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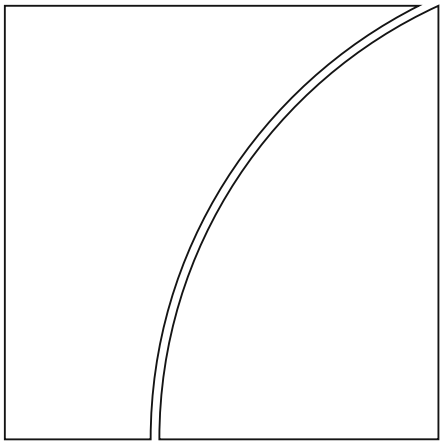

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Developing an Underlying Inflation Gauge for China

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Developing an Underlying Inflation Gauge for China[1]

A TIPS-like inflation gauge

Marlene Amstad, Ye Huan, Guonan Ma

Abstract

The headline consumer price inflation (CPI) is often considered too noisy, narrowly defined, and/or slowly available for policymaking. On the other hand, traditional core inflation measures may reduce volatility but do not address other issues and may even exclude important information. This paper develops a new underlying inflation gauge (UIG) for China which differentiates between trend and noise, is available daily and uses a broad set of variables that potentially influence inflation. Its construction follows the works at other major central banks, adopts the methodology of a dynamic factor model that extracts the lower frequency components as developed by Forni et al. (2000) and draws on the experience of the People's Bank of China in modelling inflation. The paper is the first application of this type of dynamic factor model for inflation to any large emerging market economy. Our UIG for China is less noisy but still closely tracks the headline CPI. It does not suffer from the excess volatility reduction that plagues traditional core inflation measures and instead provides additional information. Finally, when forecasting the headline CPI, our UIG for China outperforms traditional core measures over different samples.

Keywords: C13, C33, C43, E31, E37, G15

JEL classification: Inflation, Dynamic Factor Models, Core Inflation, Monetary Policy, Forecasting, China

[1] This working paper is based on the following People's Bank of China (PBC) working paper (available only in Chinese): Amstad, Ye and Ma (2014), "建立中国基础通货膨胀指标- Developing an Underlying Inflation Gauge for China", *PBC Working Paper, Statistics and Analysis Department*, No. 2014 (10)".

Marlene Amstad is with the Bank for International Settlements (BIS), Ye Huan is with the PBC, and Guonan Ma is a non-resident scholar of Bruegel (and on leave from the BIS). The authors would like to acknowledge software developed by Forni, Hallin, Lippi, and Reichlin (2000). Comments by Robert McCauley, Li Bo, Aaron Mehrotra, Xu Nuojin, Frank Packer, Hyun Shin, Yan Xiandong, James Yetman and seminar participants at the PBC and BIS are gratefully acknowledged. The views expressed in this paper are those of the authors and do not necessarily reflect those of the BIS or PBC.

1. Introduction

Current and prospective inflation matters a lot to monetary policy makers and market participants. The most prominent yardstick to measure inflation in many economies is the year on year change in either the consumer price index (CPI) or personal consumption expenditures (PCE) index published by the local statistical authorities. These gauges often serve as the official and ultimate reference rate for inflation. Without questioning their status, these mentioned inflation measures suffer from at least three shortcomings.

First, the headline inflation measure often exhibits marked short-term volatility.[2] This makes it difficult to judge whether a sudden up or down move in the most recent CPI observation should be considered as temporary noise or a change in trend. Second, while the CPI and PCE differ in their compositions, they both comprise only price variables. Other variables – such as unemployment and economic slack – which are known to impact inflation albeit with a lag – are not included, even though they are publicly available at the time when a decision guided by inflation needs to be taken. In other words, available information about current and future inflation is neglected if only CPI or PCE subcomponents is considered. Third, the publishing frequency for CPI or PCE is usually monthly, which might be frequent enough in normal times. But in turbulent times – as in the recent global financial crisis – a more frequent gauge of inflation, which ideally makes fuller use of all available information at a given point in time, may be advantageous.[3]

Addressing the first shortcoming of excess volatility has led to the development of so-called "core inflation" measures.[4] Even though there is no consensus on the exact definition of core inflation, the term often refers to an indicator which is less noisy and is expected to serve as a leading indicator for inflation. Often these measures shed volatility by excluding or down weighting certain price components. Among the most prominent core measures are inflation measures that exclude food and/or energy prices.[5] By excluding the more volatile components, these core inflation measures by definition achieve the goal of lower volatility. However, this procedure implicitly assumes that big price changes are temporary. The price to pay for the lower volatility is that information that potentially might help in forecasting inflation may be muted or even neglected altogether.

To address the narrow information set and the monthly publication frequency (the second and third of the aforementioned shortcomings), inflation indicators based on market transactions are also used. One example is the break-even inflation implied by the yield difference between treasury inflation protected securities (TIPS,

[2] This is at least in part because of the circumstance that the statistical offices aim to produce an inflation measure that measures each movement in inflation as accurately as possible over time.

[3] Additionally there is no flash estimate available for the Chinese CPI in advance of the monthly CPI release.

[4] We will use the expression "core inflation" and "traditional core inflation" measures interchangeably.

[5] Another approach excludes a particular portion (eg 25%) of goods or services with the largest price changes (in absolute, percentage point terms) at each point of time, such as "trimmed mean inflation" or "median inflation" as a special case of the trimmed mean.

or real bonds) and nominal bonds (without inflation protection). Break-even inflation is available daily and market participants seem to base their judgement on a broad dataset, as break-even inflation reacts to daily news. However, it is not obvious exactly which data series the market participants include in such a broad dataset and whether they change the dataset and/or the weights they implicitly attach to different input variables when pricing TIPS.

Overall, core and market-based inflation measures address only partially the shortcomings while introducing other potential problems.[6] In the case of China, two traditional core inflation measures are publicly available on a monthly basis: CPI excluding food (CPI_nf) and CPI excluding food and energy (CPI_nfe). There are currently[7] no inflation protected bonds from which to infer break-even rates in China.

In this paper, we contribute to the literature by constructing a new gauge - an underlying inflation gauge for China - which is smooth, based on a broad dataset and can be produced daily. Our exercise is very general in nature. For brevity, we will use the acronym UIG for underlying inflation gauge that stands for an application of the methodology given in Section 2 and applied in this paper to the case of China.[8]

We emphasise that our newly developed gauge should not be interpreted as an alternative inflation measure for CPI. Instead, the approach taken in this paper is to provide a new supplementary inflation signal. UIG differentiates trend from noise, is based on a broad dataset and therefore supports the decision making of monetary authorities and market participants.

Our UIG relies on the Generalised Dynamic Factor Model as developed by Forni, Hallin, Lippi and Reichlin (2000, 2001). Its specific property to extract the lower frequency component is particularly useful when the goal is to retain a smooth underlying component from a large dataset. This model type has been proven useful in the context of forecasting economic growth (GDP) and inflation for different economies. In constructing UIG for China, we adopt the same model and parameterisation used in the Federal Reserve Bank of New York (Fed NY) staff UIG (underlying inflation gauge) for the US inflation (Amstad et. al., 2014 and Amstad and Potter, 2009) and the DFI (dynamic factor inflation) for Swiss inflation (Amstad and Fischer, 2009a). While there are many similar GDP and inflation forecast studies in the literature,[9] to our knowledge, this is the first time this model is applied to inflation of an emerging market economy or to China.[10]

[6] Hördahl (2009) shows that in addition to expected inflation 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. Furthermore, these components might change over time and hamper the interpretation of breakeven inflation.

