

The relative price of investment goods, the price level, and the “slope puzzle”

Sen Zhang Yangyang Ji Tianye Lin^{*}

Abstract

The application of Blanchard and Quah’s (1989) method to Chinese data always obtains counterintuitive responses of output and the price level to demand and supply shocks, referred to in the literature as the “slope puzzle.” Empirical findings of this paper reveal that the low-frequency movement in the price level causes this puzzle, which arises from the relative price of investment goods, and the friction in China’s financial market drives this movement.

Key words: Slow Puzzle; Price Level; BQ method; Supply Shocks; Demand Shocks

JEL Classification: E31, E32

1. Introduction

Aggregate demand (AD) and aggregate supply (AS) curves form the basis of modern macroeconomic analysis. Based on a vector autoregression (VAR) model, Blanchard and Quah (1989, BQ henceforth) proposed long-run restrictions to identify supply and demand shocks and to estimate the AD and AS curves. This method has since become a standard tool in an economist’s toolbox.

Economists have estimated China’s AD and AS curves using the BQ method; however, the results appear counterintuitive. In Chinese literature, Xu (2008) found what is referred to as the “slope puzzle.” In this paper, his result is reproduced in Figure 1(a), wherein it can be seen that both output and the price level¹ increase under a positive supply shock but respond in the opposite direction under a positive demand shock. Thus, this implies that such a result can occur

^{*} **Sen Zhang, the applicant:** Center for Macroeconomics and Finance, Peking University (email:zhangsen@phbs.pku.edu.cn). Yangyang Ji: China Economics and Management Academy, Central University of Finance and Economics. Tianye Lin: Peking University HSBC Business School, Peking University. We are grateful to two anonymous referees for extensive comments. We would also like to thank Jianjun Miao, Heng-fu Zou, Tao Zha, Chan Wang, Fangbin Qiao, Qichun He for helpful comments.

¹ Since there is no reliable unemployment data in China, economists always use price data (or inflation) to estimate the AD–AS curves instead.

only when the slope of the AD curve is positive and that of the AS curve is negative. This result is in stark contrast to the macroeconomic theory.

According to empirical research on the AD–AS curves, the slope puzzle is specific to China. Extensive research in the US supports the theoretical prediction about the slopes of the AD–AS curves (Spencer, 1996; Gali, 1999; Cover, Enders and Hueng, 2006), particularly the seminal work by Blanchard and Quah (1989). Empirical findings of the OECD countries also show no such puzzle (Cho, 2012).

Since Xu's (2008) discovery of the slope puzzle, many economists such as Gao (2010), Chen Sun and Xiong(2011), and Wang and Lin (2016) have tried to explain and solve this puzzle. They explain that the puzzle was a result of model instability, such as abrupt institutional changes, caused by, for example, China's accession to the WTO in 2001 as well as stochastic volatility, a feature of China's GDP. When adding a dummy variable that reflects exogenous institutional changes or time-varying parameters to the BQ model, no puzzle emerges.

However, Zhu and Deng (2017) found that despite the time-varying parameter VAR (TVP-VAR) model, the slope puzzle still existed. Also, they prove Cover, Enders and Hueng(2006)'s method is also invalid in solving the puzzle. They argued that previous studies on the slope puzzle solution are most likely invalid and a result of low data quality. Zhu and Deng (2017) believed that since the persistence of the supply shock of the Chinese economy is relatively low and the BQ model uses long-run restrictions to identify supply shocks, the BQ model is not applicable to the Chinese economy. On this basis, Zhu and Deng abandoned the BQ method and used sign restrictions to estimate China's supply and demand shocks.

Zhu and Deng (2017) verified that the supply shock in the Chinese economy is indeed low persistent; however, they did not establish a link between "low persistence" and "the failure of the BQ method." Moreover, the sign restrictions cannot essentially explain the slope puzzle as it primarily concerns the sign of AD–AS curves' slopes. In sum, it seems that the issue of the slope puzzle is yet to be resolved. More importantly, if the problem lies in the identification of shocks, it is imperative to ascertain the causes. Otherwise, even if the slope puzzle were to be solved, when studying China's macroeconomic problems, we would still be confused while identifying shocks.

