Understanding the Turbulence in Financial Markets of August 2015: Can modern macroeconometrics help?

Juan Antolín-Díaz*  Juan F. Rubio-Ramírez †
Fulcrum Asset Management  Emory University

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Abstract
Yes. In a context of high uncertainty about the outlook for the global economy and monetary policy, we illustrate how the tools of modern applied macroeconomics can be successfully used to gain valuable insights about the joint behaviour of the macroeconomy and financial markets which can inform policy and investment decisions. We apply two state-of-the-art econometric models to data on Chinese economic activity and US asset prices, and interpret recent developments in light of these methods. We conclude that the interaction of uncertainty about Chinese economic activity and the perception that the Federal Reserve will increase interest rates independently of economic conditions are likely to be behind the recent increase in volatility.

Keywords: Dynamic Factor Models, Structural VARs, Bayesian Methods, Monetary Policy, Asset Prices, China, Nowcasting.
JEL Classification Numbers: C320, E520, E440.

1 Introduction

August of 2015 saw the return of volatility to global financial markets, with sharp falls in equity, bond and commodity prices, and an increase in volatility indexes not seen since the depth of the Euro Crisis in 2011. A substantial amount of speculation has ensued in the financial press about the causes of this increase in volatility, and how it will affect the outlook for the economy and for monetary policy. In particular, considerable attention has been dedicated to two issues: first, the state of Chinese economic activity, and second, the outlook for monetary policy normalization in

*Corresponding author: Juan Antolin-Diaz <juan.antolin-diaz@fulcrumasset.com>, Department of Macroeconomic Research, Fulcrum Asset Management LLP, 66 Seymour Street, London W1H 5BT.
†The author is a consultant for the Federal Reserve Bank of Atlanta, but the views expressed here are exclusively the authors’ and do not represent those of the Federal Reserve Bank of Atlanta or the Board of Governors of the Federal Reserve System.
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the US. Considerable uncertainty surrounds these questions, but unfortunately little attempt has been made so far to tackle them using a coherent, quantitative approach.

In this paper we argue that the tools of modern applied macroeconomics can be readily applied to shed some light on these questions. In particular, recent improvements in the “nowcasting” literature (see Banbura et al. (2012) for a survey) offer valuable insights about how to combine the information contained in a wide number of indicators any of which might be providing a noisy and contradictory signal about the state of the economy. Following Antolin-Diaz, Drechsel, and Petrella (2015), we estimate a Dynamic Factor Model using 15 indicators of Chinese economic activity, explicitly allowing for secular shifts in the long-run growth rate of the economy, as well as variations in the volatility of the business cycle. The model allows us to assess the current outlook for the Chinese economy, and accurately characterize the uncertainty around it. Our baseline conclusion is that current growth appears to be in the region of 6% in annualized terms, and therefore far away from the so-called “hard landing” scenario, although downside risks have increased substantially.

Next, we shift focus to the normalization of monetary policy in the US, and we attempt to disentangle the underlying drivers behind recent movements in asset prices. To this end, a structural approach is required to identify the economic shocks which are ultimately responsible for the observed comovement in some key asset prices. We apply sign restrictions to the impulse response functions of a small scale VAR of US asset prices, following Rubio-Ramirez, Waggoner, and Zha (2010), and identify the contributions of monetary policy, supply, demand and risk aversion shocks. We conclude that perceptions of monetary policy shocks were the main shock affecting equity and bond prices during the summer of 2015. While a small-scale VAR cannot possibly capture the complexity of the shocks and trends affecting global financial markets, it provides a parsimonious and coherent description of recent events that can be useful to inform policy and investment decisions.

The rest of this paper proceeds as follows. Section 2 describes the current ‘nowcast’ of Chinese economic activity through the lens of the dynamic factor model. Section 3 presents the results of the Structural VAR. Section 4 provides some concluding remarks.
2 “Nowcasting” the state of Chinese economic activity

The spectacular economic growth experienced by China during the last two decades has made tracking Chinese economic activity in an accurate and timely manner a problem of first order importance. Unfortunately, in China, like in other countries, GDP and other economic indicators are released with considerable delay. Here we propose to solve this problem by using a “nowcasting” model that exploits information from many data series. The model exploits the idea that the direction of change in GDP can be extracted from a set of information sources that are known before GDP growth itself is published.

