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Tracking Chinese CPI inflation in real time

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Abstract

With recovery from the global financial crisis in 2009 and 2010, inflation emerged as a major concern for many central banks in emerging Asia. We use data observed at mixed frequencies to estimate the movement of Chinese headline inflation within the framework of a state-space model, and then take the estimated indicator to nowcast Chinese CPI inflation. The importance of forward-looking and high-frequency variables in tracking inflation dynamics is highlighted and the policy implications discussed.

Keywords**:** Nowcasting, CPI inflation cycle, mixed-frequency modelling, dynamic factor model, China.
JEL classification: C53, E31, E37.

* The opinions are those of the authors and do not necessarily represent those of the Bank for International Settlements. All errors and omissions are entirely ours. We are grateful to Emese Kuruc for her research assistance.

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Tiivistelmä

Globaalista finanssikriisistä toipumisen myötä inflaatiosta on tullut monien kehittyvän Aasian maiden keskuspankkien huolenaihe. Tässä tutkimuksessa käytetään toisistaan eroavin frekvenssein julkaistua tilastoaineistoa Kiinan inflaatiovauhdin estimoimiseksi state-space-mallikehikossa. Estimoidun indikaattorin avulla ennustetaan nykyhetken inflaatiokehitystä. Tuloksissa korostuu eteenpäin katsovien indikaattorien sekä usein julkaistavien muuttujien tärkeys inflaation seurannassa.

Asiasanat: nowcasting, KHI, inflaatiosykli, Kiina, dynaamisten muuttujien malli, ennustaminen
JEL: C53, E31, E37.

1 Introduction

Inflation rates began to rise sharply across emerging Asia soon after recovery from the global crisis got traction in early 2009. Fighting inflation re-emerged as major theme for many central banks and other policymakers. While increases in food and non-food commodity prices initially played an important role, inflation became generalized by early 2011, with core inflation picking up across emerging Asia. China's headline consumer price inflation (CPI) climbed from -1.8% in July 2009 to 6.5% in July 2011. Unlike most earlier inflationary periods, inflation this time around was driven by both demand- and supply-side factors.

China does not employ a formal inflation-targeting framework, but the government includes an annual objective for CPI growth among its targets for social and economic development.[1] China's monetary policy also explicitly mandates maintaining "the stability of the value of the currency," suggesting the primary importance placed on price stability.[2] To accomplish this goal, accurate and timely forecasts of inflation are critical to policymakers in calibrating the monetary stance.

Given the importance placed on price- and wage-setting by firms and workers, forward-looking variables are needed to anticipate future threats to price stability and design monetary policy appropriately. Here, indicators with a higher frequency than the monthly headline inflation figure may be potentially useful to the central bank and other economic agents in assessing turning points in inflation cycles.

In this paper, we nowcast the inflation process in China using indicators at different frequencies. We apply the framework suggested by Aruoba et al. (2009), which was developed for real-time measurement of business conditions. It incorporates a small-data dynamic factor model that uses series with daily, monthly, and quarterly frequencies to track movements in the monthly headline inflation figure (12-month change in the CPI). The modeling framework also allows for missing values at the end of the sample.[3]

[1] Formal inflation targeting has not been a prerequisite for successful inflation policy in the Asia-Pacific region, as Filardo and Genberg (2010) show.
[2] See http://www.pbc.gov.cn/publish/english/970/index.html
[3] This mixed-frequency strand of literature now constitutes a growing branch of the real-time GDP forecasting literature. However, only Aruoba and Diebold (2010b), Monteforte and Moretti (2009) and Modugno (2011) have nowcasted inflation using high-frequency data.

Our estimated inflation indicators track the Chinese headline inflation well, leading CPI inflation by roughly one quarter. Daily commodity prices and financial variables are found to be particularly useful in constructing the Chinese inflation indicator. Forward-looking variables, in turn, have informative power at the quarterly frequency.

Our estimated indicator predicts turning points in inflation cycles, most notably, the onset of recovery from the recent financial crisis. A real-time out-of-sample forecasting exercise suggests that our estimated mixed-frequency model outperforms the widely used random-walk model in one-month-ahead forecasts (although the performance of an ARIMA model is still superior). In any case, use of daily data grants the mixed-frequency model a timeliness advantage over conventional time series models.

The relative openness of the Chinese economy to international trade and its dependence on raw material imports readily explain the importance of commodity prices in inflation trends. However, the broader question of how a central bank should respond to increases in commodity prices is non-trivial. During the recent global recovery, as commodity prices have been increasing due to strong aggregate demand, the case of tightening monetary policy in the face of commodity price-driven inflation increases may be rather strong. Similarly, in an economy where food constitutes a large share of the consumption basket, a measure of core inflation that excludes such a commodity may be of limited value both as an indicator of the cost of living and a measure of underlying inflation.

This paper is structured as follows. The following section provides details about the data. Section 3 describes the econometric methodology and compares the constructed latent inflation indicator against headline CPI. A nowcasting exercise for Chinese inflation is presented in Section 4. The final section concludes with policy implications.

2 Data description

Our modeling approach is essentially atheoretical; it does not impose a specific model of the inflation process. We are also agnostic on the relative importance of the various factors of underlying inflation. Instead, we let the data speak. Thus, the choice of variables plays a crucial role. The two main criteria in our choices are *availability* in terms of sample length and *information value* in terms of tracking the dynamics of China’s headline inflation rate.

The types of variables used in our analysis can be divided into three categories: commodity prices, monetary conditions, and inflation expectations. *Commodity prices* are typically available at a high frequency and generally account for an important share of consumer price index in an emerging economy. Commodity price dynamics have been highly useful in recent years in explaining global inflation dynamics. *Monetary conditions* are potentially important drivers of inflation in the medium to long-run, and their inclusion is reconcilable with a monetary view of inflation. Finally, *inflation expectations* impact actual inflation outcomes via forward-looking wage- and price-setting by economic agents.[4]

Our methodology involves the search of an optimal combination of mixed-frequency indicators. While the number of indicator candidates for an emerging economy is typically small, one or more indicators are considered for each frequency.

In describing the employed series, we start with our highest frequency,[5] i.e. daily frequency for global commodity prices and monetary indicators. China only became a net importer of oil in 1993 but by 2010 it depended on imports to cover more than 50% of its oil needs. China remains largely self-sufficient in most staple foods, but international developments still play an important role in food price dynamics. For example, China has become the world's largest importer of soybeans, which in turn has had profound effects elsewhere such as land use in Brazil and Argentina. We use the composite S&P GSCI commodity price index (formerly the Goldman Sachs Commodity Index), which tracks 24 commodities from various commodity sectors, including energy products, metals, and agricultural products. We also consider the S&P GSCI agriculture index for our daily measure of agricultural products prices.[6] These two series and China's headline CPI inflation rate appear in Figure 1.

Two variables capturing monetary conditions are available at daily frequency. The first is the one-month interbank repo interest rate. Peng et al. (2006) mention that increased depth of the money market and growth in corporate bond issuance have helped develop