We find that the slope puzzle is related to low-frequency fluctuations in prices but not the model itself. Moreover, we find the important influence of low-frequency fluctuations on the slope puzzle by using different kinds of detrending methods. We also find the low-frequency fluctuation of the price level to be caused by the relative price of investment goods. As such, we give an explanation for, and a demonstration of, the cause of the puzzle, and we can solve the puzzle without changing the BQ method.

The following text is organized as follows. In Section 2, we try to prove whether the slope puzzle comes from the low-frequency fluctuation in the price level. In Section 3, we provide the economic factors behind the slope puzzle. This section also contains robustness tests. In the final section, we conclude the paper.

2. Model and Empirical Analysis

(1) Empirical method and specification

This paper uses the standard Blanchard and Quah (1989) model without other modifications. The latest explanations and detailed descriptions of this model can be found in Ramey (2016).

Generally, before estimating a VAR, the data should be checked for stationarity. Nonstationary data should be transformed into stationary ones. There are three common methods of dealing with non-stationarity: log difference, filtering, and adding linear or nonlinear time trends. According to Fernald (2007), if different methods of detrending had a significant impact on the results of model estimation, the impact of low-frequency fluctuations should be considered. Ramey (2016) believes that the best choice is to use log level data to estimate and add time trends to the model. Therefore, this paper first uses different detrending methods to process the data and estimates the model to find the cause of the slope puzzle.

The first model denoted by Model (I), estimated using log difference data, is represented in the MA form as follows:

$$\begin{bmatrix} \Delta y_t \\ \Delta p_t \end{bmatrix} = \begin{bmatrix} B^{11}(L) & B^{12}(L) \\ B^{21}(L) & B^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^p \end{bmatrix}, \text{ (Model I)}$$

where Δy_t is log difference of real GDP, that is, the output growth rate. Δp_t is log difference of the price level or the inflation rate. $B(L)$ is a polynomial in the lag operator. By using the BQ method, that is, by setting $B^{12}(1) = 0$, we can identify supply and demand shocks.

We apply different detrending methods to the price level. Output is only log-differenced in this section; however, in the next section, we apply different detrending methods to output. As such, the second model denoted by Model (II) can be written as follows:

$$\begin{bmatrix} \Delta y_t \\ p_t \end{bmatrix} = \begin{bmatrix} a_0 & a_1 \\ b_0 & b_1 \end{bmatrix} \begin{bmatrix} t \\ t^2 \end{bmatrix} + \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^p \end{bmatrix}, \text{ (Model II)}$$

where p_t represents the log level of prices and $C(L)$ is a lag polynomial. Similarly, by setting $C^{12}(1) = 0$, we impose long-term restrictions. a_0 and b_0 represent coefficients of linear time trends, while a_1 and b_1 are coefficients of quadratic time trends. It is worth noting that, theoretically, Models (I) and (II) should identify the same supply shock (Francis and Ramey, 2009).

(2) Data selection and model setting

Consistent with Zhu and Deng (2017), this paper also uses Chang et al.'s (2016)² data. More

² They constructed a standard macroeconomic time series dataset for China, which is comparable to those commonly used in the macroeconomic literature on Western economies. They interpolated seasonally adjusted quarterly nominal GDP value added with seasonally adjusted monthly nominal retail sales of consumer goods, nominal exports, nominal imports, and nominal value added of industry to get monthly nominal GDP. Further details regarding the data can be found in the works of Chang et al. (2016) and Higgins et al. (2016).

