasing effect until the sixth quarter and dies out gradually. Nevertheless, one should notice that the effect is reinforced again in the fifteenth quarter, indicating that the impulse responses measured by local projection have more persistent effects than the impulse responses from VAR. For the effects of a positive monetary shock on inflation, though the two impulse responses have similar patterns, the local projection impulse responses measure more substantial effects than the VAR impulse responses.

3.3 Impulse Response from LP under Different Regimes

3.3.1 Threshold Estimation

To study the asymmetric effects of monetary policy shocks, we use threshold estimation methods proposed by Hansen (2000) to determine the threshold values of GDP growth and CPI inflation, and analyze the responses to monetary policy shocks in different inflation regimes and GDP growth regimes.

Specifically, the equation for testing thresholds are

$$Y_t = \begin{cases} \rho_L' X_{t-1} + \xi_t^L, & \phi_{t-j} \leqslant \gamma \\ \rho_H' X_{t-1} + \xi_t^H, & \phi_{t-j} > \gamma \end{cases} \tag{4}$$

In our specification, Y_t could represent y_t, π_t, and m_t. X_t contains lags of order 1-12 of the explanatory variables y_t, π_t and m_t. The threshold variable ϕ_{t-j} could be any variable or any combinations of y_{t-j}, π_{t-j}, and m_{t-j}, where $j \in \{1, 2, ..., 12\}$. ρ_s where $s = L, H$ contains the coefficients in the low regime and the high regime, respectively. The threshold value γ

can be found by F-tests. We use the grid search method and eliminate top/bottom 5% data. We then select the best threshold value with the smallest sum of squares of residuals and bootstrap 1000 times to adjust the distribution of the best threshold value. We provide the results of the threshold estimation below.

[Table 2, 3 about here.]

This paper follows Jorda (2005)'s selection method for the final threshold value. We estimate the threshold value of the threshold variable using each explanatory variable, find the most significant ones, and then take the average to get the final threshold value. For example, when we estimate the threshold value for GDP growth, we do not get a significant value by explanatory variable y_t and get significant values 9.9% and 9.8% from explanatory variables π_t and m_t, then the final threshold value is determined by taking the average: 9.85%. Using the same token, we get the threshold value for π_t is 2.05%. We provide the F-test figures below.

[Figure 8, 9, 10, 11 about here.]

After determining the threshold values for GDP growth and CPI inflation, we split the data into two regimes – the high regime and the low regime and compute the impulse responses to a monetary policy shock in different regimes by local projection.

3.3.2 Inflation Regime-Dependent Impulse Responses

We first conduct our analysis of different inflation regimes. That is, we want to analyze how the impulse responses to a monetary shock differ during periods when inflation is high and low, respectively. We split the data into the high regime and the low regime according to the threshold value $\gamma = 2.05\%$ of inflation and present the impulse responses in Figure 12. The impulse responses during low-inflation and high-inflation regimes are displayed in the left panel and right panel, respectively.

[Figure 12 about here.]

We can observe that the impulse responses to a monetary policy shock in different inflation regimes display significant asymmetries in lag periods and magnitudes. In the high inflation regime, GDP growth (y_t) responds to monetary policy shocks up to eight quarters or two years, but the effects disappear after that; in the low inflation regime, the impulse responses do not seem to respond severely to monetary policy shocks in the beginning few quarters, but they intensify gradually and peak in the thirteenth quarter. Also note that the magnitude of the impulse response in the low inflation regime is almost twice the size of that in the high inflation regime when peaking. This suggests the asymmetries of the effects of monetary policy shocks in lag periods and magnitudes.

