Monetary and Fiscal Policy Effectiveness in China: Evidence from a FAVAR Model*

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Abstract

A common concern regarding Chinese GDP data is that it is an unreliable or noisy measure of the true state of Chinese economic activity. In this paper, we use a broad set of Chinese economic indicators and a dynamic factor model framework to estimate Chinese “economic activity” and price conditions as latent variables. Our method allows each economic indicator to have periods of missing data and a potentially different start date, which is important in the Chinese context where new indicators are regularly introduced. We incorporate our Chinese economic activity measure into a factor-augmented VAR (FAVAR) to estimate the effects of Chinese monetary and fiscal policy on economic activity. A FAVAR approach seems particularly well-suited to analysis of the Chinese economy due to the aforementioned concerns with Chinese data quality, as well as the relative lack of long time series data available and the rapid structural changes that country has undergone. Contrary to much of the literature, we find that interest rate changes in China have substantive impacts on economic activity and prices, while measures of changes in credit conditions, such as shocks to M2 or lending levels, do not. These results are robust to the use of a narrow set of indicators with common start dates to estimate the activity series, as well as the introduction of a government expenditures series as a proxy for fiscal policy. The latter series also fails to have a significant impact on the economic activity series. Overall, our results indicate that the channels of transmission for Chinese monetary policy have become closer to those of Western market economies.

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1. Introduction

China’s economy has experienced remarkable structural and institutional change in recent decades. In this context, we explore the efficacy of counter-cyclical monetary and fiscal policy for Chinese economic activity and inflation. We do so in the context of a factor-augmented VAR model along the lines of Bernanke and Boivin (2003) and Bernanke et al. (2005). Most previous studies have found that market-based monetary policies—namely, interest rates and reserve requirements—are unimportant in China relative to more direct, blunt credit policies. In contrast to this literature, we find using recent data that interest rates as well as reserve requirements are more important than direct “quantity” measures (which, on their own, are insignificant). These results suggest that, with the ongoing institutional change in China, the monetary transmission mechanism has become more standard.

Studying the monetary transmission mechanism in China raises two interesting challenges that motivated our approach of using a FAVAR model on relatively recent data. First, the well-known skepticism about the quality of Chinese data—which even Vice Premier Li Keqiang famously admitted were unreliable—leads us to use a FAVAR model. That is, we take a broad and expansive approach and use a large number of series associated with economic activity and inflation to estimate a small number of key factors. Second, the rapid pace of change motivated our focus on the recent period, which includes both the Great Recession and the ensuing recovery. As China’s economy, as well as its policy and banking institutions, have progressed, it is reasonable to think that the monetary-transmission mechanism might have evolved as well.

In terms of Chinese data, the quality of the reported output figures has long been under scrutiny (e.g., Holz, 2003, 2008). One approach, which we follow in our FAVAR model, is to focus on a range of non-GDP measures of economic activity. For example, Vice Premier Li claimed that he looked at indicators such as electricity production, rail cargo shipments, and loan disbursements to gauge Chinese

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1 Wikileaks (2007).
economic activity. In a recent study, Fernald and Spiegel (2013) validate the information content of a range of indicators of Chinese economic activity relative to an independent statistical measure of economic activity in China—namely, exports to China and Hong Kong, as reported by major trading partners (the United States, European Union, and Japan). This measure should be highly correlated with true economic activity (either through domestic absorption or through re-processing for export), but is not subject to manipulation or bias by Chinese officials. Fernald and Spiegel report that a number of the alternative indicators they examine are more informative than is GDP as measures of economic activity. Moreover, they find that these alternative indicators typically do better in combination—i.e., taking the first principal component of a set of indicators. Fernald and Spiegel find that a small set of indicators are particularly informative (electricity usage, new floor space added, China’s reported exports, and raw materials used), but the more general point is the informational content of the non-GDP indicators.

Given the data concerns, a FAVAR approach is particularly well suited for examining monetary policy effectiveness. Under this approach, one considers a large number of data series and uses the factors that come out as summary measures of the common factors that drive the systematic component of the economy. This approach minimizes ad hoc decisions about which data to include and which not. Indeed, even in the U.S. context with relatively reliable data, Bernanke and Boivin (2003) and Bernanke et al. (2005) note that even series such as output and inflation are not directly observable—there are multiple measures of each. They argue that the FAVAR approach leads to better empirical estimates.

For China, suppose each individual data series is a noisy indicator of economic activity or inflation. Our approach aggregates these data into useful factors representing Chinese real activity and price movements. The factor-model logic suggests that such activity and price factors are plausibly more accurate measures of economic activity than any individual series, and therefore may better represent the information sets relevant for policymakers or used by economic agents to make decisions.