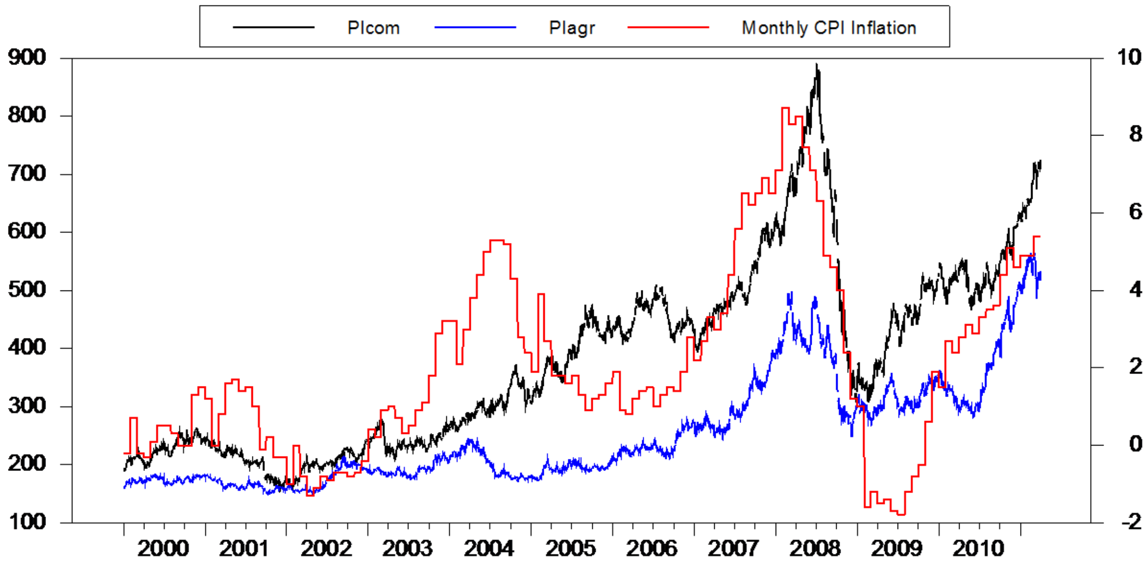
[4] Recent publications in the forecasting domain stress that incorporating information from Google Trends may offer significant benefits for real-time forecasts (see Vosen and Schmidt, 2011). Data are provided on a weekly basis. We have refrained from adding Google *Insights for Search* search query data because Google's current share of the search engine market in China is around 20%. Baidu, Google's top Chinese competitor, has a 75% market share. In any case, the Google data are only available from 2004 onwards.

[5] The underlying nowcasting variable selection problem is to extract information from data sampled at high frequency while screening out short-term nuisances that are irrelevant to an inflation assessment and otherwise suppressed in lower frequency data.

[6] We initially considered inclusion of oil future prices as daily indicators (specifically, the West Texas Intermediate Oil Future Price at the one-month horizon). While oil prices exhibit a close correlation with the commodity price index, regulation of oil prices in China creates lags between the global market and domestic price adjustment. Thus, we only consider the commodity price indices in subsequent modeling.

market-based interest rates in China.[7] However, the regulatory environment in China implies a high degree of volatility in daily interbank rates as Chinese banks have to meet their required reserve targets on a daily basis. As a result, realized interest rate volatility is typically higher in China than in countries with policy implementation frameworks based around the overnight rate and longer reserve assessment periods. Therefore, we take the weekly average of the interbank repo rate and apply the interest rate variable at a weekly frequency in our empirical analysis.

Figure 1 Daily commodity prices (left scale) and monthly CPI inflation (right scale)



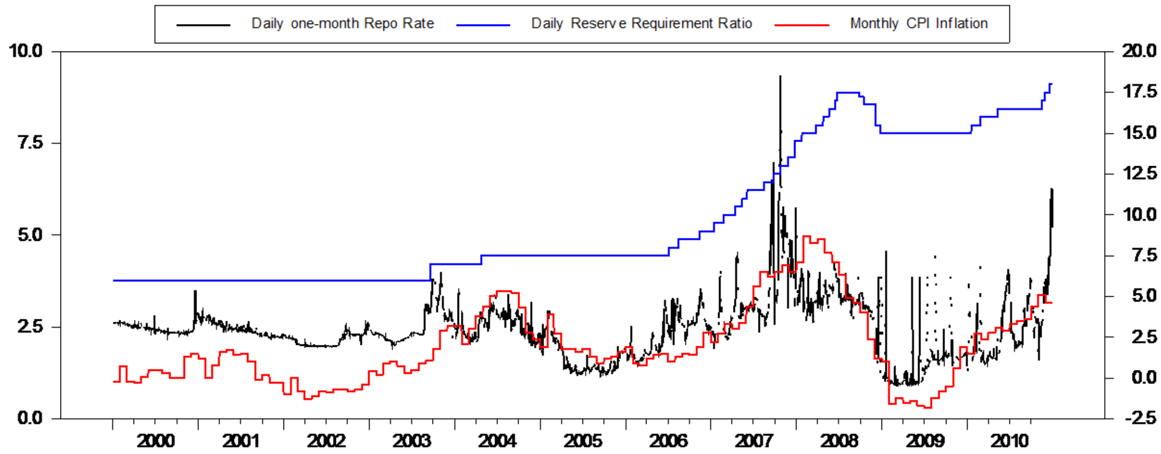
Note: S&P GSCI composite index is denoted by PIcom; S&P GSCI agriculture index is denoted by PIagr.

The other daily monetary indicator applied in our study is the reserve requirement ratio. The People's Bank of China adjusted reserve requirements frequently as the world recovered from the international financial crisis to mop up excess liquidity and contain inflation pressures (see Ma et al., 2011). In a period that includes the crisis (July 2006 to April 2011), the People's Bank of China changed the reserve requirement ratio 33 times, usually in 50-basis-point increments. The reserve requirement ratio doubled between mid-2006 and the end of 2008. The use of the reserve requirement ratio as a non-market-based sterilization instrument can be attractive due to its relatively low cost for the central bank compared to issuance of sterilization paper in the form of central bank securities. Reserve

[7] Nevertheless, Porter and Xu (2009) note that interbank rates are not independent of other regulated interest rates.

requirements have been remunerated at 1.62% p.a. since end-2008, while the yield on one-year central bank bills has been at 3–4% p.a. during 2011. Also, as Ma et al. (2011) point out, the People's Bank of China may have greater discretion at the operational level in adjusting the reserve requirement ratio than e.g. changing benchmark interest rates. The daily variables describing monetary conditions are depicted together with headline inflation in Figure 2.[8]

Figure 2 Daily reserve requirement ratio (right scale); daily one-month repo rate and monthly CPI inflation (left scale)

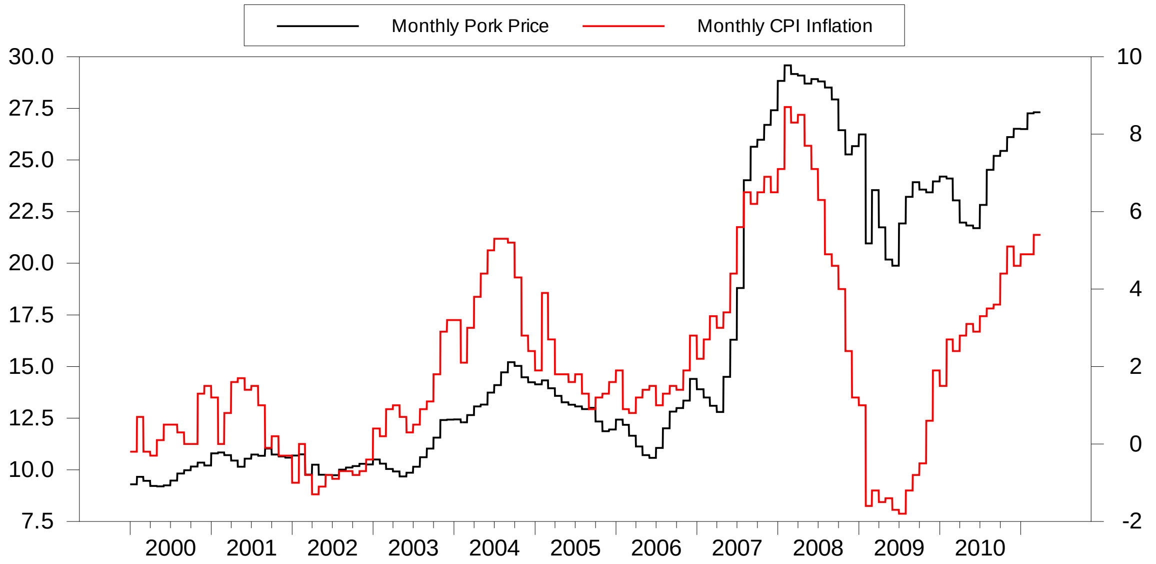


Moving on to variables observed at monthly frequency, we include the monthly price of pork. As mentioned, the importance of food in the Chinese consumption basket and its CPI weighting are high. The weighting of food was lowered slightly from 32.4% to 30.2% in early 2011, but food remains an important driver of CPI developments. It was a significant driver of inflation pressure in 2004, 2007/08, and 2010. Indeed, pork accounts for almost two-thirds of China's meat consumption – making it the largest single component of the CPI basket. Higher pork prices since 2009 have hit consumers hard and been a major factor behind the recent acceleration in the inflation rate. Unlike staples such as rice or flour, pork prices are less controlled by the government, allowing for greater market determination of

