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Keywords: financial conditions, Chinese Economy, Macroeconomic spillovers, Financial Markets spillovers, Bayesian VAR, TVP-Bayesian VAR, Impulse Responses, Variance Decomposition

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Abigail Watt[1], Carolina Martinez[2], Jeremy Lawson[3] and Rong Fu[4]

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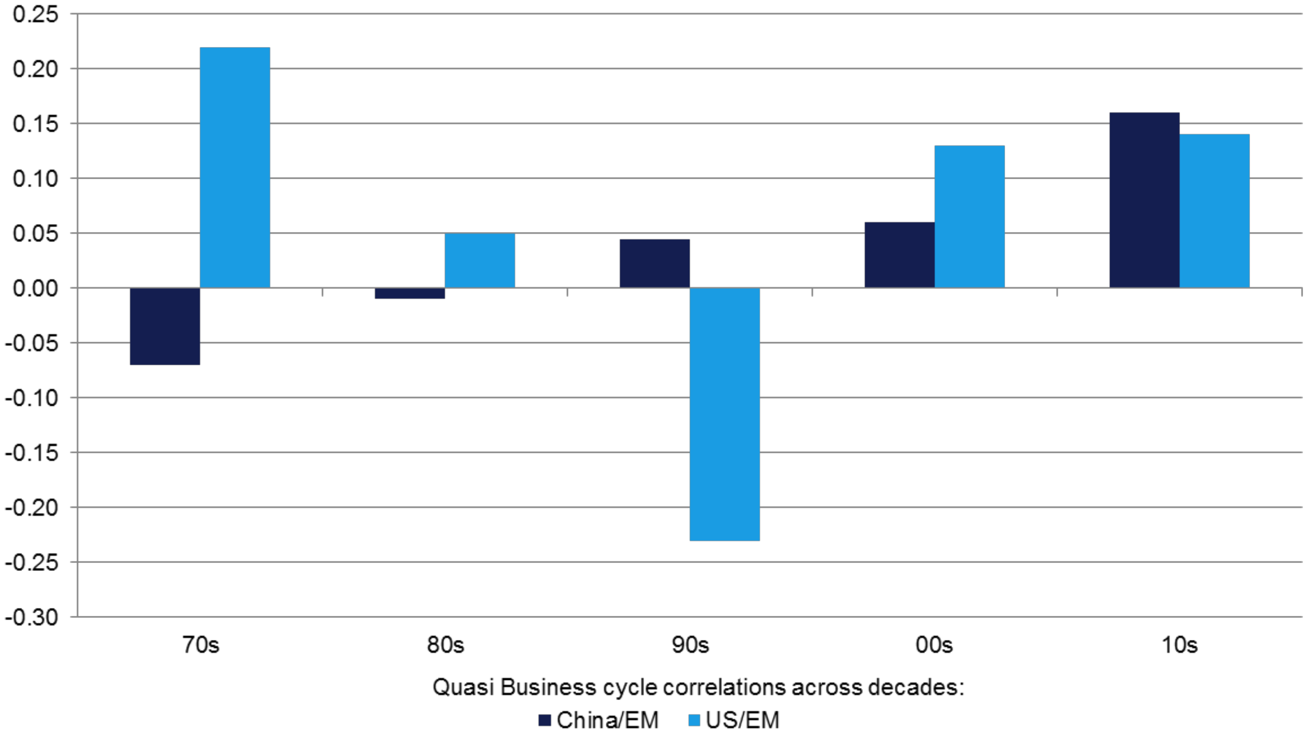
1 Introduction

China's rapid rise to become the world's second largest economy has made it critical for economists, policymakers and financial market participants to closely monitor and understand the likely impacts of Chinese macroeconomic and policy developments. Indeed, for emerging market (EM) economists, China has assumed special importance as the correlation of its business cycle with the broader EM cycle has been on a rising trend and now rivals that of the United States (Finn et al. (2019); see Figure 1.

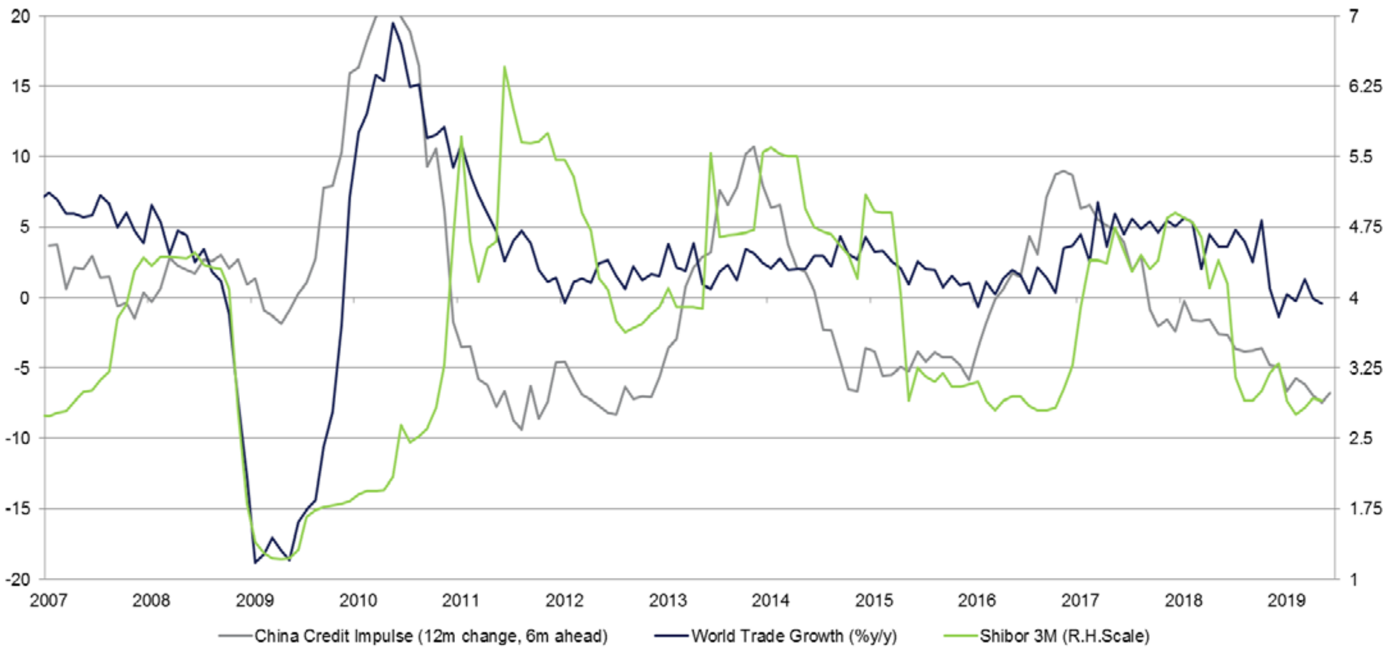
Figure 1: Correlation between business cycles in China, Emerging Markets and the United States



Source: Aberdeen Standard Investments, IMF. Quasi-correlation can be defined as follows: for a given pair of countries i and j, it is equal to the product of deviations of growth rates in i and j from their sample averages, divided by the product of standard deviations of growth rates in i and j over the sample (Duval, et al., 2014). Measured from 1970 to 2016. See Finn et al (2019) for further details.

In this paper we focus on the Chinese financial cycle and the role it plays in both driving domestic economic activity and global economic and financial conditions. Heuristically at least, the large swings in Chinese policy actions and broader financial conditions have been one of the defining features of the post-crisis economic and financial landscape. As seen in Figure 2 there is correlation between Chinese financial variables and the global macroeconomic cycle. In late 2008 and early 2009 the Chinese authorities launched a massive stimulus effort that led to the subsequent recovery in commodity prices, global trade and economic activity. Tightening efforts following this explosion of credit then preceded the global trade and industrial slowdown through 2014 and 2015. Chinese stimulus again appeared to contribute to the global synchronised upswing of 2017 and then more recently the deceleration through 2018 and the first half of 2019.

Figure 2: Chinese policy and the global economy



Source: Bloomberg, Haver and Aberdeen Standard Investments.

Examining the spillover effects from the Chinese financial cycle involves two steps in our paper. First we develop a robust measure of Chinese financial conditions that accounts for the variety of policy and regulatory tools deployed by the Chinese authorities and the complexities of how changes to those tools are transmitted through the financial system over time. The second involves developing a model suitable for capturing the endogeneity between Chinese financial conditions, the domestic economy, as well as foreign economic activity and asset prices, and thus able to robustly identify how Chinese financial shocks are transmitted through the global economic and financial system.

Measures of developed market financial stress and financial conditions have proliferated since the global financial crisis both within and outside of central banks (Angelopoulou, et al., 2013; Beaton, et al., 2009; Brave & Butters, 2011; English, et al., 2005; Kliesen, et al., 2012; Gomez, et al., 2011; Hakkio & Keeton, 2009; Hatzius, et al., 2017; Kliesen & Smith, 2010; Koop & Korobilis, 2013; Marques & Ruiz , 2017; Matheson, 2011; Xiong & Zhang, 2018). That is because the crisis itself, as well as the depth and persistence of its impacts are partly attributable to complex interaction between policy, the financial system and the real economy (Erdem and Tsatsaronis, 2013; Hatzius et al, 2010). Indeed, just as changes to financial conditions and stress can have significant effects on economic activity, central banks increasingly appear to be targeting financial conditions themselves as policy has become more unconventional and awareness of the importance of the financial cycle has grown (Adrian, et al., 2019).

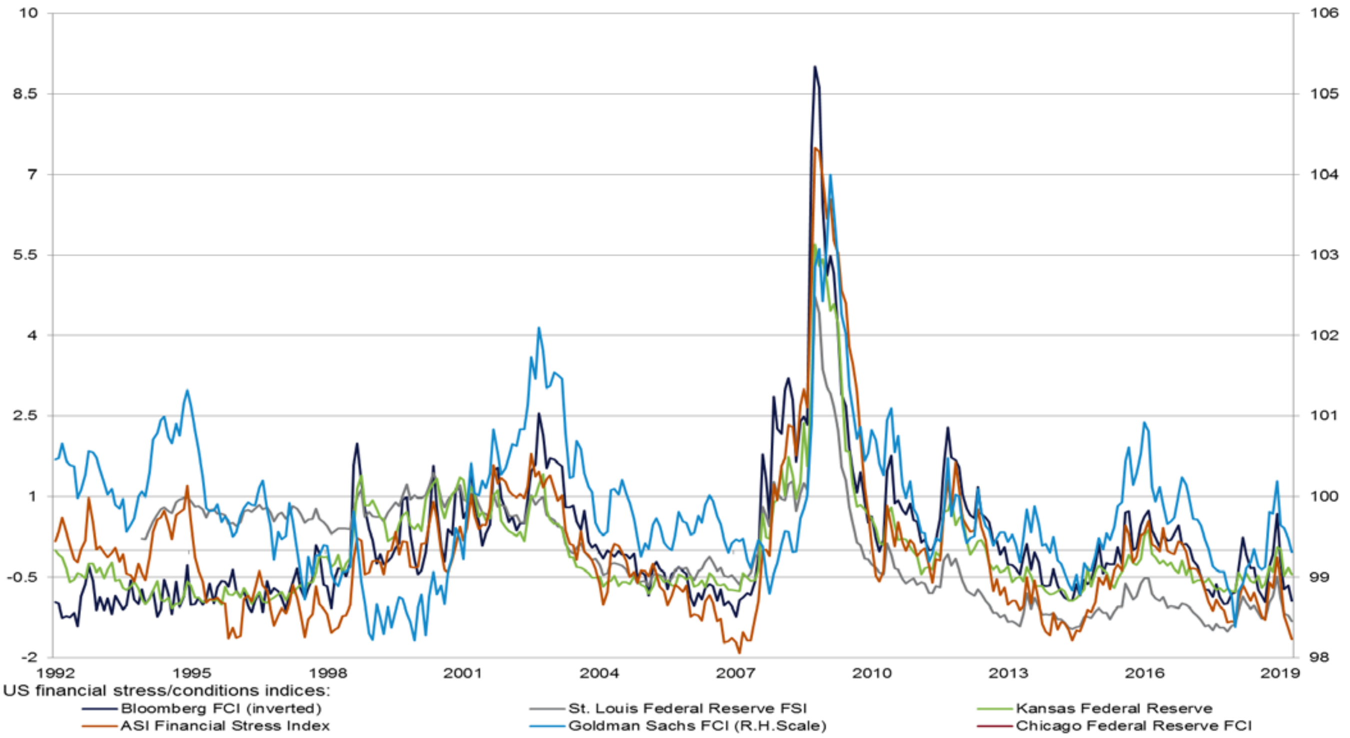
Critically though, there is a key distinction to be made between financial stress and financial conditions. The former measures the extent to which the market's perception of financial vulnerabilities and imbalances are changing, whereas the latter provides a broader measure of the current state of financial markets but also the stance of monetary policy and its transmission to the wider economy (Kliesen, et al., 2012). We focus on Chinese financial conditions in this paper because we are interested in the stance and impact of policy and conditions through the cycle and not just end-cycle vulnerabilities.