Turning to the monetary transmission mechanism, in the 1990s, market-based tools of monetary policy (such as interest rate adjustments) were generally considered inadequate to control China’s economy. Qin et al. (2005), for example, argue that this inadequacy reflected the slower pace of reforms
to the banking and financial sector relative to the rest of the economy. As a result, studies of this period suggest that interest-rate policies pursued by the Peoples’ Bank of China (PBOC) had little if any impact on the real side of the Chinese economy (e.g., Geiger, 2006, and Laurens and Maino, 2007). Instead, policymakers seeking to control cyclical fluctuations relied on relatively direct credit policies—telling banks to lend, or not to lend. Studies of monetary policies pursued by the PBOC during this period tend to find that the monetary authority pursued a simple monetary growth rule, as in the case of Burdekin and Siklos’ (2008) findings for their 1990-2003 sample period.

As the 1990s came to a close, financial liberalization in China appeared to increase the impact of monetary policy -- and interest rate policies in particular -- on the real side of the Chinese economy (e.g., Dickinson and Liu, 2007). Zhang (2009) demonstrates in a DSGE model of the modern Chinese economy that an interest rate targeting rule employed by the PBOC would likely be more effective than a money supply targeting rule in stabilizing China’s economy. Chen, et al (2011) argue that the effectiveness of non-standard forms of monetary policy, such as “window guidance” for commercial bank lending levels, are likely to diminish as financial markets become less distorted. Similarly, Fukumoto et al. (2010) argue that Chinese window guidance has been successful in the past, but that its success will diminish as the Chinese financial sector develops, in favor of more standard instruments, such as policy interest rates. Still, financial liberalization is incomplete in China, with remaining ceilings on bank deposit rates and floors on lending rates (e.g. Feyzioğlu et al., 2009).

Hence, given this institutional environment, it is an open question how “standard” China’s monetary transmission mechanism currently is. We start our analysis in 2000, and end our sample in mid-2013. In the first step of our FAVAR approach, we use principal components on monthly data to

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2 It is beyond the scope of this paper to analyze the full range of policy tools. Today, Chinese monetary policy employs multiple instruments and targets [He and Wang (2012)], and the relative importance of these instruments is unclear. He and Wang (2012) characterize China’s monetary policy framework as a “dual rate system,” where deposit and lending rates, as well as window guidance targets for lending are set by monetary authorities, while bond rates are market determined. They argue that this framework is conducive to continued liberalization of Chinese financial markets. We also do not discuss optimal policy. Liu and Zhang (2010) demonstrate in a particular model for China that a hybrid monetary policy that targets both the money supply and the interest rate would outperform one that targets the interest rate alone.
estimate two latent variables, one that represents economic activity and another that represents price conditions. In the second step, we incorporate this estimated activity series into a standard monetary VAR, identified via a recursive ordering, to study the effects of monetary, credit, and fiscal policy.

We begin with a fairly simple three-equation system, with an economic activity factor, an inflation factor, and a (single) policy variable. In contrast to previous literature, we find that increases in PBOC benchmark interest rates have the standard responses—activity slows significantly, and inflation also falls. Increases in reserve requirements also slow activity significantly. In contrast, innovations to M2 or lending do not affect activity or prices. We also include a fiscal policy measure, overall government spending, and find no significant effects from that variable.

These conclusions carry over to larger systems as well: Innovations to interest rates and reserve requirements have significant effects, innovations to lending, M2, and government spending do not. The reason for including government spending in these systems is that, to the extent policymakers use multiple levers simultaneously, what we are calling monetary innovations could, in fact, be a fiscal innovation. However, we find no evidence in our VAR that this is, in fact, a problem.

Of course, lending could still be part of the monetary transmission mechanism, as it is in standard monetary economies. That is, increases in interest rates and (to a lesser extent) reserve requirements do reduce the pace of growth of lending and monetary aggregates. The lack of independent effect of innovations to these aggregates to these variables is consistent with the typical analysis in the United States, where much of the variation in quantity aggregates reflects idiosyncratic shocks to money demand rather than to systematic policy.

We plan to use the results of our VAR to analyze the role of countercyclical policy during and since the recent global financial crisis. China’s growth experience during this period was exceptional. While economic activity in both advanced and emerging economies fell dramatically, China’s real GDP growth remained robust, averaging 7.4 percent during the period covering the U.S. recession. Given

3 These results are not completed yet.
China’s very open economy, one might have expected it to be exceptionally vulnerable to the global downturn. Were the counter-cyclical policies pursued by China during the crisis responsible for stemming the impact of the global shock? A later version of this paper will include those results.