[7] See Burdekin et. al. (1999) on previous experience of indexed government bonds introduced by the People's Republic of China in the face of the inflation panic of 1988-89 and reintroduced when inflation surged upward again in 1993.

[8] The acronym UIG for underlying inflation gauge is also used for an application on US inflation that is based on the same methodology as used in this paper (see Amstad, Potter and Rich, 2014). In this paper UIG refers to the application on China if not mentioned otherwise.

[9] For Euro Area GDP, the Centre for Economic Policy Research (CEPR) produces EuroCoin, which is publicly available on a monthly basis (Altissimo et al. ,2001). For US GDP, the Chicago Fed National Activity Index is based on the methodology of Stock and Watson (1999). For US inflation, Reis and Watson (2010) use a dynamic factor model to separate absolute from relative price changes. For

This paper focuses on the construction of UIG for China and compares its statistical properties to those of CPI and traditional core inflation measures. We leave it to further research to identify the drivers of Chinese inflation.

The remainder of the paper is organised as follows. Section 2 motivates the choice of the methodology. Section 3 discusses the dataset by addressing data categories and quality, sample length and the Chinese New Year effect. Section 4 provides the rationale for our chosen parameterisation of the model, while Section 5 examines the statistical characteristics of our 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 6 concludes that our UIG for China offers additional information for monetary policymakers and market participants, as it outperforms traditional core inflation measures in a classical forecasting exercise.

2. Methodology[11]

The choice of the model is driven by our goal to develop an empirical, smooth, model-based and "TIPS-like" inflation gauge useful for bond investors and monetary policy makers. The model should possess two features: First, it applies a smoothing procedure that retains long cycles while excluding short term cycles ('noise'). Second, it allows to use in an econometrically prudent way a large data-set comprising many variables that are potentially correlated. Both desired properties are captured by the generalised dynamic factor model developed by Forni, Hallin Lippi and Reichlin (2000, 2001), hereafter FHLR.

The FHLR approach builds on work by Brillinger (1981) to generalize 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 does not focus on estimation and forecast of the unsmoothed inflation series. Rather it estimates and forecasts inflation which is smoothed in cross section (measurement errors, local or sectoral shocks) as well as time dimension.

This section briefly reviews the FHLR model by focusing on the two properties that are key to achieve an inflation gauge introduced in Section 1.[12]

the case of Euro Area inflation, see Cristadoro et al. (2001). Altissimo et al. (2009) use a dynamic factor model to investigate the persistence in aggregate Euro Area inflation. Also, see Giannone and Matheson (2006) for a quarterly inflation measure in New Zealand.

10 Previous studies used different models and usually smaller number of variables. Funke et al (2014) use a state-space model to track Chinese CPI in real-time with eight selected variables. We differ in several respects as our goal is not to track CPI itself but to estimate its underlying trend. Therefore, we use a broad set covering 473 time series of five data categories (prices, economic activity, labour market, money and credit, financial markets). Furthermore, we apply a dynamic factor model that allows recovering the underlying trend in the frequency domain.

11 This Section draws on the technical appendix in Amstad and Potter (2009).

12 The precise estimation procedure follows Altissimo et al. (2001) and Cristadoro et al (2001). The technical details are given in Appendix B.

2.1. Extracting the lower frequency component

The model that best suits our requirements should be capable of producing a smooth signal in order to distinguish between noise and trend without fully neglecting variables. Note that this is the opposite approach to traditional core inflation measures, which are smooth at the cost of excluding variables that may contain important information. In that respect, a Fourier transformation seems an appropriate econometric approach.

A Fourier transformation is the mathematical formula that rewrites a time series (the so called "time domain") into several sine waves (the so called "frequency domain").[13] This allows removing a clearly defined frequency band – e.g. all frequencies or cycles in a given variable that last only up to 1 year. The definition of noise versus trend is therefore in control of the econometrician. Section 4.1 shows UIG for China based on different choices of frequency band. It also motivates our choice of frequency band – as cycles lasting only up to one year – that is applied on the UIG for China used in the forecasting exercise in Section 5.

2.2. Handling a large dataset

Apart from smoothing, the model best suited to producing a gauge as described in the introduction should summarise many variables in only one or a few variables. In that respect, the econometric class of factor models seems an obvious choice. The number of factors needs to be defined – we motivate our respective choice in Section 4.2. Within the factor model approach, the generalised factor model of Forni et al. (2000) is particularly well suited for our purposes for two reasons.

First, the FHLR approach applies a Fourier transition that allows the smoothing of the used input variables (see Section 2.1).

Second, the chosen factor model should be capable of handling a particularly large dataset, as our aim is to develop a signal which can be regularly updated. Over time, the relevance and therefore weighting of a given variable may change. This is particularly likely in the case of a fast developing emerging market economy like China. Frequent changes of the used dataset would make it difficult to judge whether a change in the resulting signal is only due to the changed data coverage or the changed weightings. Therefore, it seems advantageous to include most of the variables possibly relevant for inflation. The factor model will then decide each time when it is updated – in our approach possibly daily or weekly – about the weights of the different input variables to explain inflation at each point in time.

We assume a panel of $i = 1,..N$ 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:

[13] 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).

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

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 erros and local shocks). $\boldsymbol{b}_i(L)$ is a vector of lag polynomials of order s and considers the 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 quite a strict assumption especially for $N \to \infty$, as it ignores local shocks, which affect only a small subset but more than only one variable.

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

3. Data

This section describes the dataset compiled to generate 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 473 time series covering key aspects of the Chinese economy.[14] While the model we use asks that all the variables have the same start date (balanced at start), they may have different sample lengths due to different publishing schedules (unbalanced at the end).

3.1 Data coverage and quality

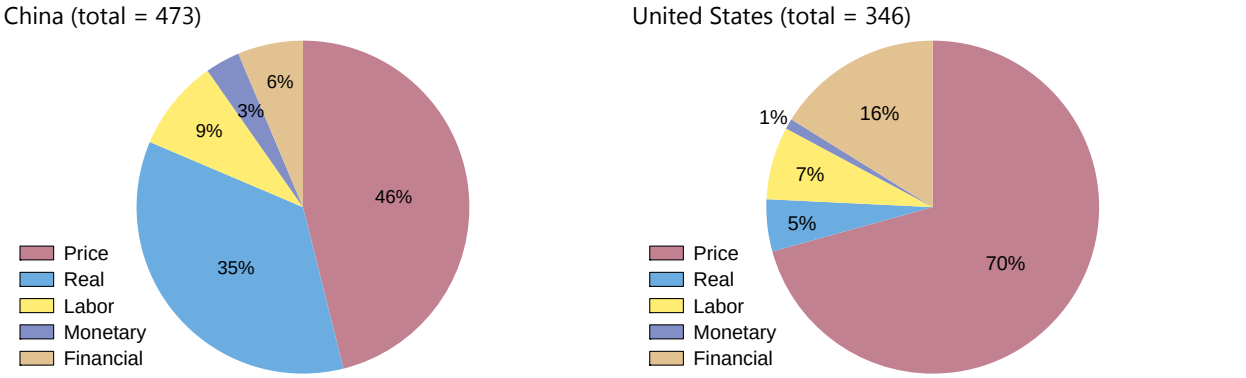
Our goal is to develop an inflation signal based on a broad dataset so as to detect the turning points in underlying inflation pressure and to learn more about the driving forces behind inflation. Therefore the dataset should cover a broad set of variables which possibly influences inflation.[15] Our 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. Our benchmark UIG for China will be estimated using all these categories, though we also estimate different UIGs for China using price data only (UIG_ponly). In practice, we aim to keep the size of the dataset manageable, by focusing on those variables that the People's Bank of China (PBC) regularly monitors in its inflation analysis and forecasting.

