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David Lodge, Michel Soudan

Credit, financial conditions and the business cycle in China

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Abstract

This paper presents empirical evidence of the role of financial conditions in China's business cycle. We estimate a Bayesian-VAR for the Chinese economy, incorporating a financial conditions index for China that captures movements across a range of financial variables, including interest rates and interbank spreads, bond returns, and credit and equity flows. We impose sign restrictions on the impulse response functions to identify shocks to financial conditions and shocks to monetary policy. The model suggests that monetary policy, credit and financial conditions have played an important role in shaping China's business cycle. Using conditional scenarios, we examine the role of credit in shaping economic outcomes in China over the past decade. Those scenarios underscore the important role of credit growth in supporting activity during the past decade, particularly the surge in credit following the global financial crisis in 2008. The financial tightening since the end of 2016 has contributed to a modest slowing of credit growth and activity.

Keywords: Monetary policy, credit conditions, financial conditions index, Bayesian VAR

JEL Classifications: E32, E44, E51, E17

Non-technical summary

China's debt has risen sharply since the 2008 global recession. High debt has been accompanied by greater complexity in the financial system, driven by increased shadow financing which accounted for about two-fifths of new credit in 2016. This combination of rising debt and increased complexity has heightened concerns about the potential fragility of China's economy.

Mindful of the potential adverse consequences of very high debt levels, over the past year Chinese authorities have placed greater emphasis on addressing financial stability risks. Regulators have instituted rules forcing banks to recognise off-balance sheet exposures, curbed interbank borrowing and leverage, and set new rules for asset managers. These measures prompted a broad tightening of financial conditions in the early part of 2018; aggregate credit growth has slowed.

Yet the government has competing aims and efforts to encourage deleveraging are likely to conflict with its desire to maintain high rates of activity growth. The government remains wedded to ambitious growth targets that aim to double China's real GDP between 2010 and 2020. And, for much of the post-crisis period, high credit provision has been an important component of China's growth model. Tightening financial conditions could therefore jeopardise achieving that goal. With this in mind, communication from the central bank has suggested that it has been aiming to target different instruments towards different goals. While it allowed interbank and broader financial conditions to tighten early in 2018, the central bank has left unchanged its traditional monetary policy instruments such as the 1-year benchmark lending rate. The contrast reflected the government's competing policy aims: on the one hand it hoped to restrain rising leverage, particularly in the non-bank financial sector, by tightening financial conditions; on the other hand, it hopes to protect the flow of credit to the non-financial sector, as it continued to pursue ambitious GDP growth targets, which (on past experience) has been accompanied by a steady flow of credit.

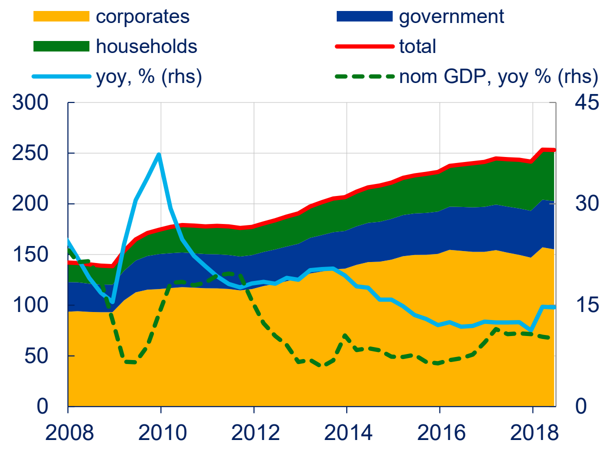
This paper seeks to understand the role of monetary policy, credit and financial conditions in China's business cycle. The paper estimates a structural BVAR model which incorporates a financial conditions index for China that captures movements across a range of financial variables, including interest rates and interbank spreads, bond returns, and credit and equity flows. We use sign restrictions to identify shocks to financial conditions and monetary policy for China.

The model suggests that monetary policy and financial conditions shocks have played an important role in shaping China's business cycle. Financial conditions and monetary policy shocks account for a significant fraction of fluctuations in activity and inflation. Moreover, our model highlights the reliance of China on continued increases in leverage to support high rates of economic expansion, which has been highlighted as a key medium-term vulnerability for the Chinese economy. Counterfactual scenarios underscore the important role of credit growth in supporting activity during the past decade, particularly the surge in credit following the financial crisis which contributed strongly to the swift recovery in output in China after the global financial crisis. Thereafter, although credit growth has slowed, it has nonetheless continued to support activity. However, the financial tightening since the end of 2016, has contributed to a modest slowing of credit growth and activity. Looking ahead, were financial conditions to continue to tighten, this could act as a significant drag on activity.

1. Introduction

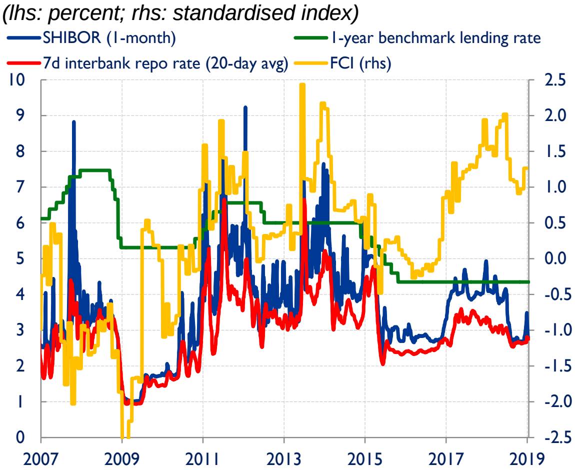
Despite heightened concerns about the risks for the economic outlook posed by high indebtedness, credit continues to expand at a rapid rate in China. China's debt has risen sharply since the global recession with the debt stock of the non-financial sector reaching 253% of GDP by mid-2018. Credit growth still outpaces nominal GDP growth, though the difference has narrowed over the last few years (Chart 1). Through much of the post-crisis period, high debt has been accompanied by increased complexity in the financial system, driven by increased lending by non-bank entities through shadow finance which accounted for about two-fifths of new credit by 2016. This combination of rising debt and increased complexity has heightened concerns about the potential fragility of China's economy.

Chart 1: Credit growth in China
(lhs – percent of GDP; rhs – year-on-year percentage change)



Source: BIS and NBS. Latest observation: June 2018

Chart 2: Financial conditions in China
(lhs: percent; rhs: standardised index)



Sources: People's Bank of China, National Interbank Funding Centre. Latest observation: 15 January 2019 (interest rates), December 2018 (FCI).
Notes: The Financial conditions index (FCI) is the principal component of a set of financial market prices in China (Wacker, Lodge, Nicoletti, 2014). A value above zero represents a tightening of financial conditions relative to average.

Over the past year, however, there have been signs that authorities are placing greater emphasis on addressing financial stability risks and financial conditions have tightened. Regulators have curbed interbank borrowing and leverage, instituted rules forcing banks to include off-balance sheet exposures such as wealth management products (WMPs) into macro-prudential assessments; and instigated a new regulatory regime for asset management firms. The measures have prompted a broad tightening of financial conditions (Chart 2). In late 2016, authorities allowed liquidity conditions to tighten in the interbank market, leading SHIBOR (the Shanghai Interbank Overnight Rate) to rise more than 100bp. Sovereign bond yields also rose sharply and aggregate credit growth slowed. These developments were explicitly justified by Chinese authorities as an attempt to stem high leverage in the financial sector, particularly the shadow banking sector. This momentum seemed to be confirmed by the Communist Party's National Work Council in July 2017 which emphasised the need to contain systemic financial risks. Indeed, the Chinese President, Xi Jinping, has underscored that "deleveraging… is of the utmost importance" (Financial Times, 2017).

Yet the government has competing aims and efforts to encourage deleveraging are likely to conflict with its desire to maintain high rates of activity growth. While authorities are showing signs of concerns about the consequences of rising leverage, the government remains wedded to ambitious growth targets that aim to double China's real GDP between 2010 and 2020 (IMF, 2017a). And, for much of the post-crisis period, high credit provision has been an important component of China's growth model (Dieppe et al., 2018). Tightening financial conditions could therefore jeopardise achieving that goal (IMF, 2017b). With this in mind, PBoC communication suggested that it has been aiming to target different instruments towards different goals. In 2017, although interbank conditions tightened, the central bank left unchanged its traditional monetary policy instruments such as the 1-year benchmark lending rate. Required reserve ratios also remained unchanged at first, although the PBoC eventually enacted reductions during 2018, resulting in looser financial conditions and lower interbank rates. These developments appear to reflect the government's competing policy aims: on the one hand it hoped to restrain leverage in the financial sector, particularly in the shadow financing sector, by tightening financial conditions; on the other hand, it hoped to protect the flow of credit to the non-financial sector, as it continued to pursue ambitious GDP growth targets, which (on past experience) has been accompanied by a steady flow of credit.

Inspired by these recent events, this paper attempts to understand the role of financial conditions and the credit cycle in China's economy. Along the lines of Bernanke et al. (2005) we estimate a Bayesian VAR for the Chinese economy, incorporating a financial conditions index which summarises information from a range of financial variables, including interest rates and interbank spreads, bond returns, and credit and equity flows. This approach is used to identify the transmission of financial shocks, which might manifest themselves in different ways over time, reflecting changes in China's monetary policy framework or financial market development. This is akin to a number of recent papers, such as Fernald et al. (2014), which apply a similar approach to study the effects of interest rates on economic developments in China. However, for China, analysis of the role of credit supply and financial conditions shocks is largely missing. The exception is a recent paper by Breitenlechner and Nuutilainen (2017) which explores the transmission of Chinese monetary policy through loan supply and demand effects. In this paper, we follow Busch et al. (2010) and Darracq et. al (2014), by imposing sign restrictions on impulse response functions to identify shocks to financial conditions and shocks to monetary policy. Following Aikman et al. (2017), we interpret shocks to financial conditions as reflecting the ease of credit access which will affect economic behaviour. We then use the model to understand the effects of credit growth and financial conditions in driving activity in China. Using conditional scenarios, we examine the role of credit in shaping economic outcomes in China over the past decade. We also conduct scenario analysis to understand the role that tighter financial conditions might play in the outlook for activity in China.

A number of papers have analysed the role of interest rates in China's economy, reflecting the evolving role of monetary policy over the past two decades. Traditionally, China's monetary policy reflected a mix of price and quantity controls (Koivu, 2009): China relied heavily on administrative control of lending and deposit rates; so-called 'window-guidance' was used to steer the provision of credit by banks to the economy. For Lardy (2008), those policies reflected a state-led growth strategy that used financial repression to provide corporates, particularly state-owned firms, with cheap credit, subsidised (mainly) by household depositors. For authorities, those policies rather reflected the only means of control for an economy without hard budget constraints, particularly for state firms (He et al., 2015). But, as China's financial system has liberalised and opened-up, the literature suggests that financing has become more market-based (Koivu, 2009; He and Wang, 2012; Sun, 2015), driven partly by the explosion in the availability of so-called "shadow" financing (Wang et. al, 2018; Hachem and Song, 2016). In response, the PBoC's operational conduct of monetary policy has also relied more on a market-based system and policy interest rates have become the main instrument of monetary policy (He et al., 2015; IMF, 2017c). Thus, while earlier studies found that market-based monetary policies, such as interest rates or reserve requirements were unimportant in shaping China's business cycle (e.g. Fan et al., 2011; He et al., 2015), studies of more recent periods have argued that interest rates in China have had substantial impacts on economic activity and that the monetary policy transmission mechanism in China is not too dissimilar from advanced economies (Fernald et al., 2014; IMF 2017c). Other studies have identified structural changes in estimated monetary policy rules for China that suggest that the PBoC has paid increased attention to inflation in recent periods (Burdekin and Skilos, 2008; Zhang, 2009; Xiong, 2012, Girardin et al., 2017).

Linked to this literature, there has been increasing attention on the role of credit in China's economy and the potential risks posed by the rapid increase in indebtedness. China's credit growth took off following the $4trn economic stimulus plan launched at the end of 2008. While the stimulus helped China withstand the Great Recession (Wen and Wu, 2014), the literature suggests the consequence of this credit surge was increased resource misallocation (e.g. Huang et. al, 2016; Bai et. al, 2016; Ansar et. al, 2016; Cong and Ponticelli, 2017). In addition, a number of papers have attempted to understand the role of credit and excess investment in shaping China's potential growth (Bailliu et al., 2016; Albert et al., 2015; Maliszewski and Zhang, 2015). Finally, many institutions have highlighted the important role of credit in driving China's growth over the past decade and the possible risks associated with this development (IMF 2017b; Dieppe et. al, 2018).

Less attention, however, has been given to the role of financial conditions in shaping China's business cycle – although the work of Breitenlechner and Nuutilainen (2017) is a recent exception. A fast growing literature has used sign restrictions to identify credit supply shocks for other economies (Busch et. al, 2010; Eickmeier and Ng, 2011; Peersman, 2011; Gambetti and Musso, 2012; Bijsterbosch and Falagiarda, 2014). However, to the best of our knowledge, this has not yet been applied to China. Typically in these models, the important identifying assumption separating a credit supply shock from a monetary policy shock is in the bank lending spread – measured as the difference between the rates set by central bank to conduct monetary policy and the (weighted-average) lending rate to the non-financial sector. Both a negative credit supply shock and contractionary monetary policy shock depress activity and lending volumes but a (restrictive) credit supply shock is associated with a widening of the bank lending spread. For China, however, such data are not available with a sufficient long run of data. But recent papers show that financial conditions indices can also help to identify credit supply shocks (Darracq et. al, 2014; Kapetanios et. al, 2017). Aikman et al. (2017) also use directly a financial conditions index to understand the role of financial shocks for the United States. A number of financial conditions indices have been estimated in the literature for China (for a survey see Zheng and Yu, 2014). We use the series of Wacker et. al (2014) to summarise financial conditions to help identify credit supply shocks in China.

Our results suggest that credit and financial conditions have played an important role in shaping business cycle fluctuations in China. Shocks to financial conditions and monetary policy have accounted for a significant proportion of variations in activity, inflation and credit in China. Moreover, our model underscores the important role of credit growth in supporting activity during the past decade. Counterfactual scenarios suggest that the surge in credit following the financial crisis contributed strongly to the recovery in output in 2009. Thereafter, although credit growth has slowed, it has nonetheless continued to support activity. The financial tightening since 2016, however, has contributed to a modest slowing of credit growth and activity. Conditional forecasts suggest that, were credit growth to continue at the same (relatively) subdued pace as recorded in the first part of 2017, the drag on activity could amount to about 0.5pp on annual GDP growth. Our main results are robust to a wide set of robustness checks such as using alternative measures of activity, inflation and credit, measuring China’s monetary policy differently or using different shock identification schemes.

