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Developing an underlying inflation gauge for China

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Contents

Abstract 4
1 Introduction 5
2 Traditional core measures 7
3 Identifying a persistent common component in a broad dataset 9
3.1 Extracting the lower frequency component 9
3.2 Handling a large dataset 10
4 Broad dataset of price and non-price variables 11
4.1 Data coverage and quality 11
4.2 January 2001 as our dataset starting point 13
4.3 Chinese Lunar New Year Effect 16
5 Parameterisation of the UIG for China 16
5.1 Removing frequencies higher than a year 17
5.2 Allowing for two factors 17
6 Statistical properties and forecasting performance 18
6.1 Statistical properties 19
6.2 Forecasting CPI inflation 21
7 Conclusions 24
References 25
Tables and graphs 28
Appendix 35
Data appendix 36

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Abstract

Inflation in emerging markets is often driven by large, persistent changes in food and energy prices. Core inflation measures that neglect or under-weight volatile CPI subcomponents such as food and energy risk excluding information helpful in assessing current and future inflation trends. This paper develops an underlying inflation gauge (UIG) for China, extracting the persistent part of the common component in a broad dataset of price and non-price variables. Our proposed UIG for China avoids the excess volatility reduction that plagues traditional Chinese core inflation measures. When forecasting headline CPI, the proposed UIG outperforms traditional core inflation measures over a variety of samples.

JEL Classification: C13, C33, C43, E31, E37, G15

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1 Introduction

Current and prospective inflation are key indicators for monetary policymakers and market participants. However, the main inflation measures – the consumer price index (CPI) and the personal consumption expenditures (PCE) index – may be too volatile to provide proper guidance for policymaking or long-term investment decisions. Consequently, a large body of literature has emerged suggesting various measures of underlying inflation that better interpret the CPI and PCE numbers. Most prominent are core measures that rely on a subset of less volatile components in the CPI and PCE. These typically involve stripping out noisier inflation components such as food and energy prices.

Less noise in core measures, however, can come at the cost of muting or eliminating information helpful in forecasting inflation. For instance, energy prices experience recurrent phases with large, persistent changes, so their exclusion from the inflation measure hampers forecast performance. To highlight this weakness, Stock and Watson (2008) show that a random walk is as good as core measures in forecasting CPI in the case of the US. Rich and Steindel (2007) also suggest that no single core measure outperforms another in terms of forecasting CPI.[1]

The excessive volatility reduction problem and poor forecasting record of traditional core measures are particularly relevant to economies where volatile subcomponents such as food and energy represent a substantial share of overall CPI dynamics. This is common for emerging markets as illustrated in ADB (2008). China seems particularly prone to excessive volatility reduction in core measures – almost a third of CPI subcomponents relate to food and almost a tenth to energy. Graph 1 highlights this by omitting food (CPI_ExFood) and energy (CPI_ExFoodExEnergy) components from simple plots of publicly available core inflation. Both core measures remain around 1% between 2004 and the end of 2008, while the CPI falls from 5% to 1% and the climbs back to 8%. After removing these crucial components, the core measures show negligible dynamics and are hardly helpful in signalling changes in CPI. The lower part of Graph 1 shows CPI and core measures for the US. Food and energy prices take up a much lower share of the CPI components in the US, so the volatility reduction is less severe than for China.

Our study contributes to the literature in three ways. First, we construct an underlying inflation gauge (UIG) for China that differentiates trend from noise.[2] The UIG is based on a broad

[1] For a summary of shortcomings of US core measures, see Bullard (2011) and the references therein.
[2] The acronym UIG for underlying inflation gauge has also been applied to a study of US inflation based on the same methodology as used here (see Amstad, Potter and Rich, 2017). Here, UIG refers to the case of China unless otherwise noted.

dataset that includes price and non-price variables and can be updated daily. We apply the generalised dynamic factor model developed by Forni, Hallin, Lippi and Reichlin (2000, 2001) and Cristadoro et al. (2005), taking advantage of its specific property of retaining a smooth underlying component when dealing with a large dataset. While similar gauges have been developed for advanced markets, this is the first time to our best knowledge that this particular model has been applied to gauging inflation of a major emerging market economy. We specifically note two measures for developed markets.[3] Cristadoro et al. (2005) have been the first to suggest the method underlying UIG with an application on Euro Area inflation. For the US the New York Fed staff underlying inflation gauge, has been calculated daily since 2005 for a sample starting in 1993 (Amstad, Rich and Potter, 2017; Amstad and Potter, 2009). The UIG for the US has proven to be particularly useful in early detection of turning points. Monthly publications by the New York Fed started in September 2017.[4] Where possible we compare the UIG for China with the US case.

Second, we compare UIG for China's statistical properties to those of CPI, traditional core inflation measures and a core measured used internally by the People's Bank of China (PBC). While our exercise is general in nature, it is well suited to emerging market economies where traditional core inflation measures are plagued by excess volatility reduction. Previous studies used different models and usually fewer variables. Funke et al. (2014) use a state-space model to track Chinese CPI in real-time with eight selected variables. Our goal, however, is to estimate the underlying CPI trend rather than track CPI itself. Thus, we use a broad dataset covering 395 time series for five data categories: prices, economic activity, money and credit, labour market and financial markets.

Third, our goal is to obtain an inflation signal based on a broad dataset that detects turning points in underlying inflation pressure and tells something about driving forces behind inflation. We calculate two versions of the gauge: "UIG" based on a broad dataset, and "UIG prices" based solely on price data.

We find that UIG for China provides additional information to monetary policymakers and market participants. In a classical forecasting exercise UIG and UIG prices significantly outperform traditional core measures, including the PBC's own internal measure. Our results are robust across

[3] Other similar measures for inflation in developed markets include: Altissimo et al. (2009) use a dynamic factor model to investigate the persistence in aggregate Euro Area inflation. Reis and Watson (2010) use a dynamic factor model to separate absolute from relative price changes. For a Swiss inflation indicator, see Amstad and Fischer, 2009a. For a quarterly inflation measure in New Zealand see Giannone and Matheson (2007). For Canada, see Khan, Morel, and Sabourin (2013). The latter two studies use the prices-only version of the UIG discussed later in this article.
Aside from inflation dynamic factor models have more widely been used for GDP: For Euro Area GDP, the EuroCoin indicator produced by the Centre for Economic Policy Research (CEPR) is released on a monthly basis (Altissimo et al., 2001 and 2010). For US GDP, the Chicago Fed's National Activity Index is based on the methodology of Stock and Watson (1999).

[4] For monthly updates see https://www.newyorkfed.org/research/policy/underlying-inflation-gauge.

different samples and different panels. Unlike the US case, the forecast performance for UIG for China is less driven by the inclusion of non-price variables and the lead at turning points is shorter.

As a caveat, same as UIG for US also UIG for China should *not* be interpreted as an alternative inflation measure for CPI or a substitute for traditional core measures. Our goal here is simply to identify a supplementary inflation signal for core measures that supports the decision-making of monetary authorities and market participants.

The remainder of the paper is organised as follows. Section 2 discusses properties of traditional core measures. Section 3 considers the methodology choices for the UIG for China. Section 4 discusses the dataset, addressing the issues of data categories and quality, sample length and the Chinese New Year effect. Section 5 provides the rationale for our chosen parameterisation of the model. Section 6 examines the statistical characteristics of the UIG for China by comparing smoothness, correlation with CPI and added information content against traditional core inflation measures. Following Cogley (2002) and others, we investigate the relative performance of various underlying inflation measures in terms of forecasting inflation. Section 7 concludes.

2 Traditional core measures

The most popular inflation yardsticks are the year-on-year change in the consumer price index (CPI) or the index of personal consumption expenditures (PCE) published by national statistical authorities. These gauges routinely serve as the official reference rate for inflation in many economies. Without questioning this status, CPI and PCE as well as measures solely based on their subcomponents suffer from at least three shortcomings as far as policy makers or investors are concerned.

First, headline inflation often exhibits marked short-term variability, making it difficult to judge whether a sudden up or down move in the most recent CPI observation is transient noise or a trend shift. This partly reflects the fact that statistical offices strive to produce the most accurate inflation measure over time. The purpose of core inflation measures is to overcome the excess variability issue. While there is no consensus on the definition of core inflation, the term generally refers to a less-noisy indicator that can serve as a leading indicator for inflation. Eckstein's (1981) definition still serves as an excellent starting point, i.e. the "core rate of inflation is the rate which would occur on the economy's long term growth path provided the path were free from shocks and the state of demand were neutral." The CPI excluding food and energy, as suggested by Eckstein (1981) and popularised by Gordon (1975), is the best-known core measure. Other core inflation measures include the CPI trimmed mean and CPI median. These also advocate the exclusion of the most volatile CPI subcomponents and share an implicit assumption that big price fluctuations are transient. Because volatility is shed by excluding or down-weighting the more volatile price components, core inflation measures by definition produce a smoother trend than the CPI.

Second, while the CPI, PCE and corresponding traditional core measures differ in composition, they rely solely on price variables. Other variables such as unemployment and economic slack known to impact inflation (albeit with a lag) are overlooked, even though they are publicly available at the time when the policy decision based on inflation is taken. In other words, available information about current and future inflation may be ignored if only the CPI or PCE and their subcomponents are used.

Third, the CPI and PCE and corresponding traditional core measures are typically published monthly. This may be frequent enough in normal times, but in turbulent times like the recent global financial crisis it may be advantageous to use a more frequently measured gauge of inflation that makes fuller use of available information. This holds particularly true for the case of China where no flash estimate for the Chinese CPI in advance of the monthly CPI release is available.

To address the narrow information set and the monthly publication frequency, inflation indicators are used. They may be based on *surveys* such as the Survey of Professional Forecasters (SPF) produced by the Federal Reserve Bank of Philadelphia, or *market transactions* such as break-even inflation implied by the yield difference between treasury inflation protected securities (TIPS, or real bonds) and nominal bonds. Both break-even inflation and survey-based inflation gauges are conceptually different from core measures as they refer to future inflation. Core measures typically refer to the current underlying trend in inflation. Further, market and survey participants, who appear to base their judgement on a broad dataset in their reactions to daily news, do not provide easy clues as to which data series in the broad dataset should be included, what weightings are appropriate or how such series and weights evolve over time. In addition to expected inflation, Hördahl (2009) shows that there are three additional components that constitute the break-even rates between real and nominal bonds: inflation risk premia, liquidity premia and technical market factors. These components may change over time and hamper the interpretation of break-even inflation. Further, in the case of China no inflation-protected bonds from which to infer break-even rates are available.[5]

In summary, core, market and survey-based inflation measures introduce new potential problems while only partly addressing the above-mentioned CPI shortcomings (i.e. high volatility, dataset narrowness and low availability frequency).

[5] See Burdekin et. al. (1999) on the episodes stemming from the introduction of indexed government bonds by the People's Republic of China in the face of the inflation panic of 1988–89 and their reintroduction during the 1993 inflation surge.

3 Identifying a persistent common component in a broad dataset

Our choice of model is driven by our goal of developing an inflation gauge useful to bond investors and monetary policymakers who want to look beyond short-term variability in inflation.[6] Such a model should possess two features. First, it should retain long-term cycles and exclude short-term cycles (i.e. noise). Second, it should be applicable to a large dataset that comprises many potentially correlated variables. Both desired properties can be captured in one step using the generalised dynamic factor model introduced in Forni, Hallin, Lippi and Reichlin (2000, 2001).

This "FHLR" model has proven useful in applications for various economies and economic variables (see intro and footnote 3). The precise estimation procedure follows Altissimo et al. (2001) and Cristadoro et al. (2005). The FHLR approach builds on work of Brillinger (1981) in generalising the traditional dynamic factor models (Sargent and Sims, 1977) for large panels. In contrast to factor models popularised by Stock and Watson (1999, 2002), the FHLR approach estimates and forecasts inflation smoothed in cross section (measurement errors, local and sectoral shocks) and in the time dimension.[7] Below we briefly review the FHLR model and focus on two of its key properties in designing our UIG for China.

3.1 Extracting the lower frequency component

The model best suited to our requirements should produce a smooth signal that distinguishes between noise and trend without neglecting variables. This is the opposite approach to traditional core inflation measures in which smoothing comes at the cost of excluding variables that could contain useful information.

A Fourier transformation allows us to rewrite a time series ("time domain") into multiple sine waves ("frequency domain"),[8] and thereby make it possible to extract a clearly defined frequency band (e.g. all frequencies or cycles in a given variable that last only up to 1 year). This puts definition of noise versus trend under the control of the econometrician.

[6] The section draws heavily on the exposition used in Amstad, Rich and Potter (2017) and references provided therein.
[7] Estimated in the time domain without smoothing Antonello and Giannone (2012) find no significant difference in the predictive ability of the factor models of Stock and Watson (2002) versus Forni, Hallin, Lippi and Reichlin (2005) using a large panel of US macroeconomic variables.
[8] Any time series can be written as the sum of several sine waves. The individual sine waves differ in amplitude (the peak deviation from average), frequency (the number of cycles that occur within a second) and phase (lead or lag). A high frequency refers to a volatile time series, while a low frequency refers to a smooth time series (at the extreme a constant).

Section 4.2 shows UIG for China based on different choices of frequency band. It also motivates our choice of frequency band (cycles of up to one year) for the UIG for China used in our forecasting exercise in Section 5.