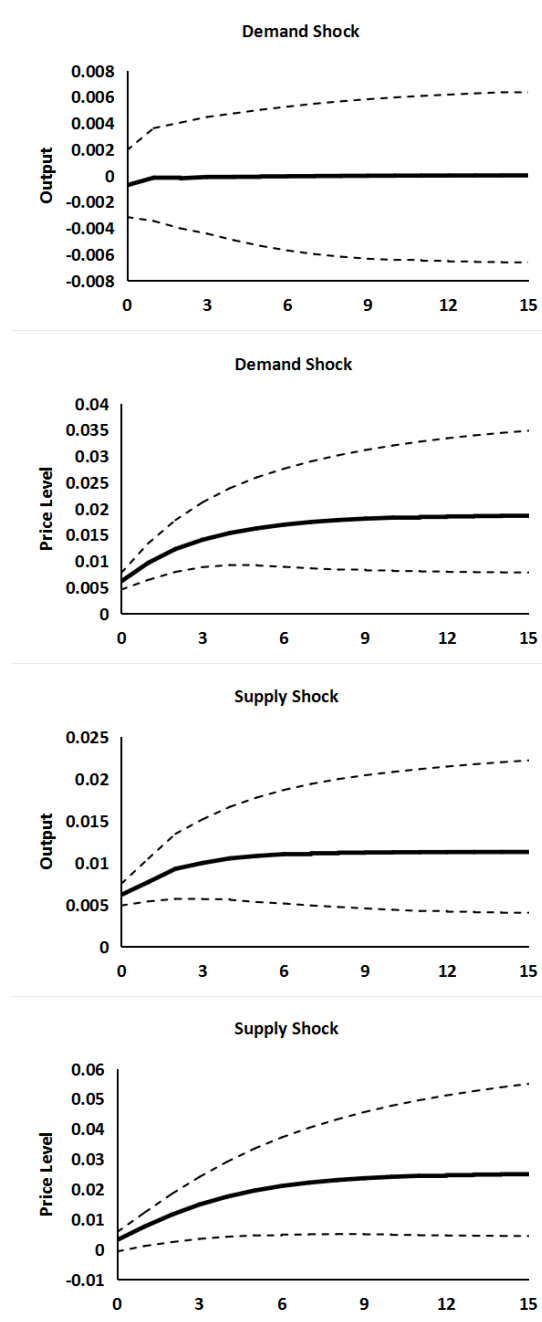
specifically, we use the real GDP and the GDP deflator to measure output and the price level, respectively. The sample spans from the first quarter of 1992 to the second quarter of 2018.

The lag-order selection is based on the values provided by the Akaike information criterion (AIC), Bayesian information criterion (BIC), or Hannan–Quinn information criterion (HQ). However, we will consider orders both used in previous research and selected by AIC, BIC, and HQ.

(3) Empirical analysis

We plot impulse response functions of the two models in one graph for comparison. Figure 1(a) presents the result of Model (I) and Figure 1(b) the result of Model (II).

(a) Log difference of price level



(b) Log level of the price level

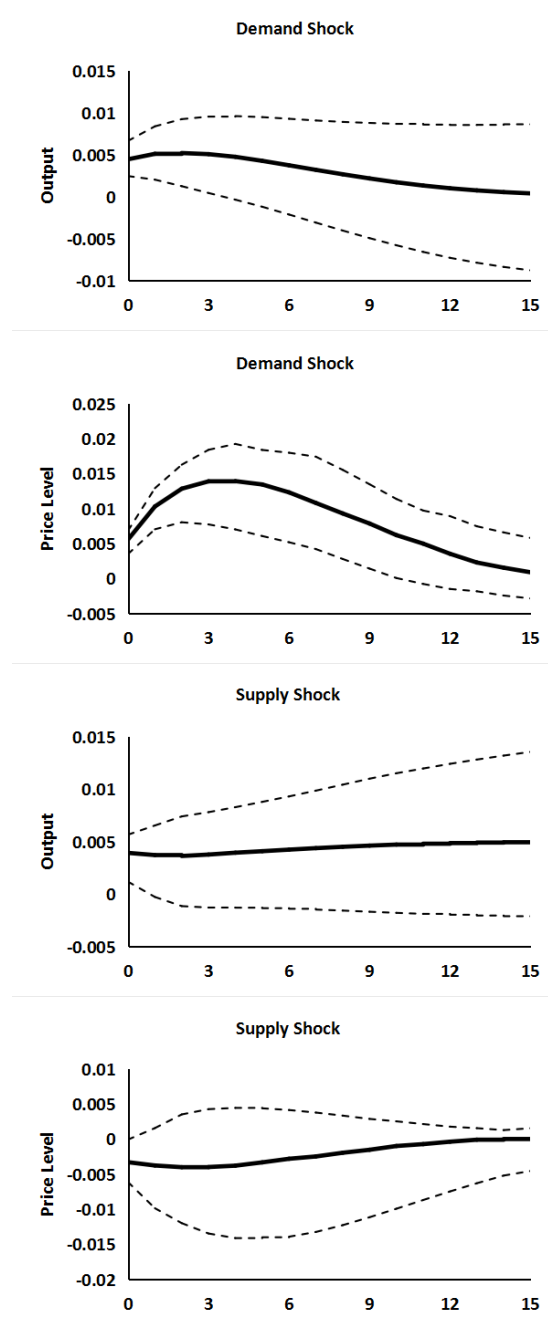


Figure 1. Impulse response function of China's macroeconomic supply and demand shocks from the first quarter of 1992 to the second quarter of 2018 (the dotted line in the figure indicates the 95% confidence interval).

