Are Prices Sticky in Large Developing Economies? An Empirical Comparison of China and India

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Are Prices Sticky in Large Developing Economies? An Empirical Comparison of China and India

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Abstract: This paper compares the role of macroeconomic and sector-specific factors in price movements for China and India, taking into account the features unique to developing economies. We find that fluctuations in the aggregated prices in China are more persistent than the underlying disaggregated prices. Compared to China, prices in India respond more promptly to macroeconomic and monetary policy shocks. We also show that the urban CPI in China responds more sharply than rural CPI when facing sector-specific shocks, while the opposite is true for India.

Keywords: Disaggregated Prices; Persistence; Common Factors

JEL Classification: E13, E31, E32, E52

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1. Introduction

Sticky prices have been an important subject of debate since the Keynesian revolution in post WWII. (Taylor, 1980; Rotemberg, 1982; Calvo, 1983; Akerlof and Yellon, 1985; Mankiw, 1985). Empirical work examining the dynamics of price behavior in response to real and monetary shocks has demonstrated that aggregated prices respond to monetary innovations with a delay of up to two years (Bernanke and Blinder, 1992; Leeper, Sims and Zha, 1996; Christiano, Eichenbaum and Evans, 1999).[2] Recent studies, however, suggest that disaggregated prices may be more flexible than aggregated prices. For instance, Amirault, Kwan and Wilkinson (2005) and Bils and Klenow (2004) find that prices change on average every three to four months. Klenow and Kryvtsov (2008) show that sales price adjustment takes seven months and Nakamura and Steinsson (2008) document that the median duration of retail prices is between eight and eleven months.[3] Boivin, Giannoni and Mihov (2009) (hereafter BGM) find that disaggregated prices adjust progressively to macroeconomic shocks, but are flexible to sector-specific shocks. The observation that disaggregated prices is less sticky and more volatile than aggregated prices is consistent with the New Keynesian theory.

Empirical evidence for a dynamic interaction of aggregated and disaggregated prices is most common in developed economies. This paper breaks from this norm by examining such price fluctuations in the world's two largest developing economies, China and India. There are several reasons why more attention to the documentation of macroeconomic fluctuations in developing economies is needed. First, existing literature has documented that business cycle fluctuations between developing and developed economies do differ significantly (Neumeyer and Perri, 2005; Aguiar and Gopinath, 2007). These dissimilarities accentuate the need for a thorough investigation for developing economies at a disaggregated level. Second, from an analytical standpoint, documenting empirical similarities and observing whether they are the same across different levels of incomes provide an empirical basis for constructing models of short-run fluctuations. Such models give way to the

[2] Standard micro-founded macro models of inflation determination (Calvo, 1983; Rotemberg, 1982) have often been criticised for not being able to deliver enough aggregated inflation persistence (Mankiw, 2001).

[3] Evidence from the Bank of England (2006) indicates that out of 300 firms, over half change prices at least five times a year.

incorporation of features and relationships that are particularly important for large developing countries like China and India. This paper builds upon existing literature by taking into consideration some characteristics unique to developing economies. Specifically, we will examine the differing ways to which rural and urban prices respond when faced with similar exogenous shocks. Moreover, regional disparities and market imperfections in factor and product markets across reasons creates difficulties in assuming a standard measurement of inflation, which has caused insufficient analysis of data from developing countries. Thus, empirical findings may possess important policy implications and could be used, for instance, in the design of regional and industry-level stabilization and adjustment programs for employment, wages, and prices.

To understand the discrepancies between aggregated and disaggregated prices in a single consistent framework, we estimate a factor augmented vector autoregression (FAVAR) model. This allows us to disentangle the sources of aggregated and disaggregated inflation in terms of three shocks: common factor shocks, sector-specific shocks, and monetary policy shocks. The results imply that using a balanced panel FAVAR model has significant advantages over smaller standard VAR models in terms of allowing for more accurate responses to a monetary policy shock. It is found that, for both countries, sectoral prices are more volatile than aggregated prices. Prices in India exhibit much weaker persistence compared to prices in China. For China, fluctuations in the aggregated prices are more persistent than the majority of the underlying disaggregated prices. There is little evidence of any relationship between persistence and price volatility in China's sectors. These two findings suggest an aggregation bias in the Chinese price series. However, sectors in India with high persistence tend to be correlated with sectors that have lower volatility, which is consistent with the predictions of the sticky price model. Most of the fluctuations in aggregated (disaggregated) prices in China are due to common macroeconomic (sector-specific) shocks. In contrast, fluctuations in both aggregated and disaggregated prices in India are due to sector-specific shocks. In addition, disaggregated prices peak relatively quickly in India when responding to monetary policy shocks, whilst the converse is true for China.

The rest of the paper is organized as follows: Section 2 presents the empirical model and provides a description of the data. Section 3 presents the estimation results of the FAVAR model on the volatility, persistence, and the correlation between the two for aggregated and disaggregated price fluctuations. Sections 4 and 5 document the effects of macroeconomic, sector-specific and monetary policy shocks in China and India. Section 6 concludes the paper.

2. Model and Data

Unlike reduced VARs and their structural equivalents, FAVAR models are able to incorporate a large set of macroeconomic indicators. The basic structure of the FAVAR model can be expressed as two equations: (1) an observation equation, wherein we apply factor analysis, and (2) a transition equation, which is similar to a standard VAR,

$$X_t = \Lambda C_t + e_t \quad , \tag{1}$$

where

$$C_t = \begin{bmatrix} F_t \\ R_t \end{bmatrix} ,$$

$$C_t = \Phi(L) C_{t-1} + v_t \quad , \tag{2}$$

where X_t is a $N \times 1$ vector of macroeconomic indicators, C_t is a $(K+1) \times 1$ vector of common components comprising of two parts: a $K \times 1$ vector of latent factors F_t, which is obtained through a principal component analysis on X_t, and a monetary policy instrument R_t. The common factor, C_t, reflects the underlying economic conditions such as activity or pricing pressures. Since F_t is the latent factor representation of X_t, K is smaller than N. These latent factors summarize the information contained in X_t, reflecting general macroeconomic conditions. The matrix Λ in equation (1) is an $N \times (K+1)$ matrix of factor loadings, with e_t in equation (1) an $N \times 1$ vector of series-specific innovations, which are uncorrelated to the common component, C_t. These series-specific errors are serially correlated and weakly correlated across variables. Equation (2) is a reduced form VAR model for C_t, where $\Phi(L)$ is a conformable lag matrix, which may contain a priori restrictions. Similar to standard VARs, the error term v_t is assumed to be *i.i.d*. with zero mean and constant finite variance.

We estimate the empirical model using a two-step principal component approach. In the first step, we extract latent common factors from a large set of macroeconomic indicators by using principal component analysis. In the second step, we append the monetary policy instrument R_t to the estimated factors F_t to form a common component vector C_t. To guarantee that the estimated latent factors, F_t, are independent of R_t, we adopt an iteration algorithm to exclude the effects of R_t from the vector macroeconomic indicators X_t. This algorithm involves the following iterated steps: (*i*) start from an initial estimate of $F_t^{(0)}$, which is obtained from the first K principal components of X_t; (*ii*) regress X_t on $F_t^{(0)}$ and R_t to obtain $\widehat{\lambda}_R^{(0)}$; (*iii*) compute $\widehat{X}_t^{(0)} = X_t - \widehat{\lambda}_R^{(0)} R_t$; (*iv*) estimate $F_t^{(1)}$ as the first K principal component of $\widehat{X}_t^{(0)}$; (*v*) repeat (*ii*) –(*iv*) .

This algorithm, which is a semi-parametric, two-step estimation approach, was also adopted by BGM and does not impose distributional assumptions on the observation equation. This approach is advantageous since it is computationally efficient and easy to implement.[4] In order to address the "uncertainty problem" caused by the generated regressors $\hat{F}_t$ and to obtain reliable confidence intervals for the impulse response functions, the bootstrap procedure of Kilian (1998) is used.[5]

2.1 Monetary Policy Instrument

[4] The BBE study shows an alternative one-step estimation method. They use the Bayesian likelihood method and Gibbs sampling to estimate the factors and the dynamics simultaneously. However, while the advantage of this one-step approach is modest, calculation is cumbersome. The likelihood-based method is fully parametric, and thus may imply different biases and variances depending on how well the model is specified.