[14] The list of variables is available on request.

[15] Several studies indicate that Chinese inflation is driven by a broad set of variables. Cai and Du (2011) evaluate the contribution of labour market developments, Zhang (2012) studies demand-pull versus cost push factors and Nagayasu (2009) provides evidence that inflation can be explained by economic fundamentals such as money, credits, productivity, and exchange rate growth.

Our dataset consists of 473 variables in total, compared to 346 for a similar inflation gauge for the US (Amstad, Potter and Rich, 2014) and 454 for Switzerland (Amstad and Fischer, 2009a and b). Graph 1 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 almost half the entire dataset in the case of China and two thirds for the US.

Number and composition of input variables for China and the US[1] Graph 1



[1] Percentages may not total 100 due to rounding.

Source: Authors' calculations.

In detail, 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 group together 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 also includes major international commodity prices as well as selected data on China's top five trade partners.[16] Each of these trade partners represents no less than 5% of China's total exports, collectively accounting for 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, ideally, all of the time series 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

[16] 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 US, EU, Japan, Korea and Taiwan.

consistent way for all the variables when applying the same common approach on the basis of our filter.[17] Fourth, however, we have addressed the Chinese Lunar New Year effect for those affected series; in light of its irregular seasonable pattern caused by this holiday moving between January and February from one year to the next (see Appendix A1 for details). Fifth, all of the included time series have been tested for stationary and treated accordingly, in order to construct an unbiased signal (see Appendix A2 for details).

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 breaks are two common difficulties. For our purpose, labour market statistics are the most problematic (Ma, McCauley and Lam, 2012), as the Philips curve assigns a prominent role to labour market conditions in driving inflation. The Chinese labour statistics tends to be of limited coverage and low quality. They cover only urban areas and start relatively late: though the series of total average wage starts from December 1999, the average wage of different industries starts only from 2008. 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. Some variables, such as the urban unemployment rate, are known to bear little relevance to the actual labour market conditions. Nevertheless, we still 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 could increase going forward as their quality improves over time.[18] We also include household income survey data to supplement the wage data and to mitigate their quality risks.

3.2 Sample length

Another important issue is the starting point of our dataset. Our methodology requires data that all have the same starting date, but they can differ in their sample lengths.[19] This gives rise to a trade-off between breadth and length when choosing the 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, more new variables are being introduced but only for shorter periods. Hence the longer the sample is, the less broad it is. In particular, most of the newer and shorter series are the subcomponents of some existing older series.

Our approach towards this trade-off is balanced and practical. We choose to start our data sample from January 2001 mainly for two reasons.

[17] See Section 3: the filter we use comprises a spectral density analysis, which allows us to exclude a given high frequency part (in our case: frequencies higher than 1 year) in all variables.

[18] This study is the base for a new underlying inflation indicator that can be used and updated regularly over time. Therefore we keep those variables that are problematic now but may improve in the future to make sure that our dataset is complete and consistent.

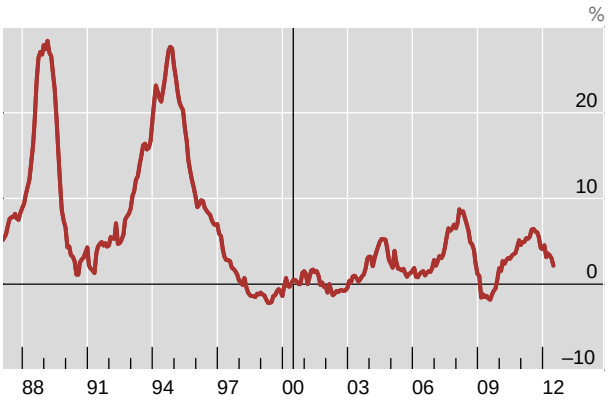
[19] The econometric methodology to handle the end of sample procedure is described in Appendix B and follows Forni et al. (2005) and Cristadoro et al. (2005).

First, many series have more detailed breakdowns after 2001. For example, in the case of CPI data, the most important data category in our study, the monthly headline CPI in China starts from January 1985, but the food subcomponent and its further breakdowns start only in January 1994, while 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 before 2001, there would be too 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. So our starting point of January 2001 balances breadth and length. Moreover, by the late 1990s, most of the Chinese consumer prices had been liberalised so that the observed prices in the 2000s better reflect the underlying inflation pressure.

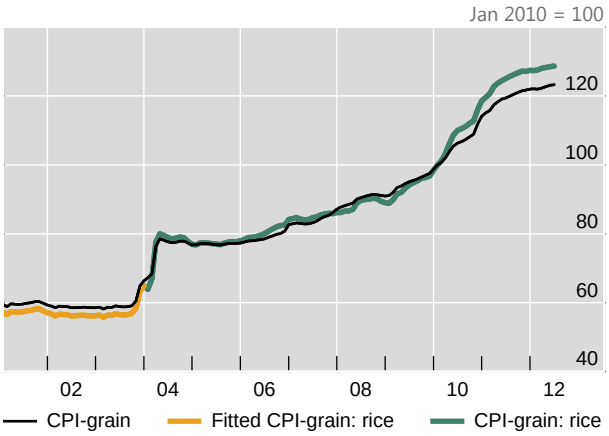
Secondly, there appears to be a distinct regime change in China's inflation dynamics around 2000-01 (the left panel of Graph 2). Before 2000, the Chinese inflation rate was much higher and more volatile, fluctuating between peaks of above 20% and troughs of outright deflation. The mean and standard deviation of monthly year-on-year inflation between 1987 and 2000 reached 8.8% and 8.7%, respectively. During 2001 and June 2012, however, they dropped to 2.5% and 2.4%, respectively. In this latter period, the Chinese economy has experienced at least three full "well-behaved" inflation cycles between January 2001 and June 2012. Clearly, inflation in these three post-2000 cycles is much lower and less volatile than the two cycles in the 1980s and 1990s. Moreover, China's post-2000 inflation dynamics appears to be more associated with domestic and external cyclical shocks and less related to liberalisation of administered prices and soft-budget behaviour of investment and wage setting (Kojima et al, 2005).

Consumer price index in China — Graph 2

Year-on-year growth of CPI



CPI component indices: grain and rice



Source: CEIC and authors' estimation.