Despite the extensive literature that has emerged, measures of a country's financial conditions differ according to the input variables and the estimation method chosen. For example, a financial conditions index that includes indicators of market volatility will produce different results than an index that excludes them. The same holds for indices that use different measures of corporate credit spreads.

Methodologically, the construction of most indices involves standardising and rendering stationary the raw data and then applying weights to the underlying series. However, weighting schemes range from the simple averaging technique employed by Bloomberg to more complex data reduction techniques such as principal component analysis. An alternative, used by Goldman

Sachs (Hatzius et al, 2017), determines the weights for the input series by calculating the magnitude of impulse responses of key macroeconomic variables of interest to the shocks in input series. Another approach is to estimate a dynamic factor model, in which a single factor is constructed to summarise the stance of financial conditions. One example is the Chicago Federal Reserve Financial Conditions Index (Brave & Kelley, 2017). This allows for the extraction of the common component driving the overall data by explicitly allowing for the idiosyncratic or series specific variation to be captured in the error term. The upshot is that as Figure 3 shows although there are similarities in the profiles of financial conditions arising from these different methodological approaches, there are also important differences in timing and amplitude.

Figure 3: Different measures of US financial conditions



Source: Bloomberg. See cited works for original papers.

There are far fewer indicators of financial conditions in emerging markets and China in particular. Xiong (2012) constructs an index for China focused specifically on the transmission mechanisms of monetary policy. But whilst useful for capturing the pass-through of policy changes this choice does not provide a summary statistic of broader financial conditions in China. On the other hand, Wacker et al. (2014) attempt to capture financial conditions in China by considering a broader array of indicators such as measures of risk and wealth, as well as monetary and credit aggregates. We use a similar approach to this latter paper but consider a different variable set with the inclusion of volatility and duration measures and less emphasis on different measures of equity returns.

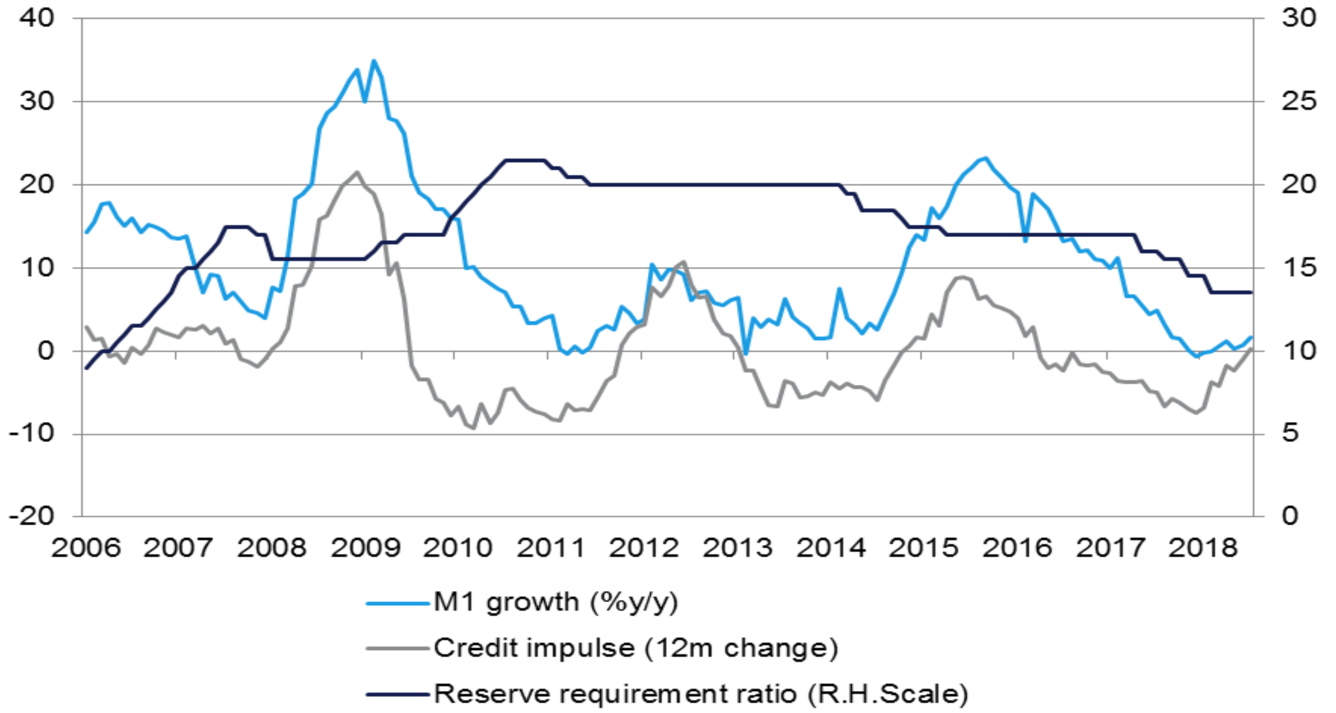
Our paper attempts to combine the best of these approaches by incorporating five main variable categories:

- Policy and Duration – which covers mostly policy, bank and market interest rates;
- Money and Credit – which focuses on indicators of money growth and the credit impulse;
- Risk Premia – which includes measures of corporate credit spreads and equity prices;
- Volatility – the variance of bond and equity prices; and
- The currency - and in particular the nominal effective exchange rate.

We tailor our variable section to match the policy instruments used and targeted by the People's Bank of China that are illustrated in Figure 4, as well as the most important transmission channels. For index construction we use principal component analysis similar to both the Kansas and St. Louis Federal Reserve banks (Hakkio and Keeton,2009; and Kliesen and Smith, 2010).

Critically, we find that the turning points in our measure of financial conditions match the qualitative experience of the Chinese financial cycle and that Money & Credit and Policy & Duration factors are important drivers of past changes in financial conditions.

Figure 4: Key indicators of Chinese financial conditions



Source: Aberdeen Standard Investments, Haver Analytics and Bloomberg.

Extending the analysis of Lodge and Soudan (2019), we then quantify the effects of changes in Chinese financial conditions, as characterised by our index, on domestic macroeconomic variables, and the spillovers to foreign economies and financial markets within a Bayesian VAR (BVAR), finding evidence of significant effects.

Finally, we consider whether and how the impact of Chinese financial conditions has changed over the past decade by using a time varying parameter BVAR. We find that the impact of shocks to Chinese financial conditions on Chinese activity, advanced economy industrial activity, Chinese equities, EMBIG spreads and US financial stress has been declining.

The remainder of this paper is structured as follows. In section 2 we present the data, methodology and results for the construction of the Chinese financial conditions index, including robustness checks. In section 3 we present the data, methodology and results of the Bayesian VAR analysis including the extension of this to consider the time-varying nature of the impact of changes in financial conditions, as well as extensive sensitivity analysis of our results. Section 4 then summarises the main takeaways from the paper and offers some thoughts on potential extensions.

2 Constructing the ASI Chinese Financial Conditions Index

2.1. Data

Given the complexities of Chinese monetary policy and the broader Chinese financial system, a Chinese financial condition index ‘needs to capture the key instruments deployed by the authorities, the main credit and demand transmission channels to the real economy and markets, while also taking into account the fact that financial conditions are endogenous to the Chinese business cycle. To capture this multidimensionality, we incorporate variables from five broad categories:

- *Policy & Duration:* Capturing the interest rates that summarise the official stance of monetary policy, the base financing rate in the market but also developments in the Chinese government bond market. Whilst the Chinese bond market is currently largely domestic, foreign participation is increasing and thus it is likely to become a more important transmission channel for policy and influence on the real economy over time.
- *Money & Credit:* In China's heavily regulated financial system, monetary and credit aggregates have historically been key target and transmission channels for policy. We cast our net widely to make sure that all aspects of lending activity are captured, including shadow banking and information from survey data.
- *Risk premia:* The prices of risk assets are a core feature of most developed economy financial conditions indices and although China's credit and equity markets are still deepening, we want to allow for some effects while future proofing the index as the financial system continues to develop.
- *Volatility:* The volatility of an asset price is a measure of both its absolute and perceived risk. It can also affect financial conditions by amplifying liquidity effects through the financial cycle.
- *Foreign exchange (FX):* The exchange rate has been a target of policy for the PBOC for much of its history, either in terms of a level or a path, or against the US dollar or a basket of currencies. Since 2015 it has also become more heavily influenced by market forces, though it is still managed by the authorities to prevent rapid destabilising changes. We use the nominal effective exchange rate in our index because it is closer to the basket currently being targeted.

In total we draw on 21 monthly variables to construct the ASI financial conditions index. They incorporate information from each of the five categories above while also having long enough histories for us to understand the dynamics of Chinese financial conditions over multiple policy cycles. The sample period for our analysis starts from Jan 2007. Each series is rendered stationary and smoothed where necessary, with the period over which any variable is transformed chosen to maximise the signal from the data.

We also impose sign restrictions on our variables before we run our estimation procedure, such that if they have an inverse relationship with 'financial conditions' then we apply a negative sign to the input series. This ensures that an increase in the index corresponds to a loosening in financial conditions. Values that are more than +/-2.5 standard deviations from the sample mean are identified as outliers and are capped at this level. To account the impact of Chinese New Year effects, we control for the seasonality in the dataset by using a moving holiday dummy seasonal adjustment. The descriptions of the data series, transformations and sign restrictions are presented in Table 1.