[5] According to Bai and Ng (2006), when N is large relative to T, the uncertainty problem of the estimated factors can be ignored. The bootstrap procedure we adopt here is similar to the ones in BBE and BGM.

Both China and India have undergone substantial reforms in their monetary policy regimes since the early 1990s. The People's Bank of China (PBOC) has adopted a broad money supply target – in this case M2 – to hold up a pro-growth agenda, partly through its administratively determined loans and deposit rates. Thus, China does not explicitly target a short-term interest rate measure. Similarly, monetary policy in India has multiple objectives, which aims to maintain a balance between price stability and economic growth. Until 1997-98, monetary policy in India was conducted with broad money (M3) as an intermediate target. The aim was to regulate money supply so that the level was consistent with expected economic growth and projected inflation rates. The Reserve Bank of India (RBI) switched over to a multiple indicator approach from 1998-99. Apart from M3, interest rates on government securities and exchange rate volatility are also taken into account. The RBI has actively intervened in the foreign exchange markets to reduce excess volatility and prevent the emergence of destabilizing speculative activities. For this reason, it is difficult to use a single indicator to perfectly capture monetary policy in India over the sample.[6] In this paper, we choose M2 as the monetary policy instrument for China and adopt the short-term bank rate of the RBI for India. To ensure robustness, different monetary policy indicators, such as the PBOC's base rate and the RBI's M3 money growth measure, are also examined.

2.2 Data

All data series used in this paper are retrieved from the CEIC and International Monetary Fund (IMF) databases, and are adjusted for non-stationarity. Overall, first differences of logarithms (growth rates) are used for real quantity variables and for each disaggregated price series. The datasets for China and India consist of two parts. The first part is a large set of time series macroeconomic indicators, which include industrial production, employment, international trade, banking statistics, stock market indices, and bilateral exchange rates. The second part includes the disaggregated price indices. Our dataset consists of 156 macroeconomic indicators and 36 disaggregated price series for China spanning 2001:2 till 2008:12 at a monthly frequency. Due to data limitations, the disaggregated prices for China are based on the

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[6] See Kramer, Poirson and Prasad (2008).

Producer Price Index (PPI) as a proxy.[7] Including the monetary policy measure, M2, implies a balanced panel FAVAR model containing 192 time series variables. Analogously, India's dataset consists of 72 macroeconomic indicators and 59 disaggregated price series spanning 1996:M6 till 2008:M10 at a monthly frequency. The disaggregated prices for India are based on the Wholesale Price Index (WPI) because it is the measure of inflation that most concerns the RBI. Along with the monetary policy instrument M3, the balanced panel FAVAR model for India will contain 131 time series variables.

3. Fluctuations in Disaggregated Prices

To investigate the sources of fluctuations in aggregated and disaggregated prices, we derive the following equation from equations (1) and (2) in Section 2:

$$\pi_{it} = \lambda_i^{'} C_t + e_{it} \tag{3}$$

where π_{it} is the monthly log difference for each price series i. This may include prices from each sector of the economy (i.e., sectoral inflation rate) or the aggregated price index (i.e., overall inflation rate). Equation (3) allows us to disentangle price fluctuations into two parts: those due to common macroeconomic disturbances (C_t) and those from sector-specific shocks (e_{it}). Equation (3) also provides an opportunity to examine how much of the persistence in sectoral price changes can be attributed to macroeconomic factors or sector-specific conditions. Note that while the common component C_t is the same for different sectoral inflation rates, the factor loadings λ_i are sector-specific. Thus, the common component can affect each sector differently.

3.1 Sources of Price Fluctuations and Persistence

To obtain equation (3), we estimate systems (1) and (2) using three latent factors for both China and India in equation (1), with two reduced form lags in equation (2) for

[7] Under normal circumstances, PPI is a leading indicator of CPI in China. The current trend of the PPI will decide the general direction of CPI. Since manufacturing and exports, rather than consumption and services, form the bulk of economic activity in China, the PPI is a good indicator of price pressures.

China, and four lags in equation (2) for India.[8] The results for China and India are presented in parts A and B of Table 1 respectively.

3.1.1 Inflation Volatility and Persistence

Starting with the case of China in part A of Table 1, the results show that total volatility over the sample period is 0.87 percent. Price volatility is higher in the heavy industry and producer good sectors, with standard deviations of 1.1% and 1.43%, respectively. In contrast, the standard deviation for price indices in the consumer goods and light industry sectors are smaller at 0.33% and 0.35%, respectively. Most of the aggregated fluctuations in prices have been due to common macroeconomic shocks. The R^2 for the common component is 77 percent. The estimates of the FAVAR model also show that the volatility of sectoral prices in China is higher than that of aggregated prices. The average standard deviations of the aggregated and 36 disaggregated price sectors for China are 0.87% and 1.3%, respectively.[9] The largest (smallest) standard deviation is for the petroleum and natural gas production (beverage manufacturing) sector, with a standard deviation of 7.66% (0.35%). In contrast to the aggregated price results, most of the fluctuations in sectoral inflation are the result of sector-specific disturbances.

The price volatility results for India in part B of Table 1 are similar to those presented for China. The volatility of sectoral prices (2.2%) in India is higher than that of aggregated prices (0.6%). This differential is larger than that of China. Similar to the case of China, aggregated price volatility in India is higher for manufacturing/industry related sectors, such as primary articles, and fuel and power, with standard deviations of 1.31% and 1.77%, respectively. The average price volatility of the 59 sectors is 2.2%. The largest (smallest) standard deviation comes from the non-food primary articles (manufacturing transportation equipment) sector, with a standard deviation of 7.64% (0.50%). In contrast to China (and the results found by BGM for the US), most of the price fluctuations in India are due to sector-specific shocks. The R^2 for the

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[8] The number of lags used is determined by lag length tests. Three latent factors are chosen owing to a considerable drop in the explanatory power of the fourth factor, which explains a considerably smaller amount of the dynamic interactions between the variables in the model compared to the first three factors.

[9] BGM also find aggregated price series to be less volatile than disaggregated price series for the US economy. An explanation for this is that sectoral inflation price fluctuations canceling each other out, leading to a less volatile aggregated price index.

common component is 35% (7%) for aggregated (disaggregated) prices, indicating that sector-specific shocks account for about 65% (93%) of the fluctuations.

The last three columns of Table 1 part A report the degree of persistence for China's aggregated and disaggregated prices. The degree of persistence of aggregated inflation for π_{it}, $\lambda_i C_i$ (common factor) and e_{it} (sector-specific) are calculated by the sum of the AR coefficients. The results show that fluctuations in aggregated prices are more persistent compared to disaggregated prices: 0.62 as opposed to 0.22. This corroborates similar findings in Clark (2006) and BGM (2009) for the United States and Altissimo, Mojon and Zaffaroni (2007) for the Euro zone. Also note that common factor inflation is more persistent than sector-specific inflation at both the aggregated and disaggregated level.

The last three columns of Table 1 part B report the persistence of India's aggregated and disaggregated prices. The results for India differ from those of China. First, persistence is much lower for both aggregated and disaggregated prices in India. More importantly, the sector prices are more persistent than aggregated prices, contrasting with many findings in the existing empirical literature. The persistence is quite low for the aggregated prices, as measured by the common component. For the disaggregated variables, the common component is more persistent than the sector-specific prices (0.35 versus 0.12). Both disaggregated and aggregated prices have low persistence and are mainly driven by sector-specific shocks, suggesting that Indian products and goods markets are less competitive than their Chinese counterparts. Less competition allows firms to pass on changes in prices more easily. In contrast, more competitive sectors may be unable to adjust their prices easily.[10] Models of price adjustment (Barro, 1972) predict a higher frequency of price changes in more competitive markets. Table 1 shows that the volatility of disaggregated prices is lower in India, which supports the view that there is less competition in Indian goods markets compared to China. Thus, individual price changes by firms in India would have a large effect on the aggregated price. This is consistent with continuous price adjustment models of Christiano, Eichenbaum and Evans (2005).

[10] Firms in less competitive industries have more power over changing their prices, whereas firms in more competitive industries may find it difficult to pass the impact of either sector-specific or general macroeconomic shocks on to customers by changing prices.