A host of factors may help explain this regime shift in the inflation cycles post 2000, possibly including the transition from a command to a more market-based economy, progress in price deregulations, increased supply, the enhanced institutional capacity of macroeconomic management, the evolving exchange rate regime and external shocks (Giradin et al 2014). By the late 1990s, much of the price liberalisation was completed so that the headline CPI inflation since has mostly responded to market demand and supply (Kojima et al, 2005; Zhang and Clovis,

2010).[20] Most notably, China's accession to the WTO in 2001 appears to be a major turning point for its economy. One reason for this is the wide-ranging structural transformation of the domestic economy that took place in order to prepare for increased foreign competition. Another reason is the growing integration of the Chinese economy into the global market.[21] For our purposes, this apparent structural break in Chinese inflation also helps to justify starting our sample in January 2001, allowing us to extract an inflation signal that reflects the more recent Chinese inflation pattern.

In sum, we choose January 2001 as the starting point of our dataset on the balanced consideration of greater data availability, better data quality and the apparent regime changes in China's inflation dynamics.

Even so, there are still about one third (176) of the data series in our sample that start only after 2001. We deal with the missing observations in the beginning of these series using a simple regression approach called the "bridge equation". This approach permits us to generate the missing values for the earlier segment of a shorter series without introducing additional information to our dataset (see Appendix A3 for more details). The right panel of Graph 2 shows the "bridged" rice component of the CPI for 2001-2003. To verify that the extended short series do not distort the final signal, we have conducted the following experiment: we also compare the two signals extracted, respectively, from the whole dataset and the dataset excluding the 176 extended series and find them to be very similar.

Still, why do we still include the short series in our dataset? A main consideration here is that some of these short series could become more important in providing information for the inflation signal in the future and that the role of their fitted values for the initial years should fade as time passes.

4. Parameterisation of UIG for China

This section empirically motivates the choice of the parameterisation of the model outlined in Section 2 using the dataset given in Section 3. We identify two main parameters that need to be set exogenously: the definition of noise or in technical terms the decision which frequency band (b) shall be removed from each input variable and the number of factors (q) to be estimated.

[20] The China Price Yearbooks (Zhongguo Wujia Nianjian) give the share of prices that are market-determined increased between 1990 and 1993 for agricultural procurement from 51.6% to 87.5%, for retail sales from 53.0% to 93.8% and for producer goods from 36.4% to 81.1%.

[21] In preparation for the 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. On the other hand, these favourable productivity shocks might have generated large income windfalls, contributing to China's large current surplus and growing domestic liquidity under a tightly managed exchange rate regime. Finally, China's increased demand for energy and other resources could also have meaningfully influenced international commodity prices.

4.1. The choice of degree of smoothness – frequency band

We define as noise the frequencies shorter than 12 months.[22] There are three main considerations for our choice of excluding cycles shorter than 12-month.[23]

First, the rationale behind this choice is that 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 advisable to consider a similar time horizon as the central bank – since the central bank can be expected to act on the signal of its choice.

Second, in the cases of comparable measures for the US and Switzerland, the Fed NY and the SNB, respectively, decided to neglect cycles which pertain less than one year.[24]

Third, we show the sensitivity of UIG for China when based on different choices of frequency band in Table 1 and Graph 3 (left-hand panel). For a frequency band of up to 12 months, the resulting UIG for China captures 80% 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 65% and 49%, respectively – a big drop in volatility and, with that, potentially also a significant loss of information.

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. Table 1

	CPI inflation	b=3	b=6	b=12	b=24	b=36
S.D.	2.59	2.23	2.23	2.08	1.67	1.25
Portion (%)		86%	86%	80%	65%	49%

Note: S.D. is Standard Deviation. 3 or 12 months here refer to frequencies higher than 3 or 12 months.

Source: Authors' calculations.

4.2. The choice of the number of factors

The main feature of any factor model is that it summarises the information of many input variables in just 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, second, etc. factors. The number of factors should be high enough to represent the underlying input variables and low enough to assure a parsimonious model. Whatever statistical criterion is used as guidance, the number

[22] Please note that according to common terminology used in the literature, the term "above or longer than 12 months" refers to "lower or longer frequencies". Vice versa the term "below or shorter than 12 months" refers according to the terminology to "higher or shorter frequencies".

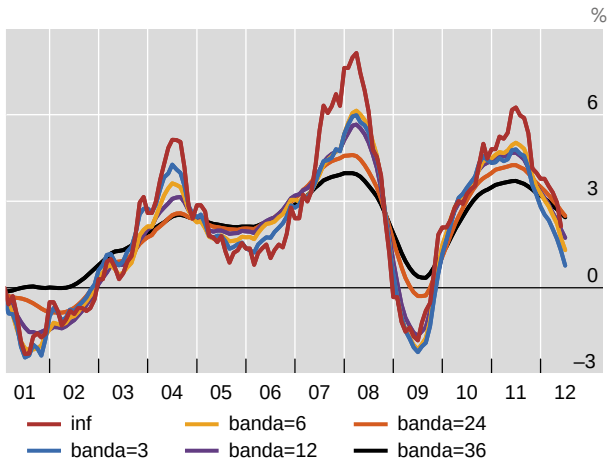
[23] Please note that the choice of this parameter setting is not model implied but our exogenous reasoned judgement call which we could change if another choice would be regarded as more informative based, for example, on considerations in the following paragraph.

[24] In frequency domain terminology, this refers to higher frequencies above 12 months.

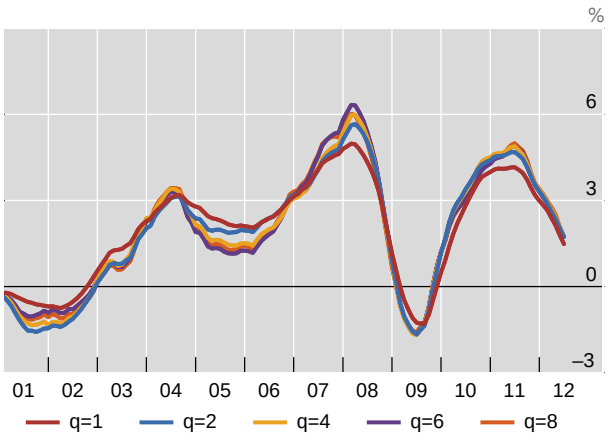
of factors and therefore the choice of the variability share of the input variables to be reflected in the factors is always an exogenous one. Therefore many factor model applications motivate the choice of factor number with economic reasoning. For macroeconomic applications, the consensus is that the input variables should be captured by two factors, which are more or less directly identified as reflecting real and nominal driving forces, respectively, in constructing the underlying inflation gauge.[25]

Inflation and different UIG for China parameterisation — Graph 3

Where frequencies higher 3, 6, 12, 24 and 36 months have been muted



With different number of factors from 1 to 8



Source: Authors' calculations.

We follow this 2-factor approach in this paper for three reasons. First, in our application, we use the factors not directly as our signal but only use the information contained in the factors to regress on inflation, with this estimate defined as UIG. Second, two factors have also proven appropriate for comparable application for US (Amstad, Potter and Rich, 2014) and Switzerland (Amstad and Fischer, 2009b). Third, our sensitivity analysis shows that the impact of the number of factors above two is quite limited.

The right panel of Graph 3 illustrates the resulting UIG for China based on different choices of number of factors as 1, 2, 4, 6 and 8. These UIGs for China 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 66% of the S.D. in our target variable headline CPI inflation. This share rises and stays at around 80% in the case of UIG for China is based on 2 and more factors (Table 2).