Table 1: Data description for Chinese Financial Conditions Index

Category	Variable	Code	Trans	Sign
Policy & Duration	Shibor 3m	SHIBO3M BKBJ Index*	level	inverted
	Benchmark lending rate	CHLR12M Index*	12m difference	inverted
	Required reserve ratio	CHRRDEP Index*	level	inverted
	CGB 10y/UST 10y spread	GCNY10YR Index* - ftb10y@usecon+	level	inverted
	CGB 10y/CGB 1y	GCNY10YR Index* - GCNY1YR Index*	level	inverted
	CGB 10y	GCNY10YR Index*	level	inverted
Money & Credit	Credit Impulse	CHBGREVA Index*	level	
	FX reserves as % M1 (real)	N924LFX@EMERGEPR+ % H924FM1@EMERGEPR+/H924PC@EMERGEPR+	1m log difference	inverted
	Govt credit as % of domestic credit	CKAJJC@CHINA+ % CKAJJB@CHINA+	6m log difference	
	M1 (real)	H924FM1@EMERGEPR+/H924PC@EMERGEPR+	3m log difference	
	M2 (real)	H924FM2@EMERGEPR+/H924PC@EMERGEPR+	1m log difference	
	Banking business climate survey	N924VF@EMERGEPR+	6m difference	
	Loan demand index	N924VFML@EMERGEPR+	6m difference	
Risk Premia	SSE Composite returns	SHCOMP Index*	3m log difference	
	Corporate bond/CGB 5y spread	I08275CN Index* - GCNY5YR Index*	level	inverted
	Interest rate swap 1y/CGB 1y	CCSWO1 Curncy*	level	inverted
	Repo 7d/CGB 1y	RP07 Index* - GCNY1YR Index*	6m difference	inverted
Volatility	CGB 10y yield volatility	GCNY10YR Index*	6m rolling vol	inverted
	Shibor 3m yield volatility	SHIBO3M BKBJ Index*	6m rolling vol	inverted
	SSE composite return volatility	SHCOMP Index*	6m rolling vol	inverted
FX	Nominal Effective Exchange Rate	N924XJNB@EMERGEPR+	6m log difference	inverted

+indicates sourced from Haver Analytics, * indicates sourced from Bloomberg

2.2 Methodology

Given the large number of variables considered for our index, we chose to extract the common information in the dataset using a data dimensionality reduction technique called principal component analysis (PCA). PCA generates the principal components (PCs), a new set of variables which are linear combinations of the original series. Mathematically, PCs are the eigenvectors of the covariance matrix of the original dataset computed through singular value decomposition. With PCA, we extract a single component which explains the largest proportion of common variation in the data set and then use this as our index of financial conditions, following Hatzius et al. (2010) and Wacker et al. (2014). In our analysis the first principal component accounts for approximately 25% of the total variation in our data.

2.3 Results

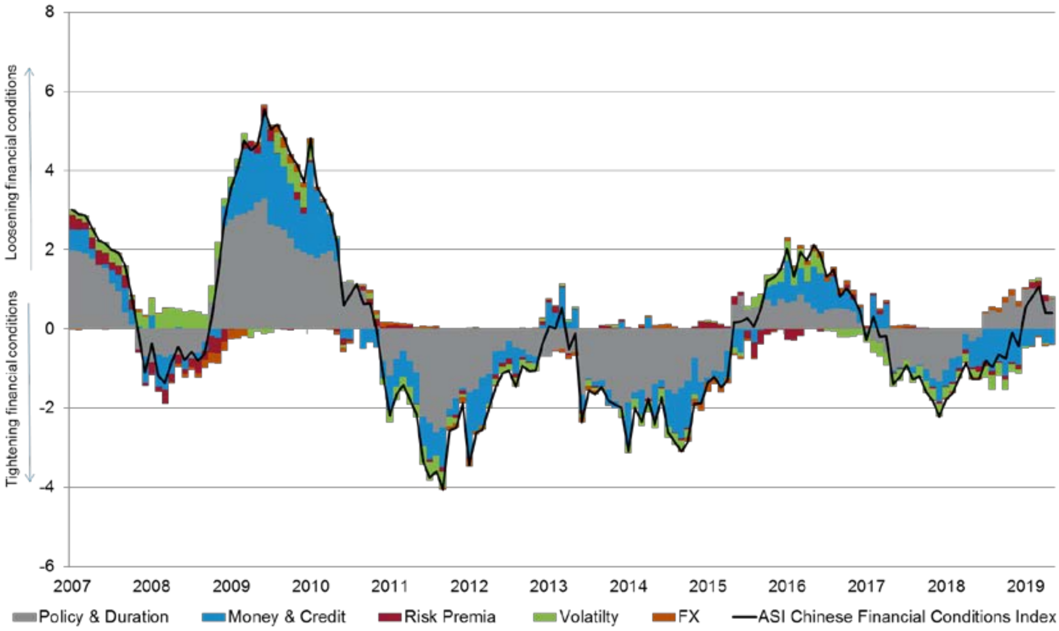
The index in Figure 5 follows our qualitative understanding of Chinese financial conditions relatively well. It correctly signals the stark tightening in financial conditions immediately before the GFC and the subsequent loosening in conditions as policy levers kicked in throughout 2009. It also picks up the significant tightening of policy and financial conditions through 2010 and 2011 as the authorities sought to rein in the excesses of the earlier loosening and prevent the economy from over-heating, as well as the subsequent mini-cycles engendered by the desire to put the economy on a more balance growth path. More recently our index shows that conditions have been on a loosening trend since the middle of 2018 though that it has so far fallen well short of what took place in the past three easing cycles.

Figure 5: The evolution of Chinese financial conditions over time

Source: Aberdeen Standard Investments, Bloomberg and Haver. Grey shading highlights a period of tightening financial conditions with the index falling and green shading highlights a period of loosening financial conditions with the index increasing.

In addition to signalling whether financial conditions are tightening or loosening, we can decompose the index into changes in the underlying categories of data. For example, the index suggests that the tightening in financial conditions that initially took place between the middle of 2016 and the end of 2017 was mainly attributable to the Policy and Duration variables, while the Money and Credit variables played an important role on the index during 2018 as seen in Figure 6. The indicators of market volatility also contributed to these changes, though in much smaller magnitude.

Figure 6: Changing contribution by category to Chinese financial conditions



Source: Aberdeen Standard Investments, Bloomberg and Haver. See table 1 for details of the variables in each category.

2.4 Robustness Checks

PCA stability. We check the robustness of estimating our first principal component on an expanding window of data by testing its stability in a real-time estimation exercise. To do this we start with 3 years of data (January 2007 to January 2010) and then subsequently expand the estimation window by one month at a time. Figure 7 shows the dispersion in the estimation of the first principal component. Clearly the dispersion is higher in the early part of our sample period where we have a larger number of different estimates of the first principal component. Nevertheless, the same broad cycle of tightening before the GFC, easing during and immediately after the GFC and then tightening again is picked up. This suggests to us that our original estimation method is reasonably robust while having the added benefit of allowing us to understand and decompose the historic nature of conditions as well.

Figure 7: Expanding window estimation of first principal component

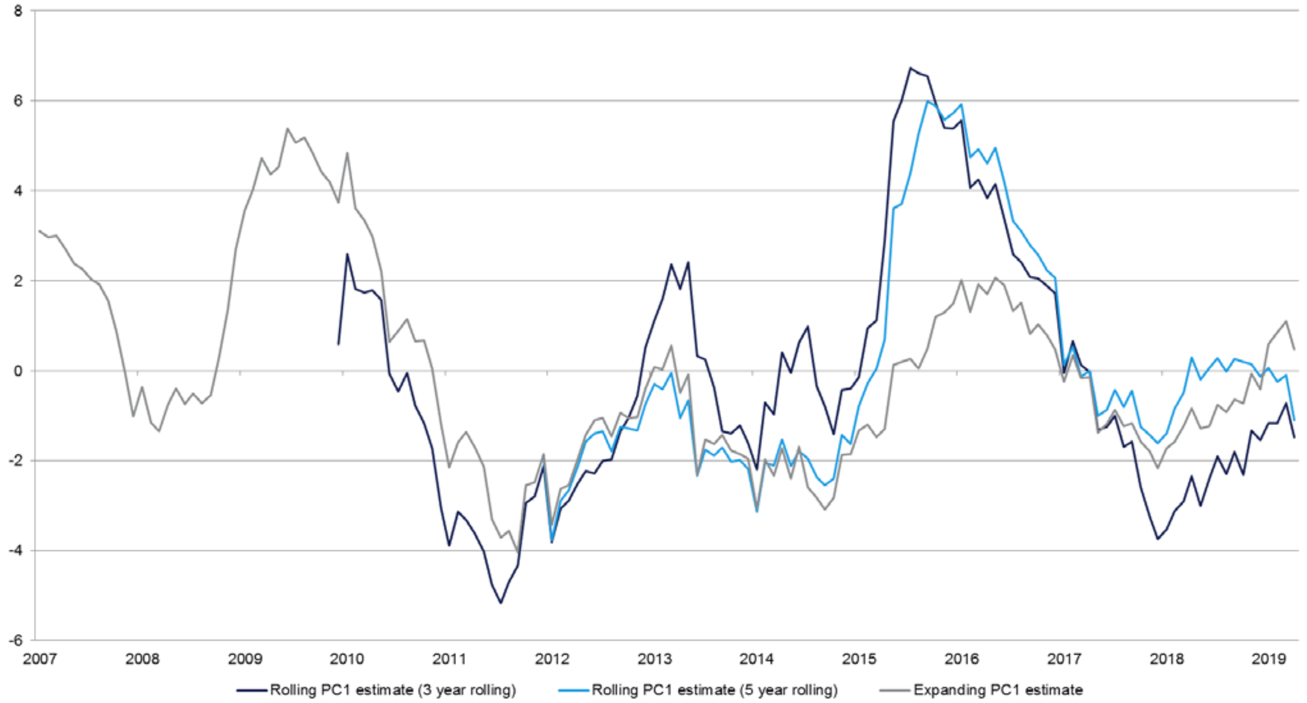
Source: Aberdeen Standard Investments, Bloomberg and Haver. This chart shows the estimation of the first principal component on a rolling window basis. The lighter the line is the longer the estimation sample used e.g. the lightest line uses the sample 2007M01-2019M06 whilst the darkest line uses 2007M01-2010M01.

A further robustness check was to test the impact of estimating the principal component on a rolling window rather than an expanding window. In this exercise instead of expanding the window for estimation of the covariance matrix we have a fixed period over which this is measured and then rolled over the full sample. In Figure 8 we compare three methods for estimating the first principal component: 1) the 1st principal component measured using an expanding window from January 2007 to December 2018; 2) the 1st principal component measured over a 3 year rolling window beginning in January 2010; and 3) the 1st principal component measured over a 5 year rolling window beginning in January 2012.

The broad profile of the index is similar when we use rolling windows, with turning points in the index occurring at roughly the same points in time. However there are clear differences in the magnitude of the peaks and troughs of the index. This makes sense; when the high amplitude policy and financial cycle around the GFC crisis is included in the estimation of our entire expanding window index then the current loosening in conditions (as well as that of 2015/16) appears to be relatively small in comparison.

There is a basic trade-off here. By using the rolling window PCA we are able to account for changes in the underlying structure between the variables over time. However the interpretation of the relative magnitude of the index becomes less clear, the decomposition of the index into the different drivers is not as easily attainable or intuitive, and we would lose part of the already short estimation period. That latter is necessary to robustly examine the spillover effects. We have therefore used the expanding window principal component analysis in the estimation of our ASI Chinese financial conditions index.

Figure 8: Expanding versus rolling window estimation outputs



Source: Aberdeen Standard Investments, Bloomberg and Haver. The chart compares the estimation of the first principal component on a fixed window (three and five years) and rolled over the sample period versus the first principal component estimated on an expanding window starting with 2007M01-2010M01 as the initial estimation period.