[8] Figure 2 gives the unweighted reserve requirement ratio. Recently, the People's Bank of China broadened the asset base that banks will need to reserve against to control lending and battle high inflation. The new asset base includes customer margin deposits, i.e. what is paid by bank clients to secure the issuance of bankers' acceptance, letters of guarantee, and letters of credit.

prices.[9] The close correlation between the monthly pork price and headline inflation is shown in Figure 3.[10]

Figure 3 Monthly pork price, CNY/kg (left scale) and monthly CPI inflation (right scale)



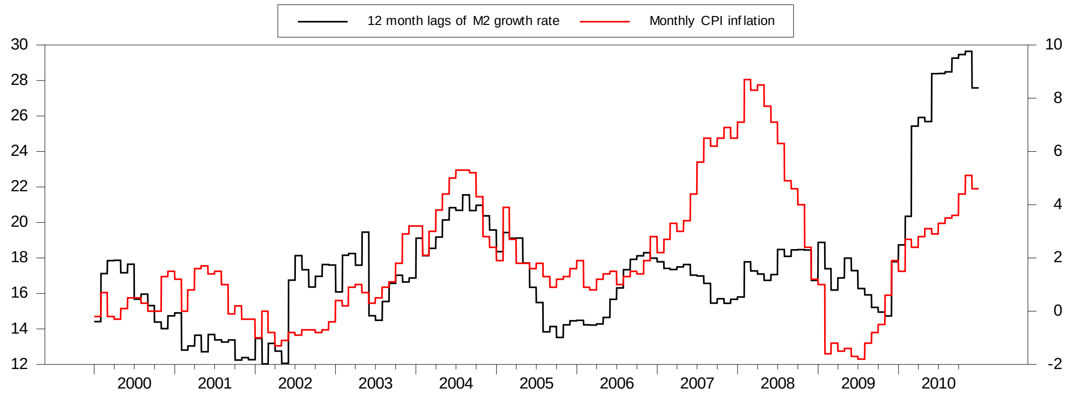
As a monetary indicator at a monthly frequency, we include broad money M2 (cash, currency in circulation, demand deposits, and savings deposits). Although M2 serves as an intermediate target for the PBoC, there is no consensus in the empirical literature on whether monetary aggregates convey information that is not already captured in other macroeconomic fundamentals such as interest rates or survey measures of future inflation. In the case of the US economy, Estrella and Mishkin (1997) argue monetary aggregates have low information content, while Aksoy and Piskorski (2006) counter that money provides useful information about US inflation and output when corrected for foreign holdings of dollars. Figure 4 displays the 12-month lag for the growth rate of M2 used in our analysis and CPI inflation. A fall in the monetary growth rate preceded the deflationary period of

[9] We use monthly pork prices, as daily pork prices have only been available since 2008. In the estimates, the number of observations is an issue because the estimates are only asymptotically correct, i.e. they provide the correct values only as the number of observations approaches infinity. Method performance is affected when the number of observations is small.

[10] Pork prices have been rising since 2009 due to several years of swine disease pandemics and high grain prices. Moreover, demand for meat has been rising in China as consumers have become richer.

the early 2000s. Similarly, strong growth in broad money heralded the pickups in inflation registered in 2004 and 2010.

Figure 4 12-month lag of M2 growth rate, % (left) and 12-month CPI inflation, % (right)

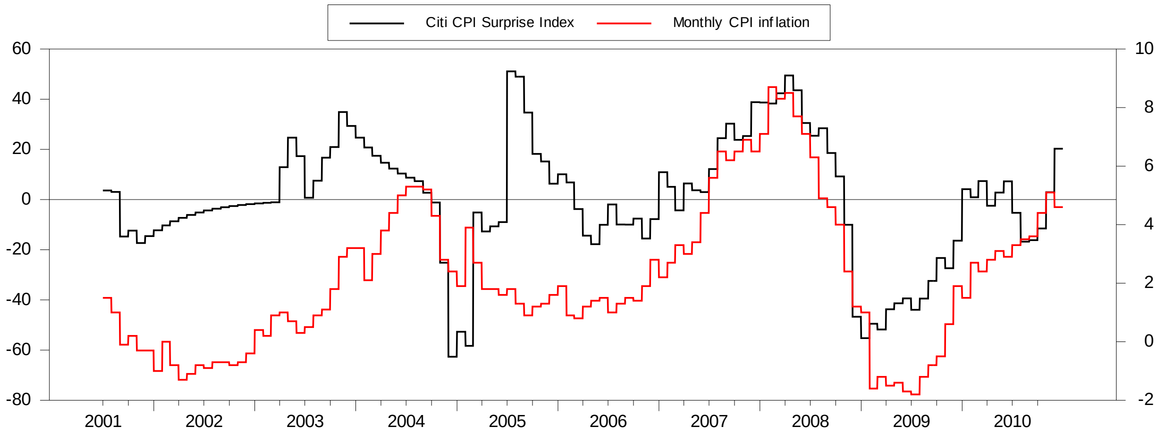


As our final monthly indicator, we include a series capturing inflation expectations. The empirical literature has long noted a strong correlation between inflation sentiment indicators and future inflation.[11] The importance of expectations is obvious as expected inflation affects forward-looking price- and wage-setting behavior, and thus actual inflation outcomes. Forward-looking inflation also plays an important role in setting policy (see e.g. the framework of inflation forecast targeting described by Svensson, 1997). Our series here is the closely-watched Citigroup "Inflation Surprise Index" for China. This monthly index measures realized inflation against market expectations and has been available since 2001. The Citigroup Inflation Surprise Index is constructed so that inflation data that match market expectations receive a value of zero, inflation data exceeding expectations are assigned a positive value and inflation data falling short get a negative number.[12] Thus, a positive number means economists need to ratchet up their inflation forecast to match incoming data. When the index is negative, the actual inflation rate is below expectations. After all, markets are not built solely on fundamentals, but on how accurately those fundamentals are expected by agents. When expectations are high, the likelihood for disappointment is lar-

[11] Surveys of inflation expectations do not necessarily foreshadow future inflation as they combine forward-looking and backward-looking elements. This contradicts conventional wisdom; rational agents should drive backward-looking agents out of the market. Molnár (2007) has, however, shown that this must not be the case. Her model has two types of agents, one having rational expectations and the other using adaptive learning. She has demonstrated that the adaptive learning group survives competition with rational expectations.

ger. When expectations are low, there is more potential for upside surprise. Figure 5 presents the relationship between Chinese CPI inflation and the Inflation Surprise Index for Chinese CPI inflation during the period 2001−2011.

Figure 5 Monthly CPI Surprise Index reading (left) and Monthly CPI Inflation, % (right)



Note: See http://www.citifxpro.com/citi-fx-quantitative-investor-solutions

A few other points are worth highlighting. First, markets became more sensitive to inflation data after 2007 with both series generally moving together and spiking simultaneously in summer 2008. Another important take-away is that the Inflation Surprise Index in 2007−2008 was largely in positive territory, i.e. higher-than-expected inflation outcomes registered. At the very most, the latest data points suggest that China's Inflation Surprise Index shows no clear direction.[13] Interestingly, the relationship between the Inflation Surprise Index and actual inflation could be taken to suggest an estimated steady state inflation rate in China of roughly 5% by analysts in recent years. This is somewhat higher than the government's targets for CPI inflation rates in the past years (3% for 2007 and 2010; 4.8% for 2008; 4% in 2009).