Finding for China shows that sector-specific factors do not determine the persistence at both the aggregated and disaggregated level and common macro components are less important for disaggregated prices than aggregated ones. This suggests that any persistence in prices is driven by persistence in the general economy and that sector-specific shocks are, more often than not, transitory. What could explain the marked difference between estimates of persistence for aggregated and disaggregated prices for China? Imbs, Mumtaz, Ravn and Rey (2005) demonstrate that aggregated measures of persistence will be biased when there is heterogeneity in persistence among the disaggregated components in a PPP context. This causes aggregated estimates of persistence to be biased upwards. Thus, the aggregated estimate of persistence will be higher than the average persistence of the underlying disaggregated prices.[11] The implication is that using an aggregated inflation measure to gauge the typical behavior of prices in China might be misleading, as disaggregated prices do not behave in the same way as aggregated prices.[12] Such a bias is greater when there is a higher degree of heterogeneity across sectors. The results for China support the policy view put forward by Akoi (2001), who argues that the optimal price index for policymakers would place more weight on the prices that are sticky and less weight on the prices that are more flexible. Given the similarity between the persistence estimates for both aggregated (0.16) and disaggregated (0.14) series, price indices in India do not suffer from the aggregation bias.

3.1.2 Correlation between Price Volatility and Persistence

Table 2 reports the correlation coefficients for the volatility between aggregated and disaggregated price inflation. Theoretically, models that incorporate sticky prices imply a causal relationship between price volatility and inflation: price stickiness reduces the impact of exogenous shocks on current inflation but increases inflation persistence, suggesting that there should be a strong negative correlation between sectoral price volatility and sectoral price persistence.

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[11] Pesaran and Smith (1995) show that there is aggregation bias when one estimates aggregated inflation persistence without controlling for sectoral heterogeneity in inflation rates.

[12] Mojon, Zaffaroni and Altissimo (2007) also find fast adjustment in the disaggregated prices and slow adjustment at the aggregated level for the Euro area. They conclude that aggregation explains a significant proportion of aggregated inflation persistence.

Part A of Table 2 reports that the correlation between Sd(λ_i) and Sd(e_i) for China is 0.94. Such a highly positive correlation suggests that sectors adjust swiftly to idiosyncratic macroeconomic shocks. It is important to note that sectoral disturbances, e_i , not only include sector-specific shocks, but also measurement errors in each sectoral price series. However, as pointed out by BGM, this should not spuriously affect the estimated effects of the common factors on aggregated prices. The strong correlation between the volatility of the common and sector-specific components suggests that e_i contains more than just sampling errors for the correlation to be so high. Note also that there is a correlation of 0.22 between Sd($\lambda_i C_i$) and ρ($\lambda_i C_i$) and 0.20 between Sd(e_i) and ρ(e_i). Thus, the relationship between price volatility and persistence is weak in both sector and common factor inflation. These findings are consistent with Bils and Klenow (2004), who also report a weak correlation between price volatility and persistence for the US economy. However, the result contradicts the sticky price model, which hypothesizes that price volatility should be low and persistence should be high in sectors with highly sticky prices.

The case of India is reported in part B of Table 2. The correlation between the standard deviation of the common component Sd($\lambda_i C_i$) and the persistence of inflation to a shock in the common component ρ($\lambda_i C_i$) is -0.27, and the correlation between the analogous sector-specific equivalents (Sd(e_i) and ρ(e_i)) is -0.23. The results imply that sectors with a relatively higher degree of price stickiness have lower volatility, which is consistent with Calvo's sticky price model.

4. Effect of Macroeconomic and Sector-Specific Shocks

This section examines whether prices tend to change frequently, by large amounts, and shift in response to news about macroeconomic shocks. We document the effects of sector-specific (e_{it}) and macroeconomic shocks ($\lambda_i C_i$) on prices. Specifically, we look at the response of log sectoral prices to a one-standard deviation shock in e_{it} and $\lambda_i C_i$. The results for China and India are presented in Figure 1 and Figure 2, respectively.

The left and center panels of Figure 1 document the sectoral price response to sector-specific and common factor macroeconomic shocks. The solid line represents the average of these sectoral price changes. Results for China show that disaggregated prices adjust instantaneously to sector-specific shocks. However, these effects level off after a few months. In contrast, the response of sectoral prices to macroeconomic shocks is more persistent with a delay. On average, disaggregated prices plateau around four years following the initial macroeconomic shock. Figure 1 shows, however, that there are a few disaggregated prices whose response to macroeconomic shocks is similar to those for sector-specific shocks.

The results in the left and center panels of Figure 2 for India show that the sectoral price response to a sector-specific shock is similar to that of China and BGM for the United States. There are a few subtle differences in the magnitude of the response to macro shocks, which are smaller in magnitude and less persistent than the responses for China. In Figure 2, the average price response to sector-specific disturbances is short-lived. The response to macroeconomic shocks is more persistent, with the impulse responses taking a number of years before reaching their plateau.

4.1 Rural and Urban Price Differential

For both China and India, there are disparities in the level of economic activity and productivity between rural and urban conurbations. Literature investigating this line of research is limited. Existing studies tend to focus on rural and urban price behavior in a specific sector rather than concentrate on a composite price index for rural and urban areas. This paper attempts to fill this void by investigating the differences in the rural and urban price responses when faced with similar exogenous shocks. In particular, we investigate the impacts of sector-specific and macroeconomic shocks on urban and rural consumer price indices. The results for China and India are presented in Figures 3 and 4, respectively. For both countries, macroeconomic shocks have almost the same impact on urban and rural prices. Monetary policy shocks have a similar story. However, when facing sector-specific shocks, urban CPI responds more sharply than rural CPI in China, while the opposite is true for India. In sum, urban and rural CPIs react in a similar fashion to macroeconomic and monetary policy shocks. However, in response to sector-specific shocks, the magnitude of the response in urban–rural inflation dynamics differs. This finding has policy implications on urban-rural price difference and inequality. The results for India indicate that sectoral shocks have a larger impact on rural prices. Since the highly volatile agricultural sector dominates rural economic activity in India, the high volatility in prices could be consequence to the fact that rural households find it more difficult to smooth consumption in response to shocks.[13]

5. Effects of Monetary Policy Shocks

5.1 Identification Restrictions

To investigate the viability of the monetary policy shocks, three models are estimated. The first VAR model uses a Cholesky factorization to identify monetary policy shocks in a three-variable VAR: industrial production (measure of real economic activity), the price level, and the monetary policy instrument. The second model, labeled 'VAR+1', is composed of the first model plus the first latent factor. The first latent factor is chosen as it predominantly captures the variation in general economic activity (Stock and Watson, 2005). The final model is the baseline FAVAR model, as estimated in Section 4. This involves explicitly including the policy rate, R_t, in equation (2) as one of the common factors and then ordering the policy rate last, and treating its innovations as monetary policy shocks. Thus, monetary policy can respond contemporaneously to common factor fluctuations. The results are presented in Figures 5 - 8.

5.1.1 China Impulse Responses

Figures 5 and 6 imply that regardless of whether M2 or the interest rate is used as a measure of monetary policy, according to the standard VAR and VAR+1, monetary shocks have a large long-term impact on industrial production in China. In addition, neither the VAR nor VAR+1 show any evidence of the price puzzle. The similarities between the VAR and VAR+1 model suggest that the first latent factor does not contain much additional information over and beyond the standard VAR to fundamentally change the picture. In contrast, the impulse responses generated by the baseline FAVAR with 3 latent factors indicates that industrial production returns to its

[13] Giles and Yoo (2007) show that rural households tend to engage in less precautionary saving.

steady state value after four years. Note from Figure 6 is that an increase in M2 immediately stimulates industrial production in the short-run. Our results, together with the findings of Burdekin and Siklos (2008), suggest that the PBOC has targeted M2 in an effort to ensure economic growth throughout the last decade.