3. Assessing the Effect of CFCI on Macro economy and Financial Markets

3.1 Methodology

Bayesian Vector Auto-regressions (BVAR). In order to capture the spill-over effects of Chinese financial conditions to domestic and foreign economic and market variables, we use an extension of the common Vector Auto-regression (VAR) framework, called a Bayesian VAR (BVAR). A VAR is a model in which most of the variables are treated as endogenous to one another, allowing each variable to be explained by its own lags and lags of all other variables in the system. Moreover, it assumes that there is a lag structure by which changes to one variable in the system will affect the other variables over time. Using this approach allows us to link Chinese economic activity, measures of the emerging and developed market industrial cycle, equity market returns and credit spreads, to innovations in Chinese financial conditions, while taking account of the two-way causation and transmission between the variables.

A traditional unrestricted VAR does not impose restrictions on the parameters and hence provides a very general representation of what are complex data interrelationships. However, this high level of generality implies a large number of parameters even for systems of moderate size. This increases the risk of over-parameterization and hence estimation bias in our system. Therefore, given our aim is to incorporate as many variables as required to accurately explore the importance of Chinese financial conditions globally, we adopt a Bayesian VAR approach, which treats the VAR parameters as random variables, and provides a framework to shrink and update probability distributions about the unobserved parameters conditional on the observed data.

A general VAR model with n endogenous variables, p lags and m exogenous variables can be written as:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + C x_t + \varepsilon_t , \qquad \varepsilon_t \sim N(0, \Sigma) \qquad (1)$$

where $y_t = (y_{1,t}, y_{2,t}, \dots y_{n,t})$ is a $n \times 1$ vector of endogenous data, $A_1, A_2 \dots, A_p$ are p matrices of dimension $n \times n$, C is a $n \times m$ matrix, x_t is a $m \times 1$ vector of exogenous regressions and $\varepsilon_t = (\varepsilon_{1,t}\, \varepsilon_{2,t} \dots \varepsilon_{n,t})$ is a vector of residuals following a multivariate normal distribution. In our analysis, we have eleven endogenous variables which are described in Table 2 and in detail in the section that follows. Our chosen lag length p is 6. We check the robustness of this specification choice in section 3.4.
In a more compact notation:

$$Y = XB + \boldsymbol{\varepsilon} \tag{2}$$

With:

$$Y = \begin{pmatrix} y_1' \\ y_2' \\ \cdots \\ y_T' \end{pmatrix}, X = \begin{bmatrix} y_0' & y_{-1}' & \cdots & y_{1-p}' & x_1' \\ y_1' & y_0' & \cdots & y_{2-p}' & x_2' \\ \vdots & \vdots & & \vdots & \vdots \\ y_{T-1}' & y_{T-2}' & \cdots & y_{T-p}' & x_T' \end{bmatrix}, B = \begin{pmatrix} A_1' \\ A_2' \\ \cdots \\ A_p' \\ C \end{pmatrix}, and\ \boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_1' \\ \varepsilon_2' \\ \cdots \\ \varepsilon_T' \end{pmatrix}$$

Reformulates as:

$$y = \bar{X}\beta + \varepsilon \tag{3}$$

Where:

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

Specially, Ω represents the variance-covariance matrix of β.

Given the number of variables and lags in our VAR framework, it would be impossible to estimate all the coefficients using conventional VAR. Bayesian methods, on the other hand, have become an increasingly popular way of dealing with this problem of over-parameterization. The general idea is to use informative priors to shrink the unrestricted model towards a parsimonious naïve benchmark, thereby reducing parameter uncertainty and improving forecast accuracy.

We adopt the independent Normal-Wishart prior for our Bayesian VAR estimation, where Σ from equation (1) is treated as unknown, and an arbitrary structure proposed for Ω_0, with no assumed dependence between the residual and coefficient variance. Gibbs sampling is used to obtain random draws from the unconditional posterior distributions of the parameters of interest. The detailed information about priors, posterior distribution and sampling algorithm can be found in Dieppe, Romain and Björn (2015).

3.2 Data

China, as the second largest economy in the world, has strong linkages with the rest of the world, through global supply chains, commodity demand and supply, as well as financial markets. It is therefore important to capture the impact of external variables on China's economy and financial conditions to mitigate potential misspecification in the Bayesian VAR model. Consequently, we include two US variables in our system: a US financial stress index developed by Lawson and Amaro (2016) and US "nowcast" developed by Watt (2018), both of which are in-house indicators of the US economic and financial cycle.

We use the Caixin composite Chinese PMI as our measure of Chinese economic activity. Although this is not a direct measure of economic activity it has the virtue of being collected independently. We think this will generate a more reliable signal of the growth cycle than the national accounts data, for which there is evidence of excess smoothing (Chen, et al., 2019).

To examine the influence of broader financial conditions on China's investable financial markets, we include MSCI China as a separate variable in our analysis. The Goldman Sachs commodity price index is included because China accounts for a large share of global commodity demand and commodity prices are a key transmission channel for the Chinese economic and financial cycle to the rest of the world.

To gauge the impact of Chinese financial conditions on economic activity and asset prices in emerging markets excluding China, we further include a measure of industrial production; MSCI EM ex-China and the spread of the J.P. Morgan EMBI global spread, to capture the impact of Chinese financial shocks on EM equity prices and market pricing of sovereign credit risk respectively. Similarly, in terms of developed markets (DM), we include aggregate DM industrial production and an MSCI developed market equity index (see the data description in Table 2).

Table 2: Variable description for BVAR

Variable Name	Description	Source/Code	Transformation
Chinese composite PMI	Composite purchasing managers index	S924TG@MKTPMI⁺	level
Goldman Sachs Commodity Price Index	Broad measure of commodity prices.	GSCI@WEEKLY⁺	log difference
Emerging Market Industrial Production (IP) ex. China	Constructed by extracting Chinese IP from headline IP series.	S200DPP@EMERGE⁺ (EM headline),WBIPCHN Index* (China IP)	log difference
Advanced Economy IP	Index of industrial production from the CPB.	S110DPP@G10⁺	log difference
Chinese Offshore Equity Index	MSCI China	MXCN Index*	log difference
Emerging Market Equity Index	MSCI EM ex. China	M1CXBRV Index*	log difference
Developed Market Equity Index	MSCI World (ex. EM)	MXWO Index*	log difference
EMBIG Spread	EMBIG spread to worst	JPSYAGSW Index*	level
Chinese Financial Conditions Index		Section 2 of this paper	level
US Financial Stress Index	ASI measure of financial stress in the United States.	See Lawson and Amaro (2016)	level
US Nowcast	ASI measure of underlying momentum in activity in the United States.	See Solberger and Spanberg(2017), Watt(2018)	level

⁺indicates sourced from Haver Analytics, * indicates sourced from Bloomberg

The ordering of the endogenous variables we consider in the BVAR is as follows:

$$\left(\begin{array}{c}\text{Chinese Activity Indicator}\\ \text{Goldman Sachs Commodity Price Index}\\ \text{Emerging Market Industrial Production (IP) ex. China}\\ \text{Advanced Economy IP}\\ \text{Chinese Offshore Equity Index}\\ \text{Emerging Market Equity Index}\\ \text{Developed Market Equity Index}\\ \text{EMBIG Spread}\\ \text{Chinese Financial Conditions Index}\end{array}\right)$$

This ordering implies that our fast-moving financial variables react contemporaneously to the shocks from the slow-moving macroeconomic variables. Contrastingly, macroeconomic variables only respond to the shock from financial variables with a one-period lag. In the robustness checks section, we explore the extent to which our results are sensitive to alternative orderings.

3.3 Results

Impulse response functions. To obtain accurate impulse response functions, we orthogonalise shocks and identify a structural VAR using the Choleski decomposition.

We present the results of impulse response functions to a one unit shock to the Chinese financial conditions index (equivalent to around 1/8th of the 2009 stimulus) in Figure 1 and study how a loosening in Chinese financial conditions affects domestic and external economic activity, as well as equity and credit market variables. We find that a positive shock to the CFCI leads to a significant increase in the Chinese composite PMI, with the peak response of around 0.44 units occurring around 8 months after the shock.

We find that the Chinese PMI reacts positively and significantly to a loosening CFCI shock, increasing 0.4 units around 8 months after the initial shock. EM industrial production quickly reaches its maximum response around 0.08% after 5 months once the shock of Chinese financial conditions takes place. Advanced economy industrial production, on the other hand, reacts slightly stronger and increases the most by 0.1% after 7 months. The impulse responses of commodity prices, offshore Chinese equities and DM equities are not statistically significant but all show a positive impact in the median impulse response. The response of EM equities is significant, but only in the earlier portion of the response period, with the peak response of 0.4% occurring after 5 months. The loosening in financial conditions also leads to a narrowing in EM bond spreads as captured by the EMBIG. The peak in tightening in spreads of 10bps occurs after 11 months. The impact of Chinese financial conditions on the Chinese PMI, commodity prices, EM and advanced economy industrial production and the EMBIG spread seems to be persistent, with CFCI's effect lasting for 41 months. Moreover, the timing of the peak responses suggests that equity market variables react first, then macro variables and commodity prices, then EMBIG spreads and the US FSI.