3.2 Handling a large dataset

Apart from smoothing, the model best suited to producing a gauge as described in the introduction should summarise many variables into a few variables (or even just one variable). In that respect, the econometric class of factor models seems an obvious choice. The number of factors needs to be defined, of course, and we address this in Section 4.2.

Within the factor model approach, the generalised factor model of Forni et al. (2000) is well suited to our purposes. The FHLR approach applies a Fourier transition that allows smoothing of the used input variables (see Section 2.1) in one step. It also handles large datasets. Finally, our aim is to develop a signal that can be regularly updated as the relevance and weighting of any variable may change, particularly in the case of a fast-developing emerging market economy like China's. Frequent changes in the dataset make it difficult to judge whether a change in the signal is due to changed data coverage or changed weightings. Therefore, it is advantageous to include many potentially relevant variables and let the factor model determine each time it is updated (here, daily or weekly) the appropriate weights of input variables used to explain inflation at a point in time.

We assume a panel of $\mathrm{i} = 1, \dots, \mathrm{N}$ time series, $x_{it} = (x_{1t}, x_{2t}, \dots, x_{Nt})'$which are realisations of a zero mean, wide-sense stationary process and thought of as an element from an infinite sequence. As in the traditional dynamic factor approach, each time series is assumed to be measured with error and can be decomposed into the sum of two unobservable orthogonal components:

$$x_{it} = X_{it} + \xi_{it} = \boldsymbol{b}_i(L)\boldsymbol{u}_t + \xi_{it} = \sum_{j=1}^{q} b_{ij}(L)u_{jt} + \xi_{it}, \qquad (1)$$

where X_{it} is the common component, driven by q dynamic common shocks $\boldsymbol{u}_t = (u_{1t}, .., u_{qt})$ with non-singular spectral density matrix and ξ_{it} is the idiosyncratic component reflecting measurement errors and local shocks. $\boldsymbol{b}_i(L)$ is a vector of lag polynomials of order s and considers factor dynamics. ξ_{it} is orthogonal to the common shocks $\boldsymbol{u}_{t-k}$for all k and i. The traditional dynamic factor model assumes mutual orthogonality of the idiosyncratic components ξ_{it}. This is a strict assumption, especially for $\mathrm{N}\rightarrow\infty$, as it ignores local shocks that affect only a small subset (but more than one) of variables.

Unlike the above-mentioned traditional dynamic factor models, Forni et al. (2000) propose a generalised dynamic factor model that eases this assumption and allows for limited dynamic cross-correlation. As orthogonality cannot serve as a theoretical distinction between X_{it} and ξ_{it}, additional assumptions such as those given in Forni et al. (2000) are needed. Under these assumptions, the above-described model is a generalised dynamic factor model.

4 Broad dataset of price and non-price variables

This section describes the dataset compiled to generate the UIG for China and discusses the issues of data coverage and quality, sample length and the Chinese Lunar New Year effect. The dataset is a panel of 395 time series covering key aspects of the Chinese economy. Our sensitivity analysis uses subsamples (e.g. comprising only price series) and a broad panel of 472 time series available through 2016. While the model we use asks that all the variables have the same start date (balanced at the start), they may have different sample lengths due to different publishing schedules (unbalanced at the end).

4.1 Data coverage and quality

Since our goal is to develop an inflation signal based on a broad dataset that detects the turning points in underlying inflation pressure and teases out driving forces behind inflation, the dataset should cover a broad set of variables influencing inflation. Indeed, multiple studies indicate that Chinese inflation is driven by a broad set of variables, including Cai and Du (2011), who evaluate the contribution of labour market developments; Zhang (2012), who studies demand-pull versus cost push factors; and Nagayasu (2009), who provides evidence that inflation can be explained by economic fundamentals such as money, credits, productivity and exchange rate growth.

Our dataset consists of the following five main categories: (1) prices; (2) economic activity; (3) the labour market; (4) money and credit; and (5) the financial market. We estimate our benchmark UIG for China using all these categories, as well as UIGs for China using price data only (UIG_prices). We try to keep the size of the dataset manageable by focusing on variables that the PBC regularly monitors in its inflation analysis and forecasting.

Our main dataset (Panel A) consists of 395 variables in total, slightly more than the 346 used in a similar inflation gauge for the US (Amstad, Potter and Rich, 2017) and slightly fewer than the 454 for Switzerland (Amstad and Fischer, 2009a, 2009b). Graph 2 shows the composition among the five categories for the Chinese and US datasets. As the target variable is inflation, the price category is the largest, accounting for more than 43% of the dataset in the case of China and two-thirds for the US. For China, a broader dataset was available (Panel B) up to end-2016, but thereafter some variables, particularly price and labour variables, were discontinued or altered. Thus, we include panel B for our sensitivity tests, but focus on panel A that includes currently available time series. The Data Appendix provides a complete list of variables in panels A and B.

The price category includes all major price indicators such as CPI and its components, retail price index (RPI), producer price index (PPI), corporate goods price index (CGPI) and import/export price indices. The category of economic activity covers both nominal and constant-price data such as industrial value added, investment, retail sales, trade and household and firm surveys. The labour market data mostly consist of average and total wages, employment and unemployment. The money and credit data include key monetary aggregates, bank loans and deposits. The financial market data include interest rates, exchange rates and stock price indices. Finally, in light of China's increasing integration with the global market, our dataset contains major international commodity prices and selected data on China's top five trading partners. Borio and Filardo (2007) illustrate the importance of global output gap for domestic inflation developments in a broad cross-section of economies by showing that proxies for global economic slack substantially add to the explanatory power of conventional inflation rate equations. In the case of UIG for China, we include price, growth, labour and interest rate data for the US, EU, Japan, Korea and Taiwan. These trading partners each account for at least 5% of China's total exports, and collectively represent around 70% of China's exports.

There are five important features of our dataset worth highlighting. First, while most of the input variables are of monthly frequency, some activity and labour market variables are quarterly data and most financial market series are daily. Second, all of the time series ideally should be in nominal value. However, because of limited data availability, we also consider variables in the form of real value, nominal year-on-year growth rate and real year-on-year growth rate. Third, none of the time series in the dataset has been seasonally adjusted as this will be done in a consistent way for all variables when applying the same common approach on the basis of our filter.[9] Fourth, In light of the irregular seasonable pattern caused by the Chinese Lunar New Year holiday that moves between January and February from year to year, we address the affected series (see Appendix A1 for details). Fifth, all included time series are tested for stationary and treated accordingly to construct an unbiased signal.

Despite considerable progress made over the years, there are well-known challenges to the quality of the Chinese statistics (Holz, 2004; Brandt and Rawski, 2008). Data reliability and repeated

[9] See Section 3. The filter we use comprises a spectral density analysis that allows us to exclude a given high frequency part (here, frequencies higher than 1 year) in all variables.

breaks are two common difficulties. As the Philips curve assigns a prominent role to labour market conditions in driving inflation, labour market statistics are the most problematic for our purposes (Ma, McCauley and Lam, 2012). Indeed, Chinese labour statistics tend to be of limited coverage and low quality. They only cover urban areas and start relatively late. For example, while the series of total average wage starts from December 1999, the average wage in different industries starts only from 2008. Moreover, there are only annual data on wage and employment for private enterprises and self-employed individuals, while quarterly data are available only for state and urban collective enterprises above certain size. Variables such as the registered urban unemployment rate are known to bear little relevance to the actual labour market conditions. Nevertheless, we include the labour market data in our data sample on the grounds that even if they for now might not contribute much to detecting inflation turning points, their relevance might increase in the future if their quality improves.[10] We also include household income survey data to supplement the wage data and mitigate quality risks.

4.2 January 2001 as our dataset starting point

Our methodology requires all data to have the same starting date, while permitting different sample lengths. Our econometric methodology to handle the end-of-sample procedure follows Forni et al. (2005) and Cristadoro et al. (2005). This gives rise to a trade-off between breadth and length when choosing our dataset. On the one hand, the dataset should ideally be broad enough to cover all the main categories discussed above. On the other hand, the dataset should be long enough to cover several inflation cycles in order to construct a stable inflation signal. As the Chinese statistics system is developing rapidly, new variables for shorter periods are being added. In other words, the longer the sample, the less broad it is. In particular, most of the newer and shorter series are the subcomponents of existing older series.

Taking balanced and practical approach to this trade-off, we choose the starting point for our data sample to be January 2001 for two reasons.

First, many series have more detailed breakdowns after 2001. For the most important data category in our study, CPI data, the monthly headline CPI in China starts from January 1985, but the food subcomponent and its further breakdowns start only in January 1994. The non-food subcomponent and its breakdowns start only in January 2001. Even more detailed subcomponents within the CPI categories were introduced for the first time in January 2005. If our sample starts

[10] This study is the basis for a new underlying inflation indicator that can be used and updated regularly over time. Therefore, we keep variables that are problematic now it they could improve in the future to make sure that our dataset is complete and consistent.

before 2001, there would be many short series. If it starts after 2005, the sample length would be too short to construct a reliable signal. The case for other data categories is similar. A starting point of January 2001 balances breadth and length. Moreover, by the late 1990s, most of the Chinese consumer prices had been liberalised. Thus, observed prices in the 2000s better reflect underlying inflation pressure.

Second, there appears to be a distinct regime change in China's inflation dynamics around 2000–2001 (Graph 3a). Before 2000, the Chinese inflation rate was much higher and more volatile, fluctuating between peaks of above 20% and troughs of outright deflation. The mean and standard deviation of monthly year-on-year inflation between 1987 and 2000 reached 8.8% and 8.7%, respectively. During 2001 and June 2016, however, they dropped to 2.3% and 2.2%, respectively. In this latter period, the Chinese economy experienced at least three full "well-behaved" inflation cycles between January 2001 and June 2012. Inflation in these three post-2000 cycles is clearly lower and less volatile than the two cycles in the 1980s and 1990s. Moreover, China's post-2000 inflation dynamics appear to be more associated with domestic and external cyclical shocks than liberalisation of administered prices or soft-budget behaviour of investment and wage-setting (Kojima et al., 2005).

A host of factors may help explain the regime shift in the inflation cycles after 2000. These include the transition from a strict command economy to one with market-based features, progress in price deregulation, increased supply, enhanced institutional capacity in macroeconomic management, an evolving exchange rate regime and external shocks (Giradin et al., 2014).

Most price liberalisation measures had been implemented by the late 1990s, so headline CPI inflation thereafter has largely responded to market demand and supply (Kojima et al., 2005; Zhang and Clovis, 2010). The China Price Yearbooks (Zhongguo Wujia Nianjian) report that the share of market-determined prices in agricultural procurement increased from 51.6% to 87.5% between 1990 and 1993, while the share for retail sales rose from 53.0% to 93.8% and for producer goods from 36.4% to 81.1%.

China's accession to the WTO in 2001 appears to be a major turning point for the economy. It triggered a wide-ranging structural transformation of the domestic economy to prepare for increased foreign competition. It also heralded growing integration of the Chinese economy with the global market. In preparation for WTO accession, trade liberalisation and corporate restructuring enhanced the resilience of the Chinese economy to shocks, mitigating inflationary pressure and volatility. Foreign investment, technology transfers and increased competition also helped lift potential growth. Arguable, these favourable productivity shocks generated large income windfalls that contributed to China's large current surpluses and growing domestic liquidity under a tightly managed exchange rate regime. China's increased demand for energy and other resources may also have substantially influenced international commodity prices, which in turn could affect domestic inflation dynamics.

Finally, there is the apparent structural break in Chinese inflation to justify starting our sample in January 2001. Any inflation signal we extract reflects Chinese inflation pattern of this new era.

Thus, the choice of January 2001 as the starting point of our dataset on the balanced consideration of data availability, data quality and an apparent regime change in China's inflation dynamics. Even so, about a third (119) of the data series in our sample start after 2001. We include these short series in our dataset by approximating their starting values. This is based on the consideration that some of these short series could become more important in providing information for the inflation signal in the future. Further, the importance of their fitted values for the initial years fades as time passes and the gauge is regularly updated.

We deal with the missing observations in the beginning of the series using a simple regression approach called a "bridge equation." This permits us to generate the missing values for the earlier segment of a shorter series without introducing additional information to our dataset. For a sample range from t to T and a short series Y from t' to T, we fill in the missing values in Y from t to t'. For the bridge equation approach (see Data Appendix Graph A), we define a series X that covers the whole sample range of t and T as a regressor on Y to estimate a simple linear equation $Y = \alpha + \beta * X$ for the period of t' and T. The estimated coefficient values of α and β should allow us to obtain the fitted values of Y for the period of t and t'. The series Y for the full period of t and T is thus obtained by combining the fitted values from t to t' and the actual values from t' to T.

In this approach, the long series X acts as a bridge and therefore should be carefully chosen to be highly correlated with Y. In most cases, we choose the broader and full-sample variable as the bridge for shorter sub-components. For example, we use the long CPI-grain series as the regressor in the bridge equation for the shorter CPI-rice series. Graph 3b shows the "bridged" rice component of the CPI for 2001–2003 (the orange line is the fitted value as the substitute for the missing values).