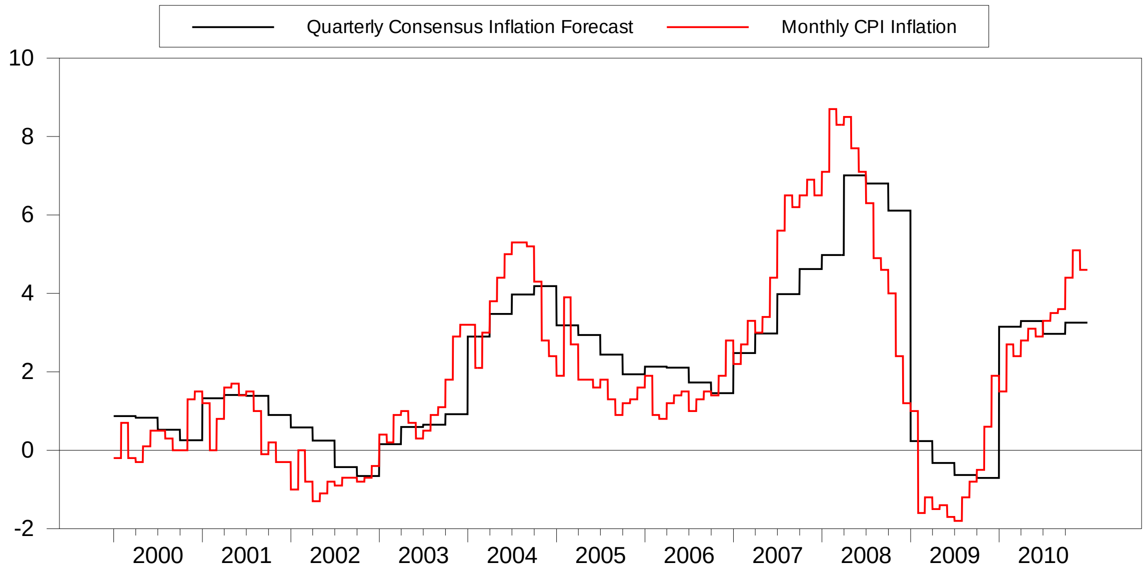
The only quarterly variable employed is also of a forward-looking nature. We use the quarterly Consensus Forecast of China's headline inflation rate, published regularly at the eve of every new quarter. This forecast is obtained by a survey of international fore-

[12] In one sense, the index is simply a measure of the quality of the CPI inflation estimates of analysts. If inflation data always lined up with expectations, there would never be positive or negative surprises and the index would always obtain a value of zero.

[13] The slightly moderating index may, however, be a temporary phenomenon. One reason why the softer patch at the cutting edge is likely to prove temporary is that there is still little rebalancing of the economy. On the contrary, the implementation of the 12th Five-Year Plan acts as a massive stimulus to various investment projects.

casters. The consensus forecast is plotted together with the headline inflation rate in Figure 6. The comovement of both series is striking even if the lead times of the survey indicator vary.

Figure 6 Quarterly Consensus Inflation Forecast and Monthly CPI Inflation



We now turn to the methodology allowing for timely updates of inflation projections and some illustration of how this general framework can be applied in practice.

3 Econometric framework and estimation results

Many financial variables are sampled at a daily, or even at intraday, frequency. In contrast, most macroeconomic variables are sampled on a weekly, monthly, or quarterly basis. To deal with these combinations of sampling frequencies, we adopt the modeling approach laid out by Aruoba et al. (2009) and Aruoba and Diebold (2010a), which allows us to estimate any parameter of interest in an internally consistent fashion.[14] Unlike dynamic factor

[14] The appeal of this approach lies in its ease of calculation. Two main alternative methods have been used in the literature. The first is the distributed lag mixed data sampling (MIDAS) approach originally proposed by Ghysels et al. (2007). Subsequent papers have extended and evaluated the approach. Guérin and Marcellino (2011) have recently presented a Markov-switching mixed data sampling (MS-MIDAS) framework that allows for the use of mixed-frequency data in Markov-switching models. Kuzin et al. (2011) have recently compared MIDAS with a mixed-frequency VAR (MF-VAR) model. A second strand of the literature has recently suggested the use of large-scale factor models. The idea is to include a broad dataset to use all avail-

models, this technique is based on a sparse-data environment and models series with mixed frequencies. It handles any pattern of data availability within a unified framework and facilitates updating of nowcasts as new data become available. To describe the approach more formally, let x_t denote (unobserved) CPI inflation at day t which evolves with covariance-stationary *AR(p)* dynamics

(1) $$x_t = \rho_1 x_{t-1} + \rho_2 x_{t-2} + \ldots + \rho_p x_{t-p} + \mu_t \,.$$

The time index t denotes a day, and equation (1) holds for $t = 1, \ldots T$. μ_t is a white noise error term. To identify the factor model, Aruoba and Diebold (2010a) introduce the cumulator variable suggested by Harvey (1989, 313-318) to handle temporal aggregation of variables. The cumulator variables summarize all the information needed to construct aggregated variables at the observable lower (nondaily) frequency. Specifically, we define the monthly cumulator variable as

(2) $$C_t = \xi_t C_{t-1} + x_t = \xi_t C_{t-1} + \rho_1 x_{t-1} + \rho_2 x_{t-2} + \ldots + \rho_p x_{t-p} + \mu_t ,$$

where

(3) $$\xi_t = \begin{cases} 0 & \text{if } t \text{ is the first day of a week/month/quarter} \\ 1 & \text{otherwise} \end{cases}$$

is an indicator variable. The beauty here is that changing the aggregation period to weeks or quarters only requires adjusting the definition of ξ_t in an obvious way. Without loss of generality, the *i*-th covariance-stationary measurement equation of the daily indicator $\tilde{y}_t$ is then

(4) $$\tilde{y}_t = c^i + \beta^i C_t + \gamma_1^i \tilde{y}^i_{t-D^i} + \gamma_2^i \tilde{y}^i_{t-2D^i} + \ldots + \gamma^i_{q^i} \tilde{y}^i_{t-q^i D^i} + e^i_t ,$$

able information efficiently. See e.g. Banbura and Modugno (2010) and Yiu and Chow (2010). Of course, this is all part of the larger ongoing discourse on the relative merits of small vs. large datasets. An early survey is provided by Croushore (2006).

where $D^i > 0$ is a scalar associated with the observable lower frequency lag of $x_{i,t}$ (e.g., D^i = 7 if $\hat{y}_t$ is observed weekly), and e_t^i is a white-noise shock, which is unrelated to all weakly (but not necessarily strictly) exogenous regressors and μ_t. In other words, the approach deals with the problem of mixing frequencies by treating quarterly, monthly, and weekly series as daily series with missing observations. For identification and to maintain parsimony, we assume that the shocks μ_t and $e_{i,t}$ are Gaussian and orthogonal. Under these hypotheses, the system can be cast in state-space form as

(5) $$Y_t = Z_t^{'} X_t + V_t + \varepsilon_t = Z_t^{'} X_t + \Gamma_t w_t + \varepsilon_t$$

and

(6) $$X_t = A_t X_{t-1} + F_t \eta_t$$

(t = 1, … T), where Y_t is an N×1 vector of observed variables (subject to missing observations), X_t is the vector of state variables, and w_t is a vector of predetermined variables. ε_t and η_t are vectors of measurement and transition shocks containing the u_t and e_t^i. In our benchmark model, we employ two daily series ($\tilde{y}_t^{D1}$ and $\tilde{y}_t^{D2}$), one weekly series ($\tilde{y}_t^{W}$), four monthly series ($\tilde{y}_t^{M1}$, $\tilde{y}_t^{M2}$, $\tilde{y}_t^{M3}$ and $\tilde{y}_t^{M4}$) and one quarterly series ($\tilde{y}_t^{Q}$). All variables are in the form of year-on-year growth rates. Compiling the components, the modeling framework corresponds to the state-space system:

$$\underbrace{\begin{bmatrix} \tilde{y}_t^{D1} \\ \tilde{y}_t^{D2} \\ \tilde{y}_t^{W} \\ \tilde{y}_t^{M1} \\ \tilde{y}_t^{M2} \\ \tilde{y}_t^{M3} \\ \tilde{y}_t^{M4} \\ \tilde{y}_t^{Q} \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} b_{11} & b_{12} & b_2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{31} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{32} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{33} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & b_{34} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & b_4 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}'}_{Z_t} \underbrace{\begin{bmatrix} x_t \\ C_t^{M1} \\ C_t^{M2} \\ C_t^{M3} \\ C_t^{M4} \\ C_t^{Q} \\ u_t^1 \end{bmatrix}}_{X_t} + \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ G_{21} & 0 & 0 & 0 & 0 & 0 \\ 0 & G_{31} & 0 & 0 & 0 & 0 \\ 0 & 0 & G_{32} & 0 & 0 & 0 \\ 0 & 0 & 0 & G_{33} & 0 & 0 \\ 0 & 0 & 0 & 0 & G_{34} & 0 \\ 0 & 0 & 0 & 0 & 0 & G_4 \end{bmatrix}}_{\Gamma_t} \underbrace{\begin{bmatrix} \tilde{y}_{t-W}^{W} \\ \tilde{y}_{t-M}^{M1} \\ \tilde{y}_{t-M}^{M2} \\ \tilde{y}_{t-M}^{M3} \\ \tilde{y}_{t-M}^{M4} \\ \tilde{y}_{t-Q}^{Q} \end{bmatrix}}_{w_t} + \underbrace{\begin{bmatrix} 0 \\ u_t^2 \\ u_t^3 \\ u_t^4 \\ u_t^5 \\ u_t^6 \\ u_t^7 \\ u_t^8 \end{bmatrix}}_{\varepsilon_t}$$