The contribution of this paper, therefore, is twofold. First, we seek to understand the role of credit and financial conditions using this sign-restriction VAR framework. Second, in doing so, we provide an understanding of the role of credit and the financial sector in shaping economic developments in China over the past decade and highlight the potential effects of tighter credit availability for future prospects. Overall, the analysis highlights the possible tensions that may emerge in the government’s competing policy aims: efforts to address the leverage and risks accumulating in the shadow financing sector by tightening financial conditions seem likely also to affect the flow of credit to the non-financial sector which may jeopardise the pursuit of the government’s ambitious GDP growth targets.

2. Methodology

To understand the impact of financial tightening for China, we estimate a structural Bayesian VAR. The model links measures of activity, inflation and credit growth, to developments in monetary policy and financial conditions. To account for the potential influence of external developments, a measure of global activity and global commodity prices are included as exogenous variables.

The representation of the VAR model is given by equation (1):

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + CX_t + \varepsilon_t \text{ , where } t \quad = 1, 2, \ldots T \qquad (1)$$

where: y_t represents the vector of *n* endogenous variables, some of which are directly observed data series and others are estimated factors (see discussion below); X_t represents a vector of *m* exogenous regressors (including a constant); $A_1, \ldots A_p$ is the matrix of lagged influences (with dimensions *n x n*); C is the matrix of influences of the exogenous regressors (dimensions *n x m*); and ε_t is a vector of residuals following a multivariate normal distribution with mean 0 and variance Σ (with dimensions *n x n*).

To estimate the model we use Bayesian methods, described in more detail below, using the BEAR toolbox of Dieppe et al. (2016). We assume a Normal-wishart prior distribution to obtain the posterior estimates for equation (1) of the reduced-form parameters θ_p, ϑ, and errors u_t. The structural shocks are then identified using sign restrictions (see section iii).

In practice, our estimation proceeds in three steps: we first estimate the factors to be used in the model; we then include those and other directly observed variables in estimating equation (2); thereafter we use sign restrictions to identify the structural shocks in the model.

(i) Data and variable construction

China is an open economy with strong trade links, particularly through global supply chains, and heavy reliance on commodity imports. Ignoring the role of foreign variables in China's growth could therefore lead to mis-specification errors. Thus we include two exogenous variables to capture external influences on China's economy: an aggregate measure of world GDP growth (excluding China), weighted by GDP at purchasing power parities; and the IMF's commodity price index. In section 4 we explore the robustness of our results to excluding the exogenous variables them from the model.

For China's domestic variables, we use reported real GDP growth, the GDP deflator and a measure of credit provided to the non-financial sector from the BIS. This approach is motivated by a desire to understand the impact of shifts in financial conditions on macroeconomic aggregates of key interest (i.e. GDP). Worried by concerns about the quality of China's activity data, however, Fernald et al. (2014) adopted a different approach, summarising several indicators of economic activity with a principal component. That follows wide commentary on the reliability of China's national accounts data. Prominent Chinese political leaders have admitted to doubts: in 2007, Vice Premier Li Keqiang stated, "GDP figures are 'man-made' and therefore unreliable", suggesting it is more informative to follow developments in diverse indicators such as electricity production, rail cargo shipments and loan disbursements. On the other hand, Fernald and Spiegel (2015) validate the information content of China's GDP data against a range of external indicators (e.g. exports to China as reported by major trading partners) finding little evidence of significant manipulation or bias in China's GDP figures. That suggests that including published GDP figures in our VAR is appropriate. Nonetheless, in section 4 we explore the robustness of our results to alternative measures of activity and inflation in China that exploit a wider data set through principal component analysis.

A further challenge is dealing with changes in China's trend rate of growth. Compared to an average of around 10% during the 1990s and 2000s, the literature finds that China's potential growth has decreased to around 7-8% in recent years (Alberola et al. (2013); Bailliu et al. (2016); Albert et al. (2015); Maliszewski and Zhang (2015)). Bonomolo et al. (2017) note that not integrating this information into the model means that the deterministic coefficients and, hence the steady-state, will be entirely determined by the data which may result in long-term forecasts at odds with other evidence. In our benchmark estimation we capture the changing trends in China's GDP growth over our sample by measuring GDP growth as deviations from potential growth (i.e. the rate of GDP growth less the rate of potential growth). The estimates of potential in China are taken from a standard Cobb-Douglas production function (Manu, 2013). However, in section 4 we explore differences in our results using alternative estimates of trend growth.

To track changes in financial conditions we use an index from Wacker et al. (2014), which captures movements across a range of financial variables, including among others interest rates and interbank spreads, bond returns, and credit and equity flows. The index in Wacker et al. (2014) is constructed as the first principal component of the set of financial variables.[1] An important benefit of the approach used by Wacker et al (2014) is in its treatment of missing (or partially missing) data, using the Expectation Maximization algorithm (EMA) as proposed by Stock and Watson (2002a) which allows us to extend the index further back in time even when some data are not available. The series is shown in Annex 2 – an increase in the FCI denotes tighter financial conditions.

Measuring the monetary policy of the PBoC is complicated by the fact that the central bank has used a variety of instruments, directed towards a number of goals. The PBoC's instruments include price and quantity tools. And it has used those instruments towards both monetary policy goals but also financial stability and macro-prudential concerns. To capture appropriately the separate components of monetary policy and financial stability policy, we need to consider carefully how to represent policy.

[1] Note that Wacker et al. (2014) propose two FCIs: an unconditional index and a conditional index. The latter is the principal component of financial variables that have first been purged of business cycle effects through regressions on GDP and inflation. In this study we use the unconditional FCI which is the first principal component of the financial series.

Various approaches have been taken in the literature. Fernald et al. (2014) use the PBoC's benchmark 1-year interest rates in their VAR model for China. That has the benefit of simplicity but it potentially excludes developments in other instruments the PBoC employs. Other studies suggest that the 7-day interbank rate provides a good 'shadow' measure of Chinese monetary policy (IMF 2017c). Certainly, that is consistent with most recent policy: the PBoC has communicated that is increasingly using short-term interest rates to signal policy changes principally through the 7-day repo rate (PBoC, 2016), with the 7-day interbank rate viewed as the appropriate operating target. At the same time, interbank rates variations have also reflected other factors not directly related to monetary policy – including endogenous shifts in liquidity demand in the financial sector, and other aspects of policy such as macro-prudential and financial stability measures. For our research, we aim to separate these factors, isolating the role of monetary policy and financial conditions shocks.

Given these concerns, we chose to follow the approach of Girardin et al. (2017) and use a summary index of monetary policy that combines changes in the different policy instruments in a consistent manner to form a comprehensive 'shadow monetary policy rate'. Building on the work of He and Pauwels (2008), Xiong (2012), and Girardin et. al. (2017), we construct an index which translates changes in each monetary instrument into an equivalent basis point change in the policy interest rate and then aggregates them to a single index. Girardin et al. (2017) constructed their monetary policy index (MPI) thus: a 50 basis point reserve ratio requirement change is judged to be equivalent to a 27 basis point change in the policy rate; net liquidity withdrawals / injections from open market operations (OMO) and bank bill issuance above a threshold of RMB 200bn/350bn/500bn are judged to be equivalent to a 27/54/81 basis point tightening (loosening) of policy respectively; finally the effects of window guidance are approximated by unusual loan growth developments (with large shifts in credit growth associated with periods of easing policy). Our approach is detailed in Annex 1. It broadly follows Girardin et al. but we differed from their approach in two important respects. The deviations reflect our desire to differentiate between changes in monetary policy and broader shocks to financial conditions. That requires us to make some choices about which instruments to include in our MPI. This particularly applies to the role of quantity-based instruments such as bank bills, OMOs and liquidity facilities. Although they can be interpreted as signalling changes in the monetary policy stance, in the past, they have also been used to influence wider financial conditions – for example, when interbank rates soared during the mid-2013 credit squeeze. Because of the ambiguous nature of these instruments, we construct two versions of our MPI: (1) a *narrow MPI* only based on the rate-based instruments, which we use in our baseline model; and (2) *a broader MPI* which also includes the quantity-based instruments, which we use in our sensitivity analysis in section 4. Finally, in neither MPI do we include informal credit quota (or "window guidance"). This is an instrument unambiguously geared towards influencing wider credit conditions and should be captured by our FCI.

The model is estimated at a quarterly frequency over the period 2001Q1 to 2017Q2. Given concerns about some seasonality in Chinese data, variables are expressed in year-on-year growth rates, except for the monetary policy and financial conditions indices which are included in differences (see Annex 2).[2] We limit the lags (*p*) to four.

(ii) Bayesian estimation of VAR model

To estimate the model we use Bayesian methods. To obtain the posterior estimates for equation (2), we use a Normal-Wishart prior (see Kadiyala and Karlsson (1997)), which is a natural conjugate prior that assumes a normal distribution for the VAR coefficients and an inverse-Wishart distribution for the covariance matrix.

Following Dieppe et al (2016), equation (1) can be reformulated as:

$$y = \bar{X}\beta + \varepsilon \tag{2}$$

where

$$Y = \begin{bmatrix} y_1' \\ y_2' \\ \dots \\ y_T' \end{bmatrix}, X = \begin{bmatrix} y_0' & y_{-1}' & \dots & y_{1-p}' & x_1' \\ y_1' & y_0' & \dots & y_{2-p}' & x_2' \\ \dots & \dots & \dots & \dots & \dots \\ y_{T-1}' & y_{T-2}' & \dots & y_{T-p}' & x_T' \end{bmatrix}, B = \begin{bmatrix} A_1' \\ A_2' \\ \dots \\ A_P' \\ C \end{bmatrix}, \text{and } \upsilon = \begin{bmatrix} \varepsilon_1' \\ \varepsilon_2' \\ \dots \\ \varepsilon_T' \end{bmatrix}$$

and

$$y = vec(Y), \bar{X} = I_n \otimes X,\ \beta = vec(B),\ and\ \varepsilon = vec(\upsilon)$$

and

$$\varepsilon \sim N(0, \bar{\Sigma}),\ and\ \bar{\Sigma} = \Sigma \otimes I_T$$

The likelihood function $f(y|(\beta, \Sigma)$ can be written as:

$$f(y|(\beta, \Sigma) \propto |\bar{\Sigma}|^{-1/2} exp\left[-\frac{1}{2}(y - \bar{X}\beta)'\bar{\Sigma}^{-1}(y - \bar{X}\beta)\right] \tag{3}$$

[2] We noted different approaches in the literature. Darracq et. al (2014) use the FCI and interest rates in levels; Kapetanious and Price (2017) include these variables in differences. The results of our model were largely unchanged depending on this choice.

For β we assume a multivariate normal distribution for the prior

$$\pi(\beta) \sim N(\beta_0, \Sigma \otimes \Phi_0) \tag{4}$$

Litterman (1986) suggested that for unit root variables an appropriate choice for $\beta_0$would be a value of 1. In our VAR, variables are expressed in year-on-year percentage changes or year-on-year changes – we therefore choose a prior for the elements of β_0 related to the first own lags of a variable of 0.8. For coefficients on further lags, cross-variable lag coefficients and exogenous variables we set the prior to zero.

The variance-covariance matrix $\Sigma \otimes \Phi_0$ is assumed to be diagonal. Σ is a diagonal matrix with each diagonal set to the residual variance of individual AR models run on each variable in the VAR. For Φ_0, we follow the strategy of Karlsson (2012) and, using the terms set out in Dieppe et al (2016), assume that for parameters in β relating to their own lags and cross-term lags, the variance is given by:

$$\sigma^2_{a_{ii}} = \left(\frac{1}{\sigma_j^2}\right)\left(\frac{\lambda_1}{l}\right)^2$$

where l is the lag considered and λ_1 is an overall tightness parameter, and σ_j^2 denotes the residual variance of an autoregressive model for variables j.. The parameter $\lambda_1$governs the tightness of the prior. A lower value of $\lambda_1$entails a tighter prior, implying a greater weight is placed on the prior beliefs relative to the data. A higher value of $\lambda_1$by contrast means a looser prior and entails that the posterior estimates depend more on data. The use of the lag term l also means that prior parameter variances become tighter around zero as the lag length increases. As is common in the literature, we choose for λ_1 a value of 0.1.

For exogenous variables, we define the variance as:

$$\sigma_c^2 = (\lambda_1 \lambda_4)^2$$

where λ_4 is set to 100.

Thus the prior density for β is:

$$\pi(\beta) \propto |\Sigma|^{-(np+m)/2} exp\left[-\frac{1}{2}(\beta-\beta_0)'(\Sigma \otimes \Phi_0)^{-1}(\beta-\beta_0)\right] \tag{5}$$

For Σ the prior distribution is assumed to be an inverse Wishart distribution:

$$\Sigma \sim IW(S_0, \alpha_0)$$

where, following Karlsson (2012), S_0 is defined as a diagonal covariance matrix with diagonal elements defined as the residual variance of individual AR models run on each variable in the VAR and α_0 is set to *n*+2.

Thus the prior density for Σ is given by:

$$\pi(\Sigma) \propto |\Sigma|^{-(\alpha_0+n+1)/2} exp\left[-\frac{1}{2}tr(\Sigma^{-1}S_0)\right] \tag{6}$$

It is possible to show that the posterior distribution for Σ formed by combining this prior distribution with the likelihood function is also a normal-inverse Wishart distribution, and the posterior distribution for β (conditional on Σ) is a multivariate normal distribution.

(iii) Identification with sign restrictions

To recover the structural shocks, we use sign restrictions on the impulse response functions, implementing the technique of Arias et al. (2014). This approach implies using the Choleski factorisation on the variance-covariance matrix Σ of the reduce-form residuals (ε_t) to obtain a P matrix and drawing an orthonormal matrix Q from a Haar-uniform distribution. Once P and Q are obtained, the authors propose an algorithm that makes a candidate draw for the impact matrix in the form of P * Q (that maps posterior-reduced form parameters into unrestricted posteriors), checks whether the sign-restrictions are fulfilled and retains only those draws for which the restrictions are satisfied. We then run the algorithm until we have 10,000 draws that satisfy these criteria.