Although skepticism about the accuracy of Chinese statistics is periodically reflected in the financial press, there is little evidence of systematic manipulation (see, e.g. Fernald, Malkin, and Spiegel, 2013). Thus, we take the official Chinese statistics as the starting point of the analysis but recognize that any single indicator, including GDP past observations, might give a noisy signal of the true state of the economy.

2.1 Method

Dynamic Factor Models (DFMs) in the spirit of Geweke (1977), Stock and Watson (2002), and Forni et al. (2009) provide a natural framework to implement this idea, since they can incorporate information from a large number of macroeconomic time series, each of which may be contaminated by measurement error. Giannone, Reichlin, and Small (2008) and Banbura et al. (2012) pioneered the use of DFMs to produce “nowcasts” of US GDP.

In a recent paper, Antolin-Diaz, Drechsel, and Petrella (2015) have proposed modifying the standard DFM framework to account for the possibility of secular changes in the long-run growth rate of the GDP. They document a substantial decline in the latter for the US and other advanced economies, and argue that explicitly taking into account for the low-frequency dynamics of the economy matters for obtaining unbiased “nowcasts” and forecasts of GDP. This is likely to be even more relevant for emerging economies, whose business cycle dynamics are characterized by substantial changes in trend growth (see Aguiar and Gopinath, 2007). A model that does not explicitly take into account the possibility of a decline in long-run growth of Chinese GDP will
display a tendency to quickly mean-revert towards the sample average, which in the case of Chinese GDP growth is close to 10%, upwards biasing any “nowcasting” exercise.

Antolin-Diaz, Drechsel, and Petrella (2015) (henceforth, ADP) specify that \( y_t \), a \((n \times 1)\) vector of observable time series, is driven by a latent common factor, \( f_t \). Ordering GDP growth first (therefore GDP growth is referred to as \( y_{1,t} \)) they have

\[
y_{1,t} = \alpha_{1,t} + f_t + u_{1,t},
\]
\[
y_{i,t} = \alpha_i + \lambda_i f_t + u_{i,t}, \quad i = 2, \ldots, n,
\]

where \( u_{i,t} \) is an idiosyncratic innovation specific to the \( i^{th} \) series and \( \lambda_i \) is its loading on the common factor. Unlike in the standard DFM, where all parameters are constant, in the ADP framework the intercept \( \alpha_{1,t} \) is time-dependent in equation (1), allowing the mean growth rate of GDP to vary.

The laws of motion for the factor and idiosyncratic components are, respectively,

\[
\Phi(L) f_t = \varepsilon_t, \tag{3}
\]
\[
\rho_i(L) u_{i,t} = \eta_{i,t}, \quad i = 1, \ldots, n, \tag{4}
\]

\( \Phi(L) \) and \( \rho_i(L) \) denote polynomials in the lag operator of order \( p \) and \( q \), respectively. Both (3) and (4) are covariance stationary processes. The disturbances are distributed as \( \varepsilon_t \overset{iid}{\sim} N(0, \sigma_{\varepsilon,t}^2) \) and \( \eta_{i,t} \overset{iid}{\sim} N(0, \sigma_{\eta_{i,t}}^2) \). By allowing for time-variation in \( \sigma_{\varepsilon,t}^2 \) and \( \sigma_{\eta_{i,t}}^2 \), the model introduces Stochastic Volatility in the innovations to the factor and to the idiosyncratic components of all series, which as we will see below is critical to provide a realistic assessment of the risks to the “nowcasts.”

For the purposes of “nowcasting” Chinese GDP growth, we use 15 quarterly and monthly variables that include both official data and surveys collected by the private sector, with observations starting in January 1995. They constitute a broad panel of indicators covering the industrial, construction, consumer, and external sectors. The specific series included are real GDP, industrial production, electricity consumption, output of steel products, consumption of cement, passenger car sales, passenger car output, freight traffic in railways and civil aviation, volume of transportation in major harbors, exports, imports, the HSBC Manufacturing PMI, and the official PMI indices for manufacturing and services.