The closest antecedent to this paper is a study by He et al. (2013), who use also use a FAVAR approach to estimate the efficacy of Chinese monetary policy. Contrary to our results, He et al. find that industrial production responds modestly to a shock to either the benchmark lending rate or “market-based” PBOC policies, measured by choosing 15 data series including interest rate and reserve requirement policies as indicator variables. In contrast, they find strong responses to shocks to total lending or M2.4

Our paper differs from He et al. (2013) in a number of respects: First, we use more recent data, with more coverage of the global financial crisis. Second, our FAVAR specification estimates economic activity and price conditions as latent variables, as in Ang and Piazzesi (2003), while He, et al (2013) estimate the policy variable as a latent factor. Finally, we consider the impact of monetary policy in an environment that also allows for fiscal spending shocks. This addition is important for the case of China, where monetary policy decisions can have substantive implications for the government’s budget balance due to the gains and losses from sterilization activity under a closed capital account [e.g. Chang, et al (2013)].

A concern that may arise with a broad FAVAR exercise such as ours or that in He, et al (2013) is that adding more data can, in some cases, have perverse effects. This was shown by Boivin and Ng (2006), who demonstrate that adding data can reduce the forecasting quality of a series. This surprising outcome can occur when the idiosyncratic errors of included factors are cross-correlated or if a factor with substantial forecasting power is dominant in a small dataset but is a dominated factor in a larger dataset.

4 Lescaroux and Mignon, (2009) also construct a FAVAR model for China. However, their primary interest is in gauging the impact of global oil shocks on the Chinese economy. They do include M2 among their indicator variables.
Recall that Fernald and Spiegel (2013) argue for taking the first principal component of a small set of activity indicators, electricity usage, new floor space added, China’s reported exports, and raw materials used to construct a factor explaining Chinese economic activity. We therefore also use this narrower set of indicators as a robustness check on the results of our more comprehensive factor model (excluding raw materials, which are available only quarterly). Fortunately, it turns out that, when it comes to addressing the question of whether interest-rate changes an important instrument of policy, our results are robust to using the narrow or broad set of indicators.

The remainder of this paper is organized into 5 sections. Section 2 introduces our FAVAR methodology. Section 3 overviews our data. Section 4 reviews our results, Lastly, Section 5 concludes.

II. FAVAR Estimation Method

Economic agents in China and elsewhere look at a wide variety of economic indicators to synthesize a view of the state of the economy. However, estimating a standard vector autoregression (VAR) for a large system of variables is infeasible without a very long history of data. This is particularly problematic for China, due to its combination of limited data availability and rapid structural transformation. In practice, then, the relatively short samples of consistent data that we have for Chinese series makes estimation of large VARs either impossible or highly unreliable due to overparameterization.

In a dynamic factor model, however, a small number of essential factors are extracted from the set of all observable data—for example, a Chinese “economic activity” factor can be extracted from data series on industrial production, electricity use, rail cargo shipments, loan disbursements, international trade data, and so on. By focusing attention on the essential underlying factor (economic activity), the dimensionality of the model can be greatly reduced, allowing for estimation of a VAR in the underlying factor.

In particular, we assume that our Chinese economic indicators, \( X \), are determined by only a small number of underlying factors, \( F \), plus idiosyncratic noise, \( \varepsilon \), according to:
\[ X_t = \Lambda F_t + \varepsilon_t \]  \hspace{1cm} (1)

where \( t \) indexes observations, the size of the vector \( F_t \) is less than the size of the vector \( X_t \), and where the matrix \( \Lambda \) is called the *loadings* of the indicators \( X \) on the factors \( F \). The idiosyncratic errors \( \varepsilon \) may be correlated both across series and across observations \( t \), so long as that correlation is not "too strong."\(^5\)

In a dynamic factor model, the factors \( F \) (and data series \( X \)) are related over time, typically according to a linear process:

\[ F_t = A(L)F_{t-1} + \eta_t \]  \hspace{1cm} (2)

where \( A(L) \) denotes a polynomial in the lag operator. Dynamic factor models date back to papers by Geweke (1977) and Sims and Sargent (1977). They have enjoyed a great resurgence of interest since Connor and Korajczyk (1986), Stock and Watson (1998, 1999), and Forni, Hallin, Lippi, and Reichlin (2000) showed how they can be efficiently applied to large panels of macroeconomic time series.