(7)
$$\underbrace{\begin{bmatrix} x_t \\ C_t^{M1} \\ C_t^{M2} \\ C_t^{M3} \\ C_t^{M4} \\ C_t^{Q} \\ u_t^1 \end{bmatrix}}_{X_t} = \underbrace{\begin{bmatrix} \rho & 0 & 0 & 0 & 0 & 0 & 0 \\ \rho & \xi_t^M & 0 & 0 & 0 & 0 & 0 \\ \rho & 0 & \xi_t^M & 0 & 0 & 0 & 0 \\ \rho & 0 & 0 & \xi_t^M & 0 & 0 & 0 \\ \rho & 0 & 0 & 0 & \xi_t^M & 0 & 0 \\ \rho & 0 & 0 & 0 & 0 & \xi_t^Q & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & G_1 \end{bmatrix}}_{A_t} \underbrace{\begin{bmatrix} x_{t-1} \\ C_{t-1}^{M1} \\ C_{t-1}^{M2} \\ C_{t-1}^{M3} \\ C_{t-1}^{M4} \\ C_{t-1}^{Q} \\ u_{t-1}^1 \end{bmatrix}}_{X_{t-1}} + \underbrace{\begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}}_{F_t} \underbrace{\begin{bmatrix} e_t \\ \zeta_t \end{bmatrix}}_{\eta_t}$$

where

(8)
$$\begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} \sim N\left(\begin{bmatrix} 0_{8\times1} \\ 0_{2\times1} \end{bmatrix}, \begin{bmatrix} H_t & 0 \\ 0 & Q \end{bmatrix} \right), \quad H_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{4t}^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{5t}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{6t}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{7t}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{8t}^2 \end{bmatrix}, \quad Q = \begin{cases} \begin{bmatrix} 1-\rho^2 & 0 \\ 0 & \sigma_1^2 \end{bmatrix}, if \ \rho \neq 1 \\ \begin{bmatrix} 1 & 0 \\ 0 & \sigma_1^2 \end{bmatrix}, if \ \rho = 1 \end{cases}$$

Once the model is written in state-space form, the straightforward final step consists of estimating the parameters of the hypothesized process. As discussed in Durbin and Koopman (2001) and exploited in Aruoba et al. (2009) and Aruoba and Diebold (2010a), this can be done using the Kalman filter and associated likelihood evaluation. The state-space framework lets us address the frequency conversion in a single coherent framework. From these estimates, an optimal inference about the unobserved CPI factor can be formed. This anchors our easy-to-replicate methodology in the existing literature.

Turning now to the estimation results, we note that our sample runs from July 1, 2001 to December 31, 2010 and that the correlation between the daily indicators and headline inflation increased after 2000. Stock and Watson (2002) note that a high correlation between the indicators is necessary in order to obtain reasonable estimates within the state-space framework. China joined the World Trade Organization on December 11, 2001, which helped boost the volume of external trade (also in relation to GDP). This change implies that global commodity price dynamics exerted a bigger impact on domestic inflation dynamics in our observation period than previously. In the estimations, both latent inflation and the observed variables follow simple AR(1)-processes. The resulting estimates are relatively robust and do not materially change when more complicated model structures are considered.

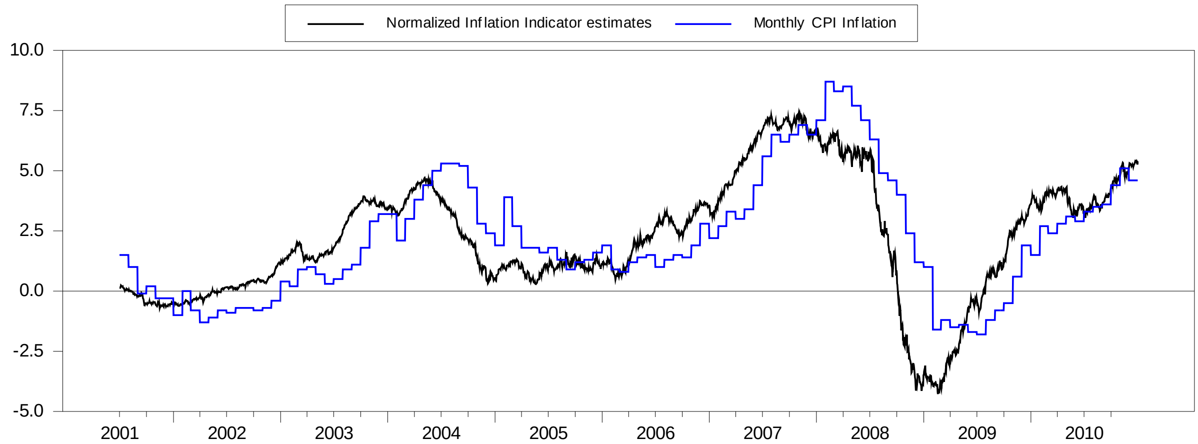
To reach an optimal combination of mixed-frequency indicators in terms of information, we first consider a high-frequency series alone and evaluate the estimation results. Then, on the basis of the estimation outcomes, two high-frequency indicators are incorporated simultaneously to form the final model. The model encompasses different perspectives of inflation process, i.e. cost-push or imported inflation (taken into account using commodity prices), monetary inflation and forward-lookingness in inflation determination.

Figure 7 shows the estimated inflation indicator from the preferred model. The main S&P GSCI and the reserve requirement ratio are used as daily variables, and the smoothed one-month repo rate is employed as the weekly variable. As monthly variables, the model employs the M2 growth rate lagged 12 months, pork prices, and Citigroup's Inflation Surprise Index. The variable at the lowest frequency is the quarterly inflation forecast. The estimated inflation indicator is in line with, but somewhat smoother than, the headline inflation rate. It leads monthly headline inflation, implying that it may be of use in near-term inflation forecasting. The simple correlation coefficient with actual inflation is highest (at 0.938) taking a 110-day lag in the estimated inflation indicator. It captures rather well the turning points in the inflation cycle. Indeed, the correlation coefficients between the lagged inflation indicator and actual inflation are highest within the subsamples where the inflation cycles turn (2003–2004; 2006–2007; 2008–2009), compared with the already high correlation within the full sample.[15]

As noted in the literature, the failure to predict turning points has been a notable feature of forecasts for years. The high reliability of the mixed-frequency indicator in predicting turning points with a lead time of about three months is thus all the more surprising. In other words, the procedure not only allows to nowcast Chinese CPI inflation, but the derived CPI factor even looks one quarter ahead.

[15] The maximum correlation coefficient (0.967) is obtained for the subsample of 2006–2007.

Figure 7 Estimated inflation indicator and headline inflation



Note: The estimated indicators are normalized to have the same mean and the same variance as the monthly CPI inflation over the same sample period.

Table 1 shows the estimation results from this model, where all the estimated coefficients apart from the growth rate of M2 are statistically significant at the 5% level. One unforeseen side-effect is that the forward-looking quarterly survey measure of inflation expectations renders M2 an insignificant variable. Correlations between the estimated inflation indicator and the different observable variables at monthly frequency are shown in Table A1 in the Appendix.