Aggregated prices respond gradually to a monetary policy shock in the FAVAR model in both Figures 5 and 6. In order to examine this in greater detail, recall that the last panel of Figure 1 shows the response of disaggregated prices to a monetary policy shock using the PBOC base rate and M2 monetary aggregate as R_t in the FAVAR. The response of the individual disaggregated price series to a monetary policy shock in the base rate varies in magnitude. The average response of disaggregated prices and the aggregated PPI shows a steady decline consistent with sticky prices, reaching a trough of 3.1% and 2.5%, respectively, after one year. Analogously, both aggregated and disaggregated prices peak approximately one year following a shock in M2. In both cases, disaggregated price series persistence is lower than the headline series, reflecting aggregation bias. Table 3 reports the autocorrelation coefficients of both aggregated and disaggregated prices in response to monetary innovations. Being aware of the degree to which the inflation process is persistent to a monetary shock provides the central bank vital information on how its policy instrument should be adjusted to achieve the desired target. After 12 months, the autocorrelation coefficients are 0.70 and 0.62 for aggregated and the average disaggregated price index respectively, signifying high levels of price stickiness in response to monetary policy disturbances.[14]

The differing response in magnitude and persistence of the individual disaggregated prices to the three shocks (sectoral, common and monetary), as presented in Figure 1 for China, conflicts with the implications from time-dependent sticky-price models (Dotsey, King and Wolman, 1999; Sims, 2003). These models hypothesize that the source of the shock should not affect the persistence of the price response. Furthermore, time-dependent models do not allow for differing responses across sectors to policy shocks. The results might be easier to reconcile with state-dependent models of price stickiness in which the frequency of price changes is endogenously

[14] This finding implies that aggregated inflation is underestimating the level of flexibility in the nominal side of the economy.

greater in the presence of more volatile shocks. For example, according to Willis (2000), price adjustments for firms can be more synchronized in response to sectoral shocks. There is certainly evidence of this when comparing sector-specific and common component shocks for China in Figure 1. Finally, the results for China show that both rural and urban prices react in a similar manner to monetary policy shocks. Both indices fall progressively and reach a trough of 0.02% after one year.

5.1.2 India Impulse Responses

Figures 7 and 8 show that the FAVAR estimates considerably improves the estimation results of the effects of monetary shocks on industrial production and the price level. Both the standard VAR and VAR+1 models exhibit evidence of the price puzzle. In addition, for industrial production, the result from the standard VAR implies that an unexpected interest rate increase leads to a rise in economic activity, which is inconsistent with standard theory. In contrast with the results for China, the first latent factor appears to contain significant amount of information and helps improve the impulse response results for the VAR+1 model over the standard VAR. However, the baseline FAVAR model is the only model of the three to contain little evidence of the price puzzle that often inflicts VAR models due to the omitted variable bias (Sims, 1992).

The last two panels of Figure 2 show the response of disaggregated prices to a monetary policy shock in both the RBI bank rate and M3 monetary aggregate. The response of disaggregated prices for India illustrates that there are a number of series that exhibit a very different response to a monetary shock. Some prices are minutely affected than others in response to a monetary policy shock.[15] The variation between individual disaggregated responses is greater in response to a shock in M3. Moreover, the difference in the magnitude of the average response of disaggregated prices and the response of aggregated PPI to a shock in M3 is considerable: aggregated prices rise by over 4%, versus just over 2% for disaggregated prices. This difference is

[15] It is worth mentioning that a shock in monetary policy can influence prices through different channels. One channel is via the reallocation of income from interest-paying debtors to interest-receiving creditors. If debtors and creditors have different preferences for spending on ranges of goods and services, then this reallocation of income could have a persistent impact on relative prices. See Waldron and Young (2006) and Mumtaz, Zabczyk and Ellis (2009).

smaller when monetary policy is measured as a one-standard deviation rise in the RBI's bank rate. The response of the average disaggregated (aggregated) prices decline slowly, reaching a trough of around 0.10% (0.15%) following the initial base rate monetary shock. In contrast, disaggregated prices plateau quickly before falling back to the steady states values after 4 years.

6. Conclusion

Empirical studies on the dynamic interaction of aggregated and disaggregated prices commonly focus on developed economies. In this paper, we adopt a unified framework to study the interaction of aggregated and disaggregated prices in China and India, and the extent to which they are driven by general macroeconomic and sector-specific shocks. Our results present new findings that are potentially relevant for policymaking in large developing economies. First, for both countries, sectoral prices are more volatile than aggregated prices. Second, for China, fluctuations in the aggregated prices are more persistent than the majority of the underlying disaggregated prices. Conversely, the opposite is true for India. This finding demonstrates that the pricing behavior of Indian firms is more consistent with the sticky price model than is the case for China. Third, the results for China suggest that aggregated prices do not accurately capture the variation in the underlying disaggregated prices because of the aggregation bias problem. The persistence of aggregated inflation is biased upwards. Compared to China, prices in India respond more promptly to macroeconomic and monetary policy shocks. This finding contrasts with the presumptions of time-dependent sticky-price models, which do not allow for differing responses across sectors to policy shocks. Finally, most of the variations in aggregated and disaggregated prices in China are due to macroeconomic and sector-specific shocks, respectively. In contrast, prices in India are driven by sector-specific shocks. The results in this paper imply that aggregated inflation measures in China do not offer a good guide to the underlying pricing behavior, and models that use aggregated prices to model the statistical properties of individual prices for China is likely to lead to spurious conclusions.

References

Aguiar, M. and G. Gopinath (2007), 'Emerging Market Business Cycles: The Cycle is the Trend', *Journal of Political Economy*, **115**: 69 - 102.

Akerlof, G. and J. Yellen (1985), 'A Near Rational Model of the Business Cycle with Wage and Price Inertia', *Quarterly Journal of Economics*, **101**: 823 - 838.

Akoi, K. (2001), 'Optimal Monetary Policy Responses to Relative-Price Changes', *Journal of Monetary Economics*, **48**: 55 - 80.

Altissimo, F., B. Mojon and P. Zaffaroni (2007), 'Fast Micro and Slow Macro: Can Aggregation Explain the Persistence of Inflation?', FRB of Chicago Working Paper No. 2007-02. Available at SSRN: http://ssrn.com/abstract=967748.

Amirault, D., C. Kwan and G. Wilkinson (2005), 'A Survey of the Price Setting Behavior of Canadian Companies', *Bank of Canada Review*, Winter.

Bai, J. and S. Ng (2006), 'Confidence Intervals for Diffusion Index Forecasts and Inference for Factor-Augmented Regressions', *Econometrica*, **74**: 1133 - 1150.

Bank of England (2006), *Agents' Summary of Business Conditions*.

Barro, R. J. (1972), 'A Theory of Monopolistic Price Adjustment', *Review of Economic Studies*, **39**(1): 17 – 26.

Bernanke, B. S. and A. S. Blinder. 1992. 'The Federal Funds Rate and the Channels of Monetary Transmission', *American Economic Review,* **82**(4): 901 - 921.

Bernanke, B. S., J. Boivoin and P. Eliasz (2005), 'Measuring Monetary Policy: A Factor Augmented Vector Autoregressive (FAVAR) Approach', *Quarterly Journal of Economics*, **120**: 387 - 422.

Bils, M. and P. J. Klenow (2004), 'Some Evidence on the Importance of Sticky Prices', *Journal of Political Economy,* **112**(5): 947 -985.

Boivin, J., M. P. Giannoni and I. Mihov (2009), 'Sticky Prices and Monetary Policy: Evidence from Disaggregated US Data', *American Economic Review*, **99**(1): 350 - 384.

Burdekin, R. C. K. and P. L. Siklos (2008), 'What has Driven Chinese Monetary Policy Since 1990? Investigating the People's Bank's Policy Rule', *Journal of International Money and Finance,* **27**: 847 - 859.

Calvo, G. (1983), 'Staggered Prices and in a Utility-Maximizing Framework', *Journal of Monetary Economics*, **12(3)**: 383-398.

Christiano, L. J., M. Eichenbaum and C. Evans (1999), 'Monetary Policy Shocks: What have we Learned and to what End?', in J. Taylor and M. Woodford, eds., *Handbook of Macroeconomics*, Vol. 1A, Chap. 2. Amsterdam: North-Holland.

Christiano, L. J., M. Eichenbaum and C. Evans (2005), 'Nominal Rigidities and the Dynamic Effect of a Shock to Monetary Policy', *Journal of Political Economy*, **113**(1): 1 - 45.

Clark, T. E. (2006), 'Disaggregated Evidence on the Persistence of Consumer Price Inflation', *Journal of Applied Econometrics*, **21**: 563 – 587.

Dotsey, M., R. King and A. Wolman (1999), 'State-Dependent Pricing and the General Equilibrium Dynamics of Money and Output', *Quarterly Journal of Economics*, **114:** 655-690.

Giles, J. and K. Yoo (2007), 'Precautionary Behavior, Migrant Networks, and Household Consumption Decisions: An Empirical Analysis using Household Panel Data from Rural China', *Review of Economics and Statistics*, **89(3)**: 534-551.