A factor-augmented VAR, or FAVAR, is a VAR in which some of the variables are factors taken from a dynamic factor model:

\[ \begin{bmatrix} F_t \\ Y_t \end{bmatrix} = A(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \eta_t \]  \hspace{1cm} (3)

where \( Y \) denotes a vector of observable variables and \( F \) denotes a vector of factors taken from a dynamic factor model. Thus, a FAVAR differs from a dynamic factor model in two main respects: First, some of the factors are assumed to be directly observed, while in a dynamic factor model this is generally not the

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\(^5\) For details, see Chamberlain and Rothschild (1983) and Stock and Watson (2000). In the classical literature on factor analysis, the idiosyncratic errors \( \varepsilon \) are assumed to be uncorrelated across series and over time. This led Chamberlain and Rothschild (1983) to coin the term “approximate factor model” to refer to the more general case considered here. Consistent with the modern literature, we use the term “factor model” to refer to the more general case.
case. Second, in a FAVAR, the econometrician is typically interested in identification of the FAVAR, rather than just forecasting. Thus, the key objects of interest in a FAVAR are typically impulse response functions or variance decompositions, rather than just forecasts.

Following Stock and Watson (1998, 1999), we use principal components to estimate the factors $F$ in the dynamic factor model (1). This method is numerically robust and computationally efficient, and is econometrically consistent for the latent factors $F$ under the standard technical conditions discussed in Stock and Watson (1998, 1999). In contrast to Stock and Watson, but consistent with some later studies in the literature (e.g., Ang and Piazzesi, 2003), we divide our economic indicators into two groups—one containing measures of output and the other containing measures of inflation—and extract the first principal component from each group to get our measures of an “output” factor and an “inflation” factor.

Given that many Chinese series have short histories or other periods of missing data, our treatment of missing data is of central importance. We first estimate the latent factors $F$ and factor loadings $A$ from the data $X$ using only those months for which we have data on all series, say from some date $t_0$ to the end of our sample $T$. We next impute values for any data that are missing in month $t_0-1$. We infer the values of the latent factors $F_{t_0-1}$ using the data that are observed in month $t_0-1$ together with the factor loadings $A$ and variances of the idiosyncratic errors $\varepsilon$ and $\nu$. Once we have imputed values for the missing data in month $t_0-1$, we reestimate the factor loadings $A$ and latent factors $F$ over the sample from $t_0-1$ to $T$. We iterate this process backward, month by month, until we have imputed missing values for all series in all months $t$. This is essentially the same procedure as advocated by Stock and Watson (1998) for dealing with missing data.

As we demonstrate below, our estimate of Chinese economic activity captures well the broad macroeconomic movements in China, particularly the impact of the global financial crisis and the

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6 Bernanke and Boivin’s (2003) preferred specification is to treat the federal funds rate as the observed variable in the model, but they also consider specifications in which output and/or inflation are also observed. For China, He et al. (2013) assume that industrial production and the CPI are observable variables. Given the questions that have been raised about the quality of Chinese data, we prefer to treat IP and the CPI as noisy indicators of the underlying latent activity and inflation factors.
subsequent recovery from that period. Following Bernanke and Boivin (2003) and Bernanke et al. (2005), we then incorporate our estimate of Chinese economic activity into a VAR. We can then apply standard VAR methods to estimate and identify the effects of Chinese monetary and fiscal policy on economic activity.

Note that a feature of our FAVAR framework is that we can use equation (3) to forecast the model’s latent factors—here, Chinese economic activity—forward into the future. We can then use this forecast for $F$, our estimated factor loadings $\Lambda$, and equation (1) to forecast our entire set of Chinese economic indicators $X$ forward.

An important question is how we identify policy shocks. For equation (3), we take the policy variables as observables, i.e., the elements of $Y$. We then assume a typical recursive ordering, with the economic activity and inflation factors first, then the policy variables. The recursive identification assumes that policy can respond endogenously to changes in activity or inflation within the month; but that policy innovations affect activity and inflation only with a lag.

III. Data

We start our sample in January 2000 and end in September 2013. In our view, because of China’s rapid structural and institutional change, using data from the 1990s would not be informative about the current workings of monetary policy.\footnote{He, et al (2013) identify a structural break in relationships among Chinese data in 2002.} Importantly, our sample period covers the sharp downturn during the global financial crisis as well as China’s rapid subsequent recovery.

Note that some of the most important series that one might want to include in a set of measures of economic activity, such as the PMI manufacturing index, are only available for China beginning relatively recently (in 2005). This highlights the usefulness of our FAVAR methodology for China. Our
methodology allows for the inclusion of variables that exhibit missing data over some portion of our sample.8

The Chinese New Year raises a specific challenge. The holiday has a major effect on monthly activity, but sometimes falls in January, sometimes in February, and sometimes it crosses both months. We address this issue for each individual economic activity and inflation variable $x_t$ by first averaging the values of the series for January and February. We then distribute that average value across the two months assuming that the growth rate from December to January equals the growth rate from January to February. This assumption addresses the large jumps in economic activity that appear in our data for March (the return to “normal months”), but also implies that we are not getting any identification out of those two months separately.