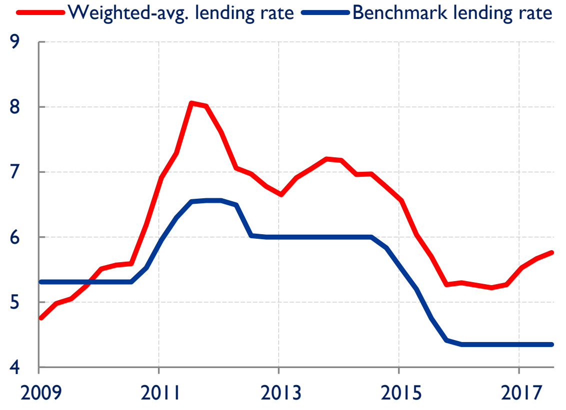
We distinguish four structural shocks: an aggregate demand, aggregate supply, monetary policy and financial conditions shocks (Table A). All the restrictions are imposed on impact. While the focus of this paper is the role of financial shocks and monetary policy, the identification of additional shocks can contribute to a better identification of those shocks under scrutiny. The restrictions put on the aggregate demand, supply and monetary policy shocks draw from standard IS/LM models. Expansionary aggregate demand shocks are assumed to raise output, inflation and the monetary policy interest. Aggregate supply shocks drive GDP and inflation in opposite directions. An expansionary monetary policy shock – i.e. a decline in the monetary policy index – has a positive impact on real GDP, inflation and credit growth.

Table A: Sign restrictions

	Aggregate Supply	Aggregate Demand	Monetary policy	Financial conditions
GDP	+	+	+	+
Consumer price inflation	-	+	+	+
Monetary policy index		+	-	+
Financial conditions index		+		-
Credit growth		+	+	+

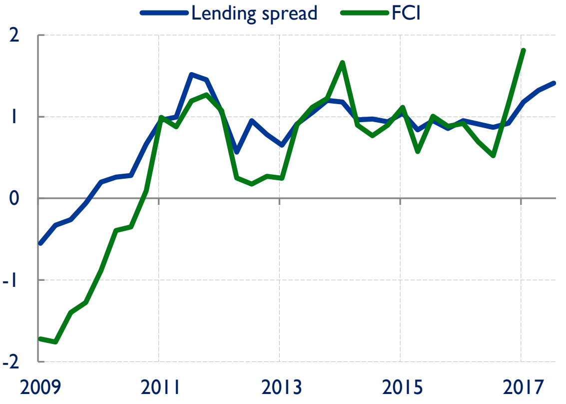
Our identification of shocks to financial conditions starts from the approach taken in the literature in examining credit supply shocks. Busch et al. (2010) assume that a positive credit supply shock is associated with a decline in the lending rate to non-financial corporations that boosts activity and triggers a tightening of the monetary policy rate – in effect, the lending spread narrows. However, this approach relies on having data for the composite lending rate for the non-financial sector. Such data are available for China only from 2009. To overcome this problem Breitenlechner and Nuutilainen (2017) use monthly PBoC statistics on the share of loans priced above/below the benchmark lending rate to proxy average lending rate. Our approach uses instead the information available in financial conditions indices (FCIs), follow Darracq et al. (2014) who use FCIs in an SVAR as a means to help the identification of credit supply shocks (see also Kapetanios et al., 2017). This approach assumes that a positive credit supply shock is associated with a softening of the financing environment (and a loosening of the FCI) which boosts activity, raises credit volumes and triggers a tightening of the monetary policy rate. Aikman et al. (2017) also use an FCI for the United States to identify shocks to financial conditions which they judge as representing the ease of access to credit which affects economic behaviour. They offer three structural interpretations for such a shock: a time-varying risk premia of investors determined by bank capital constraints; endogenous reactions of financial intermediaries to episodes of low volatility; or a change in the perceived dispersion of investment project returns. As Charts 3 and 4 show, there is a very close correlation between the lending spread and the financial conditions index over the period 2009-2017. That would suggest that the FCI has also provided a good guide to the lending rates for the non-financial sector and should help us to identify shocks that represents shifts in the ease of credit access for broader Chinese economy.

Chart 3: Interest rates
(percent)



Source: BIS and NBS

Chart 4: Lending spread and FCI
(FCI – standardised index; percent)



Sources: People's Bank of China, National Interbank Funding Centre. Notes: Lending spread is difference between weighted average lending rate and PBOC benchmark rate. A rise in the FCI indicates a tightening of financial conditions.

3. Results

(i) Impulse responses and forecast error variance decomposition

Chart 5 shows the impulse response function of the five variables to a one standard deviation of the identified shocks. The charts plot the median of the accepted draws together with the 16% and 84% confidence bands. The signs of the impulse response functions are restricted on impact through the use of the sign restriction method in line with table A. However, most effects persist for at least a few quarters and frequently for significantly longer.

Chart 5: Impulse responses

Notes: dotted lines represent 68% posterior error bands

An easing of financial conditions is associated with an increase in activity and lending volumes. These are both restricted on impact, but the effect is sustained for some quarters afterwards. Following the financial conditions shock, inflation also rises (although the effect is marginal as shown by the lower confidence band), suggesting that easing financial conditions appears to act on inflation through channel of expanding demand. Following an accommodative monetary policy shock, both GDP and the GDP deflator rise. Lending volumes also increased.

Table B shows the forecast error variance decomposition, after 12 quarters. Financial conditions shocks account for about 14% of the variation in activity fluctuations. They account for a larger proportion of inflation variations. In addition, financial conditions have accounted for close to one third of forecast error variance for our monetary policy index. Financial conditions shocks have accounted for a relatively smaller proportion of credit growth variance, with aggregate demand and supply shocks playing a greater role.

Table B: Forecast error variance decomposition

	Aggregate Supply	Aggregate Demand	Monetary policy	Financial conditions	Other
GDP	21.3%	14.3%	11.1%	14.3%	13.5%
GDP deflator	14.5%	17.5%	17.5%	27.6%	11.4%
Monetary policy index	9.8%	31.0%	7.1%	34.0%	7.6%
Financial conditions index	9.2%	29.3%	13.2%	20.5%	8.8%
Credit growth	16.2%	9.7%	11.9%	12.0%	23.9%

(ii) Shocks contributions – a historical decomposition

Based on the orthogonalised impulse responses and estimated structural shocks, one can estimate the contributions of the shocks to each variable, as shown in Chart 6. The historical decomposition emphasises the important role of credit developments and financial conditions during the global recession in 2009. The model suggests that from 2007 onwards, China's activity was affected by a combination of aggregate demand and supply shocks, as well as a tightening of financial conditions. The tightening of financial conditions is visible in a sharp reduction in lending growth (relative to the steady state). However, the effect is relatively short-lived. As China launched the large stimulus in 2009, lending volumes recovered and the contribution of the financial tightening on China's activity is reversed. Swift monetary policy action also helped boost activity during this period. As a consequence China's GDP recovered strongly through 2009 and 2010.

Chart 6: Historical decomposition

(estimated contributions to variables – deviations estimated steady state)

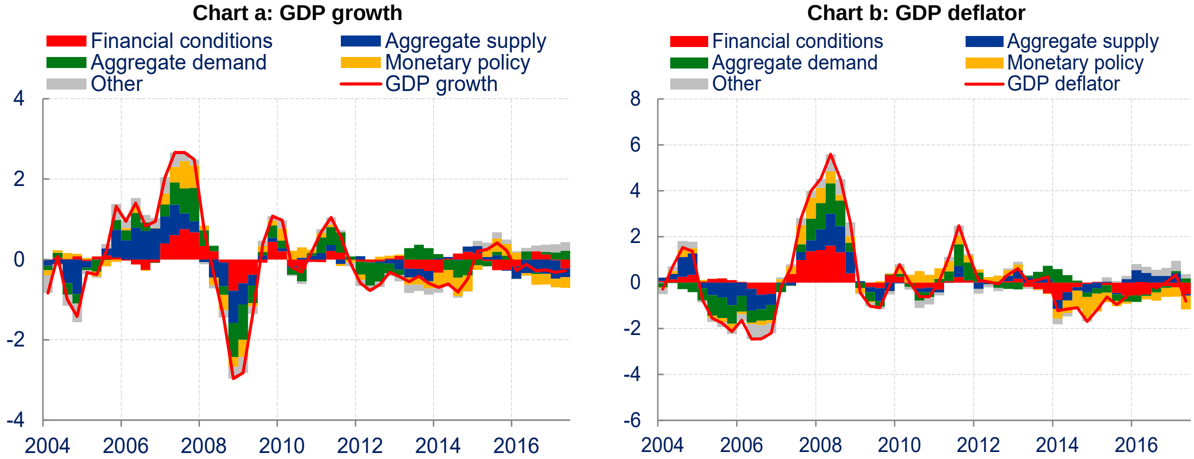


Chart 6 (cont.): Historical decomposition

(estimated contributions to variables – deviations estimated steady state)

Chart c: Monetary policy index

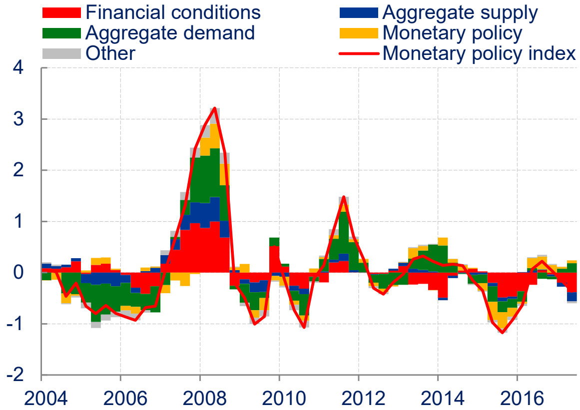


Chart d: Financial conditions index

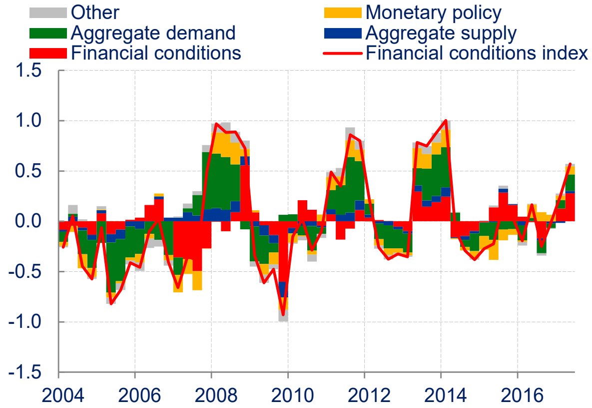
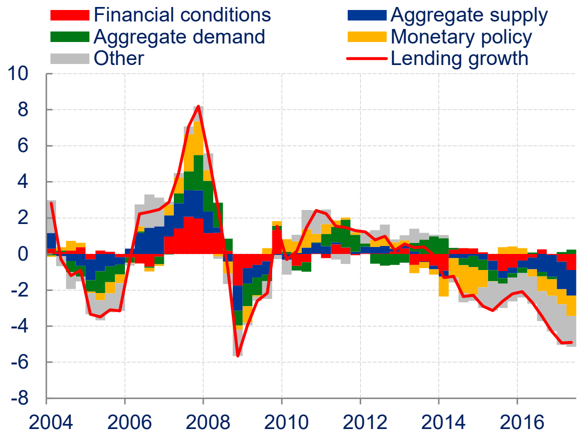


Chart e: Lending growth



Notes: Estimated contributions to each variable. Variables are expressed as deviations from estimated 'exogenous' component which includes the steady state and the effect of exogenous variables (world GDP and commodity prices)

In the two years after the initial post-crisis rebound, financial conditions played a less prominent role in shaping business cycle developments. There were pronounced fluctuations in financial conditions during this period (as summarised by the financial conditions index), but the model emphasises that they were mainly an endogenous response to changes in aggregate demand conditions rather than driven by specific financial shocks. In particular, this period saw pronounced swings in the housing market which may have accounted for activity and financial market shifts. However, from 2013 onwards, financial conditions shocks have played again a more prominent role. In particular, financial tightening is visible from mid-2015 onwards. This was a period when China suffered from sharp equity price declines, exchange rate volatility and capital outflows. Lending volumes also moderated somewhat during this period. Some monetary easing helped to support activity. But the renewed financial tightening towards the end of 2016 has again acted as a small drag on output in China.

(iii) Conditional scenarios – the role of credit since the global financial crisis

The historical decomposition underscores the role of credit growth in driving business cycle developments over the past decade. However, by its nature, such a decomposition emphasises the role of shocks to variables in deviations from the estimated steady state. For China, that means a steady state which has encompassed a significant increase in credit over our sample period: since 2007 China's debt-to-GDP ratio has risen by 110pp. To understand the role of this sharp increase in credit in shaping developments in output in China, we compare two conditional forecasts. Lenza et al. (2010) and Kapetanios et al. (2012) use a similar approach to analyse the effects of quantitative easing in the euro area and UK respectively. However, they use a reduced form approach in which the path of restricted variable is obtained through the contribution of all the possible structural shocks. By contrast, we employ a strategy in which restrictions on specific structural shocks generate the expected path of the conditioned variable. In particular, we form forecasts conditional on a path for credit growth and attribute these developments to financial conditions shocks.[3] We then observe the GDP forecast with credit growth at this predetermined rate, restricting the financial conditions shocks in such a way that it generates the desired path for credit growth (see Waggoner and Zha 1999 who derive a Gibbs sampling algorithm to construct the posterior predictive distribution of the conditional forecast; with details described in Dieppe et al. 2016).

Our conditional forecasts compare two scenarios. In the first, we forecast GDP and inflation from 2008 onwards based on the *actual* path of credit growth. We compare this with a counterfactual *'low credit'* scenario in which credit is assumed to have increased at the pace of potential GDP growth. The assumption for credit growth is relatively extreme – a difference of more than 20pp of growth in some periods – but it can help illustrate the role of credit in driving China's development in the past decade.

Chart 7 shows the assumed paths for lending growth and the conditional forecasts for GDP and inflation on that basis. An assumption of lower credit growth over the past decade would have resulted in significantly lower real GDP growth over that period. In particular, the surge in credit following the financial crisis contributed strongly to the recovery in output in 2009. The scenarios suggest that, concerns about the long-term implications of the post-crisis response notwithstanding (see Huang et. al, 2016; Bai et. al, 2016; Cong and Ponticelli, 2017), in the narrow sense of helping China "withstand recession" (Wen and Wu, 2014), the $4trn stimulus worked. Thereafter, although credit growth has slowed, it has nonetheless continued to support activity. The model attributes an even larger impact to inflation, with the GDP deflator falling into deflation during 2008 and again in 2011. Overall, the impact on nominal output is large.

[3] In setting this scenario, we also assume that monetary policy is unchanged. That is, we keep monetary policy at observed values in both scenarios.