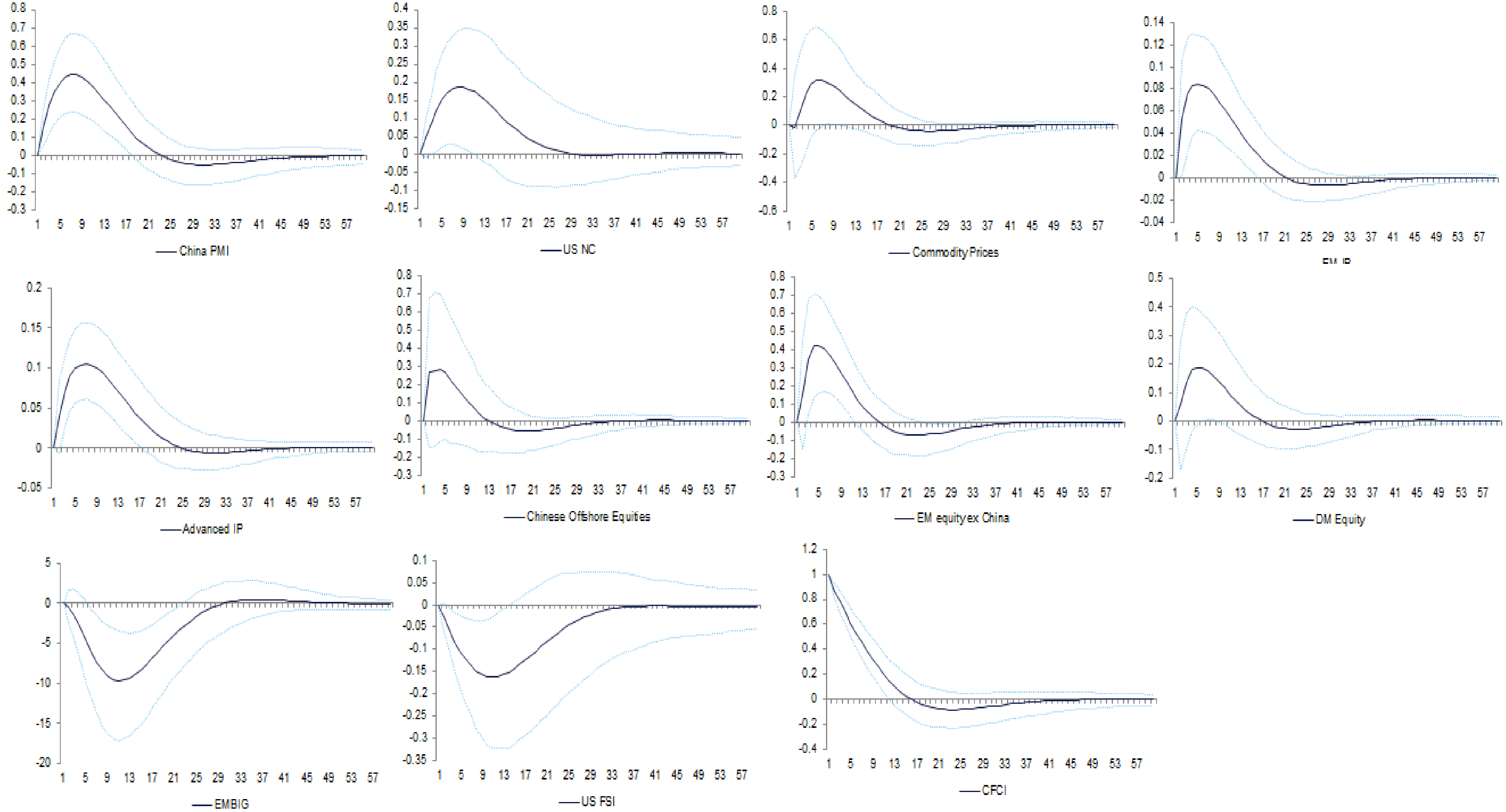
We are also interested in assessing the overall impact of a shock to Chinese financial conditions on economies and markets. Thus, we sum the impact of Chinese financial conditions presented in Figure 1 cumulatively over the 60 periods and show the results in Table 3. Whilst this does not infer the cumulative impact on the level, we are interested to see the accumulated monthly responses. We see a fairly sizable impact of Chinese financial conditions on Chinese domestic activity with the accumulated changes in the composite PMI amounting to around5 units in the 60 months after the initial shock. There is also a rather sizable spillover to the US economy with the US NC accumulated changes summing to 2.8% in total, larger than the summed impacts on EM and Advanced economy IP of 0.8% and 1.3% respectively. The largest cumulative change in equity markets can be seen in EM ex China, 2.4%, with the cumulative response of DM and Chinese offshore equities being fairly similar at 1.3% and 1.2% respectively. The period responses in the EMBIG spread, on the other hand, cumulatively narrow138bps after the shock even though the impact of Chinese financial conditions on EMBIG spread dies out after 41 months, suggesting a sizeable repricing of EM risk when Chinese financial conditions are loosened. Our measure of the US financial cycle, the US FSI, also signals lower stress with the summed impact on the index suggesting a decline of 2.9 units over the 60 month response period.

Table 3: Cumulative impact of a 1 unit shock to Chinese financial conditions

	Cumulative Impact after 60 Months
China PMI	4.8
US NC	2.8
Commodity prices	2.4
EM ex China IP	0.8
Advanced IP	1.3
Offshore Chinese equities	1.2
EM ex China Equities	2.4
DM Equities	1.3
EMBIG	-138.0
US FSI	-2.9
CFCI	5.1

Source: Aberdeen Standard Investments, Bloomberg and Haver. Table shows the cumulative impulse response following a 1 unit shock to Chinese financial conditions.

Figure 1: Impulse responses to a one unit shock to Chinese financial conditions



Source: Aberdeen Standard Investments, Bloomberg and Haver. Solid line is the median impulse response and dashed lines are the 10th and 90th percentile

Variance decomposition. The variance decomposition provides additional insights into the impact of shocks to Chinese financial conditions. In simple terms its separates the variation in an endogenous variable into the component shocks of the VAR. More specifically, it tells us what portion of the variance of the forecast error in predicting variable $y_{i,T+h}$ at a particular time is due to the structural shock e_j, therefore providing information about the relative importance of each innovation in explaining the variation in the variable of interest.

We can see in Table 4 below that the proportion of variance explained by the CFCI is highest for the Chinese PMI; this makes sense given that it is domestic activity that is being targeted by the authorities. The variable with the next highest proportion of its variation explained by the CFCI is the EMBIG spread. The other variables all have a similar proportion of their variance explained by the CFCI. Overall though, the variance decomposition implies that the variables external to China are mostly explained by non-Chinese economic and financial factors. Our results also highlight the importance of including information about the US economic and financial cycle in our model. Indeed, our US nowcast explains more of the forecast variation in the other variables than any other single variable.

Table 4: BVAR Variance Decomposition after 60 months

		Forecast Error Variance										
		China PMI	US NC	Commodity Prices	EM IP	DM IP	Chinese Offshore Equities	EM Equities	DM Equities	EMBIG	US FSI	CFCI
Proportion explained by each variable after 60 months	China PMI	71%	9%	7%	9%	7%	10%	7%	4%	10%	12%	9%
	US NC	9%	64%	4%	7%	14%	3%	15%	14%	19%	40%	36%
	Commodity Prices	3%	5%	84%	4%	6%	3%	12%	11%	21%	6%	5%
	EM IP	0%	1%	0%	72%	2%	1%	1%	4%	1%	2%	1%
	DM IP	0%	0%	0%	0%	57%	1%	0%	3%	0%	0%	1%
	Chinese Offshore Equities	3%	2%	1%	1%	2%	78%	30%	18%	17%	4%	4%
	EM Equities	1%	1%	0%	1%	1%	0%	28%	9%	10%	2%	4%
	DM Equities	0%	0%	0%	0%	0%	0%	1%	33%	2%	1%	1%
	EMBIG	1%	2%	0%	0%	1%	0%	2%	1%	9%	2%	1%
	US FSI	2%	7%	0%	0%	2%	0%	0%	0%	2%	21%	6%
	CFCI	8%	3%	1%	3%	5%	0%	2%	1%	5%	3%	29%

Source: Aberdeen Standard Investments, Bloomberg and Haver. Table shows the proportion of the forecast error variance in each variable explained by each of the variables in the system.

3.4 Time-varying Coefficient Bayesian Vector Auto regression (TVP-BVAR)

Other researchers have found evidence that the growth multiplier from a given amount of credit loosening in China has declined over the past decade (Chen, et al., 2017). To test whether that is also the case for Chinese financial conditions we make use of a time-varying Bayesian VAR. A time-varying BVAR is similar to a standard BVAR, except that it allows the coefficients and the residual covariance matrix to be time-varying. In Appendix section J, we present the priors and algorithm of the TVP-BVAR.
From the 3 dimensional charts in Figure 3 we can see that although the sign of the responses to financial conditions shocks seems to be consistent over time the magnitude has changed. The magnitudes of Chinese activity, advanced economy industrial activity, Chinese equities, EMBIG spreads and US financial stress responses in particular have become more muted in the latter periods of the sample.

To examine this more closely we focus on two specific historical episodes where financial conditions were becoming significantly easier - June 2009 in the wake of the GFC; and May 2016 when lending from the shadow banking sector was allowed to increase rapidly (see appendices A and B for full IRFs). The study of both of these episodes, as seen in Table 5, corroborates the earlier evidence in that the peak response of Chinese activity, advanced economy industrial activity, Chinese equities, EMBIG spreads and US financial stress are all lower in 2016 than 2009.

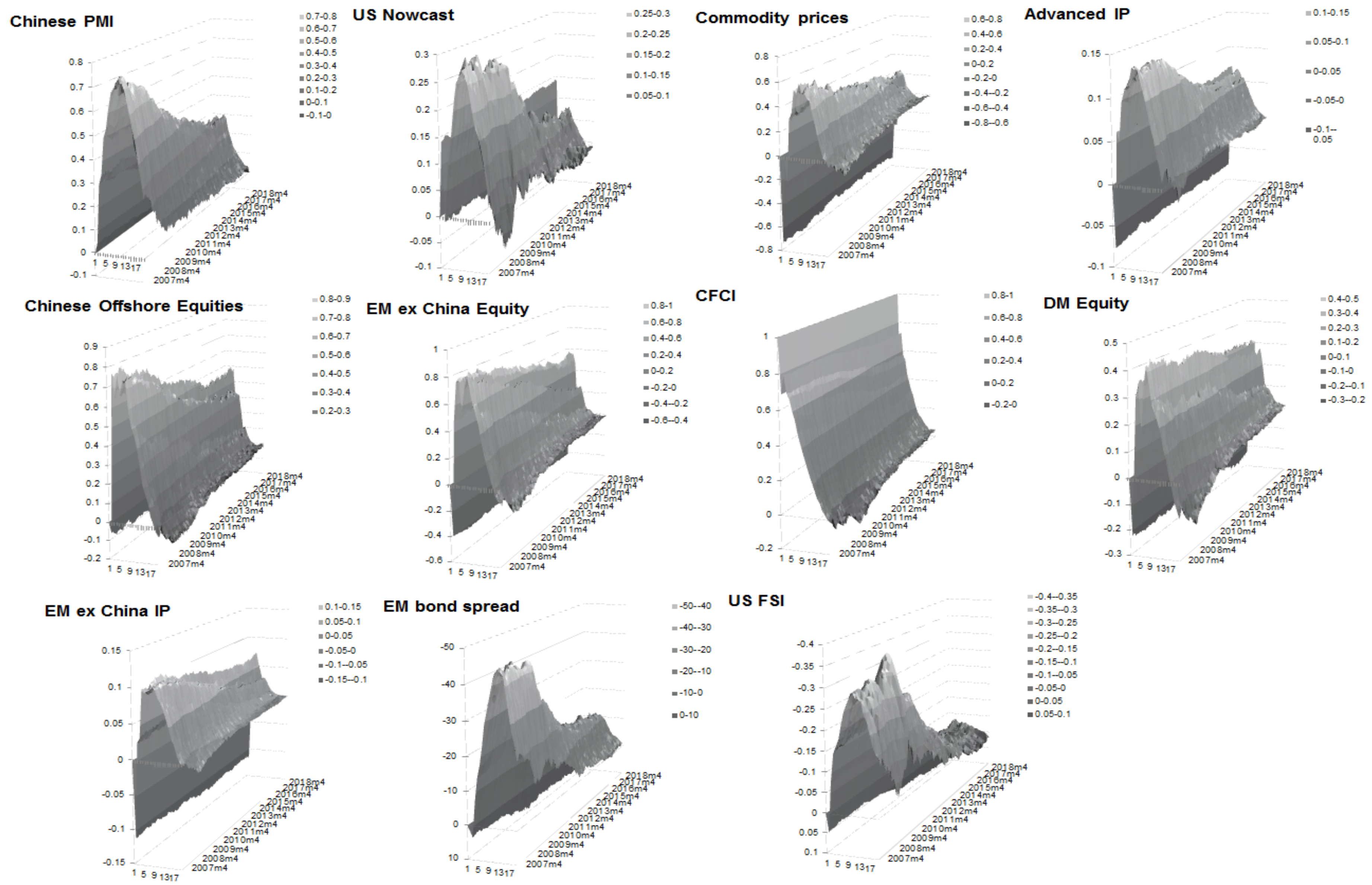
Although this is consistent with the hypothesis that the efficacy of policy easing has been declining as the country's debt burden has increased, our methodology does not allow us to be definitive and thus we leave this for future work.