After removing the effects of the Chinese New Year, we use the Census X-12 ARIMA package to seasonally adjust the raw levels of each individual activity variable.9 We control for trends by taking month-to-month growth rates (calculated as 100 times the log-change) of each series. We then apply the factor-model methodology as described above to the seasonally-adjusted monthly growth rates in order to extract the activity and price factors.

Fernald and Spiegel (2013) address concerns about the reliability of Chinese data by validating indicators of economic activity in China against an independent statistical measure of economic activity in China, namely, exports to China and Hong Kong, as reported by major trading partners (namely, the United States, European Union, and Japan). Fernald and Spiegel argue for taking the first principal component of electricity usage, new floor space added, China’s reported exports, and raw materials used.

8 Although our FAVAR model is designed to fill in missing variables, the lack of continuity in the data is also a reason for focusing on the more recent period rather than extending back to the 1990s. In particular, if most of the variables are missing, it is unclear how comparable the estimated factors are over time.

9 In principle, the X-12 package can be used to adjust for moving holidays or other calendar effects. However, those adjustments require imposing a fair degree of judgment about the impact of these calendar effects that is beyond the scope of this paper.
We use this narrower set of indicators as a check on the results of our more comprehensive factor model (excluding raw materials, which are available only quarterly).

The list of all of the variables included in our study are shown in Table 1. We divide the data a priori into two groups. Our base economic activity specification includes a broad set of 29 indicators in the economic activity series. Our “narrow” specification includes the 3 indicators in the activity factor identified as predicting Chinese import volumes well by Fernald and Spiegel (2013): exports, electricity production, and floor space under construction. We combine each of these economic activity series with the price series, comprised of four CPI measures and two producer price measures.

Figure 1 shows the resulting factors. The economic activity factors generated by the broad and narrow series are shown in Figure 1A. It can be seen that the latent variable estimates are highly correlated, although the narrow series is clearly more volatile. As our narrow series is based on indicators for which we have complete series, the overall results suggest that our methodology for filling in missing data for the latent variable estimate based on a broad set of alternative indicators does not have a marked impact on our estimates of real activity. Moreover, it can also be seen that our methodology captures well the slowdown in China associated with the global financial crisis, and the country’s subsequent recovery, although again, the narrow series appears to lead the broad series slightly. It is apparent that while China weathered the economic downturn better than most, it also was heavily hit by the global downturn.

Figure 1B shows the price factor. Again, our series appears to be picking up the effects of the crisis well, including both the downturn in prices during the crisis and the subsequent pickup in Chinese inflation during the recovery. As in the case of the activity series, the data clearly demonstrate a strong impact from the crisis on Chinese prices.

10 We also experimented with estimating an economic factor directly on 12-month changes in the data, rather than on month-to-month changes. The correlation of the resulting narrow and broad factors was 0.88. Clearly, there is much more noise in the month-to-month estimates, especially with the narrow measures. That said, the year-over-year indicators would not be appropriate given the “ordering” identification in our VAR.
Finally, as policy variables, we consider 5 observable measures of monetary policy for China: A benchmark short-term (less than 20 day) interest rate set by the PBOC; a longer-term rate (6 months or less) for loans from the PBOC; the reserve-requirement ratio; the money supply, as measured by M2; and the quantity of bank lending. The bank-lending variable should, in principle, capture changes in “window guidance,” the Chinese government’s well-documented policy of manipulating credit conditions through direct instructions to banks concerning whether to increase or decrease their lending activity. The interest-rate and reserve-requirements enter in their natural (percentage point) units, and we do not seasonally adjust them. M2 and lending enter as seasonally-adjusted month-to-month growth rates.

We also consider growth in seasonally adjusted government spending as a fiscal policy variable.\textsuperscript{11}

IV. Results

We begin by considering simple three-variable systems, with the activity factor, the inflation factor, and each policy variable individually. Our main empirical results come through in this simple specification. We then consider the policy variables in combination, but our main conclusions that policy interest rates and reserve requirements matter—but M2, lending, and government spending do not—remain robust. In all cases, we estimate our model with 2 lags for each of variables, in accordance with the AIC and BIC lag-selection criteria.\textsuperscript{12}

Figure 2 shows the results for the broad activity factor. Each row shows the responses of activity and inflation to a one-standard deviation shock to a different policy variable. In all cases, we plot cumulated responses; since the activity and inflation factors corresponds to growth rates, the cumulated responses tell us how the level of activity and prices responds to a given policy innovation.

\textsuperscript{11} We also considered the overall fiscal surplus. This variable was also insignificant in its impact on our activity series. However, we preferred the government spending variable as it was much less noisy from month to month.