Table 1 Estimation Results for the Mixed-Frequency Model

Variable	Variable Name	Coefficient	*t*-Statistic
B11	Daily Commodity Prices (y/y growth rate)	56.026	2.46
B12	Daily required reserve ratio	0.0006	3.16
B2	Weekly average of one-month repo rate	0.0825	1.95
B31	Monthly CPI (y/y growth rate)	0.0214	3.06
B32	M2 (y/y growth rate)	0.0068	1.21
B33	Monthly pork price (y/y growth rate)	0.0111	2.02
B34	Monthly Citi CPI surprise index	0.1156	2.27
B4	Quarterly survey inflation forecast (y/y growth rate)	0.0302	2.90
G1	The parameter of the residuals of AR(1) process	1.0000	385.44
G21	Coefficient of 1st-order lagged term of B2	0.9672	81.73
G31	Coefficient of 1st-order lagged term of B31	0.8381	21.25
G32	Coefficient of 1st-order lagged term of B32	0.9887	128.70
G33	Coefficient of 1st-order lagged term of B33	0.9947	125.40
G34	Coefficient of 1st-order lagged term of B34	0.8212	16.54
G4	Coefficient of 1st-order lagged term of B4	0.7890	11.79
ρ	The parameter of the AR(1) process of the latent state variable x_t	0.9884	105.74
σ_1	The standard deviation parameters in equation (8)	5.7754	12.39
σ_2		0.0049	82.87
σ_3		0.4160	30.95
σ_4		0.5676	12.78
σ_5		1.2022	14.65
σ_6		1.0107	14.39
σ_7		11.291	14.61
σ_8		1.0028	7.09

Notes: Daily Data From 2000:07:01 To 2010:12:31; number of observations: 3471; Log Likelihood: 3881.99.

Nevertheless, we offer several caveats in interpreting these results. As our results are to an important extent driven by our choice of series, it is not possible to show that our model is the “best” available for capturing China’s inflation dynamics. Nevertheless, given the fact that data availability concerns are likely to limit the number of possible different empirical models for an emerging economy, and the satisfactory nowcasting/forecasting results shown in the next section, we argue that our model meaningfully captures China’s inflation dynamics. Another caveat relates to the time-series properties of survey data. Serial correlation is particularly likely in mixed-frequency models with various survey measures of inflation as the individual projections are made at different times. Even if the individual surveys do not contain serial correlation, averaging survey measures of different vintages in the latent factor will cause serial correlation. Furthermore, individual forecasters dislike "jumpy" forecasts, preferring to adjust their forecasts in a smooth manner towards the actual. Thus, the apparent autocorrelation in the latent factor arises by nature.

The next section highlights the advantages of the approach in terms of nowcasting and forecasting.[16]

4 Out-of-sample nowcasting and forecasting accuracy

The usefulness of the estimated inflation indicator in tracking headline inflation hinges crucially on its nowcasting and forecasting abilities. In terms of nowcasting, we note that China's CPI inflation data are typically published already within two weeks after the end of the reference month − a short publication lag by any international standard. However, there are no "flash" indicators available that would provide early estimates of the inflation rate before the end of the reference month such as Eurostat's "flash" estimate for the euro area, which employs early existing price data, including energy prices. Therefore, the mixed-frequency indicator can potentially provide useful information for both policymakers and market participants.

A number of issues concerning the robustness of nowcasting and the forecasting accuracy of our indicator need to be addressed. The main message from the literature is that in-sample tests do not provide reliable guidance about out-of-sample forecasting ability, which implies meaningful tests of forecast accuracy of any leading indicator must necessarily be one-step-ahead out-of-sample tests.[17]

All forecasts are recursive pseudo out-of-sample, i.e. forecasts are based only on values of the series up to the date when the forecast was made. Parameters are then successively updated using data from the beginning of the sample through the current forecasting date. In the case of mixed frequency models, we recursively estimate ragged-edged models, each containing only the high-frequency daily and weekly data for the last month of

[16] The terms "nowcasting" and "forecasting" often overlap. Typically, next- and current-quarter forecasts are labeled as "forecasts" and "nowcasts," respectively.

[17] Forecasters generally agree that in-sample predictive ability does not necessarily guarantee out-of-sample predictive ability. In-sample tests can be biased by the use of the same data for estimation and forecast evaluation. One-step-ahead out-of-sample tests are therefore the preferred course of action. Clements and Hendry (2005) are emphatic that considerable care is needed in interpreting forecast comparisons. One reason multi-step forecasts may be poor guides on the credence of a model is that multi-step forecasts require strong exogeneity of the variables, while one-step-ahead forecasts need only weak exogeneity.

the sample period. This seems prudent as it reflects data availability in the real-time forecasting environment.[18] In the case of competing univariate time-series models, recursive estimates lead to sequences of 1-month-ahead out-of-sample forecasts.

To get an initial sense of the forecasting performance, we calculate the root-mean-square error (RMSE) and mean absolute percentage error (MAPE) for various forecasting methods.[19] We have calculated the forecast errors for two years separately as performance can vary across subsamples.

Table 2 RMSE and MAPE for Alternative Forecasts

Forecast Method	Mixed-Frequency Model	ARIMA Model	Random Walk	CPI-Surprise Index	Consensus Survey of Inflation
RMSE					
2009:1 – 2010:12	0.657	0.389	0.775	1.256	1.190
2009:1 – 2009:12	0.758	0.382	0.936	0.974	1.352
2010:1 – 2010:12	0.537	0.396	0.570	1.486	1.001
MAPE					
2009:1 – 2010:12	0.317	0.135	0.353	0.480	0.563
2009:1 – 2009:12	0.484	0.173	0.553	0.619	0.865
2010:1 – 2010:12	0.150	0.096	0.152	0.342	0.261

Note: The second column gives estimates for the ARIMA(0,1,2)x$(1,0,1)^{12}$ model. The third column has estimates for the random walk model [ARIMA(0,1,0)].

In Table 2, the random walk serves as a benchmark model, against which the merits of other forecasting procedures are evaluated. Although sometimes labeled a “naive” model, it is often difficult for other models to produce forecasts better than those of the random walk model.

A number of insights can be gleaned from Table 2. Both in terms of RMSE and MAPE, the mixed-frequency model consistently outperforms the random-walk model, the CPI Surprise Index and the consensus survey of inflation. The forecast errors are always highest for either the CPI Surprise Index or the consensus forecast. However, the seasonal

[18] Note that we have updated the mixed-frequency model without any model revision. This updating without recalibrating ultimately imposes an arbitrary handicap upon the mixed-frequency model approach.
[19] Faust and Wright (2009, 2012), among others, consider several models useful in forecasting inflation, including an autoregressive benchmark model and judgmental forecasts.

ARIMA model for all considered forecasting periods still outperforms the mixed-frequency model.[20]

When one has several reasonable forecasting models, superior forecasting performance can be identified by testing alternative models head-to-head. Traditional efforts at assessing the forecast accuracy of estimated models have revolved around the calculation of summary forecast error statistics like RMSE and/or MAPE. Formal approaches were avoided mainly due to complexities in dealing with sampling uncertainties and correlations present in forecast errors.

The first assessment in our head-to-head testing for equal predictive accuracy employed below is the Diebold and Mariano (1995, 2002) test. The Diebold-Mariano test looks at the forecast-error loss difference of two forecast methods and makes it possible to discriminate among competing economic models.[21] The null hypothesis is that they have the same forecast accuracy. The test allows for forecast errors that are non-Gaussian, have a non-zero mean, and are serially correlated. The statistic has a standard normal limiting distribution. Under the "equal accuracy" null hypothesis, the forecast accuracy of the two models is not statistically different. A significance level below 0.10 or 0.05 indicates a rejection of the null hypothesis. We also employ the encompassing test statistics for a pair of nested models developed by Clark and McCracken (2001). Again, the null hypothesis is that of "equal accuracy" for the forecast encompassing (ENC) test statistics, and the tests are all one-sided, with the only rejection regions of interest under the alternative hypothesis residing in the right-hand tail. Table 3 and 4 report the results of our out-of-sample forecast comparison tests.

[20] Examination of the autocorrelation and partial autocorrelation functions suggests that an ARIMA model with seasonal AR and MA terms, together with a nonseasonal MA term of order 2 is the preferred specification.

[21] Regarding the loss function specification, we report the results for quadratic loss. We do not show the results for the absolute loss case, as the results were qualitatively identical with both loss function specifications.