Chart 7: The role of credit in driving activity in China since the financial crisis

Chart a: Conditional paths for credit growth
(year-on-year percentage change)

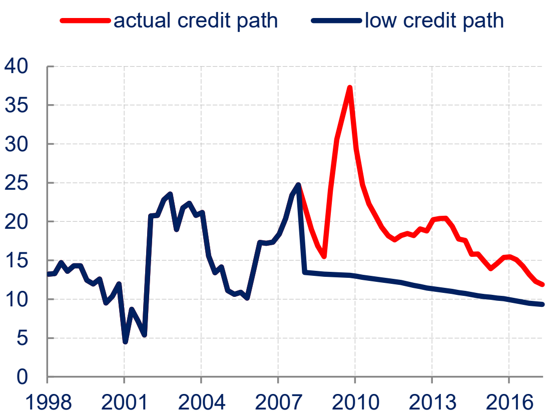


Chart b: Conditional paths for GDP growth
(year-on-year percentage change – deviations from potential growth; and percentage point contributions)

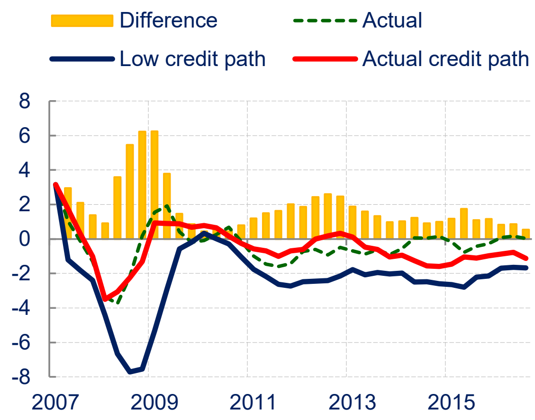
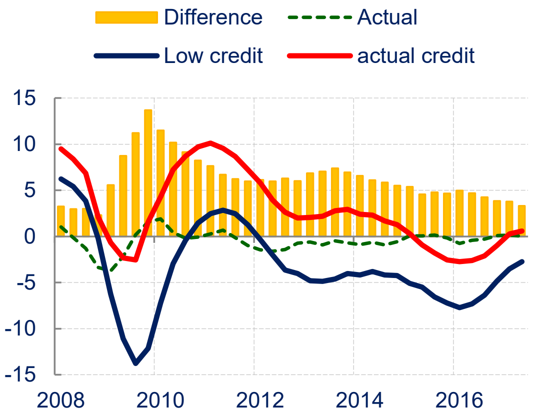


Chart c: Conditional paths for GDP deflator
(year-on-year percentage change)



Notes: Chart 7a shows conditional paths for credit growth in two scenarios. Chart 7b shows the deviation of actual GDP growth from potential growth (blue line); the conditional forecast for GDP growth based on actual credit developments (green dotted line); and the conditional forecast for GDP growth based on the low credit scenario (red line). The yellow bars show the difference in the conditional paths for GDP growth under the two scenarios. Chart 7c shows the results for the GDP deflator.

Notably, all these scenarios imply that the credit-to-GDP ratio would continue to increase. According to the unconditional projection, credit would rise from 256% to 293% of GDP by the end of 2019. Even the “declining credit growth” scenario would mean that debt would increase relative to GDP. This reflects the characteristics of China’s economy which the model is capturing. In almost every year of the past two decades, credit has outpaced nominal GDP. That means the steady state of the model is for a trend increase in the credit-to-GDP ratio. In these scenarios, even as credit growth falls, nominal GDP growth is pushed even lower, meaning that the credit-to-GDP ratio continues to rise. One implication of these scenarios, therefore, is that China cannot address the problems of rapidly increasing indebtedness simply by depressing activity. Indeed, our model highlights the reliance of China on continued increases in leverage to support high rates of economic expansion, which has been highlighted as a key medium-term vulnerability for the Chinese economy. As Dieppe et. al (2018) discusses, addressing meaningfully concerns about financial stability and rising indebtedness would need a fundamental rebalancing of the Chinese economy that would make GDP less reliant on credit (i.e. a shift in the steady state). The analysis of these issues is beyond the scope of our model.

Chart 8: The role of credit in driving activity in China since the financial crisis

Chart a: Credit growth scenarios

(year-on-year percentage change)

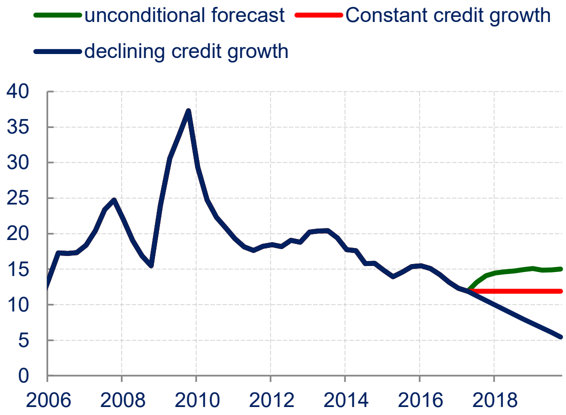
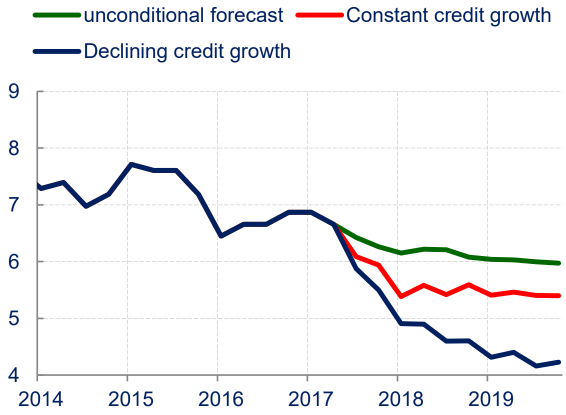


Chart b: Conditional forecasts of real GDP growth

(year-on-year percentage change)



4. Sensitivity analysis

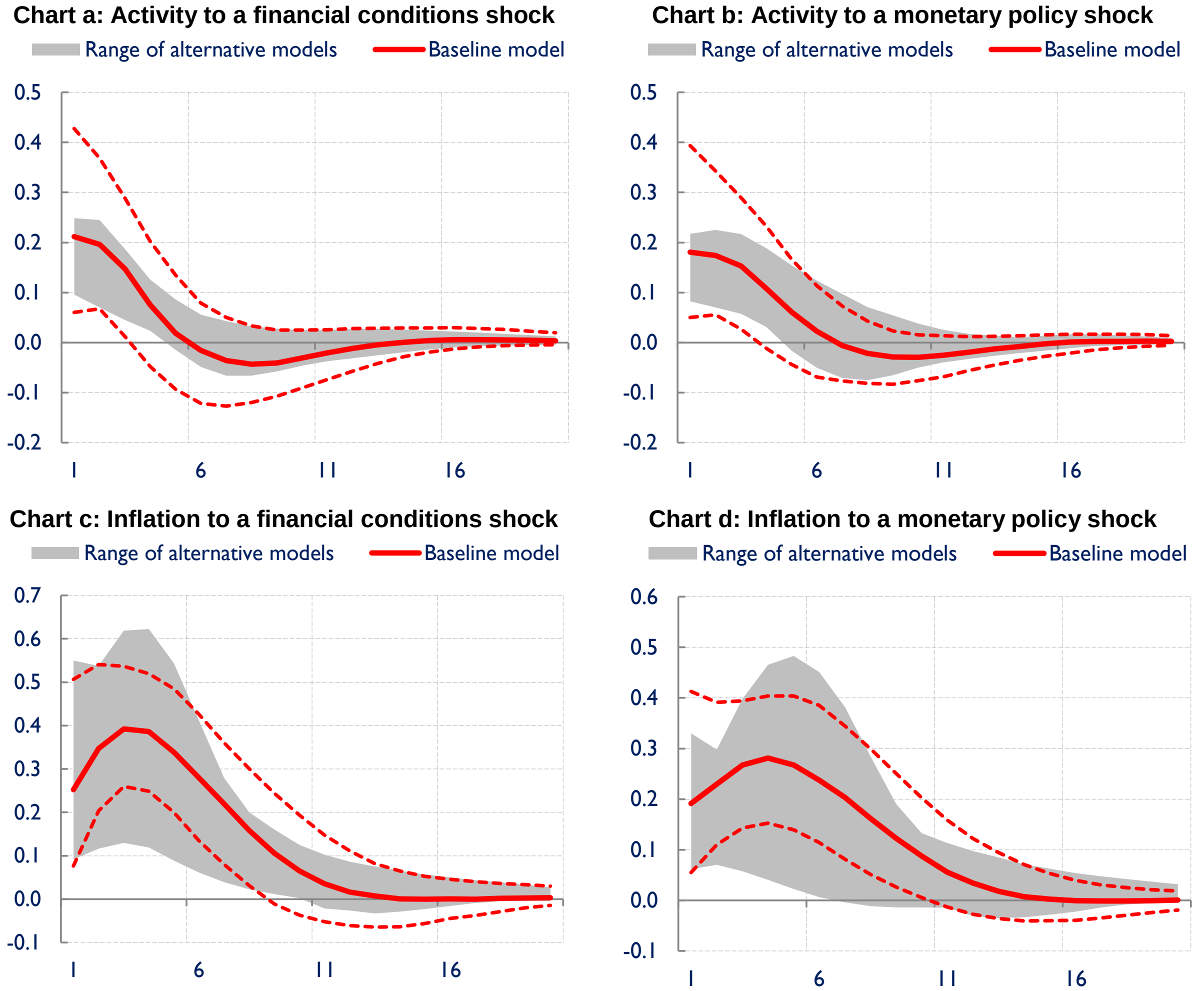
As discussed in section two, there are uncertainties about the appropriate choice of variables for China and the appropriate means of identifying the model. In this section we examine the sensitivity of our results to a number of changes in the basic set-up of our model. In more detail, we assess the implications for the model of: (i) using alternative measures of activity, inflation and credit in China; (ii) the role of de-trending GDP growth; (iii) using a different representation of monetary policy or financial conditions; and (iv) the role of exogenous variables. In each case, the model is identified through the sign restrictions shown in Table A. In the final part of this section, we examine the effects of some modifications to the sign restriction assumptions in our baseline model.

We evaluate these changes by comparing the impulse responses and the historical contributions of the financial conditions and monetary policy shocks for economic activity and inflation. In each case detailed charts are shown in annex 3. Overall, however, we find that our model and our conclusions about the role of financial shocks in China's business cycle are pretty robust to these changes. Chart 9 summarises the range of IRFs over the various alternative models we estimate in this section. Chart

10 shows the estimated contributions of financial conditions and monetary policy shocks to the historical decompositions for GDP and inflation. In almost all cases, the range of estimates from these alternative models is broadly in line with the baseline model. The following paragraphs elaborate on this sensitivity analysis.

Chart 9: Impulse responses – summaries over alternative models

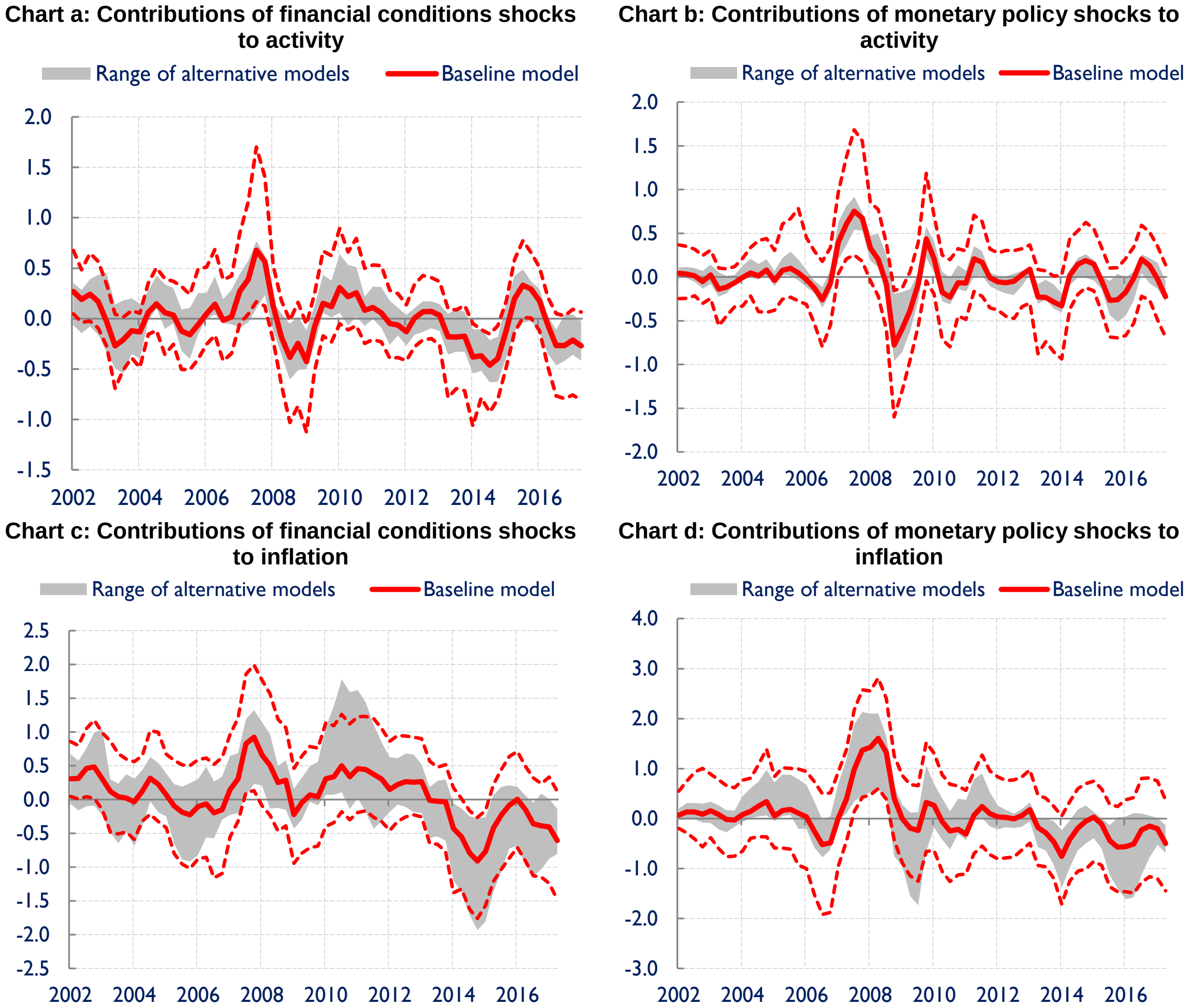
(ranges of estimates of impulse responses from sensitivity analyses conducted in section 4)



Notes: Estimated impulse responses for each variable. Dotted lines represent 68% posterior error bands for baseline model. Grey ranges summarise the estimated historical contributions for each shock over the range of estimated models in section 4, including: (i) using alternative measures of activity and inflation in China; (ii) the role of de-trending GDP growth; (iii) different representation of monetary policy or financial conditions; (iv) the role of exogenous variables; and (v) using alternative sign restrictions to identify the model. See text of section 4 for elaboration.