\textsuperscript{12} Depending on the model, the criteria typically choose between one and three lags. Results appear robust to allowing for three lags. Allowing more lags inherently leads to choppy, less precise results, given the short sample and explosion in parameters. He, et al (2013) also use two lags.
The top row shows our main result: In response to a positive shock to the PBOC short-term interest rate, both activity and (with a lag) prices fall significantly over the next two years. These responses are thus in line with standard intuition for monetary policy responses in developed economies such as the United States. It contrast, most studies of China do not find that market-based policy instruments are statistically significant. We explore the robustness of this result further below.

The second row shows that, using the PBOC rate for loans up to 6-months gives qualitatively similar results. Row three shows that increases in the required-reserve ratio reduces activity significantly, with a lag of a year or more. There is a strong price puzzle—infation rises when reserve ratios increase (tighten). A price puzzle is, of course, a common feature of estimated monetary VARs. In larger systems, below, the price puzzle is somewhat attenuated.

Interestingly, rows four and five show that innovation to monetary aggregates (M2) and bank lending are completely unimportant in explaining activity. Our FAVAR model thus suggests that movements in monetary aggregates and “window guidance” in the form of quantitative targets for lending activity are not, in fact, important channels for monetary policy over this period.

These simple results contrast with those of He, et al (2013). They find that economic activity is positively affected by increases in credit availability, as measured by the volume of bank lending. They also do not find a role for PBOC interest rates.13 We discuss some reasons for the differences below.

Finally, we find that government expenditures are also completely unimportant in this simple specification. It should be acknowledged, however, that our spending appears to be very noisy and may not be a good measure of government fiscal shocks. As such, we view the inclusion of government expenditures in our specification as primarily as a vehicle to enhance our ability to gauge the impact of different monetary policy instruments by allowing for fiscal effects.

Figure 3 shows the same results for the narrow activity indicator that follows Fernald and Spiegel (2013). Results for interest rates are a little less strong, but qualitatively similar. The decline in the level

13 Ju, et al (2013) also find a role for monetary policy to influence Chinese trade activity through its influence on the credit channel in a micro study.
of output remains significant over the first year. The larger error bands are not surprising, given that the narrow measure is much noisier, as previously shown in Figure 1. Nevertheless, it is reassuring that a much noisier, but externally verifiable, activity measure yields qualitatively similar results.

Figures 4, 5, and 6 show results for larger (five variable) systems. In terms of recursive ordering, all systems include the broad activity factor and the inflation factor as the first two variables; and the reserve ratio and the overnight interest rate as the last two variables. (We focus on the overnight rate because it was so similar to results with the six-month rate.) The “third” variable in each of the figures differs—Figure 4 has M2, Figure 5 has the quantity of lending, and Figure 6 has government spending. The ordering assumptions imply that the reserve ratio or the overnight rate can respond within the month to changes in M2, or lending, or government spending; but that those variables do not respond within the month to the reserve ratio or the overnight rate. (That said, putting M2, lending, or government last in the VAR doesn’t seem to matter much.)

The results from the simple three-variable system are remarkably robust. Shocks to the overnight interest rate reduce economic activity and prices; shocks to the reserve ratio also reduce activity. But M2, lending, and government spending remain quantitatively unimportant for activity and prices according to these models.

Still, the results do show that M2 and lending are not just noise. Both decline (lending significantly) when the interest rate rises. This suggests that some of the effect of the interest rate increases might be working through reduced lending (as one would expect), even if innovations to lending per se do not appear to matter. This would be in keeping with some of the findings in the literature [e.g. Ju, et al (2013)] that suggest that part of the impact of monetary policy is through its influence on the credit.

A question is why we find different results from previous studies, such as He et al. (2013), who also use a FAVAR approach to estimate the efficacy of Chinese monetary policy. Subsequent to identifying a structural break in China’s monetary transmission mechanism with the launch of its floating exchange rate regime in 2005, they find that industrial production responds modestly to a shock to either
the benchmark lending rate or to their estimate of the stance of “market-based” PBOC policies as a latent variable for their latter sample period estimated from 2002-2010.\textsuperscript{14} They generate the market-based policy measure by choosing 15 policy data series, including interest rate and reserve requirement policies as indicator variables. In contrast to the market-based policy stance, they find strong responses of industrial production and prices to shocks to total lending or M2 for this latter period, and conclude that controlling loan volumes or the money supply is “more effective” than manipulating market-based monetary instruments in China.\textsuperscript{15}