In the final dataset, 119 of the 395 time series are extended using a bridge equation. While this is a significant portion, most of these short series (about 60%) have missing values for no more than 2 or 3 years. For the 13 labour-market-related short series in 2008, just one long series X could be used. However, 70% of the short series Y have an X:Y ratio between 1:2.5 and 1:4.7. Since all of the long series in the bridge equations are already in our dataset, we have not introduced any additional information by extending the short series. Moreover, the importance of the lengthened parts diminishes as the gauge is regularly updated.

To verify that our extended short series do not distort the final signal, we compare the two signals extracted from the whole dataset and the dataset excluding the 119 extended series. This exercise shows both to be very similar.

4.3 Chinese Lunar New Year Effect

Some of the time series are significantly distorted by the well-known Chinese Lunar New Year Effect. The Chinese Lunar New Year is the most important traditional holiday in China. People leave work for a week of family reunions, shopping and travel. During the holidays, manufacturing activities slow or contract, while retail sales soar. The seasonal pattern is irregular, however, as the Chinese New Year may fall in January or February according to the lunar calendar. For this reason, China's National Bureau of Statistics (NBS) does not compile or publish separate January and February data for such activity variables as industrial value-added and fixed asset investment. The NBS sometimes provides the year-to-date data only for February.

As this is a familiar challenge of Chinese data, we follow the practice of others, dealing with the Chinese New Year Effect on a case-by-case basis. For series without separate January and February data, we assume the two monthly observations to be the same (Data Appendix Table A). For variables with separate January and February data where the Chinese New Year does not fall in the same month as in the previous year, there can be a big jump in the year-on-year growth rate, which may significantly distort the growth of these variables. Here, we need to determine first whether a series is significantly affected by observing the graph for its year-on-year growth rate. Once significantly affected series are identified, we follow the practical approach of taking the average of January and February to remove the Chinese New Year Effect.[11] For example, Data Appendix Graph B shows the adjustment of retail sales of consumer goods.

5 Parameterisation of the UIG for China

This section presents an empirical consideration of our model parameterisation outlined in Section 3 using our dataset choice of Section 4. Two parameters need to be set exogenously: the *noise*

[11] For instance, Shu and Tsang (2005) compare the two methods of pre-adjusting a series for the Chinese New Year Effects: taking the average of January and February and using CNY dummies. They find that accounting for the Chinese New Year Effect improves seasonal adjustments, but neither proposed method clearly outperforms the other.

definition, i.e. which frequency band (b) should be removed from each input variable, and the *number of factors* (q) to be estimated.

5.1 Removing frequencies higher than a year

We define frequencies shorter than 12 months as noise.[12] Our decision to exclude cycles shorter than 12 months is based on three considerations.

First, monetary policy typically cannot influence inflation up to one year in advance due to long and variable lags in the policy transmission process. For bond investors, it seems prudent to use similar time horizons as the central bank, since the central bank can be expected to act on the signal of its choice.

Second, for comparable measures used in advanced economies such as the US, EU and Switzerland, the central banks often neglect cycles of less than a year.[13]

Third, we show the sensitivity of UIG for China when based on different choices of frequency band in Table 1 and Graph 4a. For a frequency band of up to 12 months, the resulting UIG for China captures 84% or more of the volatility in headline CPI inflation. When frequencies shorter than two or three years are removed, the volatility share of the corresponding UIG for China drops to 63% and 49%, respectively. This is a big drop in volatility and potentially may indicate a significant loss of information.

5.2 Allowing for two factors

The main feature of a factor model is that it summarises the information of many input variables in a few orthogonal factors. It is common to number the factors according to their decreasing shares to summarise the joint variability in the input variables as the first factor, second factor, etc. The number of factors should be large enough to represent the underlying input variables, but small enough to assure a parsimonious model. Whatever statistical criterion is used as guidance, the number of factors (and therefore the choice of the variability share of the input variables to be reflected in the factors) is always an exogenous choice.

[12] We follow the common terminology used in the literature, where the term “above or longer than 12 months” refers to “lower or longer frequencies.” Correspondingly, “below or shorter than 12 months” here means the same as “higher or shorter frequencies.”
[13] In frequency domain terminology, this refers to higher frequencies above 12 months.

Many factor model applications influence the chosen number of factors. For macroeconomic applications, the consensus is that the input variables should be captured by two factors reflecting *real* and *nominal* driving forces in constructing the underlying inflation gauge.[14]

We follow the two-factor approach for three reasons. First, our application does not use the factors directly as signal, but only the information contained in the factors to regress on inflation (with this estimate defined as the UIG). Second, two factors have long been seen as appropriate for comparable applications in the US (Amstad, Potter and Rich, 2017), EU (Cristadoro 2005) and Switzerland (Amstad and Fischer, 2009b). Third, our sensitivity analysis shows that the impact of the number of factors above two is quite limited (Table 2 and Graph 4b). The UIG for China based on different choices of number of factors as 1, 2, 4, 6 and 8 differ little in terms of turning points. However, the UIG for China with only one factor parameterisation is distinct in that its standard deviation (S.D.) is only 67% of the S.D. in our target variable headline CPI inflation. This share rises and stays at around 84% for UIGs for China based on 2 and more factors.

6 Statistical properties and forecasting performance

We emphasised in our introduction that the goal here is to construct a gauge useful for policymakers and market participants. In this section, we evaluate the UIG for China against traditional core inflation measures by comparing their statistical properties and testing their forecasting performance.[15]

Graph 1 shows the UIG for China and the two traditional core inflation measures for Chinese CPI excluding food (CPI_ExFood) and CPI excluding food and energy (CPI_ExFoodEx-Energy), both as published by NBS. CPI excluding food starts in January 2005 and CPI excluding food and energy starts in January 2006. To allow a comparison of forecasts based on the estimation from 2001, we first extend CPI excluding food by assuming that the food weight from 2001 to 2004 is the same as in 2005. We then extend CPI excluding food and energy by bridge equation as described in Data Appendix Graph A using the prolonged CPI excluding food series.

[14] Different papers find that two factors explain most of the variance in US macroeconomic variables. Giannone, Reichlin and Sala (2004) show this result using hundreds of variables for the period 1970–2003, while Sims and Sargent (1977) examine a relatively small set of variables and use frequency domain factor analysis for the period 1950–1970. Watson (2004) notes that the two-factor model provides a good fit to US data during the post-war period, and that their finding is quite robust. Hence, in most large data factor model applications, the number of factors is set to two.

[15] The statistical tests and their description conducted in this paper to evaluate the statistical properties of UIG for China mirror those in Amstad, Potter and Rich (2017) and Amstad and Potter (2009) for the Fed NY Staff underlying inflation gauge (UIG) applied on US inflation.

Graph 1 illustrates the marked reduction in volatility of the two traditional core measures. While CPI fluctuates between -2% and +8%, the CPI excluding food (CPI_ExFood) and CPI excluding food and energy (CPI_ExFoodExEnergy) both vary only between -2% and +2%. In two out of three peaks of CPI, the traditional core measures fail to warn bond investors and policymakers of an increased inflation trend.[16]

For reference, we include in these tests of forecasting performance an internal core inflation measure often monitored by the PBC staff (UCPI).[17] This measure excludes the more volatile components of food prices and certain administratively set prices. The PBC apparently uses this alternative core inflation measure to remove excess volatility associated with fresh food prices and administrative price adjustments. The UCPI was introduced in January 2005. We extend it back to 2001 by bridge equation using CPI excluding food and CPI. As the UCPI is not released to the public, we do not show it in our graphs.

To ensure the robustness of our tests, we use two measures of UIG: the benchmark "UIG" based on the full dataset and "UIG prices" based solely on the subset of price variables. Otherwise, UIG and UIG_prices use the identical methodology and parameterisation. As a further robustness test, we comment where appropriate on the results using the current panel with 395 time series and the panel with 472 time series described in Section 4.

6.1 Statistical properties

In evaluating the usefulness of the UIG for China against traditional core inflation measures and the UCPI, we consider three statistical criteria: *smoothness*, *correlation with CPI* and *added information*.

The first criterion, smoothness, is desirable because it reduces the effect of short-term inflation volatility on policy decisions. Regarding the second criterion, correlation with CPI, it is clear that a constant, even if it yields maximum reduction, has no utility in gauging inflation . Therefore, we consider the correlation with CPI as an additional statistical criterion to asses an inflation gauge's usefulness. The more a low-noise inflation gauge correlates with CPI, the better. Finally, the third criterion asks where the inflation gauge comes with additional information above and beyond infor-

[16] CPI peaked in 2004, 2008 and 2011. The traditional core measures (CPI excluding food, CPI excluding food and energy) remained more or less stable during the first two peaks. Similarly, CPI troughs in 2002, 2008 and 2009 show in traditional core measures either simultaneously or with a lag.
[17] UCPI is not yet publicly available and therefore not shown in Graph 4. However, we include it in our comparison and show the corresponding results.

mation already provided by publicly available traditional core inflation measures. This third criterion is evaluated using a principal component analysis (PCA). In this regard, a useful inflation gauge is allocated in the same group as CPI, but in a different group than other core inflation measures.

In the following discussion, we show that our UIG is less noisy compared to the CPI, but does not suffer from the excessive reduction of volatility in traditional core inflation measures. Further, it closely tracks headline CPI inflation while providing additional information not included in traditional core inflation measures.

A) Smoothness

Based on the standard deviation metrics, both UIG and UIG_prices are around 25% less volatile than CPI, but more volatile than traditional core inflation measures (Table 3). Traditional core measures show less than half of the S.D. of CPI. This illustrates the often-cited dilemma of excess volatility reduction (e.g. ADB, 2008; Cheung et al., 2008) dilemma constructing traditional core inflation measures for China.[18] While the weight of food and energy prices in the official CPI is not publicly available, it is safe to say that the weight is much higher than in the US (ADB, 2008) or other advanced economies. Also, by excluding food and energy from the CPI, a considerable part of the CPI volatility is removed along with information potentially useful in forecasting the CPI.

B) Correlation with CPI

UIG and UIG_prices both closely track headline CPI inflation with a correlation of around 0.88-0.92 (Table 4). Similarly, the UCPI is highly correlated with CPI with a coefficient of 0.92. In contrast, traditional core inflation measures such as CPI excluding food and CPI excluding food and energy display much lower correlation coefficients (0.71 and 0.58) with the CPI.[19]

C) Additional information

We evaluate whether an inflation gauge is statistically similar or different from another gauge using two statistical methods: *simple cross-correlations* among various core measures and *a PCA*.

[18] Rhee and Lee (2013) generalise this finding to other emerging Asian economies. They find that, the share of food in consumption baskets is high in emerging Asian countries, reaching 50% or more in some countries. For example, the share of food in the consumption basket is 58.84% for Bangladesh, 46.71% for Sri Lanka, 44.78% for Cambodia, 39.93% for Vietnam and 39.0% for the Philippines. Thus, food price inflation may have a larger direct effect on headline inflation in these countries.

[19] The UCPI's correlation with the CPI is significantly different from the UIG's correlation with the CPI (p=0.3%). Meanwhile, correlations of UIG and UIG_prices with the CPI are not significantly different (p=65%). Similarly, CPI_ExFood and CPI_ExFoodExEnergy correlate insignificantly with the CPI (p=48%).

A low correlation between two inflation gauges suggests they are quite different inflation signals. As can be seen from Table 4, UIG and UIG_prices show the lowest correlations (0.50-0.66) with traditional core measures (CPI excluding food and CPI excluding food and energy). Meanwhile, the UCPI shows a correlation of 0.78-0.85 with traditional core inflation measures as well as our UIG and UIG_prices.

It is evident that both UIG and UIG_prices provide a different signal than the traditional core inflation measures, although this finding holds more for the CPI excluding food and CPI excluding food and energy than for the UCPI.

This finding is confirmed by a simple principal component analysis (PCA) of the CPI and the inflation gauges considered here. As shown by the factor loadings given in Table 5, 96% of the overall volatility in all the considered inflation gauges can be explained by two factors. Both UIG and UIG_prices and the UCPI are based on loadings of 0.41 grouped together with CPI inflation in the first principal component. Meanwhile, traditional core inflation measures (CPI_ExFood and CPI_ExFoodExEnergy) load with 0.46 and 0.63 on a separate second principal component. Remarkably, CPI even loads negatively on this second factor.

6.2 Forecasting CPI inflation

How does our proposed UIG for China compare in terms of forecasting performance with traditional core inflation measures of CPI excluding food and CPI excluding food and energy? To identify the best underlying inflation measure, we undertake a classical forecasting exercise in the broadly accepted setting of Rich and Steindel (2007).

For any evaluation, it is particularly important that the forecast exercise reflects a realistic setting. Therefore, an important issue for the exercise concerns the choice of forecasting sample period. A long period could be problematic because it might cover different inflation regimes, while a short period might be statistically insignificant or unrepresentative. Furthermore, in a period when inflation is successfully stabilised (e.g. industrialised countries in the years before the global financial crisis), the signal associated with the least variation might have had an advantage over signals generated from earlier periods when inflation was more volatile. The opposite result might hold for measures with more variability during the global financial crisis. Therefore, it is important to run the exercise over a sample displaying significant variation in inflation and over different sub-samples.

The behaviour of Chinese inflation since 2001 displays these features as it covers a fairly tranquil pre-2008 period and a volatile post-2008 period. However, as our sample starts in 2001 (see

Section 4.2), as the estimation period should not be shorter than the forecasting period, and as we want to account for possible sensitivity of the forecast comparisons to the selected sample periods, we consider two forecasting periods. First, a sample from 2006–2016:6 that covers several full inflation cycles. Second, a "crisis" sub-sample that captures the period from 2008 until the end of 2012. The samples are long enough to allow for meaningful statistical tests for the UIG applied to China.