Chart 10: Contributions of financial conditions and monetary policy shocks to GDP and inflation summaries over alternative models

(ranges of contributions of each shock to deviations of GDP and inflation from steady state from sensitivity analyses conducted in section 4)



Notes: Estimated contributions to each variable. Variables are expressed as deviations from estimated ‘exogenous’ component which includes the steady state and the effect of exogenous variables (world GDP and commodity prices). Dotted lines represent 68% posterior error bands for baseline model. Grey ranges summarise the estimated historical contributions for each shock over the range of estimated models in section 4, including: (i) using alternative measures of activity and inflation in China; (ii) the role of de-trending GDP growth; (iii) different representation of monetary policy or financial conditions; (iv) the role of exogenous variables; and (v) using alternative sign restrictions to identify the model. See text of section 4 for elaboration.

(i) Alternative measures of activity, inflation and lending

For China’s domestic variables, we used reported real GDP growth and the GDP deflator. However, other authors choose to exploit a wider range of activity indicators with a principal component, suggesting that this can better capture underlying developments in China’s economy (see Fernald et al. (2014)). It is also notable that measures of inflation in China have varied substantially in the past –

while producer prices were low for a prolonged period after 2012, consumer price inflation was more stable. Finally, there are a number of possible measures of credit for China such as M2, bank lending and the authorities' measure of 'total social financing'.[4] We explore the robustness of our results to these alternatives. First, we estimate the model including a measure of activity that uses the first principal component of a wider set of indicators instead of real GDP. Second we estimate the model including consumer or producer price inflation instead of the GDP deflator. Third, we estimated the model including alternative measures of credit: M2, bank assets, bank lending, and total social financing.

Neither adjustment makes a material difference to our estimated model. The model estimated with a principal component activity indicator leads to similar impulse response functions for both economic activity and inflation (Chart C1). The same is true when comparing the historical decompositions of shocks to financial conditions and monetary policy shocks of both models, which are almost identical for both models (Chart C2). Substituting the GDP deflator in the baseline model with either consumer or producer price inflation also does not significantly alter the impulse response functions (Chart C3), although we find that PPI inflation tends to respond more sharply to monetary and financial conditions shocks than either CPI or the GDP deflator. Alternative measures of aggregate credit for the economy also show very similar impulse response functions (Chart C4).

(ii) The role of de-trending of GDP

A second issue is to explore the implications of different assumptions about China's trend rate of growth. As discussed in section 2, China's potential growth has decreased over the past decade. Consequently, we de-trended GDP growth in our benchmark estimation using estimates of potential growth in China taken from a standard Cobb-Douglas production function (Manu, 2013). To understand the implications of this choice, we make two adjustments. We first re-run the model using an alternative measure of trend growth from an HP filter. We estimate trend GDP with an HP filter (with a lambda of 1,600), calculate the year-on-year growth rates and subtract these figures from actual GDP growth. Second, we estimate a model in which GDP growth is not de-trended.

The impulse response functions of both alternative specifications are very similar to the baseline model, in particular with regard to the response of inflation. The response of economic activity to a monetary policy or financial conditions shock is slightly more persistent in the model using actual rather than de-trended GDP (Chart C5). Inevitably, the model using actual GDP growth also shows a larger deviation from the estimated steady state towards the end of the sample period (Chart C6). This alternative model attributes much of this decline in real GDP relative to steady-state to aggregate supply shocks (blue bars in Chart C6). The estimated contributions of the financial conditions and monetary policy shocks over this period, however, are very similar to the baseline model.

[4] This point was made to us during helpful discussions with representatives of the PBoC.

(iii) Different representation of monetary policy or financial conditions

The variety of instruments used by the PBoC to enact monetary policy presents problems in representing appropriately monetary policy in our model. In the baseline model, we followed broadly the approach of Girardin et al. (2017) in constructing a summary index of monetary policy. To investigate the implications of this choice, we run the model using different variables to represent monetary policy. First, we take a narrow representation of monetary policy and include only the 1-year benchmark lending rate. Second, we take a more encompassing approach and include the broader monetary policy index described in Annex 1. As discussed in section 2, we did not include the effects of net liquidity withdrawals (injections) from open market operations (OMO) or liquidity facilities in our monetary policy index. We investigate the robustness of the results to the inclusion of a broader monetary policy index that accounts for these instruments. Neither adjustment makes a material difference to our estimated model. The model estimated with a either the benchmark 1-year lending rate or our broader monetary policy index have similar impulse response functions for both economic activity and inflation (Chart C7).

A second important issue is to examine alternative representations of financial conditions in China. In our baseline model, we have used a broad index which summarises movements across a range of financial variables, including among others interest rates and interbank spreads, bond returns, and credit and equity flows. As a check on our results, we investigate the effects of using a narrower measure of financial conditions using only the 1-month SHIBOR rate.[5]

A related issue is our use of financial conditions index which we use to identify shocks to financing conditions in the broader non-financial sector. As discussed, Busch et al. (2010) model credit supply shocks by incorporating measures of lending rates to non-financial corporations. They assume that a positive credit supply shock is associated with a decline in the lending rate to non-financial corporations that boosts activity and triggers a tightening of the monetary policy rate. For China, data for the composite lending rate for the non-financial sector is available only from 2009. To understand the implications of using this alternative series, we estimate a model substituting the FCI with the weighted-average lending rate for China. The model is therefore estimated over a short sample for estimation, but we conduct the exercise nonetheless to examine the consistency of our results with this alternative approach.

Chart C8 shows the impulse responses from these alternative specifications. Using SHIBOR instead of the financial conditions index makes limited difference to the impulse responses. The model estimated using the weighted average lending rate suggests that GDP and inflation are less responsive to financial conditions and monetary policy shocks – the 68% intervals are still different from zero but the response of the real economy to these shocks is more subdued. However, that

[5] In China, interbank refers to a broader repo-market that reflects transactions between both depository institutions and non-bank financial institutions, so interest rates in this market should reflect financial conditions in the banking and non-bank (including the shadow-financing) sectors.

appears to reflect the different time period used – data availability means that it can only be estimated from the first quarter of 2010. Re-running the baseline model over this period provides very similar impulse responses – i.e. a more subdued response of GDP and the GDP deflator to these shocks (impulse responses not shown). It is difficult to draw strong conclusions with sample periods that cover only 8 years. But one implication could be that the responses we find over our baseline model are influenced by the fluctuations in China's economy around the global financial crisis. Once these are excluded from the model, we find more limited effects from financial and monetary shocks. That is consistent with the recent work of Aikman et al. (2017) which document non-linearities in the role of financial conditions shocks in the United States.

(iv) The role of exogenous variables

A fourth robustness check is to understand the role played by the exogenous variables in our model. China is an open economy suggesting that it is important to include external variables in any model describing China's business cycle. However, some papers take as their baseline a model without external variables (e.g. Fernald et. al (2014)). Thus we explore the robustness of our results to excluding them from the model. Overall, we find that the impulse responses of GDP to the financial conditions and monetary policy shocks is largely unaffected by excluding exogenous variables from the model. However, we see a more pronounced response of inflation to both shocks in the absence of exogenous variables (Chart C9).

(v) Alternative identification scheme

We check the robustness of our results by modifying the sign restriction identification. A first change we make is to relax the restriction on the response of inflation to a financial conditions shock. The identifying restrictions imposed by both Busch et al. (2010) and Bijsterbosch and Falagiarda (2014) require that inflation increases following an expansionary credit supply shock. However, Gambetti and Musso (2012), argue that the effect on inflation is uncertain. While increased investment and consumption demand could heighten inflationary pressures, the lower financing costs for the non-financial sector could imply stronger supply potential, dampening price pressures. Thus we investigate the implications of relaxing this restriction. Chart C10 shows that the reaction of inflation to the financial conditions shock is broadly similar to our baseline model. On impact, inflation is largely unaffected by the financial conditions shock but in the following quarters, we see a rise in inflation in China. That is consistent with the view provided by our baseline model that the impact on aggregate demand outweighs the supply response – looser financial conditions tend to boost demand which increases inflationary pressures.

In a second check, we examine a model in which we identify only the financial conditions / credit supply and monetary policy shocks (following Darracq et al., 2014). While the identification of the aggregate supply and demand disturbances can help the identification of our shocks of interest (the financial conditions and monetary shocks), it is useful to observe whether our findings are consistent with a narrower structural perspective. As Chart C10 shows, the impulse responses from our model in which we identify only these two shocks are very similar to our baseline model.

5. Conclusions

This paper presents empirical evidence of the role of financial conditions in China's business cycle. We find that monetary policy, credit and financial conditions have played an important role in shaping China's business cycle over the past two decades. We also use conditional scenarios to examine the role of credit in shaping economic outcomes in China. Those scenarios underscore the important role of credit growth in supporting activity during the past decade, particularly the surge in credit following the global financial crisis in 2008. The financial tightening since the end of 2016, has contributed to a modest slowing of credit growth and activity. Overall, the analysis highlights the possible tensions that may emerge in the government's competing policy aims: efforts to address the leverage and risks accumulating in the shadow financing sector by tightening financial conditions seem likely also to affect the flow of credit to the non-financial sector which may jeopardise the pursuit of the government's ambitious GDP growth targets.

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Annex 1: Constructing a monetary policy index for China

Measuring the monetary policy of the PBoC is complicated by the fact that the PBoC uses different instruments simultaneously, including interest rates as well as quantity-based instruments, and has allowed the relative importance of those instruments to change over time. In order to capture changes in monetary policy, we construct a composite Monetary Policy Index (MPI) similar to Girardin et. al (2017). The aim is to combine monthly changes in the different monetary policy instruments in a consistent manner to form a comprehensive 'shadow monetary policy rate', summarising the range of instruments used by the PBoC. Table A1 lists the different interest-rate based and quantitative monetary policy instruments that can potentially be included into our MPI.

In our model, we aim to differentiate between changes in monetary policy and broader shocks to financial conditions. That requires us to make some choices about which instruments to include in our MPI. This particularly applies to the role of quantity-based instruments such as bank bills, OMOs and liquidity facilities. Although they can be interpreted as signalling changes in the monetary policy stance, in the past, they have also been used to influence wider financial conditions – for example, when interbank rates soared during the mid-2013 credit squeeze. Because of the ambiguous nature of these instruments, we construct two versions of our MPI: a narrow MPI only based on the rate-based instruments; and a broader MPI which also includes the quantity-based instruments. Note that in neither MPI do we include informal credit quota (or "window guidance"). This is an instrument unambiguously geared towards influencing wider credit conditions and should be captured by our FCI.

Table A1: PBoC monetary policy instruments

Monetary policy instruments	27 bps equivalent change
Rate-based instruments Lending and deposit rates for households Lending rate to financial institutions Interest rate on required reserves 7-day reverse repo rate (OMO)* 7-day standing lending facility rate*	27 bps (25 bps starting in 2010)
RRR	0.5%
Quantity-based instruments Repo and reverse repo open-market operations Liquidity facilities Central-bank bill issuance	0.5% of deposit base
Informal credit quota (window guidance)	N.A.

The construction of both indices follows three steps: (1) convert the impact of quantitative instruments into equivalent interest rate changes; (2) combine the impact of the different instruments into a monthly aggregate change; (3) cumulate these changes into a monthly MPI ('shadow rate').

Changes in instruments that directly influence the quantity of money (such as changes in the reserve requirements or open-market operations) are converted into equivalent interest rate changes as follows. In line with literature (Xiong, 2012, He and Pauwels, 2008) and following Giradin et. al (2017), we include in our MPI the 1-year refinancing, lending and deposit rates, the reserve requirement rate (RRR) and the interest rate on required reserves.[6] However, to reflect the shift of monetary policy at the start of 2016 towards an interest rate corridor (IMF, 2017c), we also include the 7-day reverse repo rate on open-market operations (OMOs) and the interest rate on the 7-day standing lending facility, the ceiling and floor respectively of this new corridor.

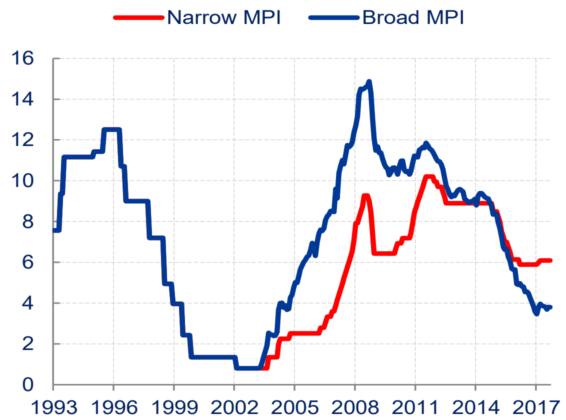
In constructing the broader MPI, we need to convert changes in quantities into an interest-rate equivalent. In line with the assumptions for reserve requirement changes, He and Pauwels considered a change of CNY 200 billion in OMO liquidity provision equivalent to a 27 bps rate change. At that time, CNY 200 billion was equivalent to about 0.5% of the total deposit base. Since then, deposits have increased about 3.6 times, implying that using the same conversion rule would overstate the importance of a change in the money supply. To avoid this, we accumulate the total monthly change in the money supply through OMOs, liquidity facilities and the issuance of bank bills over time and, each month, express this cumulative sum in percent of total deposits. We convert this outstanding amount, assuming that the equivalent of 0.5% in deposits equals 27bps (25bps starting in 2010). Differencing this series provides the monthly change generated through quantity instruments.

Following Giradin et. al (2017), we combine the monthly changes in each policy instrument through the following simple aggregation rules: (i) if different policy instruments move in opposite directions in a given month, we sum their monthly "27 bps equivalent" changes, allowing them to offset each other. (ii) if all policy instruments move in the same direction, we keep only the instrument change that gives rise to the maximum monthly "27 bps equivalent change", in order to avoid double counting. Finally, we cumulate the estimated monthly monetary policy changes into a single MPI, starting from 1993. Chart A1 shows the two MPI indices.[7]

Chart A1

(percent)

Chart of narrow and broad MPIs



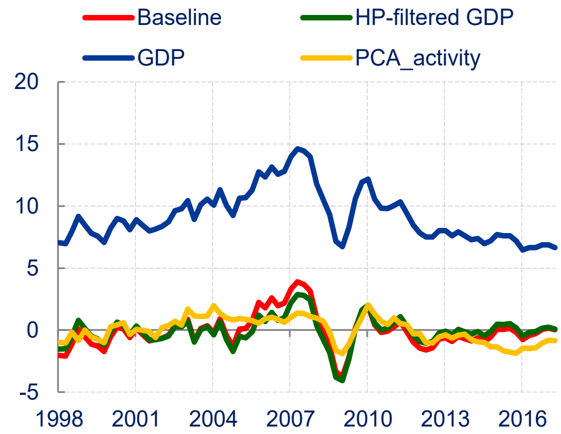
Sources: PBoC.