[25] Different papers find that much of the variance in U.S. macroeconomic variables is explained by two factors. Giannone, Reichlin and Sala (2004) show this result using hundreds of variables for the period 1970-2003, as well as Sims and Sargent (1977) who 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 U.S. data during the post-war period, and that this finding is quite robust. Hence, in most large data factor model applications the number of factors is set to two.

Standard deviation (S.D.) for inflation and UIG for China

with different number of factors from 1 to 8 Table 2

	Inflation	q=1	q=2	q=4	q=6	q=8
S.D.	2.59	1.71	2.08	2.10	2.09	2.10
Portion (%)		66%	80%	81%	81%	81%

Note: S.D. is Standard Deviation.

Source: Authors' calculations.

5. Statistical properties and forecasting performance[26]

In the introduction, we emphasised that our goal is to construct a gauge that is useful for policy makers and market participants. In this section, we evaluate UIG for China against traditional core inflation measures first by using comparing their statistical properties and then by running a classical forecasting performance test.

Graph 4 shows UIG for China and the two traditional core inflation measures for Chinese CPI excluding food (CPI_nf) and CPI excluding food and energy (CPI_nfe), both as published by the National Bureau of Statistics of China. CPI_nf only starts in January 2005 and CPI_nfe starts in January 2006. To allow a comparison of forecasts based on the estimation from 2001, we first extend CPI_nf by assuming that the food weight 2001 to 2004 is the same as in 2005. Then we extend CPI_nfe by bridge equation as described in Appendix A3 using the prolonged CPI_nf.

Graph 4 illustrates the marked reduction in volatility of the two traditional core measures. While CPI fluctuates between -2% and +8%, the CPI excluding food (CPI_nf) and CPI excluding food and energy (CPI_nfe) both vary only between -2% and +2%. In two out of three peaks of CPI, the traditional core measures did not warn bond investors and policy makers of an increased inflation trend.[27]

For reference, we also include in our tests of forecasting performance an internal[28] core inflation measure often monitored by the PBC staff (UCPI), which excludes not all but only (more volatile) parts of the food prices and some administered prices. The purpose of this alternative core inflation measure appears to remove the excess volatility associated with fresh food prices and administrative price adjustments. UCPI starts in January 2005 and is extended to 2001 by bridge

[26] 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 (2014) and Amstad and Potter (2009) for the Fed NY Staff underlying inflation gauge (UIG) applied on US inflation.

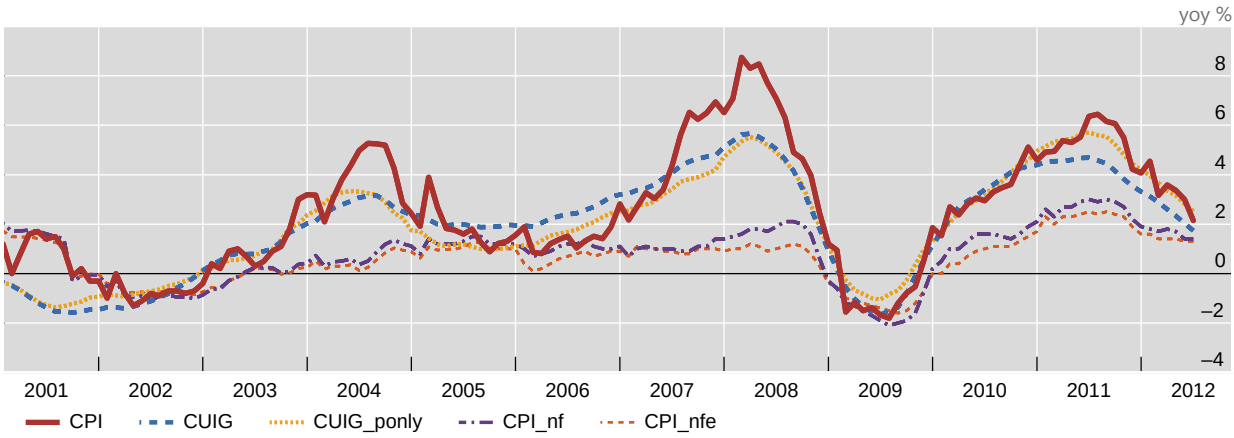
[27] CPI peaked in 2004, 2008 and 2011. The traditional core measures (CPI excluding food, CPI excluding food and energy) remained more or less stable during the first two peaks. Similarly, CPI troughs in 2002, 2008 and 2009 show in traditional core measures either simultaneously or with a lag.

[28] 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.

equation using CPI excluding food and CPI. It is not yet published and therefore not shown in Graph 4.

Inflation, UIG and traditional core measures for China

Graph 4



Note: CPI_nf= CPI excluding food. CPI_nfe= CPI excluding food and energy. UIG_ponly= UIG using only price data

Source: Authors' calculations.

5.1. Statistical properties

In this section, we evaluate the usefulness of UIG for China against traditional core inflation measures using three statistical criteria: "smoothness", "correlation with CPI" and "additional information".

Smoothness is an important property of a useful inflation gauge, as it reduces the dependence of decision-making on short-term volatility. Obviously a constant would achieve the maximum reduction in volatility. However, this could hardly be a useful inflation gauge, as it is unrelated to CPI inflation. Therefore, we consider the correlation with CPI as an additional statistical criterion to asses an inflation gauge's usefulness. The more an inflation gauge correlates with CPI – while still being smoother – the better. Finally, we evaluate as a third criteria whether an inflation gauge adds additional information over and above the information already provided by publicly available traditional core inflation measures. This third criterion is evaluated using a principal component analysis (PCA). In that regard, a useful inflation gauge is allocated in the same group as CPI, but in a different group than other core inflation measures.

We show that our UIG is less volatile compared to CPI but does not suffer from the excessive reduction of volatility in traditional core inflation measures, closely tracks the headline CPI inflation and at the same time is able to provide additional information that is not included in traditional core inflation measures. To ensure the robustness of our tests, we use two measures of UIG: the benchmark UIG based on the full dataset and that based on the subset of price variables only (UIG_ponly). Otherwise, UIG and UIG_ponly use the identical methodology and parameterisation.

(a) Smoothness

Based on the standard deviation metrics, both UIG and UIG_ponly are around 20% less volatile than CPI but more volatile than the traditional core inflation measures (Table 3). This illustrates an often cited (ADB (2008), and Cheung et al (2008)) dilemma in constructing traditional core inflation measures in China's case:[29] removing food from the CPI reduces volatility but also loses precious information (see Graph 4 and comments). Even though 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 eg in the US (ADB (2008)). Also, by excluding food and energy from CPI, a considerable part of the CPI volatility and with it a loss of the information that could potentially be useful to forecasting CPI. CPI_nf reduces half of the volatility of the headline CPI inflation and CPI_nfe even two-thirds of the volatility.

(b) Correlation with CPI

As shown in Table 4, UIG and UIG_ponly both closely track the headline CPI inflation with a correlation around 0.90-0.91. However, the traditional core inflation measures such as CPI_nf and CPI_nfe display much lower correlations (0.75 and 0.71) with CPI. UCPI shows the highest correlation with CPI with 0.95.[30]

(c) Additional information

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

A low correlation between two inflation gauges suggests they are quite different inflation signals. As can be seen from Table 4, UIG and UIG_ponly show the lowest correlations (0.69-0.73) with traditional core measures (CPI excluding food and CPI excluding food and energy). Meanwhile, UCPI often monitored by the PBC shows a correlation of 0.81-0.89 with both traditional core inflation measures as well as with our UIG and UIG_ponly.