Our paper differs from He et al. (2013) in a number of respects. First, we use more recent data, with substantively more coverage of the global financial crisis. Second, we apply our FAVAR model somewhat differently: While He, et al estimate the set of PBOC market-based policies as latent series and examine impacts on observed series, such as industrial production and price indices, we put little faith in the reliability of any individual activity or price series and instead rely on principal components to characterize economic activity and pricing conditions; we then examine the response of these factors to observed movements in policy variables, such as the overnight lending rate or reserve requirements. Our approach is more in keeping with the standard FAVAR literature (e.g. Bernanke, et al (2005)), which as discussed above is particularly suited to address the problems associated with noise in Chinese data and that country’s rapid structural transformation. It also admits consideration of the independent contributions of fiscal and monetary policies. This allows us to consider the impact of monetary policy in a more fully-specified environment that also allows for fiscal spending shocks. This addition is important for the case of China, where monetary policy decisions can have substantive implications for the government’s budget balance due to the gains and losses from sterilization activity under a closed capital account [e.g. Chang, et al (2013)]. As such, simultaneous incorporation of fiscal and monetary policy

\textsuperscript{14} They identify no impact for the early period, which runs from 1998-2005.

\textsuperscript{15} Lescaroux and Mignon, (2009) also construct a FAVAR model for China. However, their primary interest is in gauging the impact of global oil shocks on the Chinese economy. They do include M2 among their indicator variables.
may be needed to ensure that our models are not underspecified, and thereby subject to bias. Third, our
dynamic factor estimation methodology allows us to consider indicator variables with missing values,
which enables us to include a broader set of indicators to characterize both real activity and our policy
variables. This feature is particularly desirable for China, where many important series contain episodes
of missing values or start in the middle of our sample.

We are only partially able to replicate previous studies with our model. However, several results
are suggestive. First, if we end the sample period prior to the failure of Lehman Brothers (when the Great
Recession became Great), then interest rate innovations are unimportant. Thus, including the Great
Recession period matters for finding that interest rates matter. Even over this period, however, M2,
lending, and government spending remain unimportant in our VAR. Second, some studies do not control
for the Chinese New Year the way we do. For example, He et al run X-12 on raw monthly growth rates,
without controlling for the changes in timing of the New Year from one year to the next. When we
follow that approach, we find that M2 and government spending are marginally significantly
expansionary. This result appears spurious, simply reflecting the systematic, contemporaneous
comovement in activity, M2, and government spending during the Chinese New Year. Hence, these
results point to the importance of treating the Chinese New Year carefully, the way we have in this study.
Importantly, the interest-rate responses are largely unaffected by whether or not we control for the
Chinese New Year or not.

Finally, given that we find that interest-rate and reserve-requirement changes have a significant
effect on economic activity and inflation, an important question is how important they are for the actual
observed variation in activity or prices? We address this question in two ways. First, variance
decompositions (not shown) show that innovations to interest rates and reserve requirements explain only
a modest share of the variation in activity and prices. For example, in the 5-variable VAR with M2,
innovations to interest rates and reserve requirements together explain about 9 percent of the variance in
both activity and inflation at 12 months and 11 percent at 24 months. Not surprisingly, in a fast-growing,
rapidly evolving economy like China’s, non-monetary factors are much more important in explaining the
pace and volatility of growth. Second, we plan to use the estimated five-variable model (with M2) to show a counterfactual economic activity factor where we “turn off” the innovations to reserve requirements and the overnight rate. These results will be forthcoming in a later version of the paper.

V. Conclusion

This paper uses a FAVAR methodology to assess the impact of Chinese monetary policy. A FAVAR approach appears to be particularly well-suited for the Chinese economy, both due to its relatively short span of quality data available and to the likely fact that Chinese economic conditions and policy rules have changed dramatically over the recent years. Our FAVAR approach accommodates data with different starting dates, and therefore allows for a broad set of indicator variables. Moreover, the FAVAR representation allows for the incorporation of many activity and price indicator variables while retaining a parsimonious VAR specification to assess policy impacts. Again, this is particularly promising for China, as the time series available for analysis are relatively short, and the data are likely to be noisy and therefore benefit from our broad set of indicator variables.

Our results suggest that contrary to earlier papers, China’s monetary transmission mechanism is becoming more standard. In particular, we identify a substantive role for interest rate policies in the determination of both real activity and prices. The latter occurs with a lag. While these results contrast with earlier studies, they are directly consistent with a number of studies in the literature that suggest that China’s odd monetary transmission mechanisms are largely function of distortions to the Chinese economy, particularly in the Chinese commercial banking system. These studies predict that as these distortions diminish the standard monetary policy instruments are likely to gain importance in both China’s transmission mechanism and consequently, in Chinese monetary policy.