In Figure 1(b), demand shocks lead to positive responses of both output and prices, while supply shocks lead to positive responses of output and negative responses of prices; no slope puzzle was noted. However, in Figure 1(a), a slope puzzle was observed.

If the following model is used for estimation, wherein the price level is log-differenced, output remains in log level, and time trends are added,

$$\begin{bmatrix} y_t \\ \Delta p_t \end{bmatrix} = \begin{bmatrix} a_0 & a_1 \\ b_0 & b_1 \end{bmatrix} \begin{bmatrix} t \\ t^2 \end{bmatrix} + \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^p \end{bmatrix},$$

a slope puzzle will still be present. Accordingly, we believe that the slope puzzle originates from low-frequency fluctuations in the price level.

3. Cause of the Slope Puzzle

(I) Relative price of investment goods and price level

Assuming a two-sector economy, the AD is composed of investment and consumption, and the price level equals a weighted average of prices of consumption and investment goods. Figure 2 shows inflation (denoted by the right-hand side longitudinal axis) and the relative price of investment goods (denoted by the left-hand side longitudinal axis).

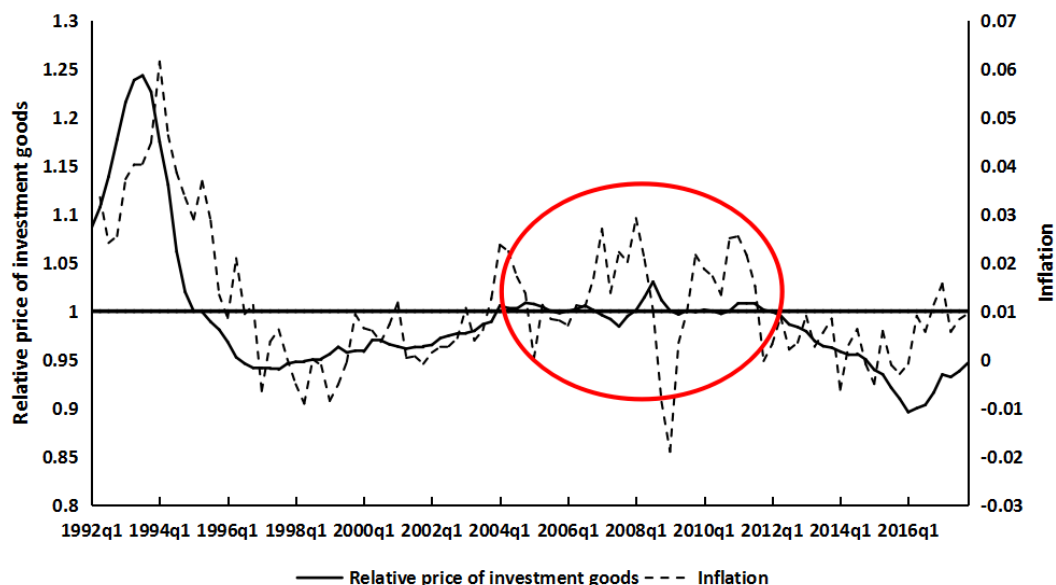


Figure 2. The relative price of investment goods and inflation from the first quarter of 1992 to the fourth quarter of 2017.

First, even if inflation is stationary, a downward trend still exists. Second, inflation shifts with the relative price of investment goods. This is not coincidental. If the relative price of

investment goods is denoted by q , the overall price level is as follows:

$$\kappa + (1 - \kappa)q,$$

where $\kappa \in (0,1)$. The price level is a positive linear function of the relative price of investment goods, signifying that these two prices should be positively correlated in theory. Since the relative price of investment goods has a trend, the inflation must have one. Finally, from an economic perspective, inflation is defined as an increase in the general price level; thus, the relative price of investment goods should be equal to 1. If this price is not 1, it will be challenging to identify demand shocks directly through the BQ method. In Figure 2, we can see that the relative price of investment goods is usually not equal to 1. The relative price of investment goods is near 1 only in the period within the red circle. Thus, we propose the following two hypotheses:

Hypothesis 1(H1): Low-frequency fluctuations in the price level lead to the slope puzzle.