Table 5: Comparing the timing and magnitude of peak response across periods

	Period of peak response		
	Jun-09	May-16	Change in peak response
China PMI	8	8	-0.34
US Nowcast	10	2	-0.11
Commodity prices	7	5	-0.20
EM IP	5	5	-0.03
Advanced IP	9	6	-0.07
Chinese offshore equity	3	5	-0.25
EM ex China equity	4	4	-0.20
DM Equity	8	5	-0.08
EMBIG	12	10	26.24
US FSI	11	5	0.28

Source: Aberdeen Standard Investments, Bloomberg and Haver. Change in peak response is measured as the difference between the peak response of each variable in May 2016 and June 2009.

Figure 3: Time-varying impulse responses to a one unit shock to Chinese financial conditions



Source: Aberdeen Standard Investments, Bloomberg and Haver. The x-axis measures the period of the response from 0 to 20 months after the shock, the y-axis caputres the magnitude of the response and the z-axis is the period in time that the impulse response is measured.

3.5 Robustness Checks

Lag Length in the Bayesian VAR. Our main results are drawn from a model using 6 lags but as part of our robustness checks we also considered specifications with 9 and 12 lags (see appendix C). We found that the use of a longer lag length led to issues in the convergence of the models likely due to the large number of parameters estimated within a relatively short sample. Despite this as is seen in Table 6 increasing the lag length to 9 does not materially alter the timing of the peak responses. In a specification of the model that assumed the US variables to be exogenous, the timing and sign of the results was not sensitive to the number of lags chosen.

Table 6: Comparison of peak impact across models with differing lag lengths

		Peak impact									
No. of Lags	Information Criteria	China PMI	US NC	Commodity Prices	EMIPxChina	AdvIPxChina	Chinese equity off	EM Equity	DM Equity	EMBIG	US FSI
6	-2024.94	7	8	7	5	7	4	5	5	11	11
9	1837.64	8	9	7	5	8	6	5	6	12	12
12	115572.4	13	13	12	11	13	8	8	12	16	16

Choice of priors in the BVAR. The choice of the normal-inverse Wishart prior follows from its common use in existing literature on Bayesian methods for shrinkage within VARs (Miranda-Agrippino & Ricco, 2018). To check the robustness of our results to our initial prior choice we have estimated the same model but using the Minnesota prior (see Litterman, 1980 and 1986 for details). The alternative prior produces similar results, only with wider confidence intervals, which is to be expected given the looser nature of the prior which we specify (see charts in appendix C).

Alternative orderings of the variables in the BVAR. Here we consider whether changing the order in our Choleski identification scheme alters the results. Although we experimented with many alternative orderings, in the interests of brevity we focus on the robustness of our results to moving the CFCI from last to the centre of the system between the macroeconomic and financial variables. As shown in appendix C the sign of all the responses remains the same but the shape of some responses are different. Additionally, the equity market responses are also less significant in this specification. We leave the Chinese financial conditions index last in our baseline results as this is consistent with other studies and also is supported by economic theory.

Making use of more principal components. By making use of only the first principal component we are implicitly assuming that Chinese financial conditions have a singular dimension. However, there may also be information content in the other principal components being discarded that is relevant to the behaviour of the other variables in our BVAR system. For example, if we examine the loadings for our variables into the principal components (see Table 7), we can see that Policy & Duration variables are a large component of the 1st principal component, whilst Money & Credit factors account for the greatest proportion of the 2nd and 3rd components. The loadings for measures of risk premia are also far higher in the 2nd and 3rd components, while Volatility is highest in the 3rd. It is therefore reasonable to consider whether we could be missing important information by excluding the further components from our analysis.

Table 7: Loadings into each principal component by category

	Proportion explained by each category		
	P1	P2	P3
Policy & Duration	49%	32%	23%
Money & Credit	32%	37%	26%
Risk Premia	6%	20%	22%
Volatility	10%	6%	22%
FX	3%	5%	8%
Total Variation Explained by Each Component	24%	18%	10%

Source: Aberdeen Standard Investments.

To consider this we choose to re-estimate our BVAR model with 2nd or 3rd principal components instead of the 1st and finally with all three principal components. The results for the impulse responses to shocks to the 2nd and 3rd principal components are presented in appendix D and E. The impulse responses here are rarely significant and the signs are counterintuitive for some variables such as EM industrial production, the EMBIG and our US variables. That said, a shock to the 3rd principal component does lead to significant responses in the advanced economy external variables such as the US nowcast, advanced IP, DM equities and the US FSI whilst the responses of Chinese and EM variables are insignificant. The impulse responses to a shock to the 1st principal component in the model in which we include all three principal components are shown in appendix F. As we can see the results here are similar to those which we obtained in our baseline model in which we used only the first principal component to represent Chinese financial conditions. However, the impact of the shocks dies out more quickly in this model. The response of the third component is insignificant and changes sign during the 60 month response period whilst the response of the second is positive and statistically significant.

Ultimately, given that neither the 2nd or 3rd component alone leads to significant responses and their inclusion with the 1st in the baseline model does not necessarily improve or alter the results we chose to use the 1st principal component alone as our measure of Chinese financial conditions.

4. Conclusions

Through our use of PCA and a large array of key policy, quantity and market variables for China we have constructed an index which quantifies both the current stance and the historic profile of Chinese financial conditions. The key finding from this is that policy, interest rates, money and credit factors have been the main drivers of the Chinese financial cycle since 2007. By contrast, returns from corporate bond and equity markets have played a much smaller role, both in absolute terms and compared with financial cycles in the advanced economies.

We then quantify the impact of changing Chinese financial conditions on both domestic and external macroeconomic and financial market measures using a Bayesian VAR framework. Our empirical modelling suggests that Chinese financial conditions do have a statistically significant impact on not just domestic activity but also EM and advanced economy industrial activity. We also find that there is a significant impact on the US economy specifically with a positive impact on the US nowcast and a fall in our US FSI. The impact on financial market variables differs across asset classes but all seems to be persistent. Especially, the EMBIG spread seems to be more sensitive to the shock to Chinese financial conditions than equity prices in both EM and advanced economies. The order of the timing in the peak responses fit fairly well with our prior expectations that asset prices should respond earlier to financial conditions shocks than economic activity variables. Importantly, these results are robust to alternative measures of financial conditions and different specifications of our BVAR.

Extending this analysis we then consider whether the impact of shocks to Chinese financial conditions have changed over time, finding that the response of domestic Chinese activity, the nowcast of US GDP growth, EM industrial production, the EMBIG spread and US FSI have all diminished. At the same time we also uncover evidence that the timing of peak responses has been brought forward for financial market variables in particular. Further work is necessary to determine whether these diminished responses are a result of declining efficacy of Chinese policy against a backdrop of more leverage.

Other potential extensions to our work could consider whether different aspects of the index have different implications for particular macroeconomic and market variables, i.e. is the response to changes in Policy & Duration factors different to that of changes in Credit & Money factors? It would also be useful to examine whether the impact of changing Chinese financial conditions differs across economies with different economic structures, such as for commodity importing versus exporting nations. Finally, we have not explicitly considered the interaction between monetary and fiscal policy, which could be important given their close interaction and the role they play in stimulating the economy.

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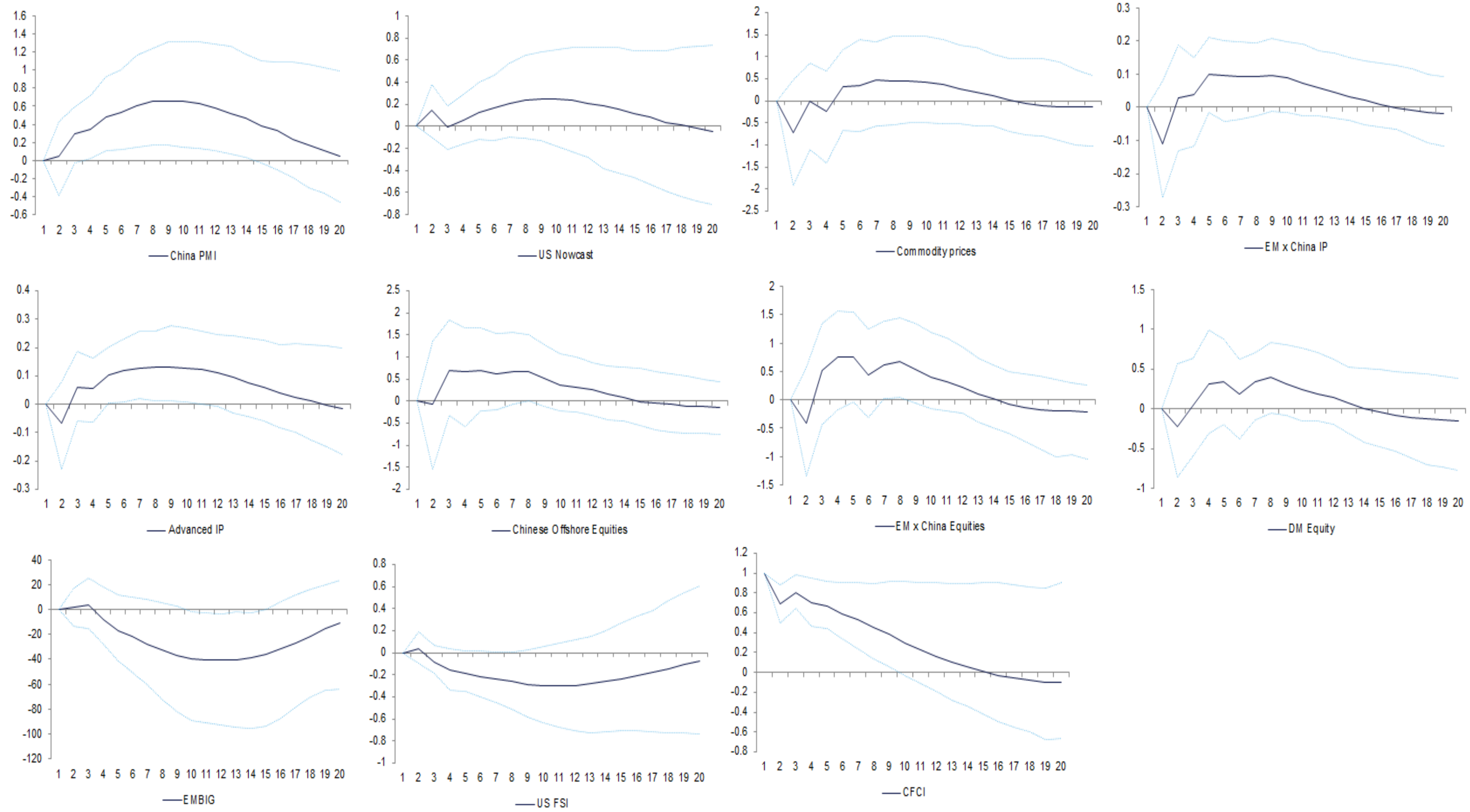
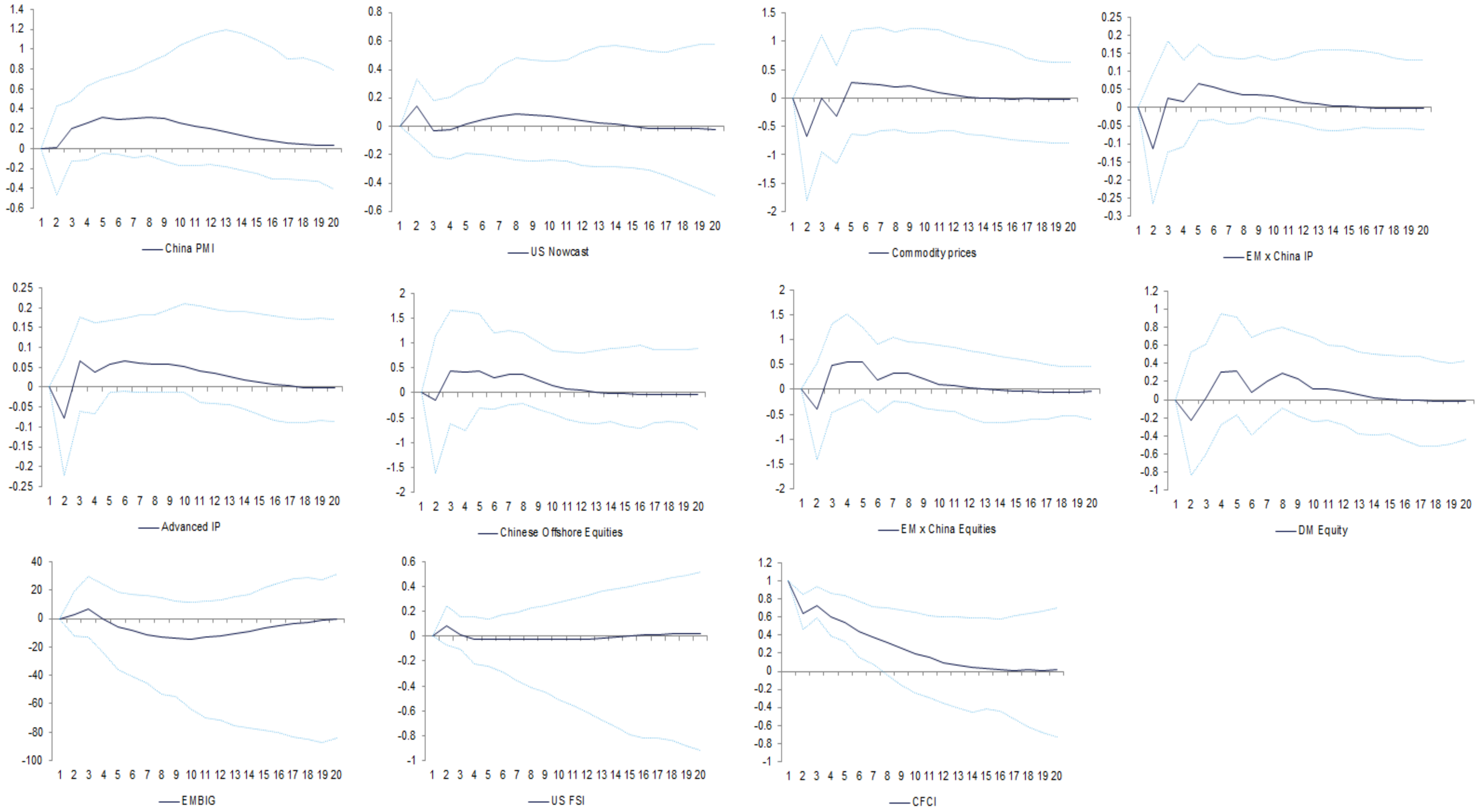
6. Appendices