Finally, forecasting exercises are often undertaken in a "pseudo" real-time manner, i.e. the estimation is conducted using a single vintage dataset. In practice, the actual data may have been revised subsequently. The impact of revisions and new data releases on the final estimate of UIG have been find to be limited in the case of US, where daily estimates since 2005 are available (see Amstad, Potter and Rich (2017)). In this paper, we work with a vintage dataset that ends on June 30, 2016.

We calculate Root Mean Squared Errors (RMSE) resulting from forecasting inflation h month ahead $\hat{\pi}_{t+h}$ based on an estimation of equation (2):

$$\hat{\pi}_{t+h} = \pi_t + \hat{\alpha}_h + \hat{\beta}_h (\pi_t - \pi_{mt}) \tag{2}$$

Where π_t is inflation in t, π_{mt} notes a given candidate as underlying inflation measure and $\hat{\alpha}_h$, $\hat{\beta}_h$ are the estimated regression coefficients using data through time t. This follows Cogley (2002) and others who evaluate the performance of the various measures of underlying inflation by estimating the same regression equation To further analyse the forecast performance of the UIG, we apply the Diebold-Mariano (1995) testing procedure.

We compare the forecast performance of the UIG to the CPI excluding food (CPI_ExFood) and CPI excluding food and energy (CPI_ExFoodExEnergy). To test for robustness, we also include UIG_prices in the forecast exercise.[20] As is common in this type of forecasting exercise, we include a random walk as a benchmark, represented by CPI inflation lagged by 12 months (CPI_LAG12).

We obtain four notable observations (Tables 6 and 7 for the current panel A with 395 variables and Tables 8 and 9 for panel B with 472 variables).

[20] An alternative would be to evaluate additional variants of the UIG. Forecasting properties may vary for different UIGs that include e.g. only a specific data category, a few pre-selected data series or specific province variants. For example, Mehrotra et al. (2010) find that the forward-looking inflation component and the output gap are important inflation drivers in provinces that have made the most progress towards a market economy and have likely experienced excess demand pressures. However, this paper focuses on the forecasting property of the UIG using the whole dataset given in Section 3.

First, UIG overall clearly outperforms traditional core measures, the PBC's internal UCPI measure and the random walk both over the full sample and during the crisis years of 2008–2012. This strong result is robust and confirmed when we use a broader panel of 472 variables. The other measures show RMSE over the full sample and the crisis period which are higher at a very high significance level of 0%. The only exception is during the crisis period when CPI excluding food and energy prints at only at a 9% significance, but still at a higher RMSE level than the UIG.

Second, the results show that overall the forecast errors from UIG are lower than those of UIG_prices. However, the difference is only significant for Panel B. While this finding differs from findings for the US (Amstad, Potter and Rich, 2017) using the same test and a similarly constructed inflation gauge,[21] it comports with Holz and Mehrotra (2013), who find that growth in labour costs in China is not passed through fully to final prices in China neither in the tradable goods sector nor in the economy as a whole. Overall, we interpret this as a further evidence for the frequently documented dominance of certain price variables, particularly food, in the Chinese CPI. While the food weight in the Chinese CPI basket is not published, we know it is significant – by some estimates around 30% (ADB, 2008) compared to 16% in the US.[22] Going forward, the importance of non-price variables might further increase and the UIG might then outperform UIG_prices. This hypothesis is in line with Zhang (2012) who argues that while inflation may appear demand-pull driven at the moment, cost-push factors like labour costs may ultimately play a more significant role. To test for this expectation, we perform the exercise using the broader panel B, which includes more labour market data (see Data Appendix). In the case of panel B, we find (Table 8 and 9) that UIG shows significant lower RMSE than the UIG prices for both the full and crisis samples.

Third, the forecasting performances of traditional core inflation measures of CPI_ExFood and CPI excluding food and energy are remarkably similar over the full sample. This is in line with the findings for the US in Rich and Steindel (2007) using the test setup and confirming that various traditional core inflation measures differ little in their forecasting performance.

Finally, all underlying inflation measures do better than the random walk measured by headline CPI inflation lagged by 12 months. Not surprisingly, the random walk forecast displays the highest forecast errors among the reported measures for both the full cycle and the crisis sample when inflation is particularly volatile.

[21] A big difference between the UIG for China and UIG for the US is sample length. The UIG for the US starts in 1994; the UIG for China in 2001. For completeness, we mention findings by Amstad and Fischer (2009a) using a similarly constructed gauge for Switzerland. The test environment is slightly different and does not cover the crisis years. Notably, the evidence for Switzerland comports with the findings of Amstad, Potter and Rich (2017) for the US case.
[22] In November 2013, the weight of food in the US CPI was 14.2% and the weight of energy 9.6%.

7 Conclusions

This paper introduces and constructs a new underlying inflation gauge (UIG) for China. We present our approach to its calculation, explain our choice of model parameterisation, discuss data challenges and compare the statistical properties and forecasting performance of the UIG against other traditional core inflation measures (CPI excluding food and CPI excluding food and energy) including a PBC's internally used core measure.

UIG for China is highly correlated with headline CPI inflation, while providing additional information above and beyond that which is available from traditional core inflation measures. We find UIG for China to be less noisy than the CPI, yet not to suffer from the extreme volatility reduction typical to traditional core measures in China. These properties clearly distinguish UIG from other core inflation measures and make it particularly useful as an additional inflation measure for monetary policymakers and market participants in emerging markets where the CPI contains a high share of food and energy components.

Our proposed UIG differentiates trend from noise, is based on a broad dataset and can be calculated on a daily basis. While calculation and interpretation of traditional core inflation measures is easy, the UIG clearly outperforms them across different samples in forecasting headline CPI. A property that sets our UIG apart from traditional core inflation measures is that it is *inclusive* of data. When specific price components like food become less important and labour and financial markets gain relevance, the importance of including additional data in forecasting inflation is likely to further increase over time.

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Tables and graphs

Table 1 Standard deviation (S.D.) for inflation and UIG for China, where volatility pertaining less than 3, 6, 12, 24 and 36 months have been excluded

	CPI inflation	b=3	b=6	b=12	b=24	b=36
S.D.	2.17	1.96	1.88	1.82	1.38	1.07
Portion (%)		91%	87%	84%	63%	49%

Source: Authors' calculations.

Table 2 Standard deviation (S.D.) for inflation and UIG for China, with different number of factors from 1 to 8

	CPI inflation	q=1	q=2	q=3	q=4	q=6	q=8
S.D.	2.17	1.45	1.82	1.93	1.93	1.91	1.91
Portion (%)		67%	84%	89%	89%	88%	88%

Source: Authors' calculations.

Table 3 Standard deviation (sample: 2001.M1–2016M6)

	CPI	UIG	UIG_Prices	UCPI	CPI_NF	CPI_NFE
S.D.	2.17	1.82	1.59	1.35	1.04	0.92
	100%	84%	74%	62%	48%	43%

Source: Authors' calculations.

Table 4 Correlations

	CPI	UIG	UIG_Prices	UCPI	CPI_NF	CPI_NFE
CPI	1.00					
UIG	0.88	1.00				
UIG_Prices	0.92	0.96	1.00			
UCPI	0.92	0.80	0.84	1.00		
CPI_NF	0.71	0.66	0.63	0.85	1.00	
CPI_NFE	0.58	0.50	0.50	0.78	0.94	1.00

Source: Authors' calculations.

Table 5 Principal component analysis

	PC1	PC2
CPI	0.43	-0.26
UIG	0.41	-0.39
UIG_Prices	0.41	-0.41
UCPI	0.44	0.06
CPI_NF	0.40	0.46
CPI_NFE	0.36	0.63
Variance Prop	0.81	0.15
Cumulative Prop.	0.81	0.96

Source: Authors' calculations.

Table 6 Forecasting performance over full sample: 2006-2016.6. Estimation period is 2001-2005

	RMSE	DM stat	DM p-value
UIG	2.210	na	na
UIG_Prices	2.178	-0.211	0.584
UCPI	3.387	3.109	0.001
CPI_NF	3.080	2.690	0.004
CPI_NFE	3.036	2.784	0.003
CPI_Lag12	3.564	2.345	0.10

Root Mean Square Error (RMSE), Diebold Mariano (DM) statistics. Diebold Mariano likelihood (DM p-value)

Source: Authors' calculations. UIG for China with 395 time series.

Table 7 Forecasting performance over crisis period: 2008-2012. Estimation period is 2001-2007

	RMSE	DM stat	DM p-valuen
UIG	2.887	na	na
UIG_Prices	2.774	-0.495	0.690
UCPI	3.925	1.875	0.030
CPI_NF	3.669	1.686	0.046
CPI_NFE	3.408	1.317	0.094
CPI_Lag12	4.692	2.013	0.022

Root Mean Square Error (RMSE), Diebold Mariano (DM) statistics.Diebold Mariano likelihood (DM p-value)

Source: Authors' calculations. UIG for China with 395 time series.

Table 8 Forecasting performance over full sample: 2006-2016.6. Estimation period is 2001-2005

	RMSE	DM stat	DM p-value
UIG	2.322	na	na
UIG_prices	2.749	1.798	0.036
UCPI	3.387	3.543	0.000
CPI_NF	3.080	3.033	0.001
CPI_NFE	3.036	2.869	0.002
CPI_Lag12	3.564	2.542	0.006

Root Mean Square Error (RMSE), Diebold Mariano (DM) statistics. Diebold Mariano likelihood (DM p-value).

Source: Authors' calculations. UIG for China with 472 time series.

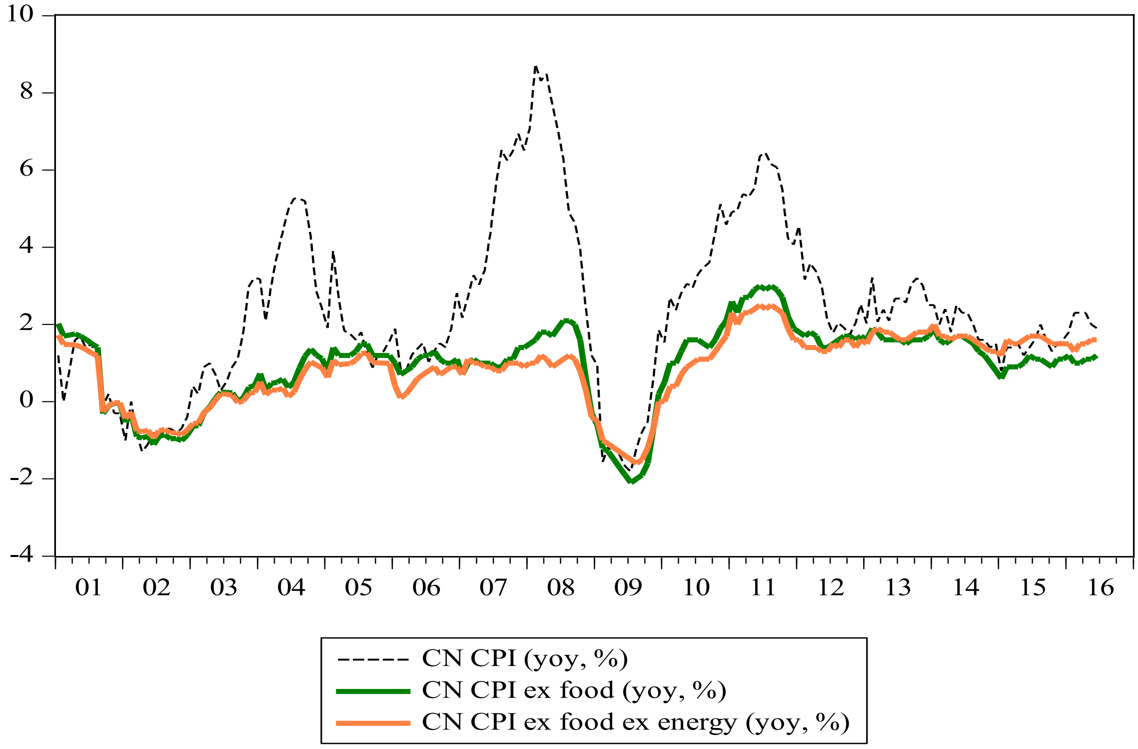
Table 9 Forecasting performance over crisis period: 2008-2012. Estimation period is 2001-2007

	RMSE	DM stat	DM p-value
UIG	2.985	na	na
UIG_prices	3.721	2.355	0.009
UCPI	3.925	2.543	0.005
CPI_NF	3.669	2.373	0.009
CPI_NFE	3.408	1.511	0.065
CPI_Lag12	4.692	2.364	0.009

Root Mean Square Error (RMSE), Diebold Mariano (DM) statistics. Diebold Mariano likelihood (DM p-value).