Hypothesis 2(H2): The relative price of investment goods leads to the low-frequency fluctuations.

To test H1, we design the following experiment according to Fernald (2007). First, we apply the CF filter to the price level and obtain its trend and cyclical terms. Second, we subtract the cyclical term from the trend to obtain a new price series. Finally, if Hypothesis 1 holds, the results of Model (I) using the two price series should be identical. In other words, even if we invert the cyclical term, the slope puzzle should still exist. As per the experimental results shown in Figure 3, the slope puzzle exists, verifying H1.

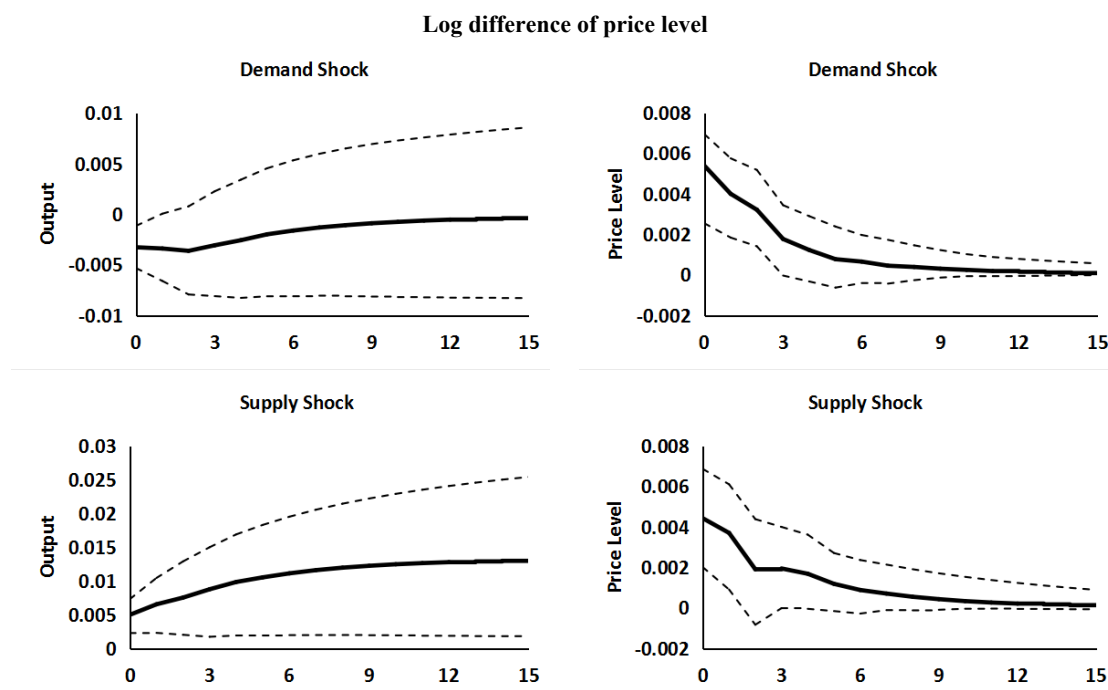


Figure 3. Impulse response function of China's macroeconomic supply and demand shocks from the first quarter of 1992 to the second quarter of 2018 in the price level data constructed according to this section (the dotted line in

the figure indicates the 95% confidence interval).

(2) Relative price of investment goods and the slope puzzle

Focus is placed on H2 here. When we assume the low-frequency fluctuations come from the relative price of investment goods, then we can directly construct the new price series by eliminating the movement of the relative price of investment goods. We construct price data by the following method:

$$P^* = \frac{P_i}{P} \frac{P_i}{q} + \frac{P_c}{P} P_c + (1 - \frac{P_i}{P} - \frac{P_c}{P}) P .$$

Here, P denotes the original price data, that is, GDP deflator. P_i denotes price of investment goods. We use the price index for gross fixed capital formation here. P_c denotes price of consumption goods. We use CPI here. q is the relative price of investment goods. The P^* then is the constructed price level data we use to prove H2.

We use log-difference of P^* , and apply BQ method. Figure(4) is the impulse response function. We can see that there is no slope puzzle. Then we prove H2, and also H1.

In fact, we also find that we can solve the slope puzzle by just using CPI as the price level data. It can prove that the slope puzzle is relative to the price level, although the result is not robust when applying different lags in our model.