We then move to the second row of the figure. In the high inflation regime, CPI inflation (π_t) responds immediately to monetary policy shocks at a substantial magnitude, then the effects decay gradually. However, in the low inflation regime, CPI inflation does not respond significantly to monetary shocks until the sixth quarter. Besides, the effects do not die out but keep persistent all the way to our maximum forecast horizon. We should also pay attention to the magnitudes of the impulse responses: the magnitude of the impulse responses in the high inflation regime is almost twice as that in the low inflation regime when they peak. The empirical results again provide evidence for the asymmetric effects of monetary shocks in China regarding the responding time and magnitudes.

The policy implication following the analysis is enlightening. Conventional monetary policy is quite effective for controlling inflation and stimulating output growth in a high inflation regime, given that a positive monetary policy shock stimulates growth timely without incurring persistent inflation. However, when the economy is in a low inflation regime, merely increasing the money supply not only fails to stimulate output growth in the short run but also causes persistent stagflation. Therefore, the results suggest that it is not appropriate to use monetary policy shocks to stimulate the economy during a low inflation period. In fact, this is precisely the prudent policy stance the People's Bank of China has been clinging to for years. Money supply growth has been given special consideration when inflation stabilizes after 2010, as in what the People's Bank of China often says, "The floodgates of the money supply should be controlled."

3.3.3 Output Growth Regime

Next, we analyze different output growth regimes. That is, we would like to analyze how the impulse responses to a monetary policy shock differ during periods when output growth is high and low, respectively. Similar to the previous section, we split the data into the high regime and the low regime according to the threshold value $\gamma = 9.85\%$ of GDP growth, and present the impulse responses in Figure 13.

[Figure 13 about here.]

We can observe that the impulse responses to a monetary shock in different output growth regimes displays significant asymmetries in lag periods and directions. In the high output growth regime, the impulse responses of GDP growth (y_t) peak in the fifth quarter, then drop a little, and peak again in the twelfth quarter. The responses gradually die out after that. In the low output growth regime, a positive monetary policy shock display mild but adverse effects on GDP growth (y_t) in the beginning seven quarters, turn positive starting from the eighth quarter, and peak in the thirteenth quarter. It is worth mentioning that the responses seem to intensify again in the sixteenth quarter, suggesting a long-lasting effect.

The discussion for inflation follows. In the high output growth regime, the pattern of the impulse responses of inflation is quite similar to that of GDP growth. It peaks in the fifth quarter, decays a bit, and peaks again in the eleventh quarter. The responses gradually die out after that. In the low output growth regime, CPI inflation (π_t) does not respond much to the monetary policy shock in the beginning eight quarters. More interestingly, the impulse responses turn negative and intensify starting from the ninth quarter. This phenomenon is exactly the "Price Puzzle" reported by Sims and Eichenbaum: they found some disconcerting phenomenons that many empirical estimates of the relationship between the federal funds rate and inflation have suggested that a surprise interest rate hike is followed immediately by a sustained increase in the inflation rate (Sims, 1992; Eichenbaum, 1992). We somehow managed to identify it based on data from China and provide further evidence to the "Price Puzzle." The analysis above suggests that merely increasing the money supply may not be effective in the short run and causes the price level to move in the opposite direction.

A major policy implication is that simply increasing the money supply is not an appropriate choice in the low output growth regime. It not only fails to stimulate output growth in the short run but also creates a lagged deflation. Instead, the government should put more effort into discovering new generators for output growth from the perspective of technological innovations and economic structural reforms. Additionally, novel monetary policy tools that improve the pertinence and flexibility of policy effects must be studied by monetary authorities. The results are especially enlightening to China since its economy has stepped into a new period – namely "The New Normal," where output growth rate gradually slows down.