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coefficients, latent factors and nowcasts of GDP growth. All time series are downloaded from the Haver Analytics database and are seasonally and Chinese-new year adjusted.\(^2\)

### 2.2 Results

At the moment of writing this paper the latest data released were the August PMI surveys and we had observed GDP growth for the second quarter of 2015. Hence the purpose is to “nowcast” the GDP growth for the third quarter of 2015 and forecast it for the subsequent quarters. The results are displayed in Figure (1). Conditional on the latest data release, panel (a) shows the observed annualized QoQ growth rate of GDP until its last observation and the fan chart for the next two years, together with its long-run growth point estimate, \(\alpha_{1,t}\), for the whole sample. The latest point “nowcast” is centered at 6\%, below the latest point estimate of long-run growth, which is close to 7\%. The outlook for the third quarter of 2015 experienced a significant downward shift from early August. Panel (b) plots the evolution of the distribution of GDP growth for the third quarter of 2015 as new data releases come available. This panel tells us that probability of GDP growth during this quarter being below 5\%, or in other words, a “hard landing”, has increased substantially. Therefore, while the point estimate of around 6\% does not represent a dramatic downgrade of the estimate for the quarter, the model’s assessment of downside tail risks has increased meaningfully.

Panel (c) shows how the point estimates of GDP growth and \(\alpha_{1,t}\) for the third quarter of 2015 change as new data releases come available. As we can see, there has been a deterioration of both estimates since mid-July. Finally, Panel (d) highlights the impressive decline in the model’s estimate of long-run growth in China, from the double digit growth of the decade prior to the crisis to just below 7\% when the latest data release is used. This panel also shows that the downside tail risks has also increased dramatically for the long-run growth.

Additional detail on some of the specific indicators that are included in the sample is provided in Figure A1 in the Appendix. While our model is not capable to make any judgment on whether the official Chinese statistics are being manipulated, it is does confirm that most series, including the surveys collected by the private sector, appear to be broadly consistent with each other, and that the published growth rate of GDP seems in line with the signals of frequently-mentioned alternative

\(^2\)ADP provide further details about the state-space representation and estimation of the DFM. Antolin-Diaz and Petrella (2014) develop the specific application of the ADP framework to China.
indicators such as electricity production or cement consumption.

To sum up, our analysis indicates that, in the context of a secular slowdown in Chinese growth, the available data is still consistent with a growth rate of GDP of about 6% for the third quarter of 2015, although downside tail risks have increased meaningfully.
Figure 1: Results of ADP-2015 model for China

Note: Panel (a) plots the actual annualized QoQ growth rate of GDP for China (solid black), together with the estimated long-run growth rate (dashed red). The fan chart is constructed so that the shaded areas represent 30%, 60% and 90% confidence bands. Panel (b) plots the predictive density of current economic activity at the three dates indicated. Panel (c) displays the real-time daily evolution of the model’s “nowcast” of current-month GDP (blue), and long-run growth (dashed black), together with 1 and 2 standard deviation bands for the former. Finally, Panel (d) plots the model’s current (smoothed) estimate of long-run growth, together with 1 and 2 standard deviation bands.
3 Disentangling the drivers of recent financial market turbulence

In this section we shift focus to the recent turbulence in global financial markets. We take a Structural Vector Autoregression (SVAR) approach using US asset price data to find the nature of the economic shocks driving the recent fluctuations in asset prices. Vector Autoregressions (VARs) have a long tradition in macroeconomics, starting with Sims (1980). Their ability to provide a flexible yet coherent description of the joint dynamics of a group of variables using a minimum of theoretical restrictions have turned them into one of the workhorse models in empirical macroeconomics. SVARs (see Stock and Watson, 2001 for a survey) combine the information contained in the data viewed through the lenses of VARs with theoretically-motivated identification restrictions to interpret VARs innovations as orthogonal “structural shocks” that have an economic interpretation.

3.1 The Method

Formally, consider the general form of the SVAR,

$$y_t' A_0 = \sum_{\ell=1}^{p} y_{t-\ell}' A_{\ell} + c + \varepsilon_t'$$ for $1 \leq t \leq T$, (5)

where $y_t$ is an $n \times 1$ vector of endogenous variables, $\varepsilon_t$ is an $n \times 1$ vector of exogenous structural shocks\(^3\), $A_0, A_{\ell}$ for $1 \leq \ell \leq p$, and $c$ are the structural parameters, $p$ is the lag length, and $T$ is the sample size.