A: Time-varying impulse responses to a 1 unit shock to Chinese financial conditions as measured in June 2009



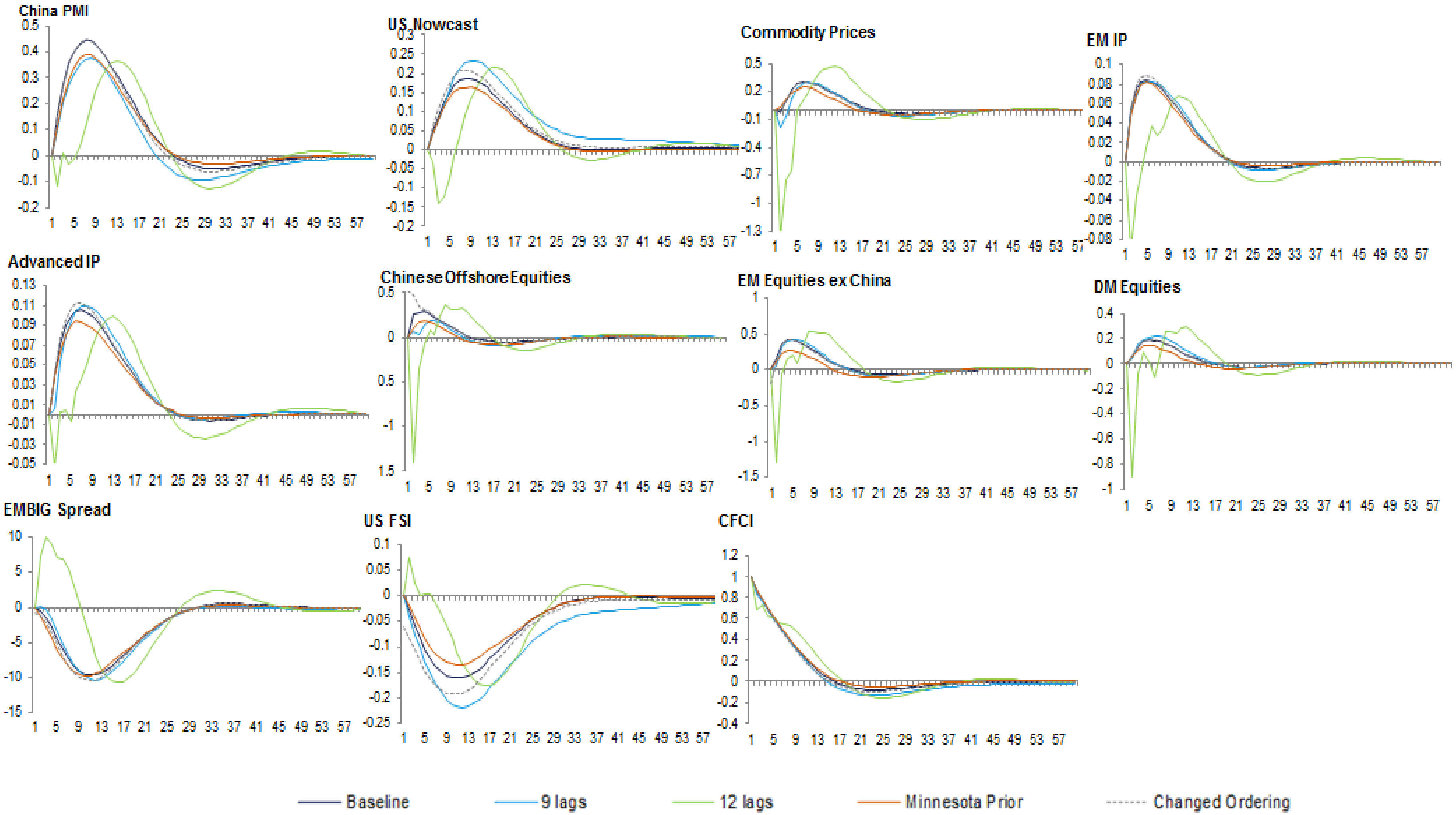
Source: Aberdeen Standard Investments. Solid line is the median impulse response and dashed lines are the 10th and 90th percentile.

B: Time-varying impulse responses to a 1 unit shock to Chinese financial conditions as measured in May 2016



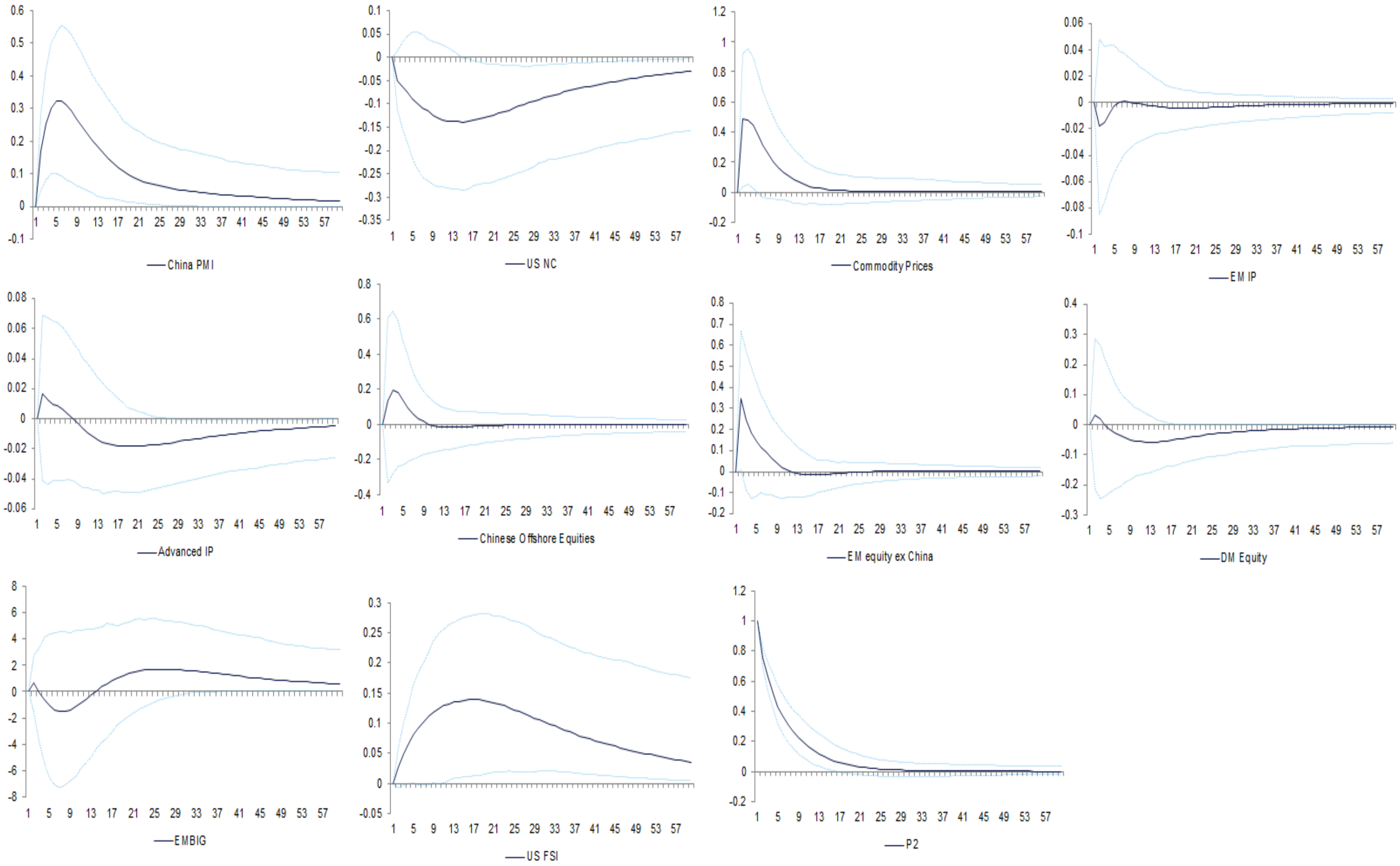
Source: Aberdeen Standard Investments. Solid line is the median impulse response and dashed lines are the 10th and 90th percentile.