Imbs, J., H. Mumtaz, M. Ravn and H. Rey (2005), 'PPP Strikes Back: Aggregation and the Real Exchange Rate', *Quarterly Journal of Economics*, **120**: 1 – 43.

Kilian, L. (1998), 'Small-Sample Confidence Intervals For Impulse Response Functions', *Review of Economics and Statistics*, **80(2)**: 218-230.

Klenow, P. J. and O. Kryvtsov (2008), 'State-dependent or Time-dependent Pricing: Does It Matter for Recent US Inflation?', *Quarterly Journal of Economics,* **123**: 863 - 904.

Kramer, C. F., H. K. Poirson and A. Prasad (2008), 'Challenges to Monetary Policy from Financial Globalization: The Case of India', *IMF Working Paper*, WP/08/131.

Leeper, E. M., C. A. Sims and T. Zha (1996), 'What Does Monetary Policy Do?', *Brookings Paper on Economic Activity*, 27(2): 1 – 78.

Mankiw, G. (1985), 'Small Menu Costs and Large Business Cycles: A Macroeconomic Model of Monopoly', *Quarterly Journal of Economics*, **100**: 529 – 537.

Mankiw, G. (2001), 'The Inexorable and Mysterious Trade-off between Inflation and Unemployment', *Economic Journal*, **111**: 45 – 61.

Mojon, B., P. Zaffaroni and F. Altissimo (2007), 'Fast Micro and Slow Macro: Can Aggregation Explain the Persistence of Inflation?', *ECB Working Paper no. 729.*

Mumtaz, H., P. Zabczyk and C. Ellis (2009), 'What Likes Beneath: what can Disaggregated Data Tells us about the Behaviour of Prices?', Bank of England Working Paper No. 364.

Nakamura, E. and J. Steinsson (2008), 'Five Facts about Prices: A Reevaluation of Menu-Cost Models', *Quarterly Journal of Economics*, **123**, 1415-1464.

Neumeyer, P. A. and F. Perri (2005), 'Business Cycles in Emerging Countries: The Role of Interest Rate', *Journal of Monetary Economics*, **52**: 345 - 380.

Pesaran, M. H. and R. Smith (1995), 'Estimating Long-run Relationships from Dynamic Heterogeneous Panels', *Journal of Econometrics*, **68**(1): 79 – 113.

Rand, J. and F. Tarp (2002), 'Business Cycles in Developing Countries: Are they Different?', *World Development*, **30**(12): 2071 - 2088.

Rotemberg, J. (1982), 'Stick Prices in the United States', *Journal of Political Economy*, **90:** 1187 - 1211.

Sims, C. A. (1992), 'Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy', *European Economic Review*, **36**(5): 975 - 1000.

Sims, C. A. (2003), 'Implications of Rational Inattention', *Journal of Monetary Economics*, **50**: 665 – 690.

Taylor, J. (1980), 'Aggregate Dynamics and Staggered Contracts', *Journal of Political Economy*, **88**: 1 – 23.

Stock, J. H., and M. W. Watson (2002), 'Macroeconomic Forecasting Using Diffusion Indexes', *Journal of Business and Economic Statistics*, **20**(2): 147 - 162.

Stock, J. and M. W. Watson (2005), 'Implications of Dynamic Factor Models for VAR Analysis', National Bureau of Economic Research Working Paper no. 11467.

Waldron, M. and G. Young (2006), 'The State of British Household Finances: Results from the 2006 NMG Research Survey', *Bank of England Quarterly Bulletin*, **46**(4): 397 – 403.

Willis, J. L. (2000), 'Estimation of Adjustment Costs in a Model of State-Dependent Pricing', Federal Reserve Bank of Kansas City Research Working Paper 00-07, December.

Table 1: China & India Volatility and Persistence

	Standard Deviation (%)			R^2	Persistence		
	Inflation	Common Component	Sector-Specific	**Common Component**	Inflation	Common Component	Sector-Specific
A. China Producer Price Index							
Aggregated series (PPI)							
Total	0.87	0.77	0.42	0.77	0.62	0.91	0.40
Light Industry	0.35	0.30	0.19	0.71	0.69	0.90	0.09
Heavy Industry	1.43	1.17	0.82	0.67	0.57	0.91	0.38
Producer Goods	1.10	0.93	0.58	0.72	0.61	0.91	0.42
Consumer Goods	0.33	0.24	0.23	0.53	0.61	0.92	0.25
Disaggregated series (PPI)							
Average	1.30	0.73	1.03	0.27	0.22	0.74	0.01
Median	0.71	0.28	0.66	0.27	0.41	0.85	0.01
Minimum	0.35	0.09	0.27	0.02	-0.75	-0.20	-0.75
Maximum	7.66	4.95	5.85	0.71	0.79	0.95	0.58
Standard Deviation	1.46	1.01	1.10	0.21	0.44	0.26	0.37
B. India Wholesale Price Index							
Aggregated series (WPI)							
Total	0.60	0.35	0.48	0.35	0.14	0.03	0.08
Primary Articles	1.31	0.88	0.97	0.40	0.04	0.05	-0.16
Fuel, Power, etc*	1.77	0.53	1.69	0.09	-0.07	0.41	0.00
Manuf. Products	0.47	0.19	0.43	0.10	0.36	0.21	0.25
Disaggregated series (WPI)							
Average	2.20	0.56	2.11	0.07	0.16	0.35	0.12
Median	1.79	0.42	1.74	0.06	0.15	0.37	0.09
Minimum	0.50	0.11	0.48	0.01	-0.42	-0.28	-0.33
Maximum	7.64	4.21	7.53	0.35	0.68	0.93	0.66
Std.	1.53	0.59	1.44	0.05	0.21	0.33	0.21

Note: * Fuel, Power, Light and Lubricants.

Table 2: Cross-Sectional Correlation

A: China Results

	Sd(π_i)	Sd($\lambda_i C$)	Sd(e_i)	R^2	$\rho(\pi_i)$	$\rho(\lambda_i C)$	$\rho(e_i)$	AC1	AC12	IFR6	IRF12
Sd(π_i)	1.00	0.98	0.99	0.42	0.29	0.17	0.26	-0.32	0.07	-0.31	-0.13
Sd($\lambda_i C$)		1.00	0.94	0.55	0.40	0.22	0.33	-0.33	0.12	-0.31	-0.12
Sd(e_i)			1.00	0.30	0.20	0.13	0.20	-0.31	0.05	-0.30	-0.12
R^2				1.00	0.84	0.39	0.61	-0.22	0.19	0.01	0.13
$\rho(\pi_i)$					1.00	0.51	0.87	-0.19	0.15	0.00	0.10
$\rho(\lambda_i C)$						1.00	0.35	-0.11	0.02	0.02	0.08
$\rho(e_i)$							1.00	-0.20	-0.01	-0.10	-0.03
AC1								1.00	-0.34	0.37	0.34
AC12									1.00	0.14	0.15
IFR6										1.00	0.97
IRF12											1.00

B: India Results

	Sd(π_i)	Sd($\lambda_i C$)	Sd(e_i)	R^2	$\rho(\pi_i)$	$\rho(\lambda_i C)$	$\rho(e_i)$	AC1	AC12	IFR6	IRF12
Sd(π_i)	1.00	0.76	0.99	0.20	-0.31	-0.16	-0.25	-0.06	-0.08	-0.16	-0.31
Sd($\lambda_i C$)		1.00	0.69	0.72	-0.35	-0.27	-0.28	-0.19	-0.19	0.02	-0.17
Sd(e_i)			1.00	0.11	-0.29	-0.14	-0.23	-0.04	-0.07	-0.19	-0.31
R^2				1.00	-0.18	-0.28	-0.14	-0.37	-0.34	0.09	-0.02
$\rho(\pi_i)$					1.00	0.36	0.95	0.09	-0.01	-0.32	-0.26
$\rho(\lambda_i C)$						1.00	0.23	0.49	0.43	-0.35	-0.30
$\rho(e_i)$							1.00	0.06	-0.06	-0.24	-0.21
AC1								1.00	0.78	-0.09	-0.08
AC12									1.00	-0.08	-0.08
IFR6										1.00	0.97
IRF12											1.00