It is evident that both UIG and UIG_ponly 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 UPCI.

This conclusion is confirmed by a simple principal components analysis (PCA) on CPI and all 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_ponly and UCPI are grouped together with CPI inflation in the first principal component, while traditional core inflation measures (CPI_nf and CPI_nfe) are grouped in a separate second principal component, in which CPI even weights negatively.

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

[30] UCPI's correlation with CPI is significantly different from UIG's correlation with CPI (p=0.3%). Meanwhile, correlations of UIG and UIG_ponly with CPI are not significantly different (p=65%). Similarly CPI_nf and CPI_nfe correlate insignificantly with CPI (p=48%).

Standard deviation

Sample: January 2001–June 2012 Table 3

	CPI	UIG	UIG_ponly	UCPI	CPI_nf	CPI_nfe
S.D.	2.49	2.08	2.05	1.54	1.16	0.94
Portion (%)	100%	84%	82%	62%	47%	38%

Note: S.D. is Standard Deviation. CPI_nf= CPI excluding food. CPI_nfe= CPI excluding food and energy. UIG_ponly=UIG using only price data. Source: Authors' calculations.

Correlations

Table 4

	CPI	UIG	UIG_ponly	UCPI	CPI_nf	CPI_nfe
CPI	1.00					
UIG	0.90	1.00				
UIG_ponly	0.91	0.96	1.00			
UCPI	0.95	0.85	0.89	1.00		
CPI_nf	0.75	0.73	0.72	0.85	1.00	
CPI_nfe	0.71	0.68	0.69	0.81	0.98	1.00

Note: CPI_nf= CPI excluding food. CPI_nfe= CPI excluding food and energy. UIG_ponly=UIG using only price data Source: Authors' calculations.

Principal Component Analysis

Table 5

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
CPI	0.42	–0.28	–0.49	0.49	0.46	–0.24
UIG	0.41	–0.37	0.52	0.44	–0.33	0.34
UIG_only	0.41	–0.38	0.32	–0.65	0.27	–0.31
UCPI	0.43	–0.04	–0.59	–0.36	–0.47	0.36
CPI_nf	0.40	0.53	0.11	0.13	–0.39	–0.62
CPI_nfe	0.39	0.60	0.16	–0.04	0.49	0.47
Variance Prop.	0.86	0.10	0.03	0.01	0.00	0.00
Cumulative Prop.	0.86	0.96	0.99	0.99	1.00	1.00

Note: CPI_nf= CPI excluding food. CPI_nfe= CPI excluding food and energy. UIG_ponly=UIG using only price data

Source: Authors' calculations.

5.2. Forecasting CPI inflation (a "horse race")

How does our UIG for China compare to traditional core inflation measures (CPI_nf and CPI_nfe) in terms of forecasting performance? To identify the best underlying inflation measure, we undertake the classical forecasting exercise (a horse race) 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 the forecasting sample period. Too long a time period can be problematic because they might cover different inflation regimes, while too short a time period might be neither statistically significant nor representative. Furthermore, in a period when inflation has been successfully stabilised (such as in industrialised countries before the global financial crisis), the signal associated with the least variation (eg a constant) might have had an advantage compared to 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 as well as over different sub-samples.

The behaviour of Chinese inflation since 2001 displays these features as it covers a relative tranquil pre-2008 period, and a quite volatile post-2008 period. However, as our sample starts only in 2001 (see Section 3.2) and the estimation period should not be shorter than the forecasting period, we use the following two forecasting samples: 2008-12 covering the crisis years and 2006-2012 covering a full up and downward inflation cycle.[31]

Finally, forecasting exercises are often undertaken in a "pseudo" real-time manner in which estimation is conducted using a single vintage dataset. In practice, the actual data used might have been revised subsequently. In this paper, we work with the data vintage that ends on June 30th, 2012.[32]

We calculate Root Mean Squared Errors (RMSE) resulting from forecasting inflation h month ahead $\hat{\pi}_{t+h}$ based on an estimation of equation (1) :

$$\hat{\pi}_{t+h} = \pi_t + \hat{\alpha}_h + \hat{\beta}_h (\pi_t - \pi_{mt}) \quad (1)$$

where π_t is inflation in t, π_{mt} denotes a given candidate as underlying inflation measure and $\hat{\alpha}_h$, $\hat{\beta}_h$ are the estimated regression coefficients using data through time t.[33] Our estimation starts in 2001. To account for possible sensitivity of the forecast comparisons to the selected sample periods, we consider two different forecasting periods. First, a sample from 2006-2012, a time range that could be considered a "full" up and downward inflation cycle as it encompasses rising as well as declining CPI inflation. Second, a "crisis" sub-sample that captures the period from 2008 until the middle of 2012.

We compare the forecast performance of the UIG to the CPI excluding food (CPI_nf) and CPI excluding food and energy (CPI_nfe). To test robustness, we also include in the forecast exercise UIG_ponly, in addition to UIG.[34] In common with the

[31] The samples are long enough to allow for meaningful statistical tests for UIG applied to China.

[32] For the impact of revisions and new data releases on the final estimate in the case of US see Amstad, Potter, Rich (2014).

[33] This follows Cogley (2002) and others who evaluate the performance of the various measures of underlying inflation by estimating the same regression equation.

[34] Another option would be to evaluate additional variants of UIG. Forecasting properties may vary for different UIGs that eg include only a specific data category, only a few but pre-selected data series or specific provinces variants. Eg Mehrotra et al (2010) find that the forward-looking inflation component and the output gap are important inflation drivers in provinces that have advanced most towards a market economy and have most likely experienced excess demand pressures.

horse race exercise, we include CPI inflation lagged by 12 months (CPI_LAG12) as a random walk benchmark for current CPI inflation.

Tables 6 and 7 show that both UIG and UIG_ponly clearly outperform the traditional core inflation measures (CPI excluding food and CPI excluding food and energy) in forecasting headline CPI for the full cycle as well as over the crisis sample. This is evident from the lowest reported RMSE over these two samples. To further analyse the forecast performance of UIG, we apply the Diebold-Mariano (1995) testing procedure and obtain five notable observations.

Forecasting performance over full period: 2006–2012

Estimation period is 2001–2005 Table 6

	RMSE[1]	DM stat[2]	DM p-value[3]
UIG	2.91	Na	na
UIG_ponly	2.93	0.08	0.47
CPI_nf	3.77	2.84	0.00
CPI_nfe	3.62	1.93	0.03
UCPI	4.08	3.06	0.00
CPI_LAG12	4.44	2.90	0.00

[1] Root Mean Square Errors (RMSE). [2] Diebold Mariano (DM)statistics. [3] Diebold Mariano likelihood (DM p-value).

Note: CPI_nf= CPI excluding food. CPI_nfe= CPI excluding food and energy. UIG_ponly=UIG using only price data. Source: Authors' calculations.