4 Conclusion

In this paper, we first use local projection methods proposed by Jorda to compute the impulse responses of monetary policy shocks in China. The impulse responses measured by local projection are more sensitive than those computed by conventional VARs. We then use nonlinear local projection to compute impulse responses to monetary policy shocks in China under different regimes of output growth and inflation rates. The results show that: First, conventional monetary policy effectively controls inflation and stimulates output growth in a high inflation regime. However, merely increasing the money supply in a low inflation regime not only fails to stimulate output growth in the short run but also causes persistent stagflation. Second, as the economy of China edged down to a new period by slowing its output growth – namely "The New Normal," simply increasing monetary supply not only causes adverse effects to economic growth in the short run but also creates a lagged deflation. This phenomenon is identified as the "Price Puzzle" based on data from China by us. We provide evidence for the asymmetric effects of monetary policy shocks in China and provide insights on improving the pertinence and flexibility of monetary policy-making in China.

Tables and Figures

Table 1: Descriptive Statistics and Unit Root Tests

Variable	Mean	Max	Min	Sd.	Unit root test	p-value
`GDPgrowth` (y_t)	9.009	14.30	-6.80	3.0077	Phillips-Perron	0.0925*
`CPIinf` (π_t)	3.761	26.90	-2.06	5.6751	ADF	<0.01***
`M2growth` (m_t)	17.035	37.31	8.00	6.6964	Phillips-Perron	0.0992*

Start: 1993Q3, End: 2020Q3, No. of Obs: 108;
Significant Codes: 1% ***; 5% **; 10% *;
Alternative Hypothesis: Stationary.

Table 2: Threshold Estimation Results for `GDPgrowth` (y_t)

Threshold Variable	Explanatory Variable		
	y_t	π_t	m_t
y_{t-1}	8.8 (0.808)	7.8 (0.148)	9.4 (0.124)
y_{t-2}	8.9 (0.857)	8 (0.379)	8.3 (0.16)
y_{t-3}	8.6 (0.915)	8.1 (0.188)	9.5 (0.116)
y_{t-4}	8.6 (0.873)	8.6 (0.191)	9.7 (0.166)
y_{t-5}	8.9 (0.794)	9.4 (0.38)	9.2 (0.137)
y_{t-6}	8.6 (0.778)	9.7 (0.413)	9.7 (0.039)
y_{t-7}	9.8 (0.808)	9.8 (0.344)	9.8 (0.212)
y_{t-8}	8.9 (0.841)	9.9 (0.331)	9.1 (0.123)
y_{t-9}	8.5 (0.884)	9.5 (0.157)	9.1 (0.149)
y_{t-10}	8.6 (0.82)	9.4* (0.07)	9.8** (0.045)
y_{t-11}	9.1 (0.803)	9.9* (0.051)	10 (0.113)
y_{t-12}	8.8 (0.737)	9.8* (0.057)	9.9 (0.178)

Significant codes: 1% ***; 5% **; 10% *;
Values given are the threshold estimates;
Bootstrap p-values are given in the bracket below them.

Table 3: Threshold Estimation Results for `CPIinf` (π_t)

Threshold Variable	Explanatory Variable		
	y_t	π_t	m_t
π_{t-1}	1.5 (0.833)	2.066667** (0.012)	1.566667* (0.074)
π_{t-2}	1.6 (0.795)	2.2 (0.312)	1.5* (0.069)
π_{t-3}	1.6 (0.653)	2.2** (0.037)	1.733333 (0.113)
π_{t-4}	1.466667 (0.789)	1.966667** (0.033)	2.033333** (0.034)
π_{t-5}	2.2 (0.708)	1.8** (0.015)	1.666667* (0.054)
π_{t-6}	2.2 (0.832)	1.966667** (0.02)	1.733333** (0.036)
π_{t-7}	2.3 (0.882)	1.966667 (0.105)	2.3 (0.204)
π_{t-8}	1.5 (0.884)	1.833333 (0.494)	2.166667 (0.256)
π_{t-9}	1.5 (0.796)	1.566667 (0.193)	2.033333 (0.259)
π_{t-10}	1.666667 (0.711)	1.6** (0.026)	2.033333** (0.029)
π_{t-11}	1.5 (0.711)	2.066667** (0.028)	2.4 (0.118)
π_{t-12}	1.466667 (0.58)	2.733333 (0.196)	2.733333 (0.516)

Significant codes: 1% ***; 5% **; 10% *;
Values given are the threshold estimates;
Bootstrap p-values are given in the bracket below them.