[6] Again in line with Girardin et. al., we also remove the big 500 bps RRR cut in March 1998, as it was not a monetary policy signal but part of the PBoC's operations to recapitalise commercial banks and unify the reserve requirement system.

[7] Contrary to Girardin et. al. who use a monthly index, we only use the end-of-quarter values, so there is no need to adjust the index for the effects of China's New Year.

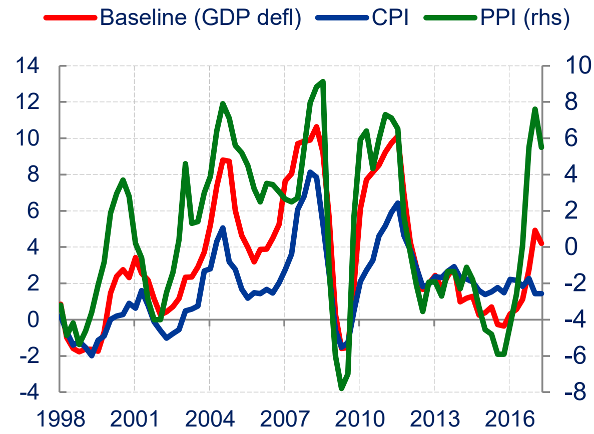
Annex 2: Variables used in the baseline model and robustness checks

Chart B1: Activity



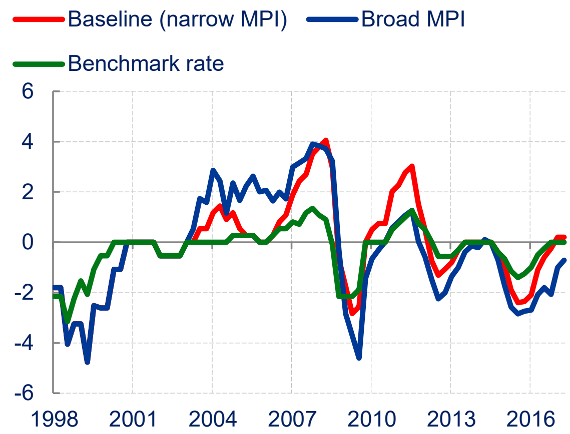
Sources: National Bureau of Statistics.

Chart B2: Inflation



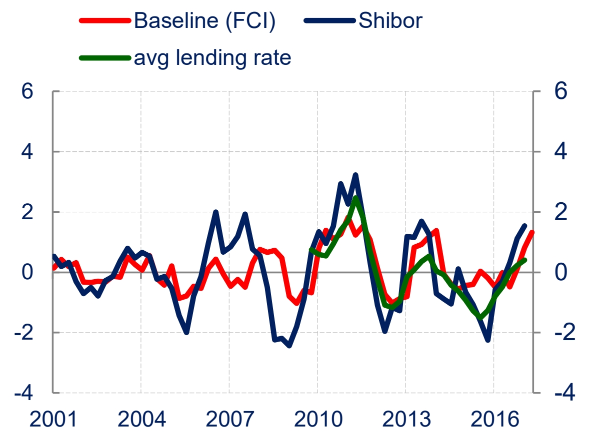
Sources: National Bureau of Statistics, PBoC.
Note: variables expressed in year-on-year differences.

Chart B3: Monetary policy



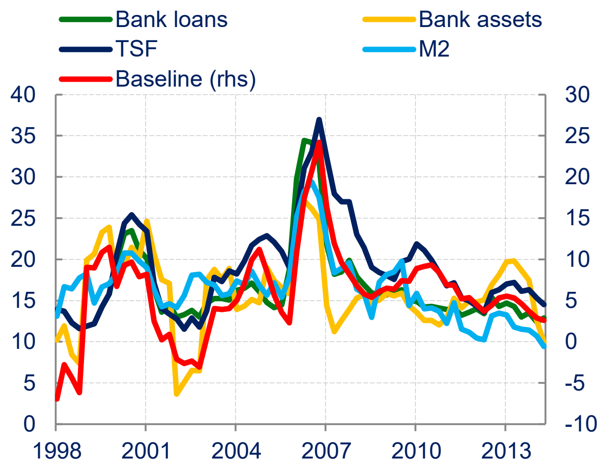
Sources: PBoC.
Note: variables expressed in year-on-year differences.

Chart B4: Financial conditions



Sources: PBoC, China National Interbank Funding Centre.
Note: variables expressed in year-on-year differences. An increase in the FCI denotes tighter financial conditions.

Chart B5: Credit



Sources: PBoC.
Note: variables expressed in year-on-year differences.

Annex 3: Sensitivity Analysis

Chart C1: impulse responses – alternative measures of activity

(from model using activity indicator from principal component analysis (PCA) instead of real (de-trended) GDP)

Chart a: Activity to a financial conditions shock

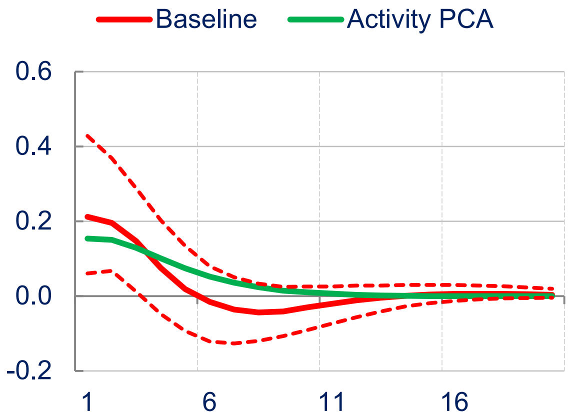


Chart b: Activity to a monetary policy shock

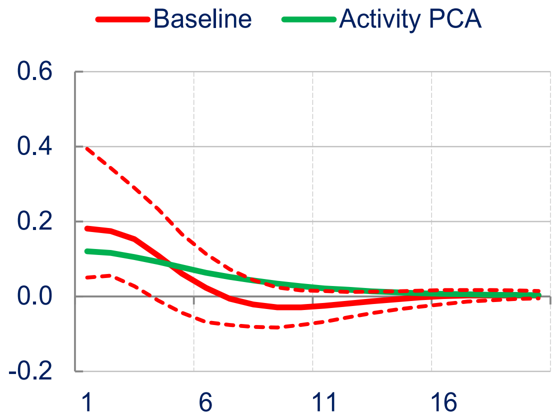


Chart c: Inflation to a financial conditions shock

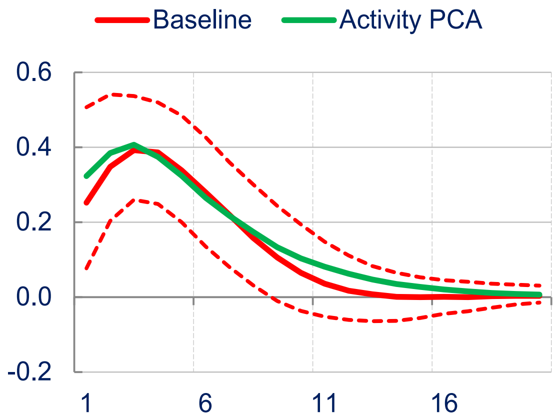
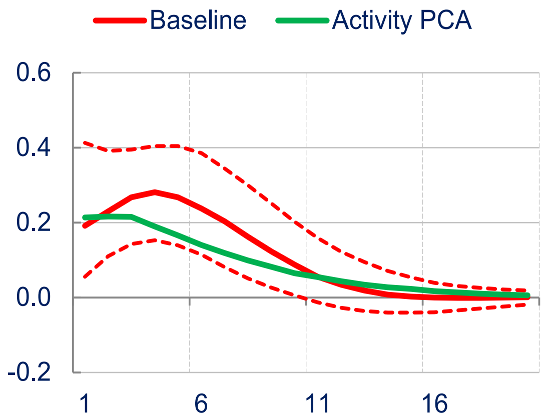


Chart d: Inflation to a monetary policy shock



Note: dotted lines represent the 68% probability interval around the baseline model.

Chart C2: Historical decompositions – alternative measures of activity

(from model using activity indicator from principal component analysis (PCA) instead of real (de-trended) GDP)

Chart a: Contribution of credit supply shocks to activity

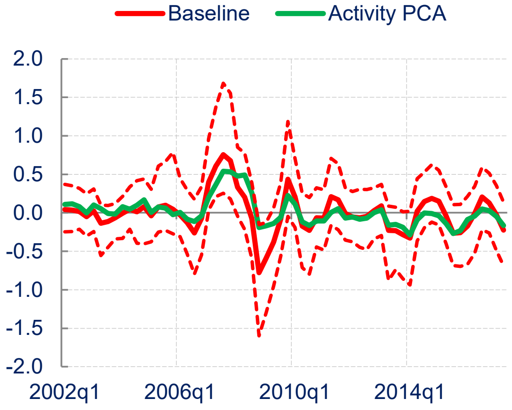


Chart b: Contribution of monetary policy shocks to activity

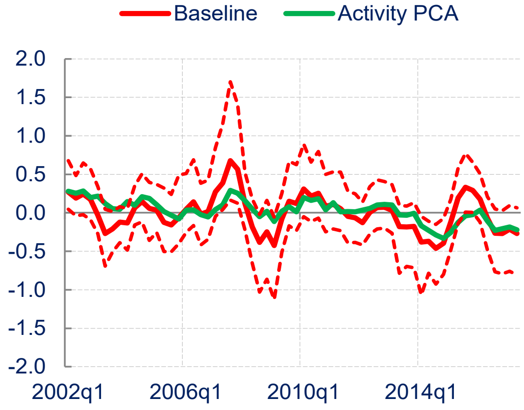


Chart c: Contribution of credit supply shocks to inflation

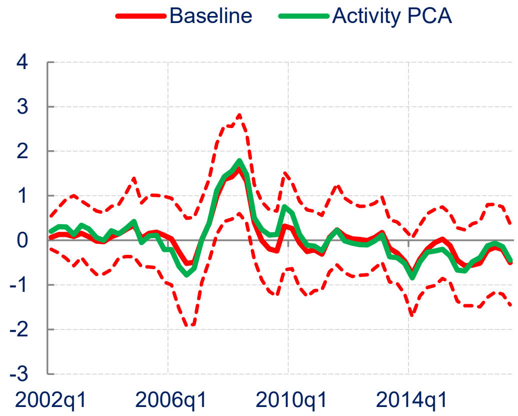
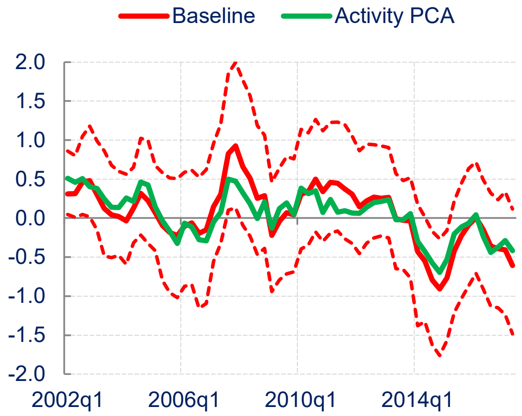


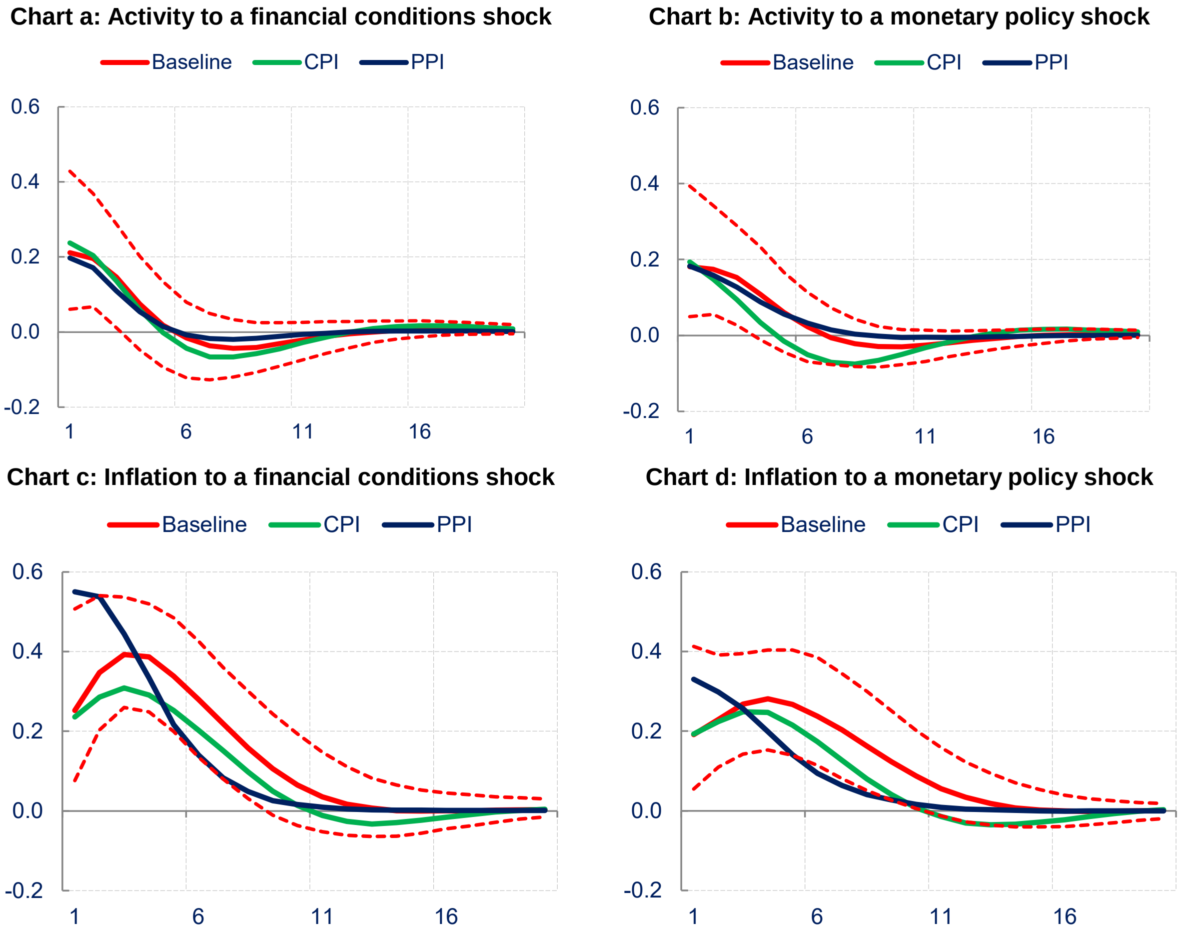
Chart d: Contribution of monetary policy shocks to inflation



Note: dotted lines represent the 68% probability interval around the baseline model.