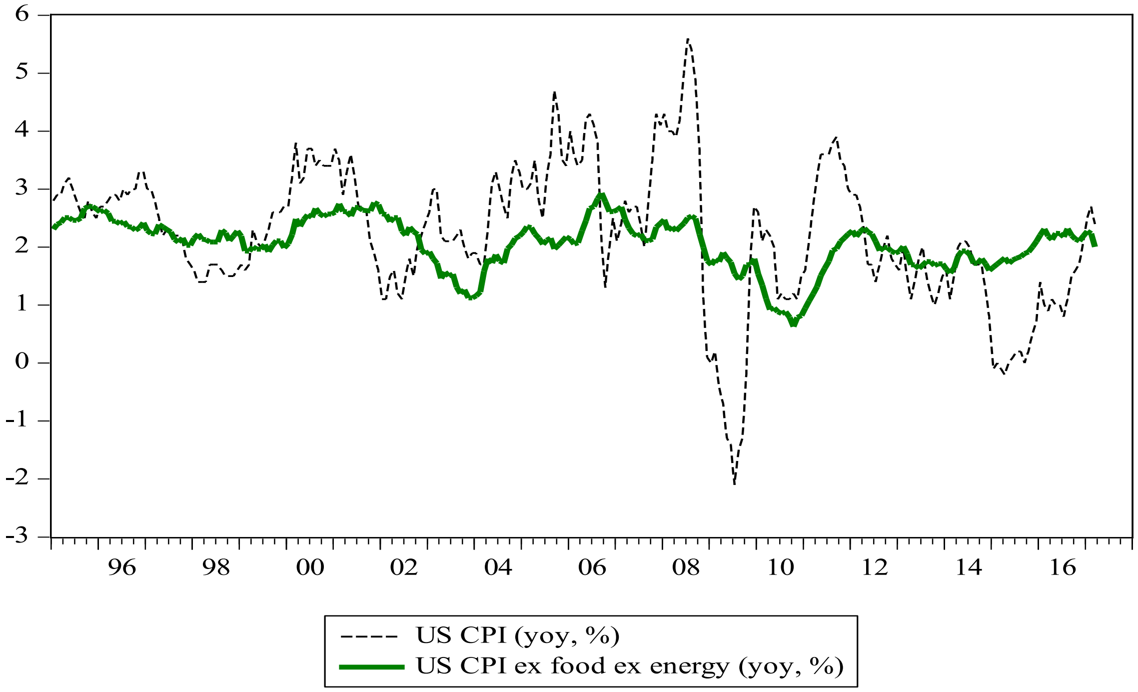
Source: Authors' calculations. UIG for China with 472 time series.

Graph 1a Chinese consumer price index (CPI), consumer price index excluding food, consumer price index excluding food, y-o-y in %



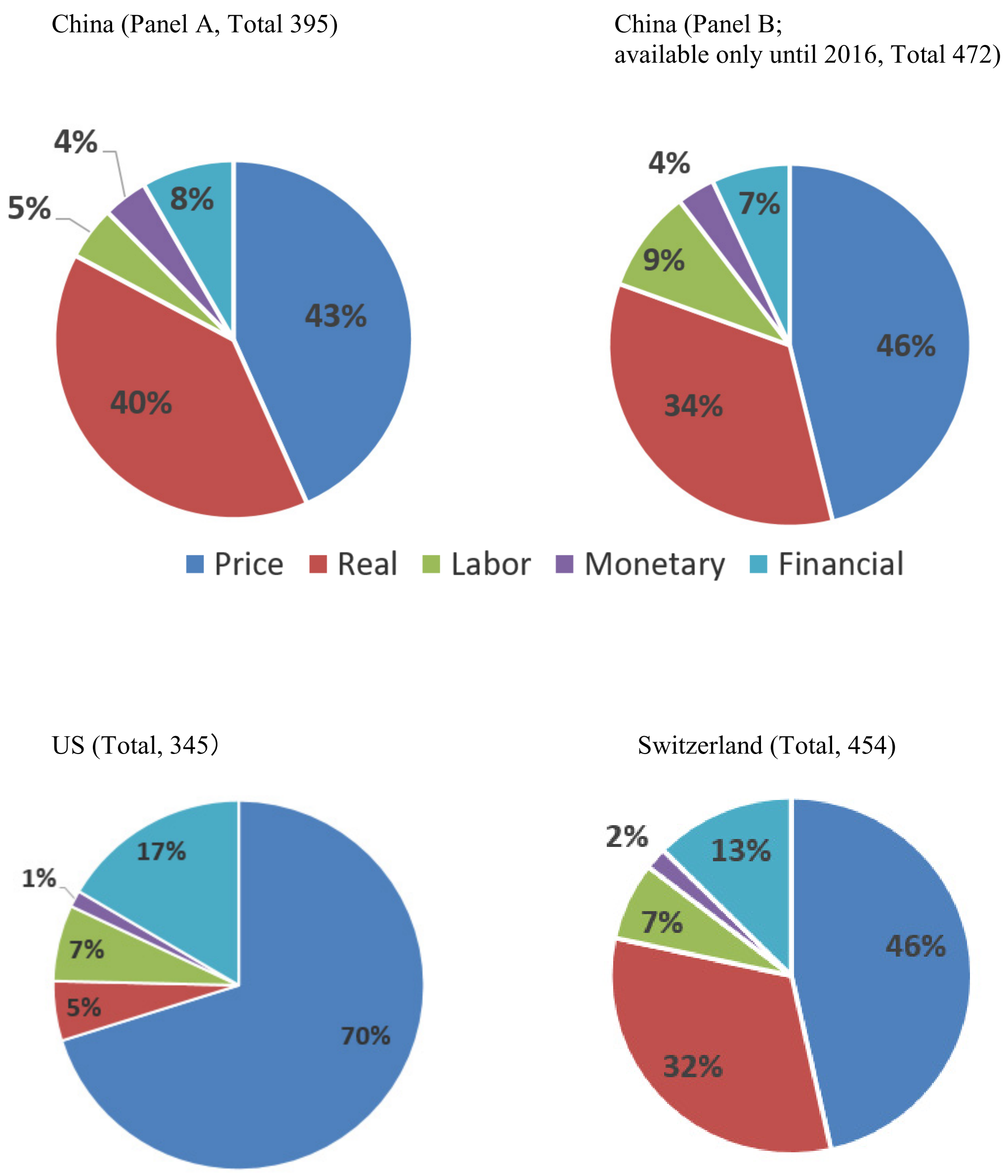
Source: Authors' calculations.

Graph 1b US consumer price index (CPI), consumer price index excluding food and excluding energy, y-o-y in %



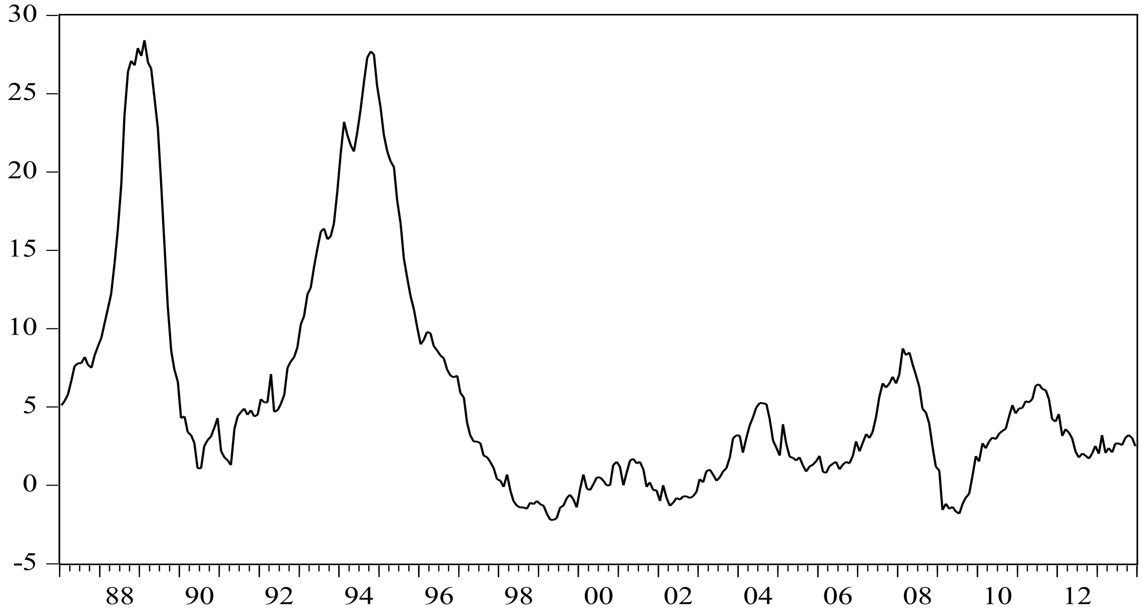
Source: Bloomberg.

Graph 2 Number and composition of input variables for China (long and short sample) and the US (New York Federal Reserve Underlying Inflation Gauge)



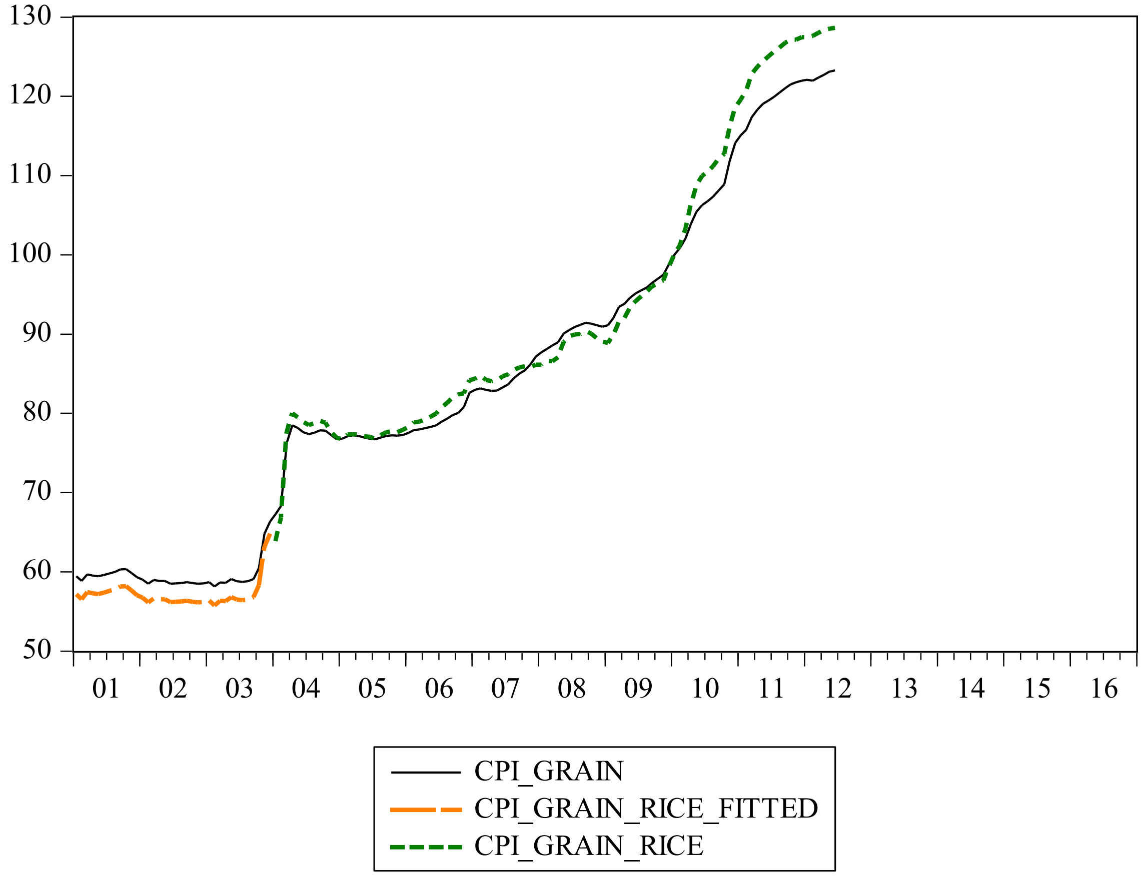
Source: Authors' calculations.

Graph 3a Consumer price index in China, y-o-y in %



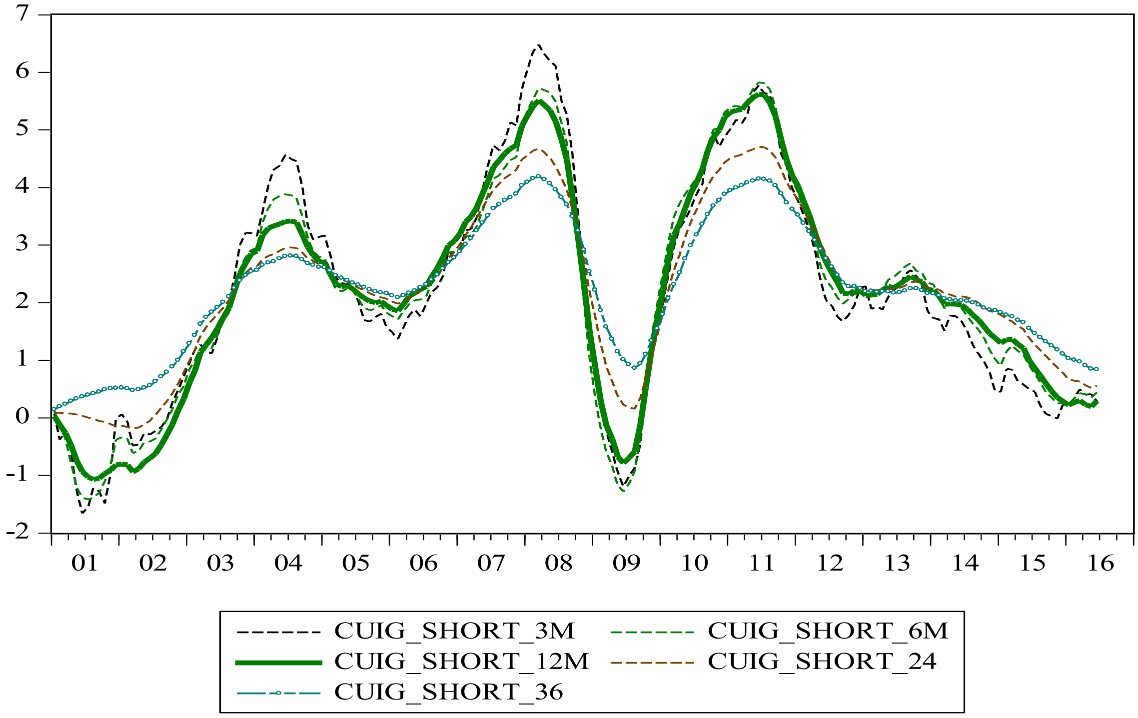
Source: Bloomberg.