In general, the parameters implied by equation (5) cannot be estimated, since there are an infinite number of structural parameters that produce indistinguishable movements in the data. The key problem in structural VAR analysis is therefore to pin down the structural parameters using economic theory. In the present exercise, we will follow the approach of Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005), as implemented by Rubio-Ramirez, Waggoner, and Zha (2010) and find the set of structural parameters which are compatible with a of sign restrictions on the impulse responses functions (IRFS) of the endogenous variables to structural shocks.

We construct a dataset of US asset price variables containing the S&P 500 stock price index

\(^3\)The vector $\varepsilon_t$, conditional on past information and the initial conditions $y_0, ..., y_{1-p}$, is Gaussian with mean zero and covariance matrix $I_n$, the $n \times n$ identity matrix.
(which we measure in deviations from a 7% annual nominal long-run trend), an intermediate maturity real interest rate (the yield on a five-year Treasury Inflation Protected Security), a measure of expected inflation (obtained from the difference between the real and nominal bond yields of five-year maturity), and a measure of credit risk (the spread between Moody’s Seasoned Baa Corporate Bond Yield index and a treasury bond of comparable maturity).\footnote{Our dataset has weekly frequency and comprises the period January 2003 - August 2015, the maximum span for which reliable data on TIPS yields is available. The stock price index and the credit spread enter the model in log-levels, the real yield and expected inflation in basis points.} As in the last section, our methods are Bayesian: we estimate the VAR using 12 lags and shrinking towards the so-called “Minnesota prior” as in Doan, Litterman, and Sims (1983), reflecting our belief that a random walk is a sensible a priori model for asset price variables.

Table 1:

<table>
<thead>
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<th>Identification Restrictions</th>
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<tbody>
<tr>
<td>Monetary Policy</td>
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<td>-----------------</td>
</tr>
<tr>
<td>Stock Price</td>
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<tr>
<td>Real Interest Rate</td>
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<td>Expected Inflation</td>
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<td>Credit Spread</td>
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Our identification assumptions are summarized in Table 1. We identify four different structural shocks by imposing sign restrictions on the IRFS of the endogenous variables to structural shocks. All the structural shocks we identify are normalized to be contractionary. In particular, a monetary policy shock is assumed to increase real interest rates and reduce expected inflation; an aggregate demand shock will have a negative impact on stock prices, real interest rates, and expected inflation; an aggregate supply shock will also reduce stock prices and real interest rates, but will increase inflation expectations; finally, a risk aversion shock is assumed to reduce stock prices and real interest rates, while increasing both credit spreads and inflation expectations.\footnote{The latter assumption helps pin down the impulse responses to this shock and is justified by the recent literature on uncertainty shocks, which finds evidence that they are inflationary. See, e.g. Fernandez-Villaverde et al. (2011)
3.2 Results

Figure (2) displays the IRFs implied by the point estimates of the structural parameters. Monetary policy shocks are found to reduce equity prices and increase credit spreads on impact. Interestingly, while the impact of these shocks is relatively persistent, it eventually fades away, becoming insignificant after about one year. The IRFs to risk aversion shock, on the other hand appears to have more persistent effects, with long lasting effects on all asset classes, and in particular equity prices and the credit spread.

The next step is to compute a decomposition of the observed movements in the endogenous variables into the contribution of the structural shocks. Figure (3) plots these historical decomposition since mid-2014. The results are based on the structural parameters which yields IRFs closest to the median IRF. Therefore, they ignore the uncertainty around the point estimation of the IRFs, but can still be useful to provide a coherent narrative around the recent events.

Our identification assumptions attributes the observed movements in asset prices in the last twelve months to various offsetting forces. First, a sequence of positive supply shocks, which pushed up equity prices and real interest rates, and lowered expected inflation. Although our model does not explicitly include energy prices, it is noteworthy that the timing of the identified supply shocks matches well with observed declines in energy and other commodity prices. Interestingly, the supply shock appears to have pushed up credit spreads, which matches the fact that default spreads on many energy companies increased strongly during the period.\(^6\) On the other hand, negative demand shocks have generally depressed equities, real yields, and expected inflation, with little effect on credit spreads.