Chart C3: impulse responses – alternative measures of inflation

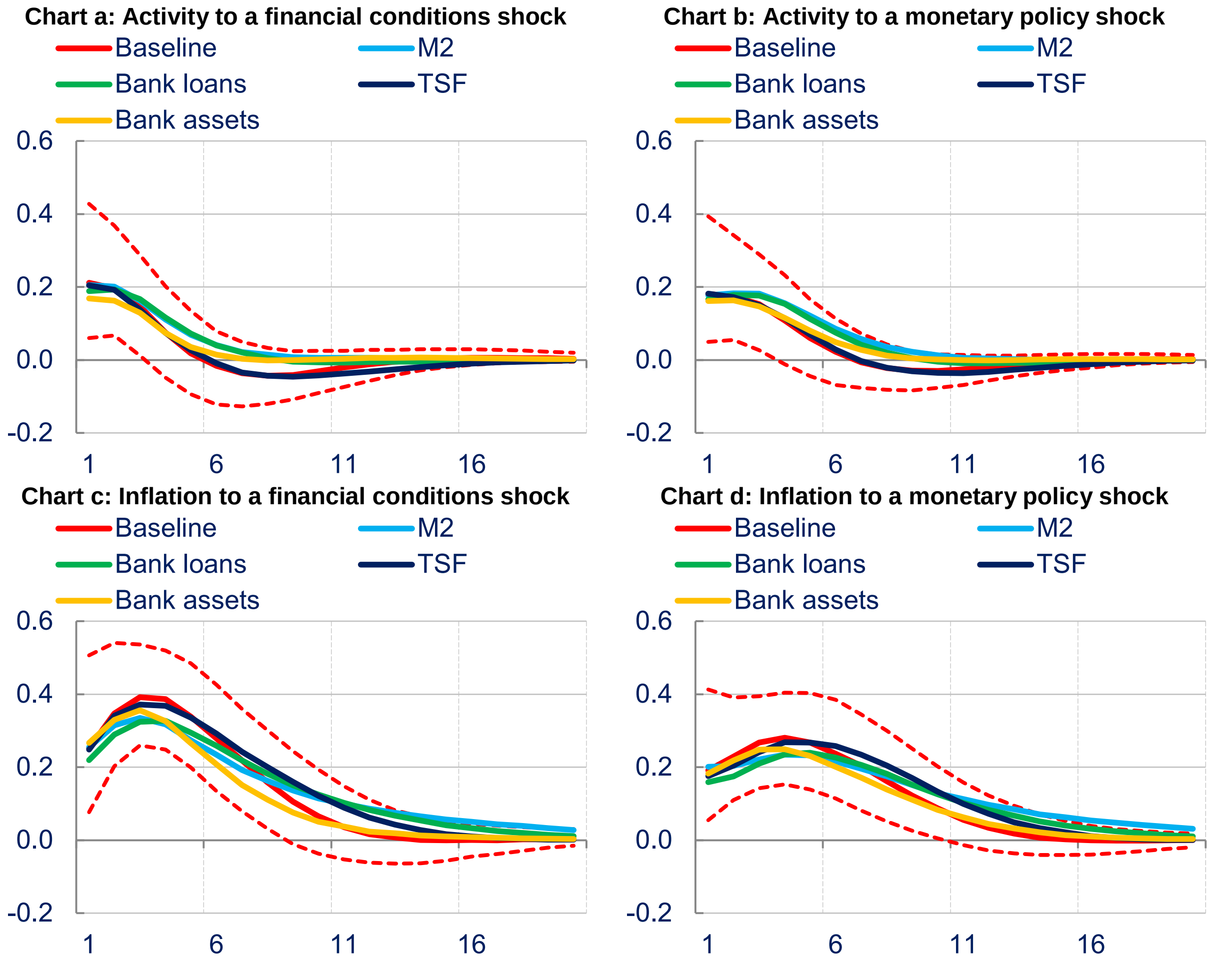
(Impulse responses from models using CPI or PPI instead of GDP deflator)



Note: dotted lines represent the 68% probability interval around the baseline model

Chart C4: impulse responses – alternative measures of credit

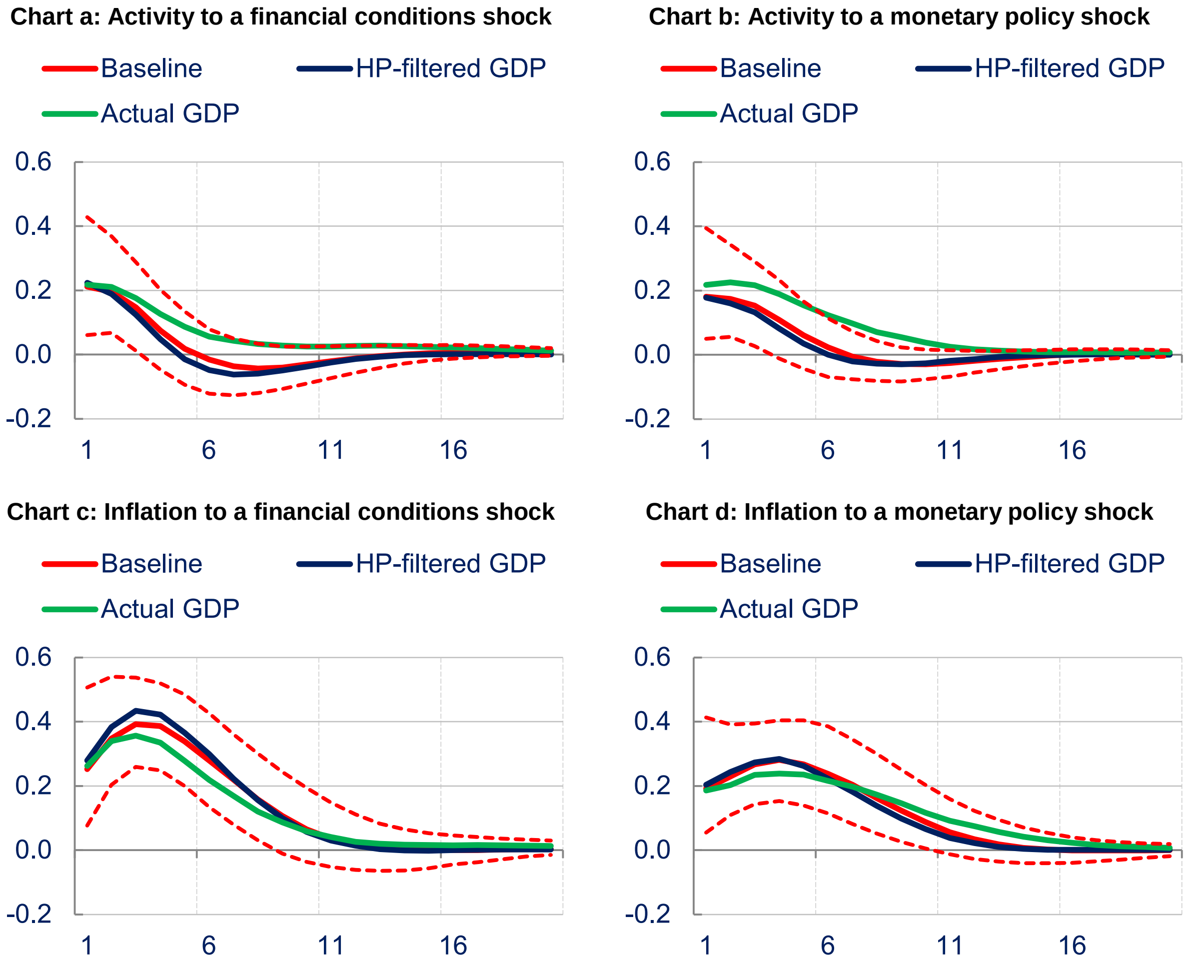
(Impulse responses from models using alternative measures of credit)



Note: dotted lines represent the 68% probability interval around the baseline model

Chart C5: impulse responses – alternative de-trending of GDP

(Impulse responses from models using actual GDP or HP-filtered GDP)



Note: dotted lines represent the 68% probability interval

Chart C6: Historical decomposition using real GDP

(estimated contributions to variables – deviations from estimated steady state)

Chart a: GDP growth

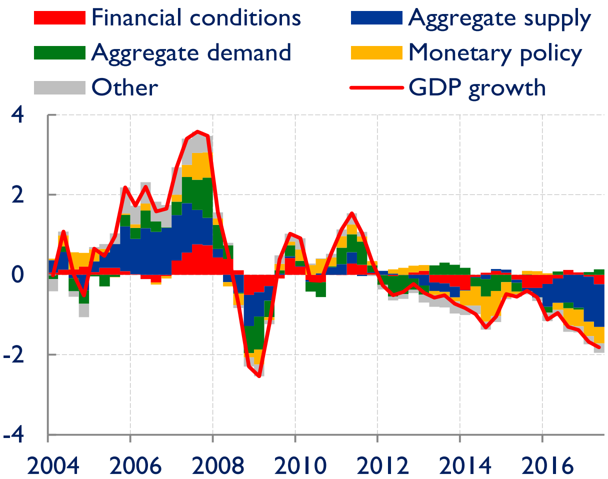


Chart b: GDP deflator

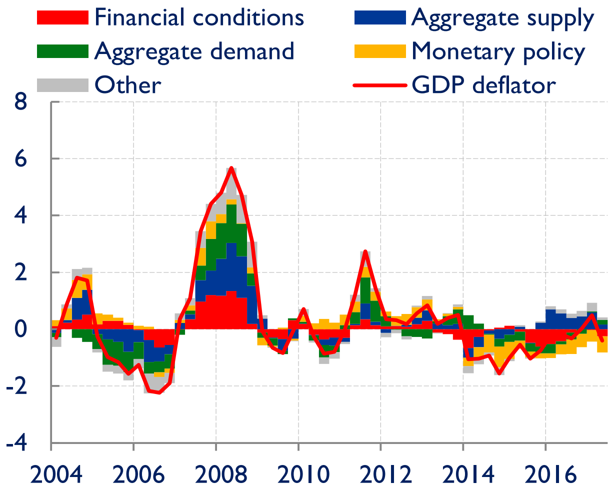


Chart c: Monetary policy index

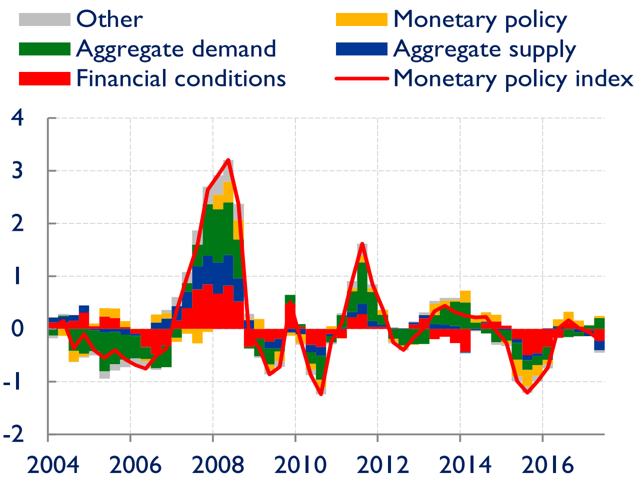


Chart d: Financial conditions index

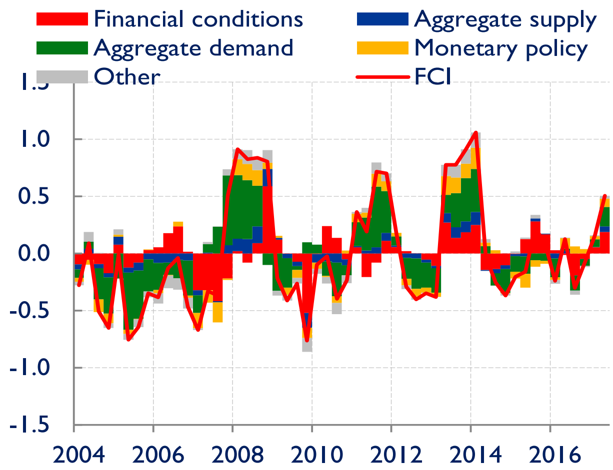
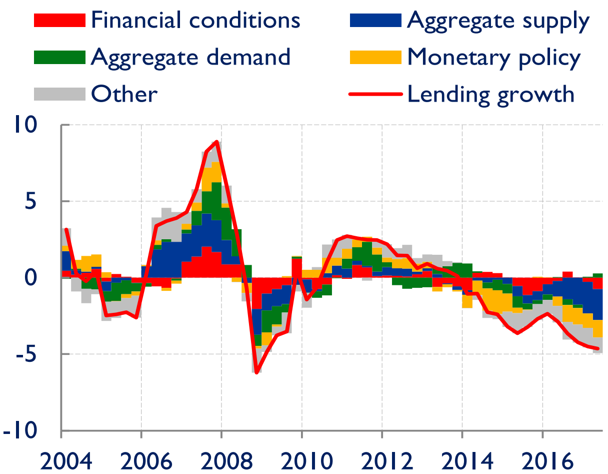