Figure 1: GDP Growth

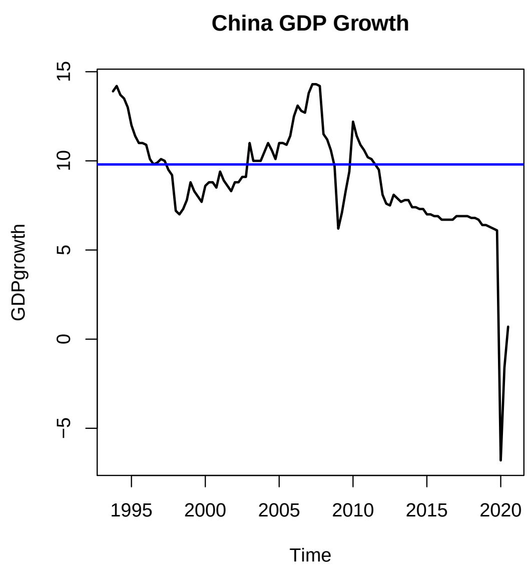


Figure 2: CPI Inflation

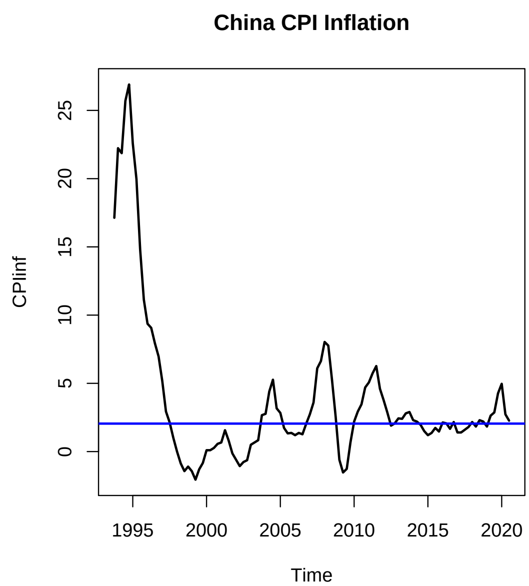


Figure 3: Money Supply Growth

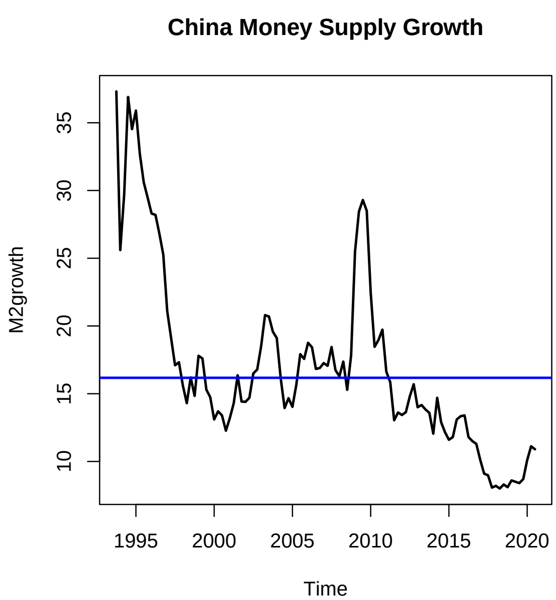


Figure 4: SVAR Impulse Response (1)