Of course, China’s economy is far from fully liberalized, and more non-standard Chinese monetary policies -- such as window guidance to Chinese commercial banks -- are likely to continue to play a role in its monetary policy going forward. Our results indicate, however, that the liberalization of
China’s economy to date, particularly in its financial sector, has left that country’s monetary transmission mechanism closer to those of Western economies than previously realized.
<table>
<thead>
<tr>
<th>Data series</th>
<th>First observation</th>
<th>Last observation</th>
</tr>
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<tr>
<td>Broad Economic Activity Factor</td>
<td></td>
<td></td>
</tr>
<tr>
<td># employees: industrial enterprise</td>
<td>2005m12</td>
<td>2012m12</td>
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<tr>
<td>Consumer Confidence Index</td>
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<tr>
<td>Trade Balance</td>
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</tr>
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<td>Foreign Reserve</td>
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<tr>
<td>FX Rate: PBOC: Month End: RMB to USD</td>
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</tr>
<tr>
<td>Fixed Asset Investment</td>
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<tr>
<td>FAI:: New Construction</td>
<td>1999m8</td>
<td>2013m10</td>
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<tr>
<td>FAI:: Equipment Purchase</td>
<td>2004m1</td>
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<tr>
<td>PMI: Non Mfg: Business Activity</td>
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<tr>
<td>Index: Shanghai Stock Exchange: Composite</td>
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<td>Index: Shenzhen Stock Exchange: Composite</td>
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<td>Index: Shanghai Shenzhen 300 Index</td>
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<tr>
<td>PE Ratio: Shanghai SE: All Share</td>
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<td>PE Ratio: Shenzhen SE: All Share</td>
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<td>Electricity consumption</td>
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<tr>
<td>Electricity production</td>
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<td>Rail freight traffic</td>
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<td>Real Estate Investment: Residential Building</td>
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<td>Crude steel production</td>
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<td>Trucks sales</td>
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<td>Floor Space Started: Commodity Building</td>
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<td>Price Factor</td>
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<td>Consumer Price Index</td>
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<td>End</td>
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<td>CPI Core (excl. Food &amp; Energy)</td>
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<td>CPI Food</td>
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<td>Purchasing Price Index: Industrial Raw Material and Semi Finished Product</td>
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<td>Policy Variables</td>
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<td>Govt Expenditure</td>
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<td>Govt Surplus or Deficit</td>
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<td>Money Supply M2</td>
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<td>Loans</td>
<td>1997m1</td>
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Note: All variables were downloaded from the CEIC Asia database.
Figure 1A: Narrow and Broad Activity Factors (maybe plot with IP, where IP has been normalized so month-to-month changes are mean zero, unit s.d?)
Figure 1B: Inflation Factor (12-month MA)
Figure 2: Three-Variable VARs (Broad activity factor, inflation, policy variable)

Note: Each row corresponds to a separate three-variable VAR, with the activity factor, inflation factor, and the policy variable shown. The left column shows the responses of the activity factor, and the right column shows the response of the inflation factor, to a policy innovation.
Figure 3: Three-Variable VARs (Narrow activity factor, inflation, policy variable)

Accumulated Response of ACTIVITY_NARROW to SHORT_RATE
Accumulated Response of INFLATION to SHORT_RATE

Accumulated Response of ACTIVITY_NARROW to CB6MONTH
Accumulated Response of INFLATION to CB6MONTH

Accumulated Response of ACTIVITY_NARROW to RRATIO
Accumulated Response of INFLATION to RRATIO

Accumulated Response of ACTIVITY_NARROW to M2
Accumulated Response of INFLATION to M2

Accumulated Response of ACTIVITY_NARROW to LENDING
Accumulated Response of INFLATION to LENDING

Accumulated Response of ACTIVITY_NARROW to GOV
Accumulated Response of INFLATION to GOV

Note: Each row corresponds to a separate three-variable VAR, with the activity factor, inflation factor, and the policy variable shown. The left column shows the responses of the activity factor, and the right column shows the response of the inflation factor, to a policy innovation.
Figure 4: Five Variable System (Activity, Inflation, M2, Req. Res., Overnight Rate)

Note: Responses to policy innovations to M2, required reserves, and the overnight interest rate. Identification is recursive, with ordering (Activity, Inflation, Lending, Required Reserve, and the Overnight Interest Rate).
Figure 5: Five Variable System (Activity, Inflation, Lending, Req. Res., Overnight Rate)

Note: Responses to policy innovations to lending, required reserves, and the overnight interest rate. Identification is recursive, with ordering (Activity, Inflation, Lending, Required Reserve, and the Overnight Interest Rate).
Note: Responses to policy innovations to govt spending, required reserves, and the overnight interest rate. Identification is recursive, with ordering (Activity, Inflation, Lending, Required Reserve, and the Overnight Interest Rate).
References