First, the results show that the forecast errors from UIG and UIG_ponly do not significantly differ from each other.[35] This finding is in contrast to the finding for the case of the US (Amstad, Potter and Rich, 2014) using the same test and a similarly constructed inflation gauge.[36] However, it is in line with eg Holz and Mehrotra (2013) who find that the 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. We interpret this as a further evidence for the frequently documented dominance of certain price variables - specifically food - in the Chinese CPI, where the food weight in the CPI basket is not publicly available but estimated to be around 30% (ADB, 2008) versus 16% in the US.[37] Going forward, the importance of non-price variables might increase and the UIG might then outperform UIG_ponly.[38]

However, this paper focuses on the forecasting property of the UIG using the whole dataset given in Section 3.

35 The DM p-value for UIG_ponly to be the same as UIG is 59% in 2008-2012 sample and 47% in 2006-2012 sample.

36 The main difference between UIG for China and UIG for the US, apart from the country difference, is the sample length. UIG for the US starts in 1994 while UIG for China starts in 2001. For completeness, we also 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. The evidence for Switzerland is in line with the findings by Amstad, Potter and Rich (2014) for the US case.

37 In November 2013 the weight of food in the US CPI was 14.2% and the weight of energy 9.6%.

38 Another option would be to evaluate different variants of UIG for China as mentioned earlier.

Forecasting performance over crisis period: 2008–2012

Estimation period is 2001–2007 Table 7

	RMSE[1]	DM stat[2]	DM p-value[3]
UIG	3.31	Na	na
UIG_ponly	3.20	-0.23	0.59
CPI_nf	3.82	3.18	0.00
CPI_nfe	3.55	1.11	0.13
UCPI	4.07	2.36	0.01
CPI_LAG12	4.84	2.07	0.02

[1] Root Mean Square Errors (RMSE). [2] Diebold Mariano (DM) statistics. [3] Diebold Mariano likelihood (DM p-value).

Note: CPI_nf= CPI excluding food. CPI_nfe= CPI excluding food and energy. UIG_ponly=UIG using only price data.
Source: Authors' calculations.

Second, the RMSEs for UIG and UIG_ponly are significantly lower than those from the traditional core inflation measures (CPI excluding food and CPI excluding food and energy). The statistical significance level is 3% for the full cycle of 2006-2012 and mostly at 2% for the crisis sample of 2008-2012. Only for CPI_nfe during the crisis years of 2008-2012 the out-performance of UIG and UIG_ponly is less clear with a 13% significance level. However, for the full cycle 2006-2012, CPI_nfe performs worse than both UIG and UIG_ponly at a 3% significance level.

Third, all underlying inflation measures do better than the 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.

Fourth, the forecasting performances of traditional core inflation measures of CPI_nf and CPI_nfe are remarkably similar over the whole sample. This is in line with the findings in Rich and Steindel (2007)[39] for the US, confirming that various traditional core inflation measures do not differ much in their forecasting performance.

Fifth, the relative forecasting performance of the popular traditional core inflation measures (CPI excluding food and particularly CPI excluding food and energy) improves during the global financial crisis. This finding is in line with that of Amstad, Potter and Rich (2014) for the US.

5.3. Implications

Taken together, the results from Sections 5.1 and 5.2 seem to suggest that it may be advantageous for policymakers and market participants to use the various core inflation measures in a complementary way. While the traditional core inflation measures are easy to calculate and interpret, UIG clearly outperforms the others in

[39] Rich and Steindel (2007) and Amstad, Potter and Rich (2014) use the same test.

forecasting exercises. UCPI appears to be a mix between these two classes.[40] One property that sets apart our UIG from all other core inflation measures considered here is that it includes – instead of excludes – data; in this it is a TIPS-like inflation gauge.

On the one hand, exclusion-based measures will always have the advantage of ease in calculation and communication. On the other hand, when some specific price components (like food) become less important and labour and financial markets gain importance[41] – the importance of including additional data in forecasting inflation might increase over time. Overall, it seems useful for policymakers and market participants to use all the considered inflation gauges, including our newly constructed UIG for China, in a complementary way.

6. Conclusion

This paper introduces and constructs a new underlying inflation gauge (UIG) for China. We present the calculation, motivate the choice of model parameterisation, discuss data challenges and compare the statistical properties and forecasting performance of UIG with other traditional core inflation measures (CPI excluding food and CPI excluding food and energy). UIG differentiates trend from noise, is based on a broad dataset and can be calculated on a daily basis. These properties differentiate UIG clearly from other core inflation measures and make it particularly useful as an additional inflation measure for monetary policymakers and market participants.

In particular, UIG for China is less volatile than CPI but does not suffer from the extreme volatility reduction typical to traditional core measures in China. UIG also closely tracks headline CPI inflation and at the same time is able to provide additional information over and above what is available from traditional core inflation measures. Finally, we show in a statistical forecasting exercise that UIG for China outperforms over different samples the traditional core measures in forecasting headline CPI.

[40] In Section 5.2, UCPI does not seem to perform statistically different from traditional core measures of CPI_nf and CPI_nfe. However, in Section 5.1, it was grouped together with UIG indicating some similarity (eg illustrating the importance that food prices are not excluded).

[41] See eg Zhang (2012) for the argument that while currently inflation seems demand-pull driven soon cost-push factors may play a more significant role.

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Appendix A: data adjustments

A1. The Chinese Lunar New Year effect

Some of the time series have been significantly distorted by the Chinese Lunar New Year Effect. The Chinese New Year is the most important traditional holiday in China when people stop working for family reunions and for shopping. During the holidays, manufacturing activities slow or even contract sharply, but retail sales rise significantly. Yet its seasonal pattern is irregular, as the Chinese New Year often alternatively falls into January and February from one year to the next, according to the lunar calendar. For this reason, China's National Bureau of Statistics does not compile and publish separate January and February data for such activity variables as industrial value-added and fixed asset investment. Instead, it sometimes provides only the year-to-date data for February.

How we treat the Chinese New Year Effect — Table A1

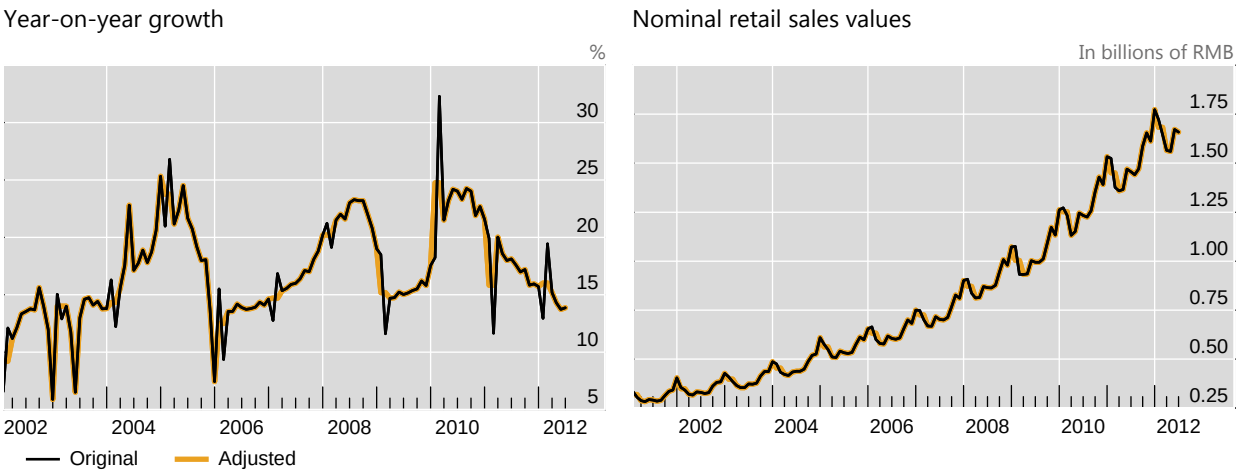
Data	Adjustment
No separate January data, yoy growth	Assuming January = February = February_orig*
No separate January data, absolute value	Averaging: Jan=Feb=(Jan_orig+Feb_orig)/2
No CNY effect, yoy growth	No adjustment
No CNY effect, absolute value	No adjustment
Big CNY effect, yoy growth	Averaging: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

* _orig denotes the original data before the adjustment. CNY = Chinese New Year.