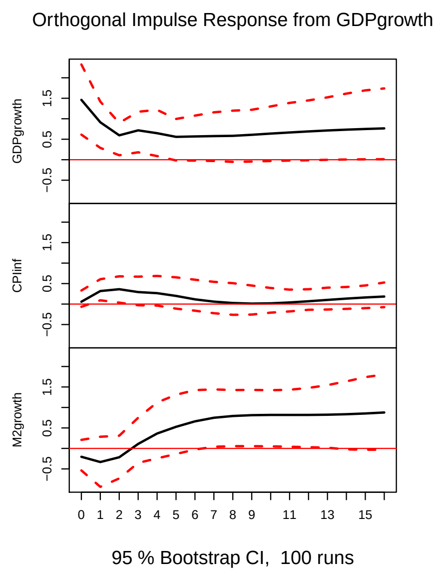


Figure 5: SVAR Impulse Response (2)

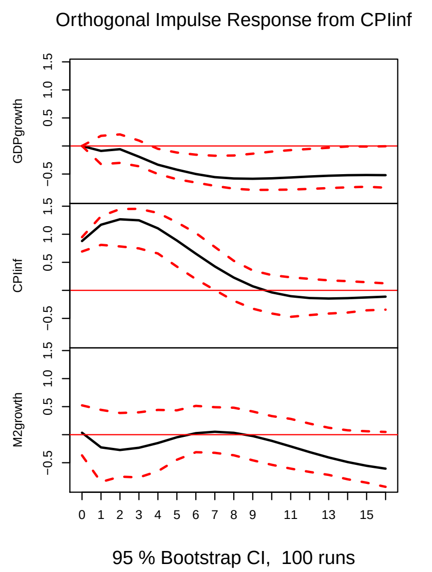


Figure 6: SVAR Impulse Response (3)