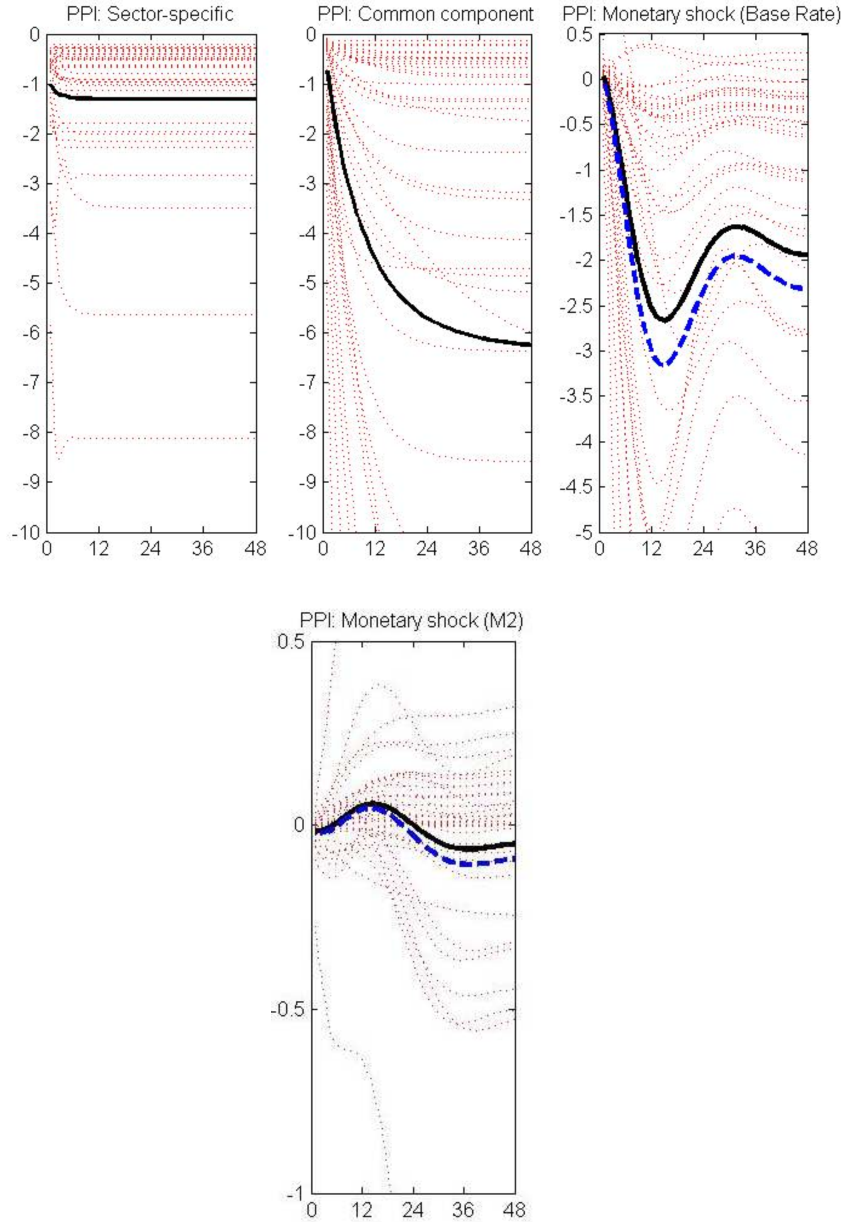
Notes: ρ() are based on the AR parameters. AC1 and AC12 are the first- and twelfth-order autocorrelation of the response of inflation (π_i) to a monetary shock. For China, the monetary policy instrument is M2. IRF6 and IRF12 are the price level responses to a monetary policy shock at horizons of 6 and 12 months, respectively.

Table 3: Response of Price Series to a Monetary Policy Shock

	Autocorrelation of π_{it} conditional on monetary policy shock				Price Responses in %	
	1st Order	3rd Order	6th Order	12th Order	6 Months	12 Months
A. China Producer Price Index						
Aggregated Price Series (PPI)						
Total	0.99	0.95	0.87	0.70	-1.82	-3.09
Light Industry	0.99	0.95	0.87	0.70	-0.01	-0.01
Heavy Industry	0.99	0.95	0.87	0.70	-0.03	-0.05
Producer Goods	0.99	0.95	0.87	0.70	-0.02	-0.04
Consumer Goods	0.99	0.95	0.88	0.70	-0.01	-0.01
Consumer Goods: Foods	0.99	0.95	0.88	0.71	-0.01	-0.02
Consumer Goods: Clothing	0.99	0.95	0.86	0.67	0.00	0.00
Consumer Goods: Daily Use Articles	0.99	0.95	0.87	0.70	0.00	0.01
Consumer Goods: Durables	0.98	0.92	0.78	0.51	0.00	0.00
Disaggregated Price Series (PPI)						
Average	0.99	0.94	0.83	0.62	-1.49	-2.61
Median	0.99	0.95	0.87	0.68	-0.34	-0.90
Minimum	0.96	0.76	0.33	-0.27	-13.15	-21.50
Maximum	0.99	0.95	0.89	0.73	0.33	0.38
Standard Deviation	0.01	0.04	0.10	0.18	2.67	4.32
B. India Wholesale Price Index						
Aggregated Price Series (WPI)						
Total	0.97	0.91	0.85	0.70	-0.02	-0.05
Primary Articles	0.97	0.89	0.84	0.70	0.00	0.00
Fuel, Power, Light & Lubricants	0.97	0.92	0.84	0.67	0.00	0.00
Manuf. Products	0.98	0.92	0.84	0.68	0.00	0.00
Disaggregated Price Series (WPI)						
Average	0.97	0.89	0.81	0.66	-0.04	-0.07
Median	0.98	0.93	0.86	0.72	-0.04	-0.07
Minimum	0.80	0.57	0.32	0.24	-0.66	-1.06
Maximum	0.98	0.94	0.88	0.74	0.32	0.41
Standard Deviation	0.03	0.09	0.13	0.12	0.17	0.25

Note: The monetary policy is an unexpected 0.25% increase in the PBOC's base rate. For India the monetary policy shock is an unexpected 0.25% increase in the RBI bank rate.

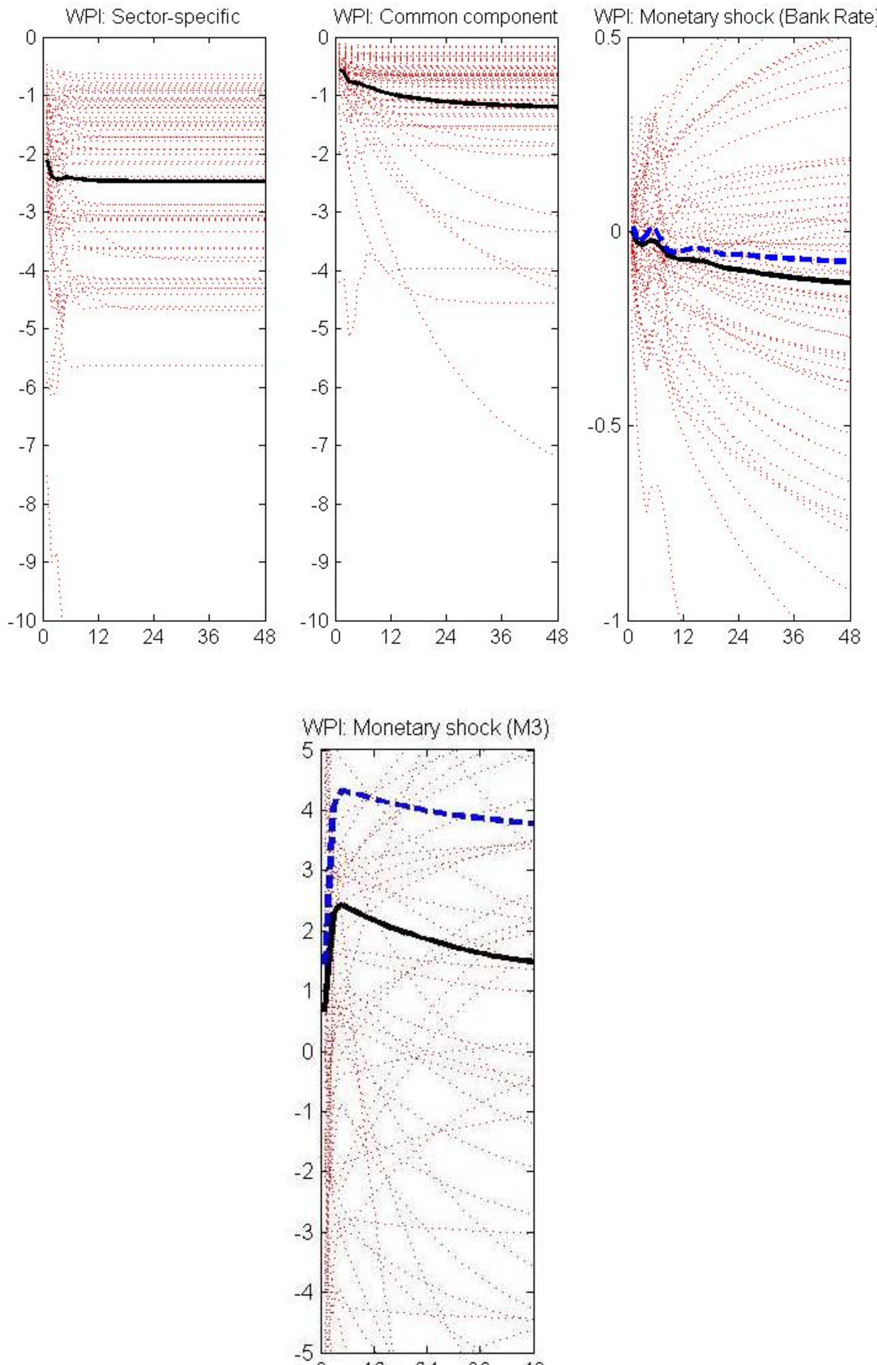
Figure 1: [16] **China sectoral price responses to shocks (Base Rate and M2 Monetary Aggregate as the monetary instrument)**