Table 3 Diebold-Mariano Test Statistics

Comparison	ARIMA Model Against the Mixed-Frequency Model	Mixed-Frequency Model against the Random Walk	Mixed-Frequency Model against the CPI Surprise Index	Mixed-Frequency Model against Consensus Forecast
Test statistic	2.439	1.223	2.282	3.425
p-value	0.007	0.111	0.011	0.0003

Note: The weighting scheme of the autocovariances follows Newey and West (1987).

Table 4 Clark & McCracken Test Statistics

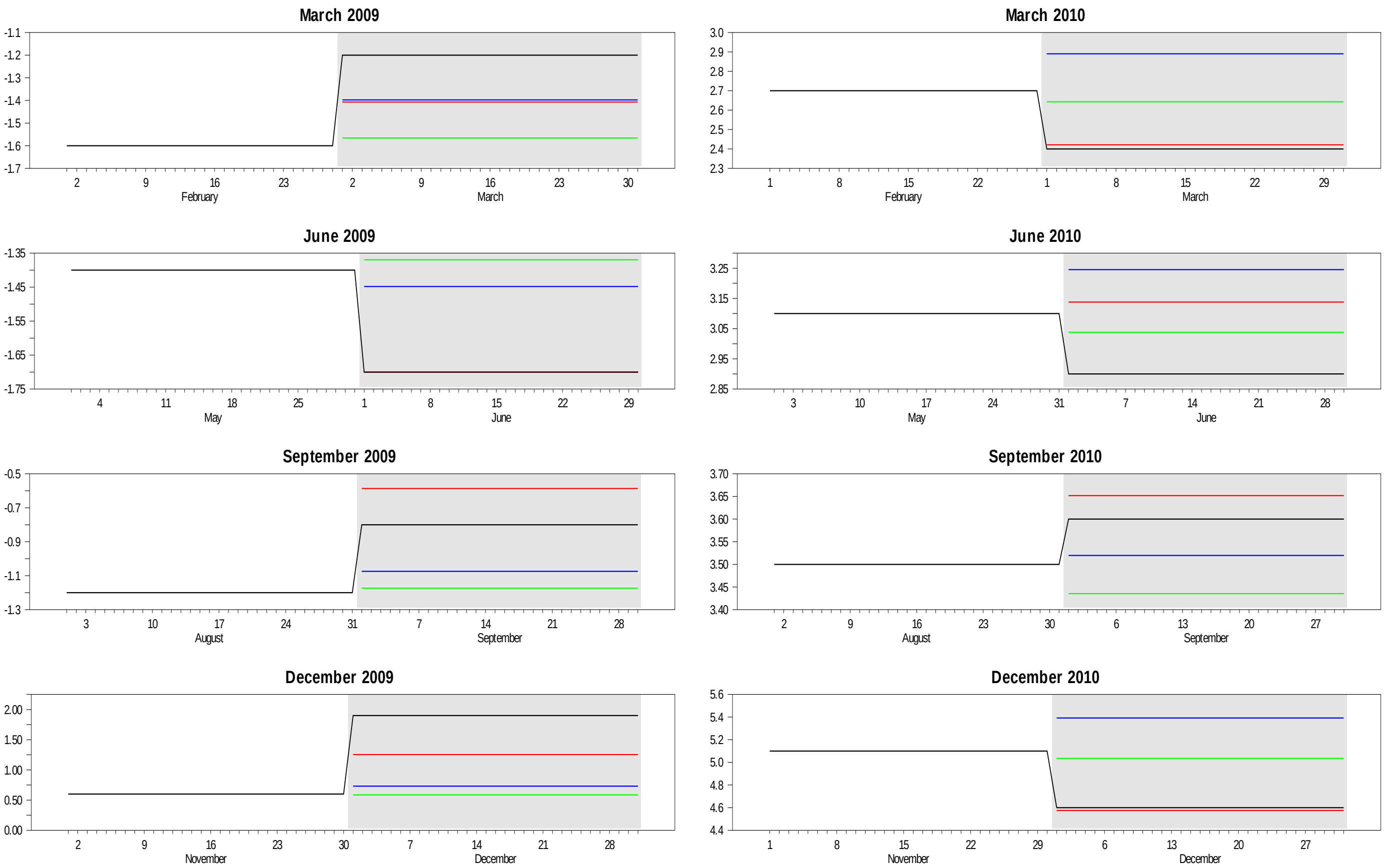
Test Statistic	ARIMA Model against the Mixed-Frequency Model	Mixed-Frequency Model against the Random Walk	Asymptotic Critical Values for 5% Significance Level	Asymptotic Critical Values for 10% Significance Level
ENC-T	3.091	1.803	1.596	1.175
ENC-REG	6.698	3.175	1.596	1.175
ENC-NEW	13.72	7.371	1.526	1.062

Note: See Clark and McCracken (2001) for the definitions of the test statistics.

The forecasting exercise yields surprisingly crisp results. The results of the tests in Table 3 strongly reject the null hypothesis of equal forecast accuracy of the mixed-frequency model and both the CPI surprise index and the consensus forecast. This evidence speaks favorably of the forecast accuracy of the mixed-frequency model. However, the null of equal forecast accuracy between the mixed-frequency model and the ARIMA model is also strongly rejected, this time emphasizing the superior performance of the ARIMA model. The hypothesis of equal forecast accuracy between the random walk and the mixed-frequency model is not rejected in Table 3. On the other hand, the results in Table 4 strongly reject equal forecast accuracy for the mixed-frequency and random walk models. In other words, the tests largely confirm the superior forecasting performance of the mixed-frequency model even compared with the widely used random walk benchmark, while at the same time acknowledging that the ARIMA model cannot be outperformed in our exercise.

Figure 8 provides a visual impression of the forecasting performance of the various models for selected months. The satisfactory performance of the ARIMA model is visible in these graphs as well. For six of the selected eight months, the one-month ahead forecast generated by the ARIMA model falls closest to the actual inflation outcome, while the random walk process performs best in June 2010.[22] The mixed-frequency model provides the best performance in March 2009, which is also the turning point in the inflation cycle. At this point, the estimated inflation indicator starts its relatively steep climb (see Figure 7); economies across emerging Asia embark on the recovery path, with actual inflation following suit in subsequent months. However, even for June 2010, the forecast by the ARIMA model is roughly identical to the one from the mixed-frequency model.

Figure 8 Comparisons of Nowcast and One-month Ahead Forecast Results for Selected Months