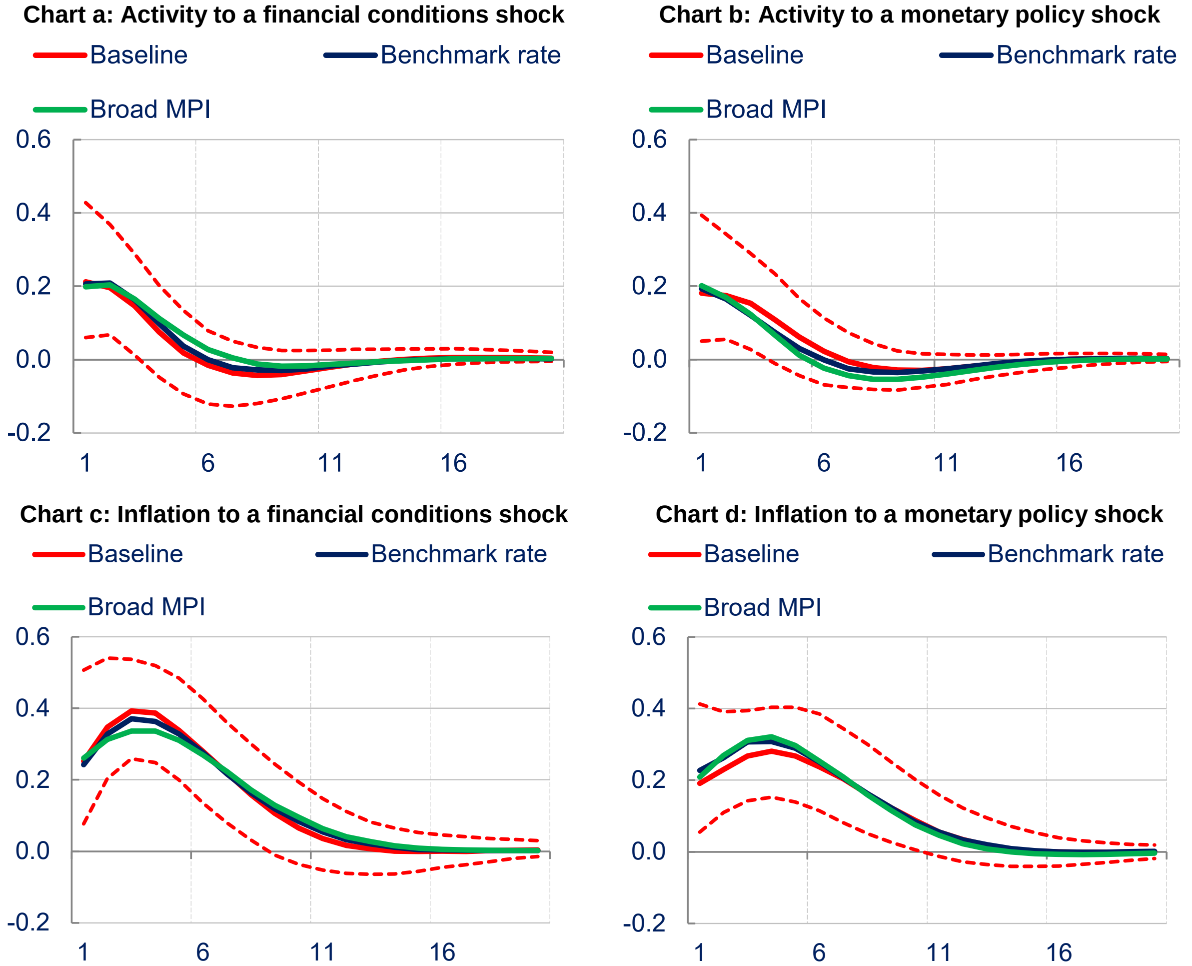
Chart e: Lending growth



Notes: Estimated contributions to each variable. Variables are expressed as deviations from estimated 'exogenous' component which includes the steady state and the effect of exogenous variables (world GDP and commodity prices)

Chart C7: impulse responses – alternative measures of monetary policy

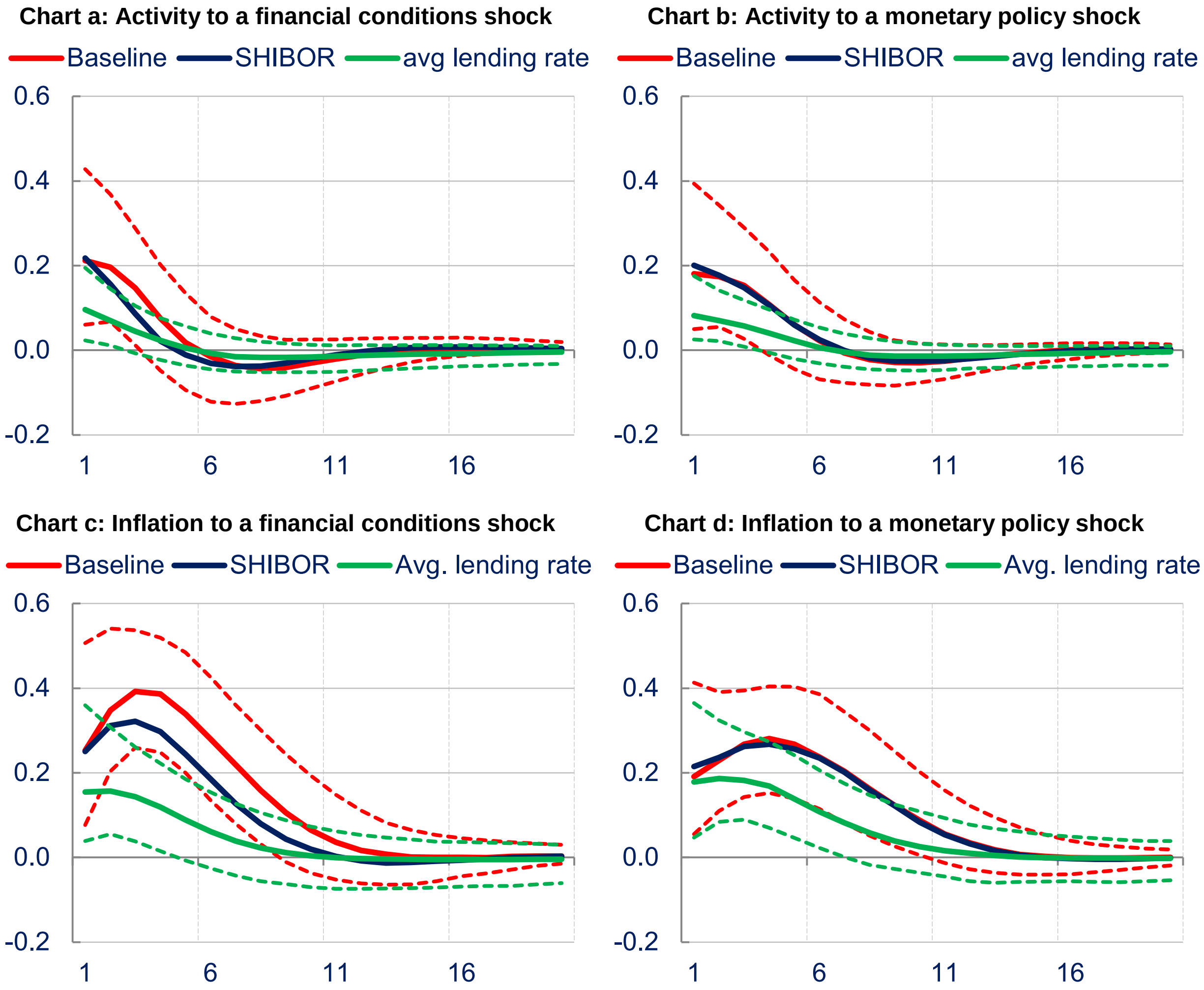
(Impulse responses from models using the benchmark 1-year lending rate or broader MPI)



Note: dotted lines represent the 68% probability interval

Chart C8: impulse responses – alternative measures of financial conditions

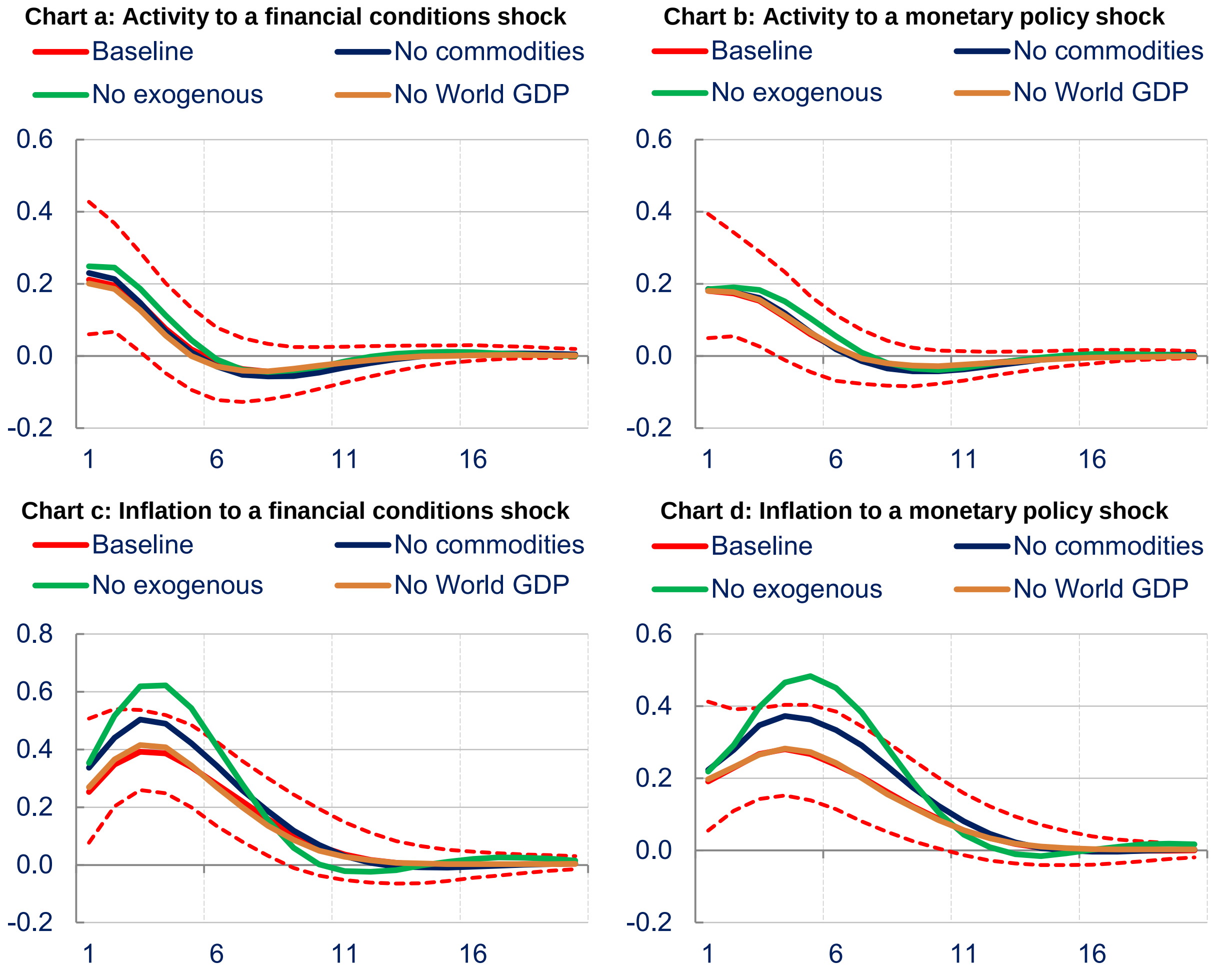
(Impulse responses from models using SHIBOR or the average lending rate)



Note: dotted lines represent the 68% probability interval

Chart C9: impulse responses – alternative exogenous variables

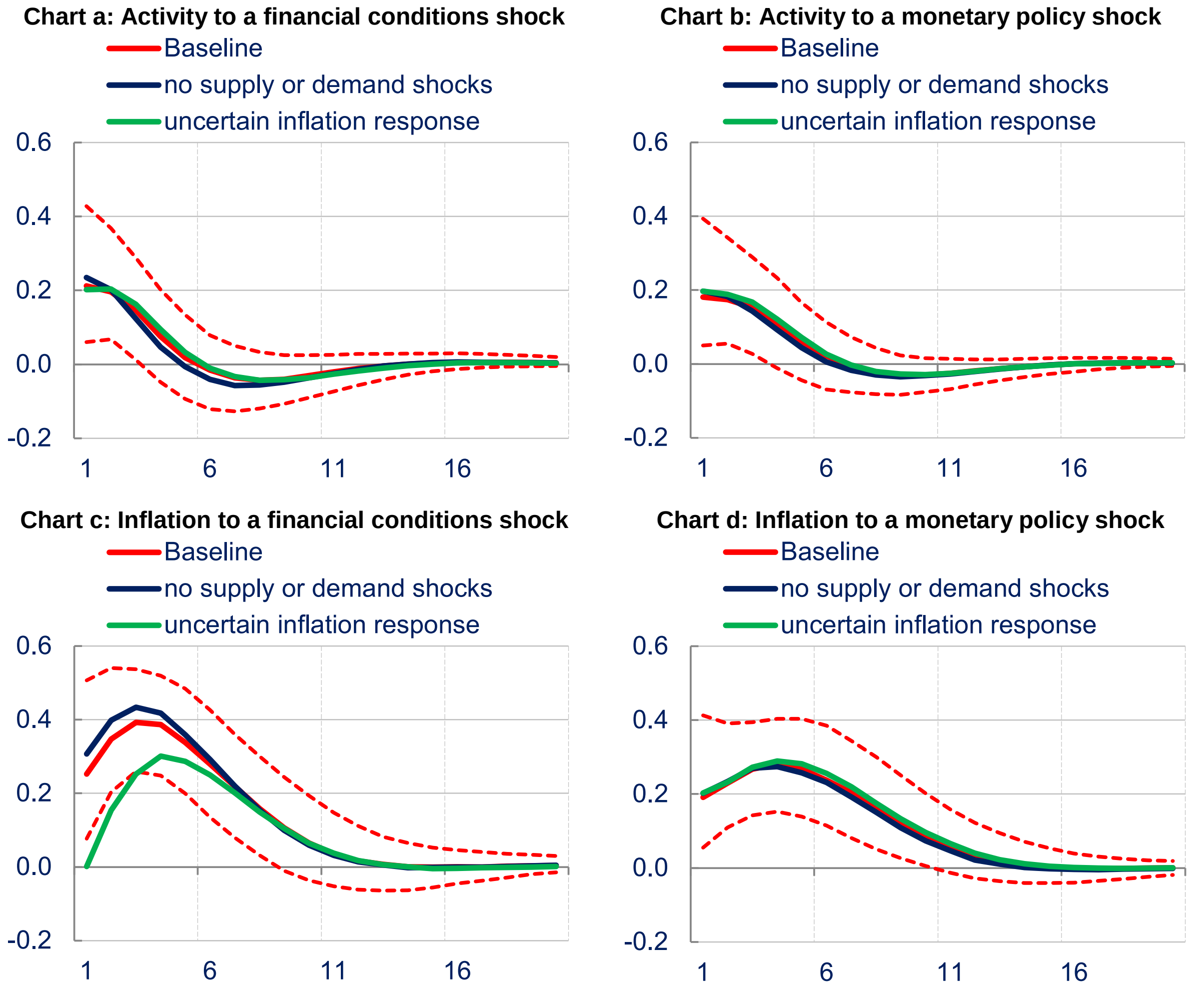
(Impulse responses from model with alternative (or no) exogenous variables)



Note: dotted lines represent the 68% probability interval

Chart C10: impulse responses – alternative identification schemes

(Impulse responses from models using alternative identification schemes)



Note: dotted lines represent the 68% probability interval

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David Lodge
European Central Bank, Frankfurt am Main, Germany; email: david.lodge@ecb.europa.eu

Michel Soudan
European Central Bank, Frankfurt am Main, Germany; email: michel.soudan@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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