Log difference of price level

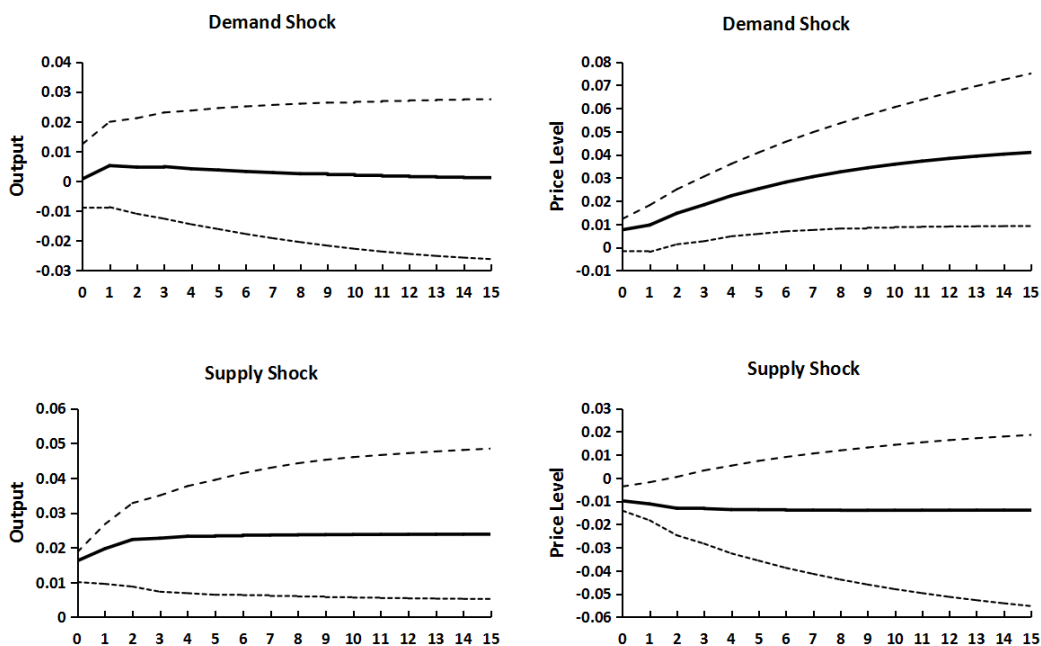


Figure 4. Impulse response function of China's macroeconomic supply and demand shocks from the first quarter of 1992 to the second quarter of 2018 in the price level data constructed according to this section (the dotted line in

the figure indicates the 95% confidence interval).

Here we prove H2 using another method. We use the sample with the relative price of investment goods equal to 1. In Figure 2, it is from the first quarter of 2004 to the first quarter of 2012 that the relative price of investment goods fluctuates closely around 1. We estimate Models (I) and (II), and Figure 5 shows the result. We can see that there is no slope puzzle, verifying H2.