Graph 3b CPI component indices: grain and rice (Jan 2010 = 100)



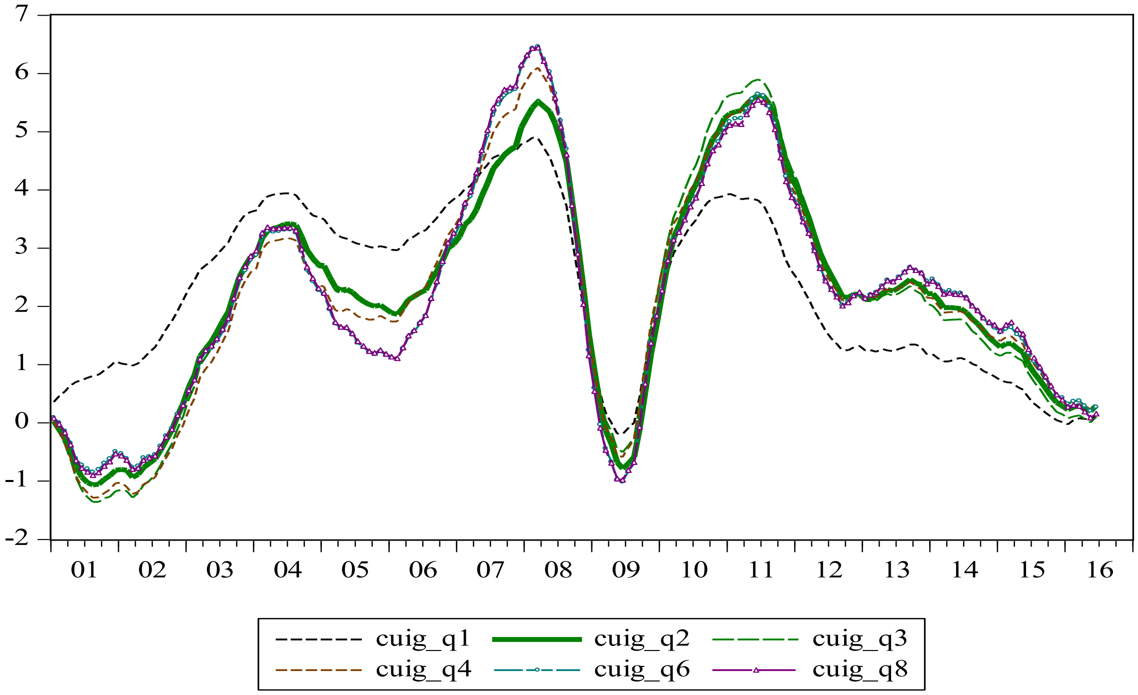
Sources: CEIC and authors' calculations.

Graph 4a Inflation and different UIGs for China parametrisation in %, (frequencies higher than 3, 6, 12, 24 and 36 months have been muted)



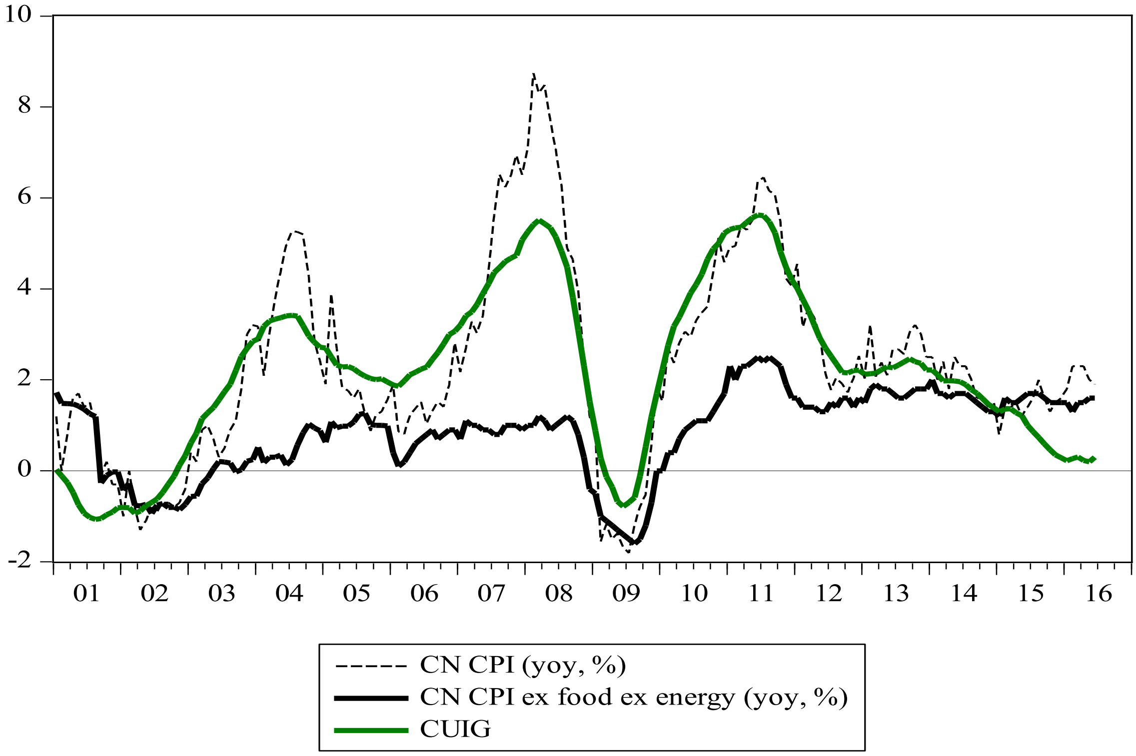
Source: Authors' calculations.

Graph 4b Inflation and different UIG for China parametrisation in % (number of factors used are 1, 2, 3, 4, 6 and 8)



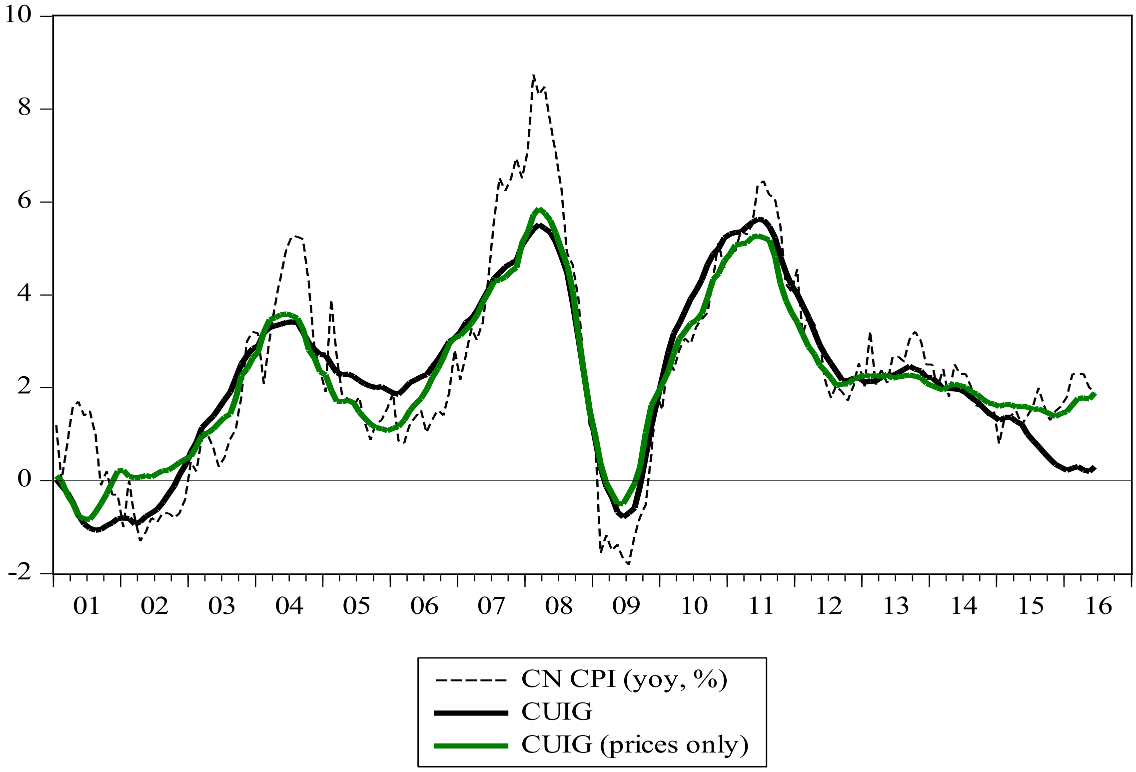
Source: Authors' calculations.

Graph 5a Inflation, inflation excluding food and excluding energy and UIG for China (%)



Source: Authors' calculations.

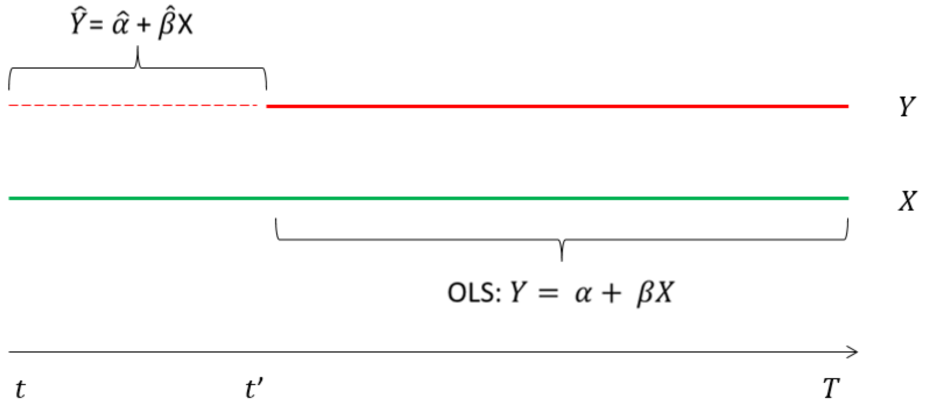
Graph 5b Inflation, UIG for China and excluding energy and UIG prices only for China (%)



Source: Authors' calculations.

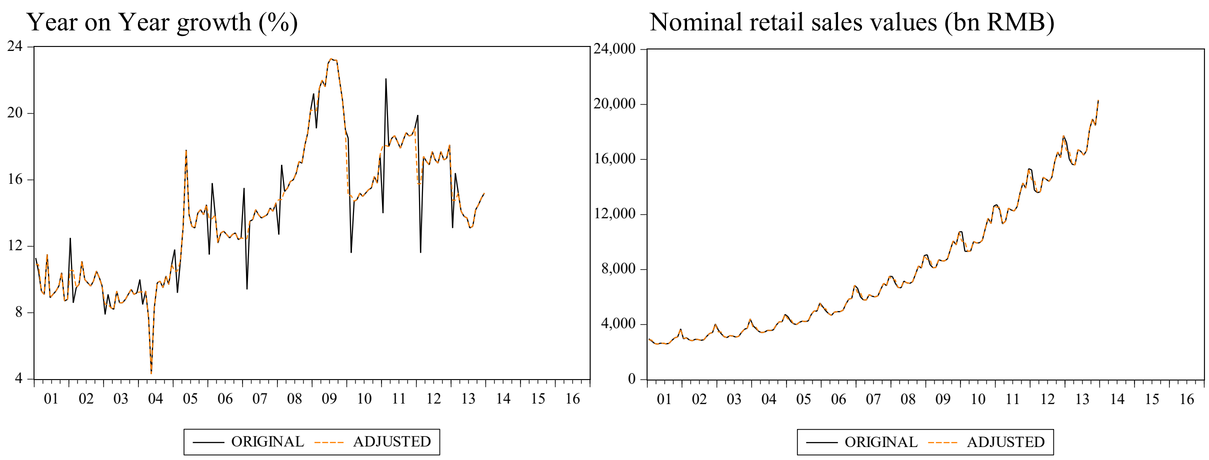
Appendix

Appendix Graph A Bridge equation illustration



Source: Authors' representation

Appendix Graph B The Chinese New Year Effect: the case of retail sales of consumer goods



Note: The Chinese New Year effect is adjusted by taking the average of January and February.
Sources: CEIC and authors' calculations.