Notes: Sectoral prices respond to a sector-specific shock (left panel: one standard deviation of e_{it}), to a common component shock (middle panel: one standard deviation of $\lambda_i' C_t$), and finally to a monetary shock (right panel). The monetary shock is an unexpected 25 basis points increase in Central Bank's base interest rate and M2 for Figure 1. Thick solid line represents the average response while the thick dashed line is the aggregated PPI response to a monetary shock.

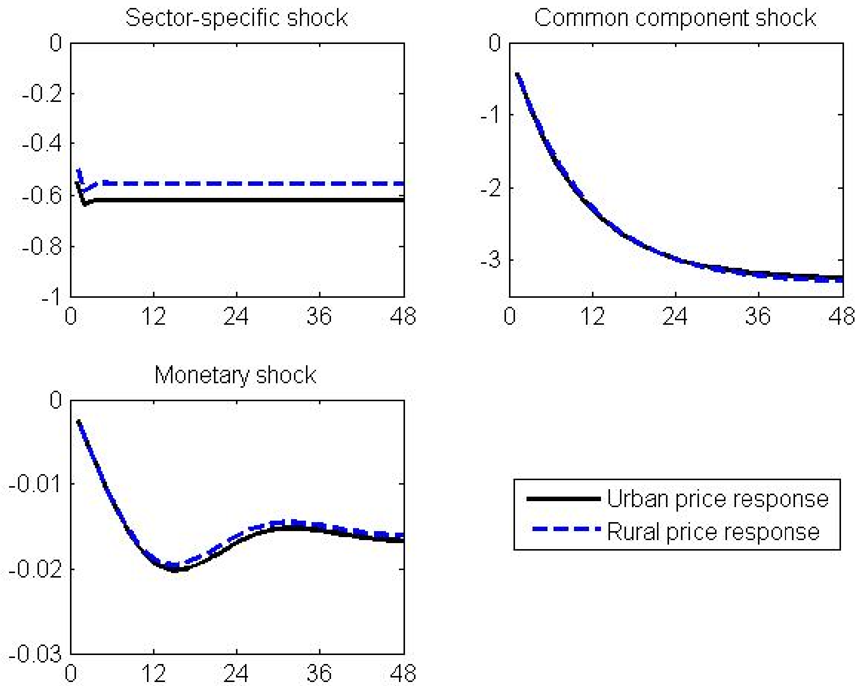
[16] For all figures below, x-axis indicates length of months and y-axis is the percentage change.

Figure 2: India sectoral price responses to shocks (Bank Rate as the monetary instrument)



Notes: The monetary shock is an unexpected 25 basis points increase in RBI's Bank Rate and M3 for Figure 3. Thick solid line represents the average response while the thick dashed line is the aggregated WPI response to a monetary shock.

Figure 3[17]: China urban and rural CPI responses to various shocks



[17] The sector-specific and common component shocks are one standard deviation of e_{it} and $\lambda_i^{'} C_t$, respectively. The monetary shock is +0.25% change in the central bank's base rate in both China and India.

Figure 4: India urban and rural CPI responses to various shocks

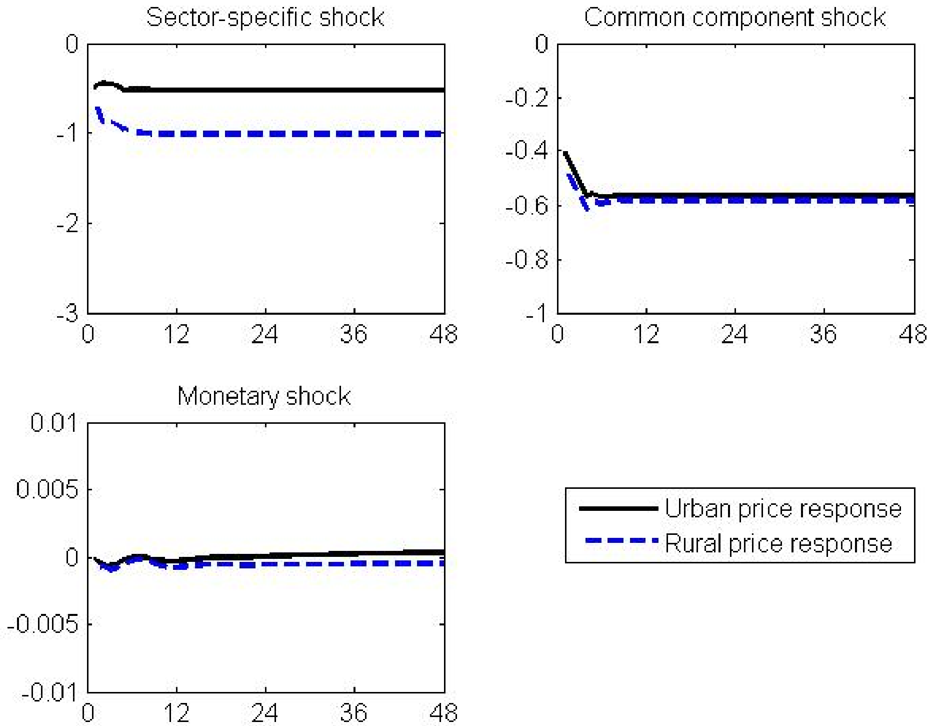
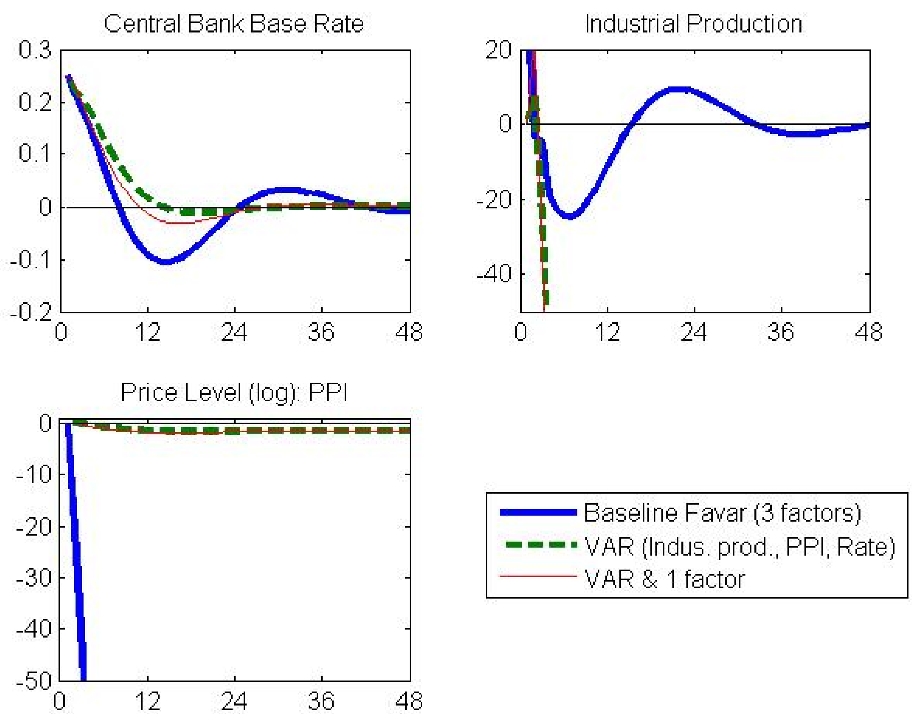
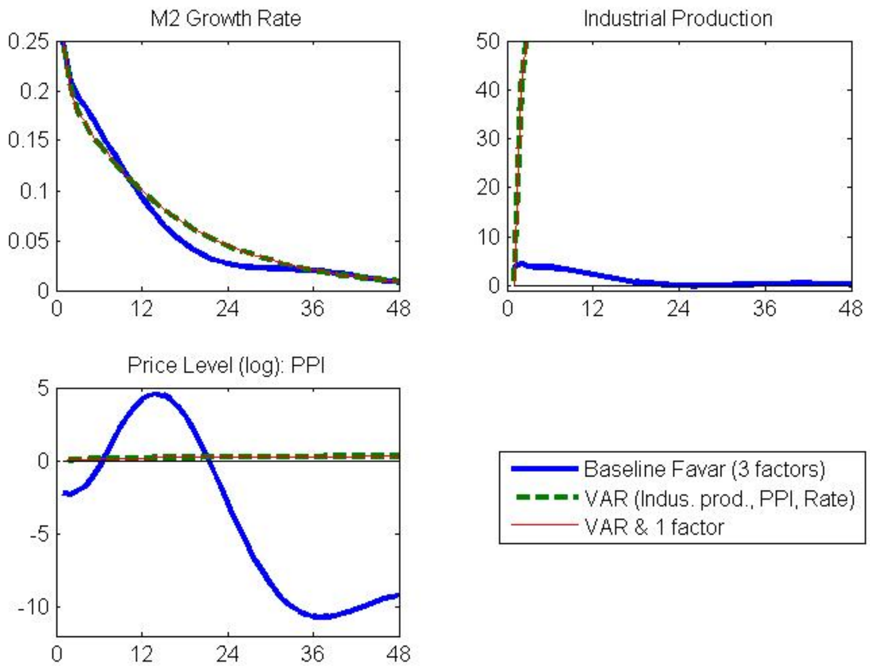