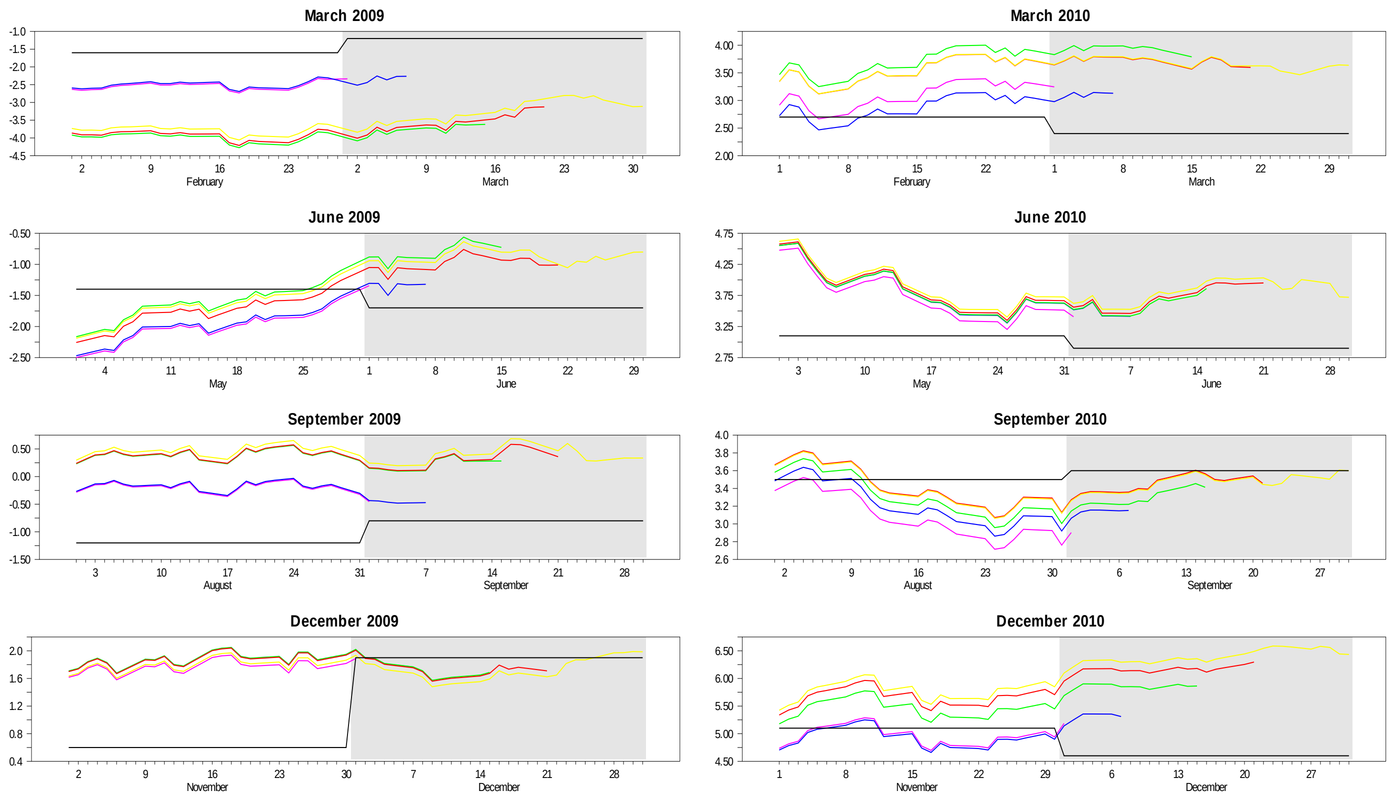


Note: The blue line denotes the real-time nowcast from the mixed-frequency model. The red line represents the one-month-ahead forecasts of the benchmark ARIMA(0,1,2)x(1,0,1)^{12} model and the green line the random walk model [ARIMA(0,1,0)]. The black line represents actual CPI inflation.

[22] The forecast of the ARIMA(0,1,2)x(1,0,1)^{12} model on June 2009 is very close to the actual CPI inflation rate of that month. Thus, only the actual outcome (solid black line) is visible.

While the forecasting accuracy of the mixed-frequency model falls short of the ARIMA model (but still outperforms the popular random walk specification), it still provides advantages in the timeliness dimension. Figure 9 illustrates this by showing how the real-time nowcasts are updated on various days of the respective months. The updates are computed at the 1st, 7th, 15th and 21st days of each month. Importantly, when calculating the real-time estimates for the 1st and 7th day of each month, CPI data for the previous month were not employed as they were not published yet. In contrast, monthly CPI data for the previous month are utilized for the real-time nowcasts at the 15th, the 21st and the last day of the month.

Figure 9 Daily Monitoring of the Mixed-Frequency Model Within Selected Months



Note: The different colors denote the updated real-time nowcasts on various days on the respective months: purple (day 1), blue (day 7), green (day 15), red (day 21), and yellow (the last day of the month). The shaded box in each graph denotes the month under examination. The black lines represent the actual CPI inflation outcomes.

For December 2009 and September 2010, in particular, the benefits of updating the nowcasts are clearly visible. The nowcasts gradually close in on the actual inflation outcome (for December 2009 the day-1 update is already close to the actual outcome, but then drifts away). Moreover, updating the nowcasts with actual inflation outcomes from the previous month does not always improve them. For example, when updated with the previous month's reported inflation, the nowcasts for December 2010 are further away than the previous updates. Even so, the timeliness advantage of the nowcasted series is quite clear for most months. In March and September 2009, December 2009, March 2010, June 2010 and December 2010, the day-1 and day-7 updates for the month are already close to the actual (final) outcome for that month. The mixed-frequency model thus strikes a balance between the accuracy-timeliness tradeoff. Overall, the results indicate that the mixed-frequency indicator serves as a valuable aid for nowcasting and short-term forecasting of Chinese CPI inflation.

5 Conclusions and policy implications

The paper demonstrates the potential mixed-frequency modeling approaches offer to nowcasters of Chinese inflation. While the model constructed here to pin down inflation dynamics in real time is atheoretical, the variables that are important in driving inflation could well provide insights in formulating policies geared to maintaining price stability. Some variables identified as important drivers of inflation are related to the formulation of the monetary policy stance.

With recovery from the global financial crisis, the issue of how monetary authorities should deal with commodity price trends has re-emerged. Should the central bank treat commodity prices as exogenous cost-push shocks and only respond when they threaten to have second-round effects in terms of higher nominal wage demands and increased inflation expectations? As an important share of commodity price pressure originates in the rapid growth of aggregate demand, they may signal economic overheating and call for a tighter monetary policy stance. Similarly, the BIS (2011) points out that commodity prices may be driven by global monetary conditions and therefore be endogenous to central bank policy decisions.

The issue about the suitable reaction to food price developments is similar to that of other commodity prices. High global demand, especially in emerging markets where income growth has been driving up demand for higher quality foodstuffs, is likely to play an important role. Moreover, in countries such as China, where food is an important component of the consumer price index, measures of core inflation may be of only limited importance in understanding inflation developments and as indicators of the cost of living. The People's Bank of China emphasizes that fluctuations in grain price has been the driving force behind changes in CPI inflation (PBoC, 2007, p. 78), and that climbing or persistently high food prices will "shove up the cost of living, feed inflationary expectations, and may cause cost-pushing inflation."

We find that broad money (M2) as a monthly variable in the smoothed inflation indicator is not statistically significant. This is in line with inflation models of the New-Keynesian type, where the role of money is limited. The global crisis has renewed the interest in monetary and credit trends, especially in their ability to reflect financial imbalances and asset-price misalignments.[23] However, financial imbalances may develop over the long horizon. [24] In the case of China, no boom-and-bust cycle caused by excessive monetary growth was apparent in our sample period. Finally, the insignificance of the money stock could simply mean that the PBoC has taken the information provided by monetary developments into account when formulating policy so that there is no excess or deficit of liquidity contributing to inflation. Indeed, the PBoC has stated that an appropriate rate of money growth should promote "economic growth positively and contribute to preventing both inflation and deflation" (see PBoC, 2005).[25] In this regard, our estimation sample coincides with the start of the use of central bank bills in China to absorb liquidity from the financial system. The first bills were issued in 2003 (three-month, six-month, and one-year bills), with three-year bills issued from late 2004 onwards.

Economic developments in emerging market economies undoubtedly involve a high degree of uncertainty. This complicates both policymaking and the construction of suitable nowcasting and leading indicators of economic activity. Against this background, our findings here provide insights into the usefulness of small-scale mixed-frequency models in the nowcasting of mainland China's CPI headline inflation. Taken together, the results suggest such a mixed-frequency indicator model is a promising, relatively low-cost thermometer for gauging Chinese CPI inflation.

[23] In early 2011, the People's Bank of China announced that it was monitoring a new quantitative indicator for monetary policy, "society-wide financing." This indicator includes, in addition to regular bank loans, trust loans and bankers acceptance bills, and financing through bond and equity markets.
[24] See e.g. Borio (2011).
[25] At the same time, the PBoC recognizes the importance of structural factors (often country-specific in nature) that affect the relationship between money and inflation (PBoC, 2010).

The notion that CPI inflation could be flagged in real time, possibly with some lead time, and that this could thereby improve monetary policy is very appealing. Recent dynamic factor model studies have shown that macroeconomic variables can be more accurately nowcasted and forecasted by combining disaggregate variables. This result naturally leads more ambitious approaches that model different economic variables measured at different frequencies simultaneously to track the high-frequency of macroeconomic variables. In real time, a continuous inflow of information occurs as new data are released non-synchronously. The modeling framework employed above allows updating estimates and nowcasting of a given macroeconomic variable in a timely manner. Viewed overall, a core advantage of this mixed-frequency modeling approach is that it is straightforward to implement. Hence, for those seeking to paint a picture of CPI inflation in real time, the methodology would appear to hold considerable promise.

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