Appendix Table A Treatment of the Chinese New Year Effect

Data	Adjustment
No separate January data, yoy growth	Assuming January = February = February_orig*
No separate January data, absolute value	Averaging: Jan=Feb=(Jan_orig+Feb_orig)/2
No CNY effect, yoy growth	No adjustment
No CNY effect, absolute value	No adjustment
Big CNY effect, yoy growth	Averaging: Jan=Feb=(Jan_orig+Feb_orig)/2
Big CNY effect, absolute value	Averaging: Jan=Feb=(Jan_orig+Feb_orig)/2

Note: * _orig denotes the original data before the adjustment. CNY = Chinese New Yea

Data appendix

Panel A comprises 395 variable and is available also after 2016

Panel B comprises 472 variables and is available only until 2016 due to adaptations and revisions of the official statistics.

Prices

Panel A	Panel B	Description
1	1	Consumer Price Index
2	2	CPI: Core (excl. Food & Energy)
3	3	CPI: non Food
4	4	CPI: excl. Fresh Vegetable & Fruit
5	5	CPI: Service
6	6	CPI: Consumer Goods
-	7	CPI: Industrial Product
7	8	CPI: Food
8	9	CPI: Food: Grain
-	10	CPI: Food: Grain: Rice
-	11	CPI: Food: Grain: Flour
-	12	CPI: Food: Starch & Tuber
-	13	CPI: Food: Bean & Bean Product
9	14	CPI: Food: Oil or Fat
10	15	CPI: Food: Meat, Poultry & their Product
11	16	CPI: Food: Meat, Poultry & their Product: Pork
12	17	CPI: Food: Meat, Poultry & their Product: Beef
13	18	CPI: Food: Egg
-	19	CPI: Food: Egg: Fresh Egg
14	20	CPI: Food: Aquatic Product
-	21	CPI: Food: Vegetable
15	22	CPI: Food: Vegetable: Fresh Vegetable
-	23	CPI: Food: Flavoring
-	24	CPI: Food: Sugar
-	25	CPI: Food: Tea & Beverage
-	26	CPI: Food: Tea & Beverage: Tea
-	27	CPI: Food: Tea & Beverage: Beverage
-	28	CPI: Food: Dried & Fresh Melon & Fruit
16	29	CPI: Food: Dried & Fresh Melon & Fruit: Fresh Fruit
-	30	CPI: Food: Cake, Biscuit & Bread
17	31	CPI: Food: Milk & its Product
-	32	CPI: Food: Milk & its Product: Fresh Milk
-	33	CPI: Food: Milk & its Product: Powder
-	34	CPI: Food: Outward Dinner
-	35	CPI: Food: Other Food & Manufacturing Service
-	36	CPI: Tobacco, Liquor and Article
18	37	CPI: Tobacco, Liquor and Article: Tobacco
19	38	CPI: Tobacco, Liquor and Article: Liquor
20	39	CPI: Clothing
21	40	CPI: Clothing: Garment

Panel A	Panel B	Description
-	41	CPI: Clothing: Clothing Material
22	42	CPI: Clothing: Footgear & Hat
23	43	CPI: Clothing: Clothing Manufacturing Service
24	44	CPI: Household Facility, Article & Maintenance Service (HA)
-	45	CPI: HA: Durable Consumer Good
-	46	CPI: HA: Durable Consumer Good: Furniture
25	47	CPI: HA: Durable Consumer Good: Household Facility
-	48	CPI: HA: Interior Decoration
-	49	CPI: HA: Bed Article
-	50	CPI: HA: Daily Use Household Article
26	51	CPI: HA: Household Service & Manufacturing Upkeep
-	52	CPI: Medicine, Medical Care & Personal Article (MP)
27	53	CPI: MP: Health Care
-	54	CPI: MP: Health Care: Medical Instrument & Article
28	55	CPI: MP: Health Care: Traditional Chinese Medicine
29	56	CPI: MP: Health Care: Western Medicine
-	57	CPI: MP: Health Care: Health Care Appliance & Article
30	58	CPI: MP: Health Care: Health Care Service
-	59	CPI: MP: Personal Article & Service
-	60	CPI: MP: Personal Article & Service: Cosmetic
-	61	CPI: MP: Personal Article & Service: Sanitation Article
-	62	CPI: MP: Personal Article & Service: Personal Accessory
-	63	CPI: MP: Personal Article & Service: Personal Service
31	64	CPI: Transportation and Communication (TC)
-	65	CPI: TC: Transportation
32	66	CN: CPI: TC: Transportation: Transportation Facility
-	67	CN: CPI: TC: Transportation: Fuel & Part
33	68	CN: CPI: TC: Transportation: Using & Upkeep Fare
-	69	CN: CPI: TC: Transportation: Incity Traffic Fare
-	70	CN: CPI: TC: Transportation: Intercity Traffic Fare
-	71	CPI: TC: Communication
34	72	CN: CPI: TC: Communication: Communication Facility
35	73	CN: CPI: TC: Communication: Communication Service
36	74	CPI: Recreational, Educational, Cultural Article & Service (RE)
-	75	CN: CPI: RE: Cultural & Recreational Durable Goods & Service
-	76	CN: CPI: RE: Education
-	77	CN: CPI: RE: Education: Teaching Material & Reference Book
-	78	CN: CPI: RE: Cultural & Recreational Article
-	79	CN: CPI: RE: Cultural & Recreational Article: Cultural Article
-	80	CN: CPI: RE: Cultural & Recreational Article: Newspaper & Magazine
-	81	CN: CPI: RE: Cultural & Recreational Article: Exp of Cult & Recreation
37	82	CN: CPI: RE: Touring & Outgoing
38	83	CPI: Residence
-	84	CPI: Residence: Building & Building Decoration Material
39	85	CPI: Residence: Renting
-	86	CN: CPI: Residence: Private Housing
40	87	CPI: Residence: Water, Electricity & Fuel
41	88	Retail Price Index

Panel A	Panel B	Description
42	89	Retail Price Index: Food
43	90	Retail Price Index: Beverage, Tobacco & Liquors
44	91	Retail Price Index: Clothings , Shoes and Hats
45	92	Retail Price Index: Textiles
46	93	Retail Price Index: Cultural & Office Articles
47	94	Retail Price Index: Medicine, Medical & Health Care Articles
48	95	Retail Price Index: Cosmetics
49	96	Retail Price Index: Books, Newspapers, Magazines & Electronic Pub
50	97	Retail Price Index: Daily Sundry Articles
51	98	Retail Price Index: Sports & Recreational Articles
52	99	Retail Price Index: Traffic and Communication Appliances
53	100	Retail Price Index: Furniture
54	101	Retail Price Index: Household Electric App & Audiovisual Apparatus
55	102	Retail Price Index: Gold, Silver & Jewellery
56	103	Retail Price Index: Fuels
57	104	Retail Price Index: Building, Hardware & Electric Materials
58	105	Producer Price Index
59	106	Producer Price Index: Producer Goods
60	107	Producer Price Index: Producer Goods: Mining and Quarrying
61	108	Producer Price Index: Producer Goods: Raw Material
62	109	Producer Price Index: Producer Goods: Manufacturing
63	110	Producer Price Index: Consumer Goods
64	111	Producer Price Index: Consumer Goods: Food
65	112	Producer Price Index: Consumer Goods: Clothing
66	113	Producer Price Index: Consumer Goods: Daily Sundry Article
67	114	Producer Price Index: Consumer Goods: Durable
68	115	PPI: Coal Mining
69	116	PPI: Petroleum and Natural Gas
70	117	PPI: Ferrous Metal Mining
71	118	PPI: Non Ferrous Metal Mining
72	119	PPI: Non Metal Mining
73	120	PPI: Agricultural & Sideline Food
74	121	PPI: Food
75	122	PPI: Wine, Beverage and Refined Tea
76	123	PPI: Tobacco
77	124	PPI: Textile
78	125	PPI: Garment and Apparel Manufacturing
79	126	PPI: Leather, Fur, Feather & its Product & Shoes
80	127	PPI: Wood Processing, Wood, Bamboo, Rattan, Palm & Grass Product
81	128	PPI: Furniture Manufacturing
82	129	PPI: Paper Making
83	130	PPI: Printing & Record Medium Reproduction
84	131	PPI: Cultural, Educational & Sports Articles
85	132	PPI: Petroleum Processing, Coking & Nuclear Fuels Processing
86	133	PPI: Chemical Material and Product
87	134	PPI: Medical & Pharmaceutical Product
88	135	PPI: Chemical Fiber Industry
89	136	PPI: Rubber and Plastic Product

Panel A	Panel B	Description
90	137	PPI: Non Metal Mineral Product
91	138	PPI: Ferrous Metal Mining, Smelting and Pressing
92	139	PPI: Smelting & Pressing of Non Ferrous Metal
93	140	PPI: Metal Product
94	141	PPI: Universal Equipment Manufacturing
95	142	PPI: Special Purpose Equipment
96	143	PPI: Automobile
97	144	PPI: Ship, Aircraft and other transportation equipment
98	145	PPI: Electric Machinery and Instrument
99	146	PPI: Communication, Computer & Other Electronic Equipment
100	147	PPI: Instrument & Meter
101	148	PPI?Other Manufacturing
102	149	PPI: Comprehensive Utilization of Resource Waste
103	150	PPI: Electricity & Heating Power Production and Supply
104	151	PPI: Gas Production and Supply
105	152	PPI: Water Production and Supply
106	153	Corporate Goods Price Index: Overall
107	154	Corporate Goods Price Index: Agricultural Product
108	155	Corporate Goods Price Index: Mining Product
109	156	Corporate Goods Price Index: Coal, Oil and Electricity
110	157	Corporate Goods Price Index: Processed Product
111	158	Corporate Goods Price Index: Primary Product
112	159	Corporate Goods Price Index: Semifinished Product
113	160	Corporate Goods Price Index: Finished Product
114	161	Corporate Goods Price Index: Investment Goods
115	162	Corporate Goods Price Index: Investment Goods: Fixed Asset
116	163	Corporate Goods Price Index: Investment Goods: Non-fixed Asset
117	164	Corporate Goods Price Index: Consumer Goods
118	165	Corporate Goods Price Index: Consumer Goods: Food
119	166	Corporate Goods Price Index: Consumer Goods: Non-food
120	167	Trade Index: Export: Unit Value
121	168	Export Unit Value Index: SITC: Primary Products (PP)
122	169	EUVI: SITC: PP: Food and Live Animals (FL)
123	170	EUVI: SITC: PP: Beverages and Tobacco (BT)
124	171	EUVI: SITC: PP: Crude Materials, Inedible, Except Fuels (CM)
125	172	EUVI: SITC: PP: Mineral Fuels, Lubricants & Related Materials (MF)
126	173	EUVI: SITC: PP: Animal and Vegetable Oils, Fats and Wax (OF)
127	174	EUVI: SITC: Manufactures (Mfg)
128	175	EUVI: SITC: Mfg: Chemicals and Related Products (Ch)
129	176	EUVI: SITC: Mfg: Manufactured Goods Classified by Material (MM)
130	177	EUVI: SITC: Mfg: Machinery and Transport Equipment (MT)
131	178	EUVI: SITC: Mfg: Misc Mfg Articles
132	179	Trade Index: Import: Unit Value
133	180	Import Unit Value Index: SITC: Primary Products (PP)
134	181	IUVI: SITC: PP: Food and Live Animals (FL)
135	182	IUVI: SITC: PP: Beverages and Tobacco (BT)
136	183	IUVI: SITC: PP: Crude Materials, Inedible , Except Fuels
137	184	IUVI: SITC: PP: Mineral Fuels, Lubricants & Related Material (MF)

Panel A	Panel B	Description
138	185	IUVI: SITC: PP: Animal and Vegetable Oils, Fats and Wax
139	186	IUVI: SITC: Manufactures (Mfg)
140	187	IUVI: SITC: Mfg: Chemicals and Related Products (Ch)
141	188	IUVI: SITC: Mfg: Manufactured Goods Classified by Material (MM)
142	189	IUVI: SITC: Mfg: Machinery and Transport Equipment (MT)
143	190	IUVI: SITC: Mfg: Misc Mfg Articles Real

Real

Panel A	Panel B	Description
144	191	Value Added of Industry
145	192	VAI: Coal Mining & Dressing
146	193	VAI: Petroleum & Natural Gas Extraction
147	194	VAI: Ferrous Metals Mining & Dressing
148	195	VAI: Textile Industry
149	196	CN: VAI: YoY: Jiangsu
150	197	CN: VAI: YoY: Zhejiang
151	198	CN: VAI: YoY: Fujian
152	199	CN: VAI: YoY: Shandong
153	200	CN: VAI: YoY: Guangdong
154	201	IP: Processed Crude Oil
155	202	IP: Cement
156	203	IP: Pig Iron
157	204	IP: Crude Steel
158	205	IP: Automobile
159	206	IP: Power Generated
160	207	Industrial Product Sales Rate
161	208	Fixed Asset Investment
162	209	CN: FAI: ytd: Inv Amount: Project Newly Started
163	210	FAI: Primary Industry
164	211	FAI: Secondary Industry (SI)
165	212	CN: FAI: ytd: SI: Manufacturing
166	213	FAI: SI: Construction
167	214	CN: FAI: ytd: Tertiary Industry (TI)
168	215	CN: FAI: ytd: TI: Transport, Storage and Postal Service
169	216	CN: FAI: ytd: TI: Real Estate
170	217	FDI: Utilized: Total
171	218	Real Estate Inv
172	219	Real Estate Inv: Residential Building
173	220	Real Estate Inv: Office Building
174	221	Real Estate Inv: Commercial Building
175	222	Floor Space Started: Commodity Bldg (CB)
176	223	Floor Space Sold
177	224	Retail Sales of Consumer Goods
178	225	Commodity Retail: Above Designated Size Enterprise
179	226	Commodity Retail: Gold, Silver and Jewelry
180	227	Commodity Retail: Furniture
181	228	Commodity Retail: Construction & Decoration Material