C: Robustness Checks – Impulse responses to a one unit shock to Chinese financial conditions with 9 lags, 12 lags, a Minnesota prior and changed variable ordering



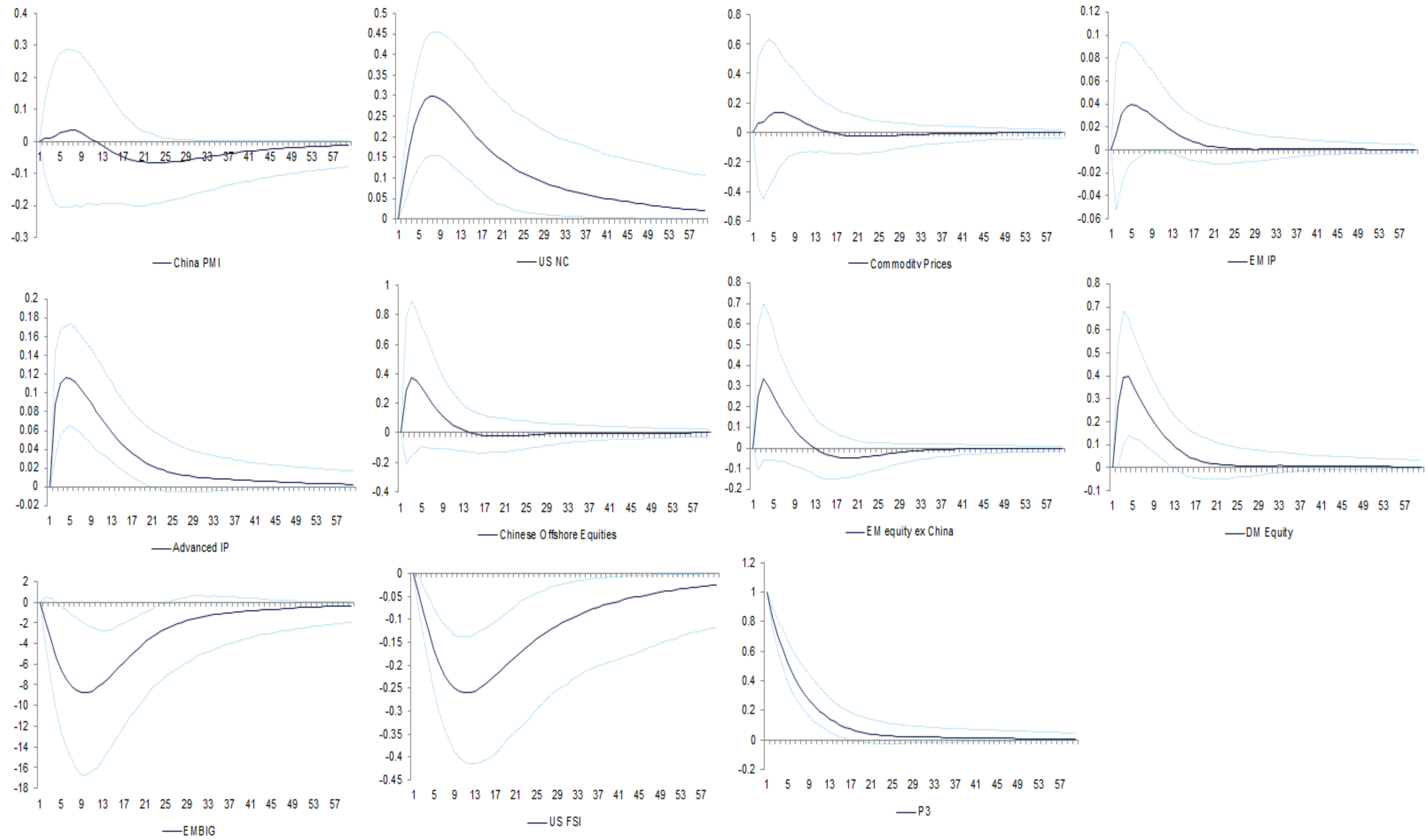
Source: Aberdeen Standard Investments.

D: Robustness Checks - Impulse responses to a 1 unit shock to 2nd principal component



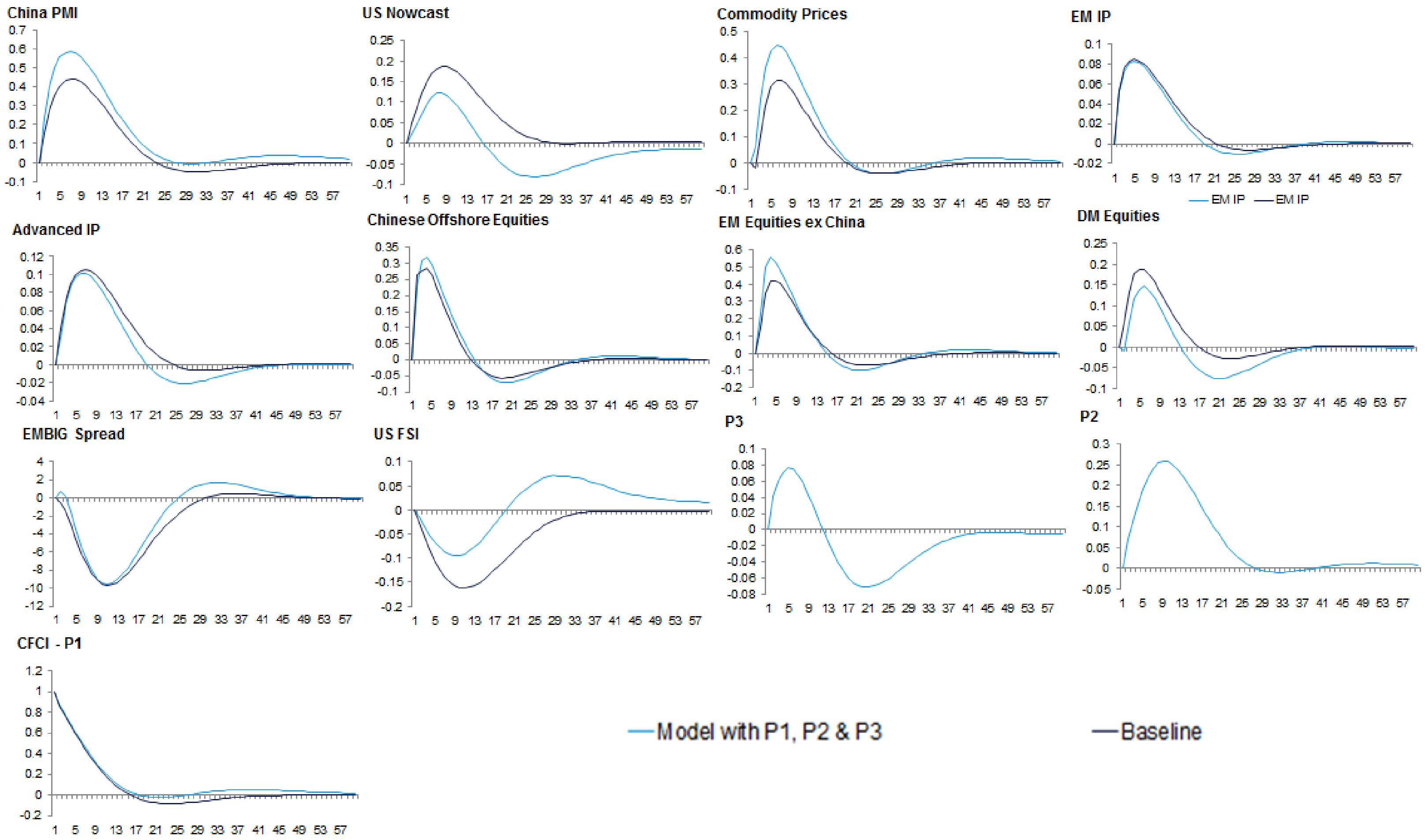
Source: Aberdeen Standard Investments. Solid line is the median impulse response and dashed lines are the 10th and 90th percentile.

E: Robustness Checks - Impulse responses to a 1 unit shock to 3rd principal component



Source: Aberdeen Standard Investments. Solid line is the median impulse response and dashed lines are the 10th and 90th percentile.

F: Robustness Checks - Impulse responses to a 1 unit shock to 1st principal component in model where we allow for the inclusion of 2nd and 3rd components versus the baseline specification



Source: Aberdeen Standard Investments.

G: General Time-varying Bayesian VAR

We apply the time-varying Bayesian VAR to study the evolving impact of CFCI. A time-varying VAR is similar to a traditional VAR, except that it allows the coefficients to be time-varying and the residual covariance matrix. Note that in this variant of our model we reduce the lag length, p, to 2 as is common in the modelling of time-varying parameter models due to the over proliferation of parameters to be estimated. Specifically, the model can still be expressed as:

$$y_t = A_{1,t}\, y_{t-1} + A_{2,t}\, y_{t-2} + \cdots + A_{p,t}\, y_{t-p} + Cx_t + \varepsilon_{t,}, \qquad \varepsilon_t \sim N(0, \Sigma_t) \tag{4}$$

The model can be written in compact form as:

$$y_t = \bar{X}_t \beta_t + \varepsilon_t \tag{5}$$

With:

$$\bar{X}_t = I_n \otimes X_t, \qquad X_t = (y'_{t-1}\, y'_{t-2} \ldots\, y'_{t-p}\, x'_t)$$

And

$$\beta'_t = vec(B_t), \quad B_t = \begin{pmatrix} A'_{1,t} \\ A'_{2,t} \\ \ldots \\ A'_{p,t} \\ C'_t \end{pmatrix}$$

The VAR coefficients are assumed to follow a random walk process:

$$\beta_t = \beta_{t-1} + \upsilon_t, \upsilon_t \sim N(0, \Omega)$$

For residual covariance matrixΣ_t, it can be decomposed as

$$\Sigma_t = F \Lambda_t F$$

F Is a lower triangular matrix with ones on its main diagonal and Λ_t is a time-varying diagonal matrix with $\text{diag}(\Lambda_t) = (\overline{s_1}\exp(\lambda_{1,t}), \overline{s_2}\exp(\lambda_{2,t}), \ldots, \overline{s_n}\exp(\lambda_{n,t}))$. Here $\overline{s_1}, \overline{s_2}, \ldots, \overline{s_n}$ are known scaling factors, while $\lambda_{1,t}$, $\lambda_{2,t}$ and $\lambda_{n,t}$ are the key to generate heteroskedasticity of the model. $\lambda_{i,t}$ Are assumed to be captured by the following autoregressive process:

$$\lambda_{i,t} = \gamma \lambda_{i,t-1} + \nu_{i,t} \qquad \nu_{i,t} \sim N(0, \phi_i)$$

The parameters of interest to be estimated are then: the VAR coefficientsβ, the covariance matrixΩ, the elements f^{-1} related to the F matrix, the set of dynamic coefficients λ and the heteroscedasticity parametersϕ. Assuming the parametersβ, Ω, f^{-1}, λ and ϕ are independent. Bayes rule for the model is given by:

$$f(\beta, \Omega, f^{-1}, \lambda, \phi | y) \propto f(y|\beta, f^{-1}, \lambda)\pi(\Omega)(\prod_{i=2}^{n} \pi(f_i^{-1}))(\prod_{i=1}^{n} \pi(\lambda_i|\phi_i))(\prod_{i=1}^{n} \pi(\phi_i))$$

The posterior does not admit analytical posteriors, so that the Gibbs sampling algorithm is required. The detailed information about priors, posterior distribution and sampling algorithm can be found from Dieppe, Romain and Björn (2015).