Figure 5: China impulse responses to an identified monetary shock (Base Rate)



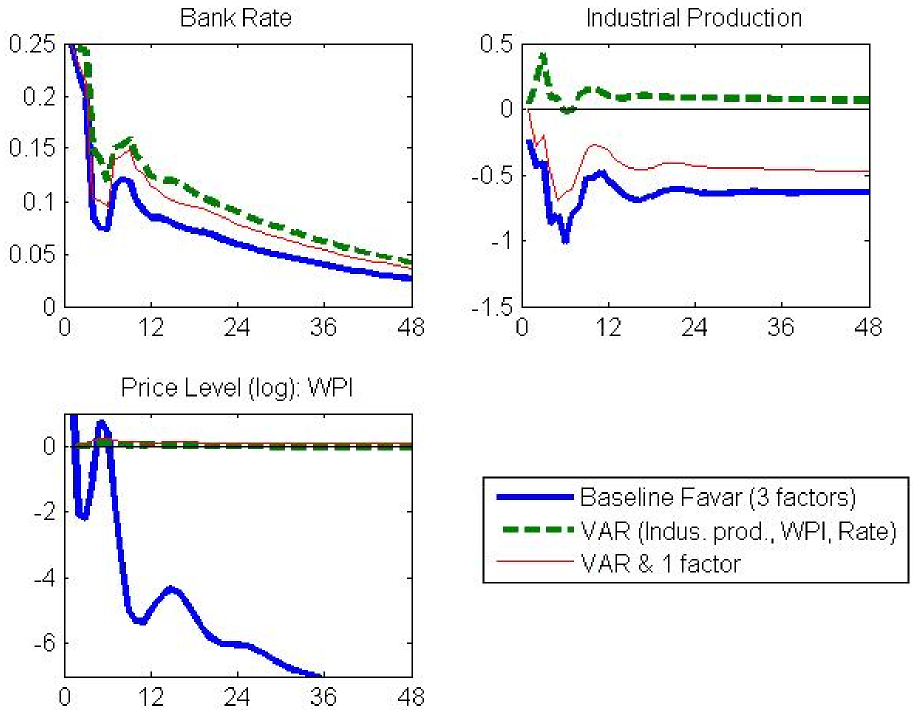
Notes: Responses (in percent) are based on three models: the proposed baseline FAVAR, an ordinary VAR with three variables, and VAR plus the first estimated principal component (factor) of the large data set. In the third graph of Fig. 5, VAR and VAR&1 factor model both predicted a permanent negative price response, but at a scale around 2% while the FAVAR estimated a negative 300% change.

Figure 6: China impulse responses to an identified monetary shock (M2)



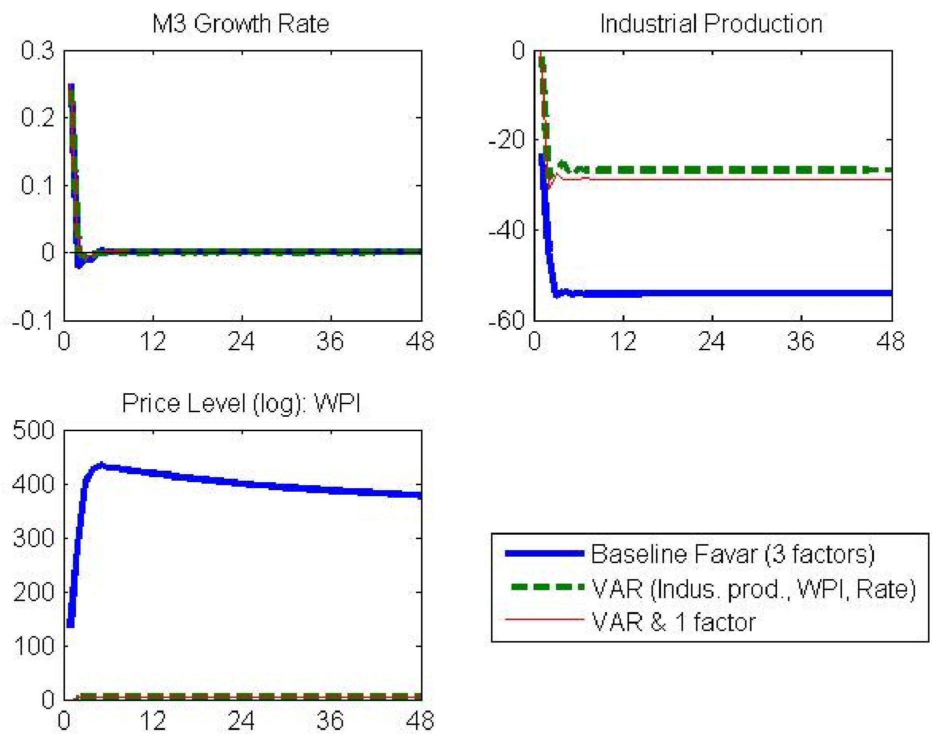
Notes: Responses (in percent) are based on three models: the proposed baseline FAVAR, an ordinary VAR with three variables, and VAR plus the first estimated principal component (factor) of the large data set. In the third graph of Fig. 6, VAR and VAR&1 factor model both predicted a permanent positive price response at around 0.3%.

Figure 7: India impulse responses to an identified monetary shock (Bank Rate)



Notes: Responses (in percent) are based on three models: the proposed baseline FAVAR, an ordinary VAR with three variables, and VAR plus the first estimated principal component (factor) of the large data set. In the third graph of Fig. 7, VAR and VAR&1 factor model both predicted a permanent positive price response, but peaked at around 0.2% while the FAVAR estimated a negative 7% change.

Figure 8: India impulse responses to an identified monetary shock (M3)



Notes: Responses (in percent) are based on three models: the proposed baseline FAVAR, an ordinary VAR with three variables, and VAR plus the first estimated principal component (factor) of the large data set. In the third graph of Fig. 8, VAR and VAR&1 factor model both predicted a permanent positive price response at around 8%.