Panel A	Panel B	Description
182	229	Commodity Retail: Automobile
183	230	Transportation: Freight Traffic
184	231	Transportation: Freight Turnover
185	232	Automobile: Sales
186	233	Govt Revenue
187	234	Govt Expenditure
188	235	Economic Climate Indicator (ECI): Leading Index
189	236	ECI: Coincident Index
190	237	ECI: Lagging Index
191	238	ECI: Business Cycle Signal
192	239	BCI: Industry
193	240	BCI: Industry: Mining
194	241	BCI: Industry: Manufacturing
195	242	BCI: Industry: Production and Supply of Power, Gas and Water
196	243	BCI: Industry: Gas Production and Supply
197	244	BCI: Industry: Water Production and Supply
198	245	Entrepreneur Expectation Indicator (EEI)
199	246	5000 Industrial Enterprises Survey: Degree of Economy Overheated
200	247	5000 Industrial Enterprises Survey: Enterpreneurs' Confidence
201	248	5000 Industrial Enterprises Survey: General Business Condition
202	249	Banking Climate Index: Degree of Economy was Overheated
203	250	Banking Climate Index: Industry Climate
204	251	Banking Climate Index: Bankers' Confidence
205	252	Banking Climate Index: Loan Demand
206	253	Banking Climate Index: Monetary Policy Sentiment
207	254	Price Expectation Index
208	255	Purchasing Managers' Index: Mfg
209	256	PMI: Mfg: Production
210	257	PMI: Mfg: New Order
211	258	PMI: Mfg: New Export Order
212	259	PMI: Mfg: Backlog Order
213	260	PMI: Mfg: Finished Goods Inventory
214	261	PMI: Mfg: Purchases
215	262	PMI: Mfg: Import
216	263	PMI: Mfg: Purchasing Price Index
217	264	PMI: Mfg: Raw Material Inventory
218	265	PMI: Mfg: Employment
219	266	PMI: Mfg: Suppliers' Delivery Time
220	267	NoMfg PMI: Business Activity
221	268	NoMfg PMI: New Order
222	269	NoMfg PMI: New Export Order
223	270	NoMfg PMI: Business Expectation
224	271	NoMfg PMI: Input Price
225	272	NoMfg PMI: Sales Price
226	273	NoMfg PMI: Employment
227	274	NoMfg PMI: Order in Hand
228	275	NoMfg PMI: Inventory
229	276	NoMfg PMI: Suppliers' Delivery Time

Panel A	Panel B	Description
230	277	CX PMI
231	278	CX PMI: Production
232	279	CX PMI: New Order
233	280	CX PMI: Employment
234	281	CX PMI: Service Industry
235	282	Consumer Confidence Index
236	283	Consumer Satisfactory Index
237	284	Consumer Expectation Index
238	285	Export FOB
239	286	Import CIF
240	287	Trade Balance
241	288	export usd yoy
242	289	import usd yoy
243	290	Export sitc: Primary Product (PP)
244	291	Export sitc: Manufacture
245	292	Export: Ordinary Trade
246	293	Export: Processing and Assembling
247	294	Export: Processing with Imported Material
248	295	Export: EU
249	296	Export: Asia: Hong Kong
250	297	Export: Asia: India
251	298	Export: Asia: Japan
252	299	Export: Asia: Korea
253	300	Export: Europe: Germany
254	301	Export: Europe: Russia
255	302	Export: North America: United States
256	303	Export by Producer: Jiangsu
257	304	Export by Producer: Zhejiang
258	305	Export by Producer: Fujian
259	306	Export by Producer: Shandong
260	307	Export by Producer: Guangdong
261	308	Import sitc: Primary Product (PP)
262	309	Import sitc: Manufacture
263	310	Import sitc: Mfg: Chemical and Related Product (CH)
264	311	Import sitc: Mfg: Manufactured Goods
265	312	Import sitc: Mfg: Machinery and Transport Equipment
266	313	Import sitc: Mfg: Misc Manufactured Article
267	314	Import sitc: MF: Coal, Coke and Briquette
268	315	Import sitc: MF: Petroleum, Petroleum Pdt & Related Material
269	316	Import sitc: MF: Gas, Natural and Manufactured
270	317	Import sitc: MF: Electric Current
271	318	Import: Ordinary Trade
272	319	Import: Processing and Assembling
273	320	Import: Processing with Imported Material
274	321	Import: EU
275	322	Import: Asia: Japan
276	323	Import: Asia: Korea
277	324	Import: Europe: Germany

Panel A	Panel B	Description
278	325	Import: Europe: Russia
279	326	Import: North America: United States
280	327	Import: Oceania: Australia
281	328	BoP: Current Account(CA)
282	329	BoP: CA: Goods
283	330	BoP: CA: Service
284	331	BoP: CA: Primary Income
285	332	BoP: CA: Secondary Income
286	333	BoP: Capital Account
287	334	Disposable Income per Capita: Urban
288	335	Disposable Income per Capita: Rural
289	336	Disposable Income per Capita: Rural: Wage and Salary
290	337	Disposable Income per Capita: Rural: Net Business Income
291	338	Disposable Income per Capita: Rural: Net Income from Property
292	339	Disposable Income per Capita: Rural: Net Income from Transfer

Labour

Panel A	Panel B	Description
-	340	No of Employee: Total
-	341	No of Employee: Mining
-	342	No of Employee: Manufacturing
-	343	No of Employee: Construction
-	344	No of Employee: Transportation, Storage & Post
-	345	No of Employee: Info Transmission, Software & Info Tech Service
-	346	No of Employee: Wholesale & Retail Trade
-	347	No of Employee: Accommodation & Catering Trade
-	348	No of Employee: Banking and Insurance
-	349	No of Employee: Real Estate Management
-	350	No of Employee: Leasing & Commercial Service
-	351	No of Employee: Scientific Research & Technical Service
-	352	No of Employee: Water Conservancy, Environment & Public Utility
-	353	No of Employee: Education
-	354	No of Employee: Culture, Sport & Recreation
-	355	Average Wage
-	356	Avg Wage: Mining
-	357	Avg Wage: Manufacturing
-	358	Avg Wage: Construction
-	359	Avg Wage: Transportation, Storage & Post
-	360	Avg Wage: Info Transmission, Computer Service & Software
-	361	Avg Wage: Wholesale & Retail Trade
-	362	Avg Wage: Accommodation & Catering Trade
-	363	Avg Wage: Banking and Insurance
-	364	Avg Wage: Real Estate
-	365	Avg Wage: Leasing & Commercial Service
-	366	Avg Wage: Sci Research, Tech Service & Geological Prospecting
-	367	Avg Wage: Water Conservancy, Environment & Public Utility Mgt
-	368	Avg Wage: Education

Panel A	Panel B	Description
-	369	Avg Wage: Culture, Sport & Recreation
293	370	Registered Unemployment: Urban
294	371	Registered Unemployment Rate: Urban
295	372	City Labor Market: Demand-Supply Ratio

Money

Panel A	Panel B	Description
296	373	Money Supply M0
297	374	Money Supply M1
298	375	Money Supply M2
299	376	Loan
300	377	Loan: Short Term
301	378	Loan: Medium & Long Term
302	379	Loan: New Increased
303	380	Deposit
304	381	Deposit: Enterprise
305	382	Deposit: Saving
306	383	Deposit: New Increased

Financial

Panel A	Panel B	Description
307	384	Required Reserve Ratio: Large Depository Institution
308	385	Nominal Lending Rate: Medium & Long Term: Over 5 Year
309	386	Household Savings Deposits Rate: Time: 6 Month
310	387	Household Savings Deposits Rate: Time: 1 Year
311	388	Shanghai Interbank Offered Rate (SHIBOR): Overnight
312	389	Shanghai Interbank Offered Rate (SHIBOR): 1 Week
313	390	Shanghai Interbank Offered Rate (SHIBOR): 1 Month
314	391	Shanghai Interbank Offered Rate (SHIBOR): 3 Month
315	392	Interbank Offered Rate: Weighted Avg: Overall
316	393	Interbank Offered Rate: Weighted Avg: Overnight
317	394	Interbank Offered Rate: Weighted Avg: 7 Day
318	395	Interbank Offered Rate: Weighted Avg: 1 Month
319	396	Interbank Offered Rate: Weighted Avg: 3 Month
320	397	Central Bank Bill: Yield to Maturity: 3 month
321	398	Central Bank Bill: Yield to Maturity: 1 year
322	399	Index: Shanghai Stock Exchange: Composite
323	400	Index: Shanghai Stock Exchange: A Share
324	401	Turnover: Value: Shanghai SE: Total
325	402	Index: Shenzhen Stock Exchange: Composite Subindex: monthly
326	403	Index: Shenzhen Stock Exchange: A Share Subindex: monthly
327	404	Turnover: Value: Shenzhen SE: Total
328	405	Foreign Exchange Rate: SAFE: Base Price: US Dollar
329	406	Effective Exchange Rate Index: BIS: Real
330	407	Effective Exchange Rate Index: BIS: Nominal

International

Panel A	Panel B	Description
331	408	Consumer Price Index: Urban: 1982-1984=100 :(US)
332	409	Producer Price Index:1982=100: (US)
333	410	Industrial Production Index: 2012=100: (USs)
334	411	Retail Sales (United States)
335	412	Policy Rate: Month End: Fed Funds Rate (United States)
336	413	Treasury Notes Yield: Constant Maturity: Nominal: MA: 10 Years (United States)
337	414	Nominal USDX: board
338	415	Nominal USDX: main currencies
339	416	Real USDX: board
340	417	Real USDX: main currencies
341	418	Employment (United States)
342	419	Unemployment Rate (United States)
343	420	Harmonised Consumer Price Index (HICP): 2015=100: European Union (EU)
344	421	Producer Price Index (PPI): 2010=100: EU 28 (EU)
345	422	IPI: swda: 2010=100: EU 28 (EU)
346	423	WRTI: swda: Val: EU 28: Retail Trade Index (RTI): 2010=100: (EU)
347	424	WRTI: swda: Val: EU 28: Wholesale Trade Index (WTI): 2010=100:(EU)
348	425	Policy Rate: Month End: Main Refinancing Operations (EU)
349	426	Government Bond Yield: Monthly Average: Euro: 10 Years (EU)
350	427	Unemployment Rate: EU 28 (EU)
351	428	Employment: EU 28 (EU)
352	429	Consumer Price Index: 2015=100: (Japan)
353	430	Producer Price Index (PPI): 2010=100: (Japan)
354	431	Industrial Production Index (IPI): Mining and Manufacturing: 2010=100: (Japan)
355	432	Wholesale Trade Index: 2010=100 (Japan)
356	433	Retail Trade Index: 2010=100 (Japan)
357	434	Policy Rate: Mth End: Complementary Deposit Facility Interest Rate (Japan)
358	435	Bonds Yield: Government Bonds: Newly Issued: 10 Years: Month End (Japan)
359	436	Employment: Total (Japan)
360	437	Unemployment Rate (Japan)
361	438	Consumer Price Index: 2015=100 (Korea)
362	439	Producer Price Index: All Commodities and Services: 2010=100: (Korea)
363	440	Industrial Prodution Index (IPI): All Industry (AI): 2010=100: (Korea)
364	441	Retail Sales Index: Nominal: 2010=100: (Korea)
365	442	Policy Rate: Month End: Base Rate: Bank of Korea (Korea)
366	443	Government Bond Yield: Long Term (Korea)
367	444	Employment (Korea)
368	445	Unemployment Rate (Korea)
369	446	Consumer Price Index (CPI): 2011=100: (Taiwan)
370	447	Wholesale Price Index (WPI): 2011=100: (Taiwan)
371	448	Industrial Production Index (IPI): 2011=100: (Taiwan)
372	449	Wholesale & Retail Trade Index: Retail Trade: 2011=100: (Taiwan)
373	450	Wholesale & Retail Trade Index: Wholesale Trade: 2011=100: (Taiwan)
374	451	Policy Rate: Month End: Discount Rate (Taiwan)
375	452	Government Bonds: Secondary Market: 10 Year (Taiwan)
376	453	Employment (Taiwan)
377	454	Unemployment Rate (Taiwan)

Panel A	Panel B	Description
378	455	CRB spot index: composite
379	456	CRB spot index: food
380	457	CRB spot index: grease
381	458	CRB spot index: livestock
382	459	CRB spot index: metal
383	460	CRB spot index: industrial raw materials
384	461	CRB spot index: textile
385	462	RJ/CRB commodity price index
386	463	LME metal index
387	464	CLAI
388	465	BJCI
389	466	SLVL
390	467	GDPI
391	468	SPCSC
392	469	SPCSENTR
393	470	SPCSINTR
394	471	SPCSPMTR
395	472	SPCSAGTR

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