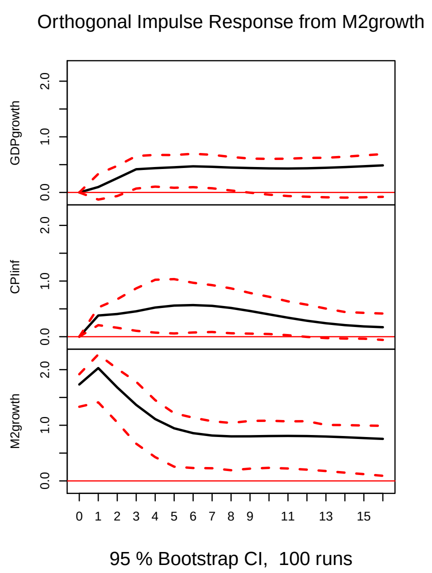


Figure 7: Linear Local Projection Impulse Response

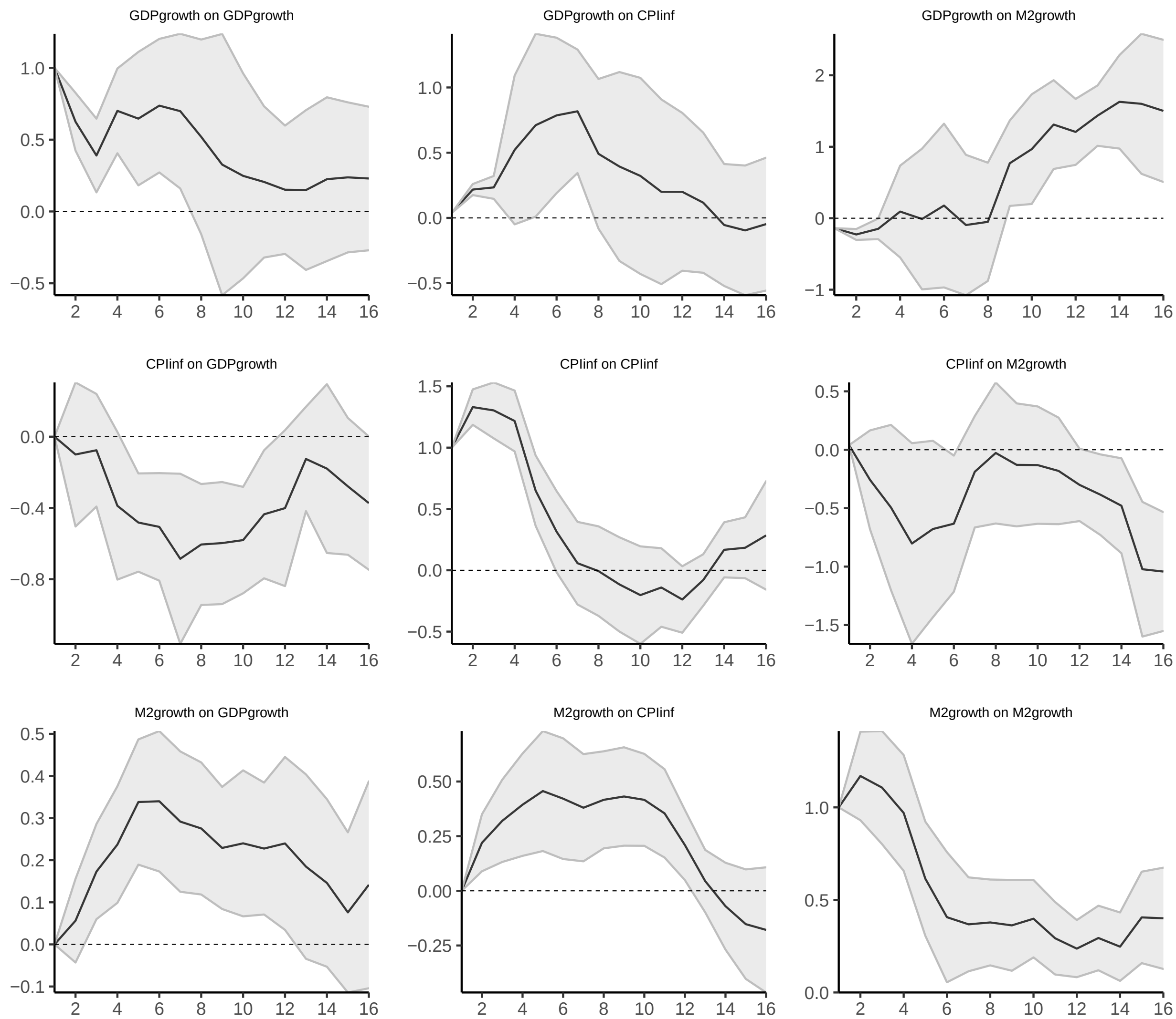


Figure 8: For y_t, Dependent π_t

Figure 9: For y_t, Dependent m_t

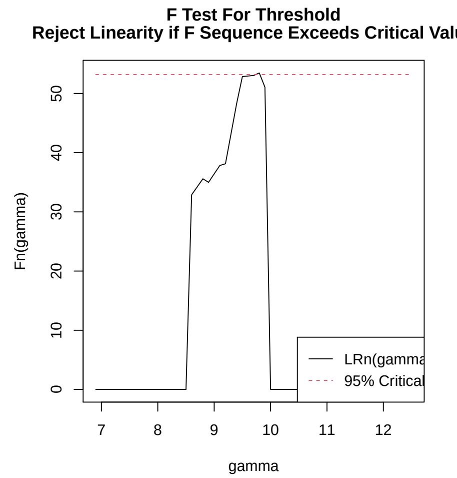


Figure 10: For π_t, Dependent π_t

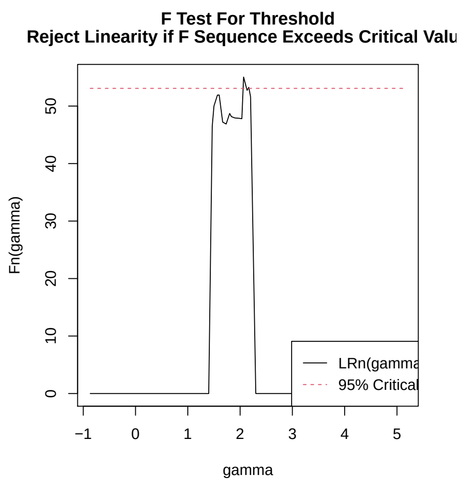