As this is a well-known challenge in working with Chinese data, we follow the practice of others. We deal with the Chinese New Year effect differently in different cases. For those series without separate January and February data, we simply assume the two monthly observations to be the same (Table A1). For those variables with separate January and February data, if the Chinese New Year does not fall into the same month as in the previous year, there might be a big jump in its year-on-year growth rate, which may significantly distort the growth of these variables. So we first need to determine whether a series is significantly affected, by observing the graph for its year-on-year growth rate. Once those significantly affected series are identified, we follow the practical approach of taking the average of January and February to remove the Chinese New Year effects.[42] As an example, Figure A1 shows the adjustment of retail sales of consumer goods.

[42] For instance, Shu and Tsang (2005) compare the two methods of pre-adjusting a series with Chinese New Year effects: taking the average of January and February and using CNY dummies. They find that taking into account the Chinese New year effects improves seasonal adjustments, but, no clear winner between the two.

The Chinese New Year effect: the case of retail sales of consumer goods Graph A1



Note: the Chinese New Year effect is adjusted by taking the average of January and February.

Source: CIEC and authors' estimation.

A2. The stationarity treatment

The filter requires that all series used are stationary. So we treat the series as following: denote the original series X and the series we use in the signal X',

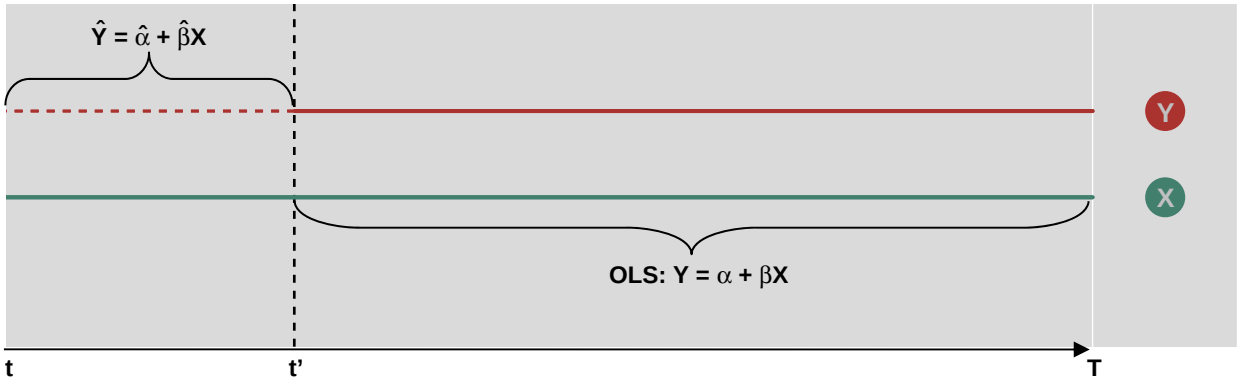
$$X'(t) = X(t), if\ X\ is\ I(0)$$
$$X'(t) = X(t) - X(t-1), if\ X\ is\ I(1)$$
$$X'(t) = \log\big(X(t)\big) - \log\big(X(t-1)\big), if\ X\ is\ I(2)$$

A3. The bridge-equation regressions

Assume that the sample range is from t to T in the Graph A3, and the short series Y is from t' to T and that we need to fill in the missing values for Y from t to t'. Our simple bridge-equation approach works as follows. First, we pick another series X that covers the whole sample range of t and T as a regressor on Y to estimate a simple linear equation Y= α+β*X for the period of t' and T. Then, the estimated coefficient values of α and β will 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.

Bridge equation illustration

Graph A3



Source: authors' representation

In this approach, the long series X is acting like a bridge and therefore should be carefully chosen so that it is highly correlated with Y. In most cases, we choose the broader and full-sample variable as the bridge for its 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. The right panel of Graph 2 shows the result of the bridge equation; the orange line is the fitted value as the substitute for the missing values.

The composition of the short series

Table A2

Starting year	Total	2002	2003	2004	2005	2006	2007	2008
Number	176	11	18	80	40	9	5	13
Portion (%)	100.0	6.3	10.2	45.5	22.7	5.1	2.8	7.4
No. of long series used		4	5	17	4	2	2	1
Number of short series prolonged by one long series		2.8	3.6	4.7	10.0	4.5	2.5	13.0

Note: for the price category, we can deduce the fixed-base index number by m-o-m growth rate and y-o-y growth rate. If the y-o-y growth rate starts from year t, we can calculate the corresponding fixed-base index number from year t-1. So the short CPI series start from 2004.

Source: Authors' calculations.

In the final dataset, 176 out of 473 time series or 37.2% of the all the series are "lengthened" this way by the bridge equation approach. This seems a big proportion, but most of these short series (about 60%) have missing values no more than 2 to 3 years (Table A4). 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 a '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. And the importance of the lengthened parts should diminish over time.

Appendix B: End of sample procedure

To consider the most up to date information of daily available information we use a dataset which is unbalanced at the end. Therefore some series end in T, others in $T+1,..,T+w$. To treat the end-of-sample unbalance and forecast we use the methodology of Altissimo et al. (2001) and Cristadoro et al (2005) by reordering the variables $x_{i,t}$ in a way that

$$x_{i,t}^{*} = \left(x_{i,t}^{1}, x_{i,t}^{2}, .., x_{i,t}^{w}\right)$$

where $x_{i,t}^{j} j = 1, \dots, w$ groups variables along the same last available observation $T+j-1$. In the same way the covariance matrix is partitioned as follows

$$\hat{\Gamma}^{*}(k) = \begin{pmatrix} \hat{\Gamma}^{11}(k) & \hat{\Gamma}^{12}(k) & \hat{\Gamma}^{1w}(k) \\ \hat{\Gamma}^{21}(k) & \hat{\Gamma}^{22}(k) & \hat{\Gamma}^{2w}(k) \\ \hat{\Gamma}^{w1}(k) & \hat{\Gamma}^{w2}(k) & \hat{\Gamma}^{ww}(k) \end{pmatrix}$$

and accordingly for the covariance matrix of the common $\hat{\Gamma}_{x}^{*}(k)$ and the covariance matrix of the idiosyncratic $\hat{\Gamma}_{\xi}^{*}(k)$ as well. After shifting the variables in such a way to retain, for each one of them, only the most updated observation, the generalized principal components is computed for the realigned vector $\hat{\Gamma}_{\xi}^{*}(k)$ to get the forecasts. The final step is to restore the original alignment. The procedure is describes in greater detail in Cristadoro et al. (2005).