The contribution of monetary policy shocks to stock prices movements has been increasingly negative since May of 2015, and became particularly large in the last week of August. Key to this result are the observed movements in real interest rates and expected inflation, which moved strongly in opposite directions during this period. Therefore, our identification scheme attributes much of the decline in the stock market during August to monetary policy shocks. Monetary policy shocks have also positively contributed to the increase of credit spreads.

\(^6\)It should be noted however, that the IRF of credit spreads to supply shocks is not precisely estimated.
Finally, risk shocks have mainly helped to contain the drop of stock prices with little contribution to the movements of any of the other three variables.

How do we interpret the result that monetary policy shocks appear to be behind the recent declines in asset prices, while there have been few important changes related to US monetary policy over this period? We speculate that the conclusions of section 2 can be linked to this finding. In the face of increasing uncertainty and downside tail risks surrounding Chinese economic activity, the Federal Open Market Committee seems committed to increase the interest rates this year. While the FOMC has indicated numerous times the data-dependent nature of this expectation, the idea that the interest rates increase will increase no matter what and that this will prove to be harmful for the ongoing economic recovery appears to have taken hold in financial markets. Thus, our results seem to reinforce the views recently expressed by Larry Summers,

“barring major unforeseen developments rates will probably be increased by the end of the year. Conditions could change, and the Fed has been careful to avoid outright commitments. But a reasonable assessment of current conditions suggest that raising rates in the near future would be a serious error that would threaten all three of the Feds major objectives price stability, full employment and financial stability.”

Since our results appears to agree with the view that financial markets’ perception that the Fed will increase interest rates independently of economic conditions is equivalent to a monetary policy shock, the reaction of the US central banks to ongoing developments will be critical going forward.

The above analysis is subject to a number of important caveats. Most critically, the small-scale nature of the SVAR means that it is unlikely that the entire set of shocks and trends affecting asset prices are captured by the four variables included in the model. If that is the case, the shocks we are retrieving will not correspond to the true structural shocks, a problem known as informational insufficiency (see Forni and Gambetti, 2014). Moreover, our specification has constant coefficients and variances, a hard to defend assumption for asset prices during the sample period and which should be seen, at best, as a first order approximation. Some of these caveats will be addressed in further research. Nevertheless, the conclusion that monetary policy shocks are responsible for

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Figure 2: Impulse Response Functions to Structural Shocks

Note: In each of the charts, the dark blue line represents the point-wise median IRF to a one standard deviation shock, and the shaded area are 68% confidence bands. The responses of stock prices and credit spreads are measured in percent, of real yields and expected inflation are in basis points. The horizontal axis displays weeks.
Figure 3: Historical Decomposition of Variables since Mid-2014

Note: This figure plots the cumulative contribution of each structural shock to the observed movement in each variable, starting at zero from June 2014. Each data point represents one week.
the recent falls in asset prices should be robust to alternative specifications and identification assumptions, given the observed co-movement between real interest rates and inflation expectations.

4 Concluding Remarks

In this paper, we have applied two state-of-the-art econometric techniques to attempt to understand the turbulence observed in financial markets since August of 2015. We argue that these tools provide valuable insights that can inform a rich and more structured discussion and aid decision making at policy and investment institutions.

Our assessment of the current state of Chinese economic activity, through the lens of “nowcasting” techniques, concludes that current growth appears to be in the region of 6% in annualized terms, and therefore far away from the so-called “hard landing” scenario, although downside risks have increased substantially. With regards to recent movements in asset prices, we conclude with the help of a Structural VAR that uncertainty about the Chinese outlook is interacting with perceptions about the normalization of US monetary policy to create fears of a monetary policy shock.

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A Additional Results on the ADP-2015 Model for China

Figure 4: Selected indicators of Chinese economic activity

Note: In each of the charts, the blue line is the indicator, $y_{it}$, the red line plots the fitted values, $\lambda_t f_t$, the dot highlights the latest available observation, and the dashed line presents the model’s prediction for that variable in the near future, which also takes into account serial correlation in the idiosyncratic component, $u_t$. 