Figure 11: For π_t, Dependent m_t

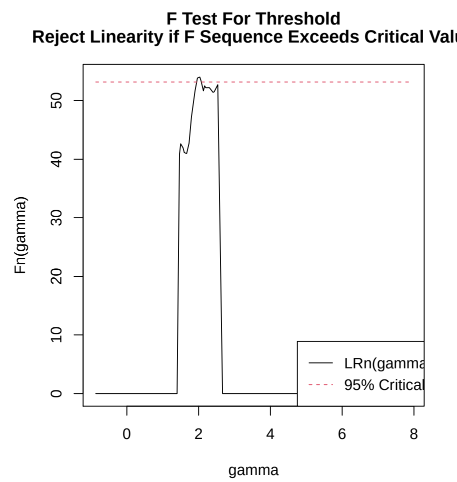
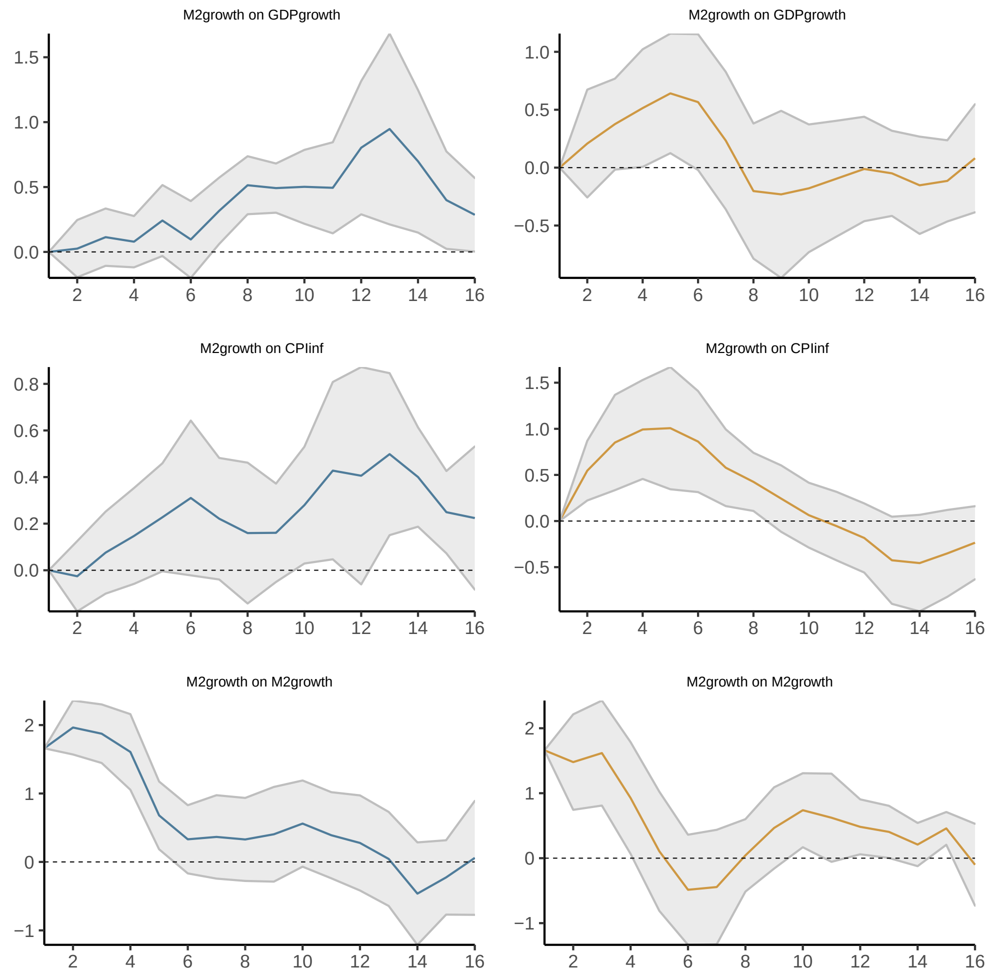
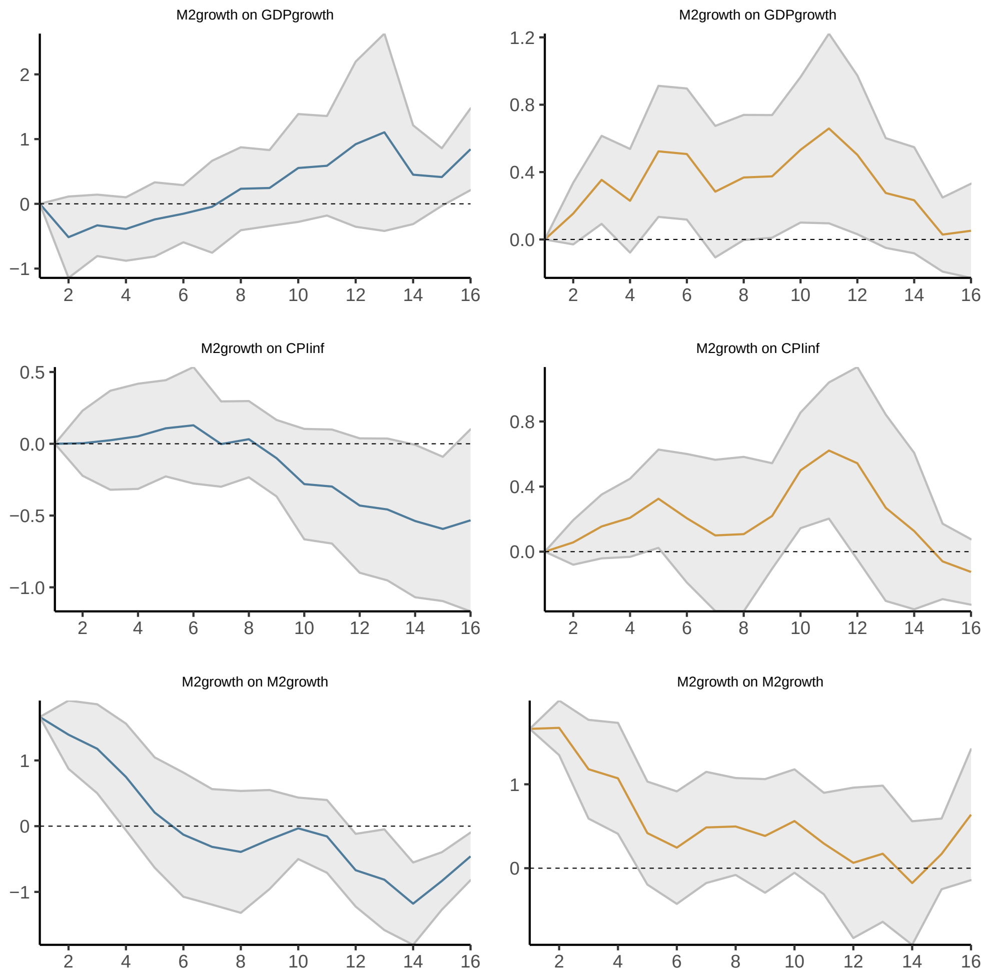


Figure 12: Inflation Regime-Dependent Nonlinear Local Projection Impulse Response



The left and right panels display impulse responses to a monetary shock in low inflation regime and high inflation regimes, respectively.

Figure 13: Output Growth Regime-Dependent Nonlinear Local Projection Impulse Response



The left and right panels display impulse responses to a monetary shock in low GDP growth regime and high GDP growth regime, respectively.

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