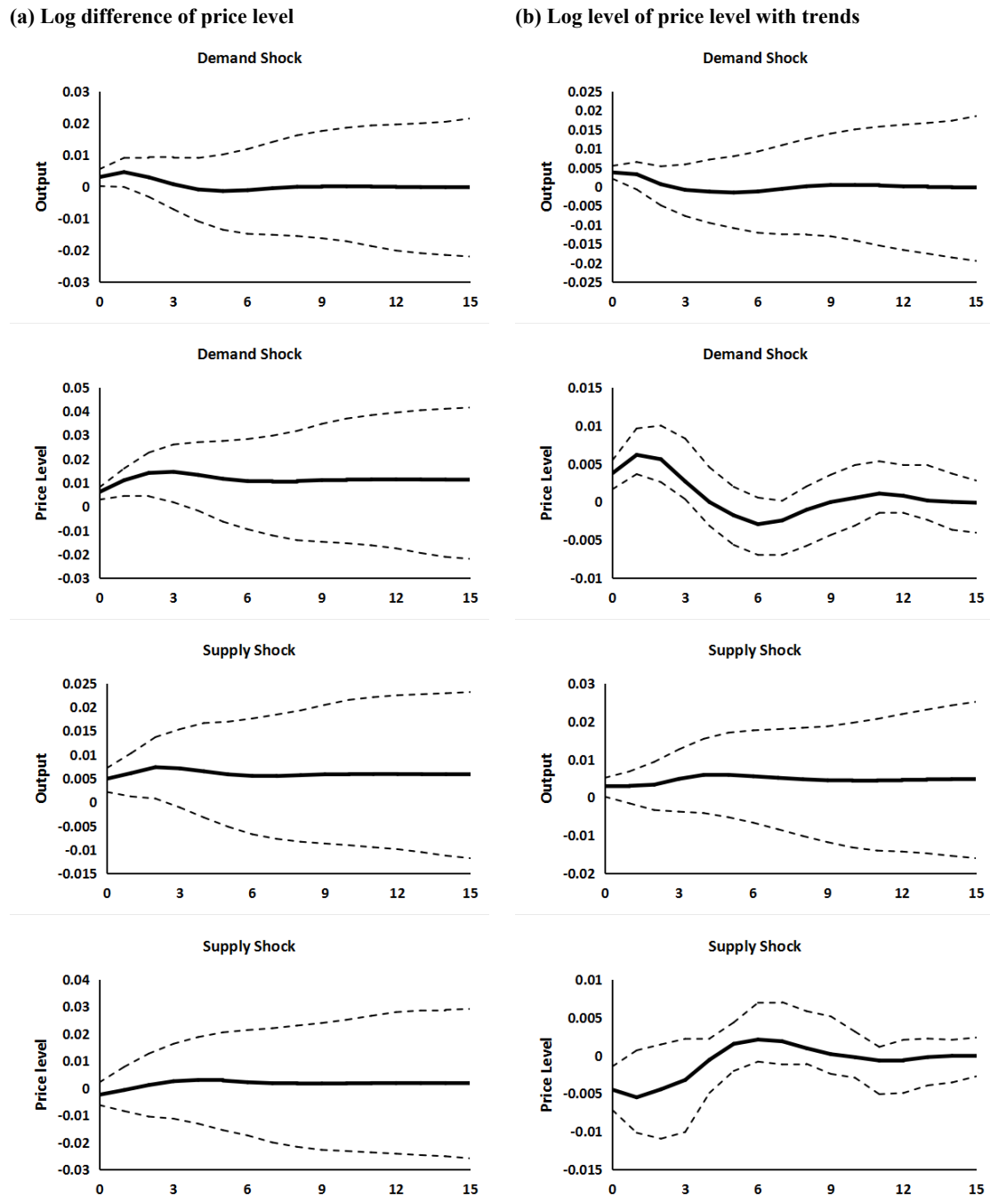


Figure 5. Impulse response plot of China's macroeconomic supply and demand shocks from the first quarter of 2004 to the first quarter of 2012 (the dotted line in the figure indicates the 95% confidence interval).

(3) An explanation of the slope puzzle

In investment theory, the relative price of investment goods reflects the marginal value of investment, or the Tobin's q . If there are financial frictions, this value may not be 1, and AS shocks can shift the AD curve (Romer, 2017; Carlstrom and Fuerst, 1997). China's financial frictions are far more complex, resulting from the interest rate control and over-investment by state-owned enterprises (Song, Storesletten, and Zilibotti, 2011), which makes it difficult to study the impact of q on supply and demand shocks. Unlike traditional investment theory, q greater than 1 represents more investment opportunities, which increases the AD. In China, the interest rate control and excessive investment not only result in an increase in the AD but also reduce the wealth of consumers due to depressed interest rates, leading to a decline in consumption and thus a decline in the AD. Thus, the financial frictions let the response of the AD curve ambiguous.

4. Conclusion

Our research results find that when applying the long-run restriction method of the VAR model to China's economy, using the log difference method to detrend price data leads to the slope puzzle. Subsequently, we find that this comes from the low-frequency fluctuations in the price level. Further, we find that the relative price of investment goods is the main source of the low-frequency fluctuation. When the relative price of investment goods is not 1, there are financial frictions, which causes problems in identifying shocks in the VAR model and then causes the slope puzzle. Certainly, the story of the financial frictions is more complicated in China. Importantly, our research not only provides a better understanding of the slope puzzle but also succeeds in solving it effectively and robustly.

Although, in the empirical analysis of China's macroeconomic problems, we should use different methods to deal with the stationarity of data and test the model's robustness, we prove that the log level model is more robust. Ramey (2016) suggested that when using SVAR, it is better to use a log level model and add some deterministic trends. Similarly, we believe that this approach is also valid for China's macroeconomic research.

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