Chinese Inflation: Measurement and Forecasting*

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Abstract

We propose a parsimonious semi-parametric model to uncover the nonlinear relationship between Chinese money growth and inflation, suggesting that the long-run nexus between these variables is significant only when money growth rates are high. We investigate if a model based solely on prices may explain inflation dynamics better in an era where money growth rates are lower and more stable. We further examine whether two unobserved components (UC) models by Stock and Watson (2016) are a good fit for China. We estimate these models with monthly CPI data during the December 2006-February 2023 period to dissect the persistent and non-persistent components of inflation. Then we run a forecasting competition among UC models, and other strong competitors from the literature, including the Bayesian vector autoregression models (BVAR) and time series models for the January 2015-February 2023 period. We find the multi-sector UC model provides successful forecasts across various horizons from 1- to 30-months ahead.

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1 Introduction

In 2009, the People's Bank of China began implementing an expansionary monetary policy to bolster the weak Chinese economy following the global financial crisis. Consequently, the money supply in China, measured by M2, surpassed that of the US and the Euro area in 2014. The year-on-year growth rate in the money supply from February 2009 to May 2010 was between 20% and 30%, and the inflation rate, measured by the consumer price index (CPI), kept climbing, following the money supply growth rate (See Figure 1). In 2011, inflation peaked at around 8%. This is why the Chinese money supply is commonly thought to be closely related to Chinese inflation. Some research, based on forecasting evaluations during this period of time, found the Chinese money growth rate to be a key variable for forecasting inflation (e.g., Higgins et al. (2016)).

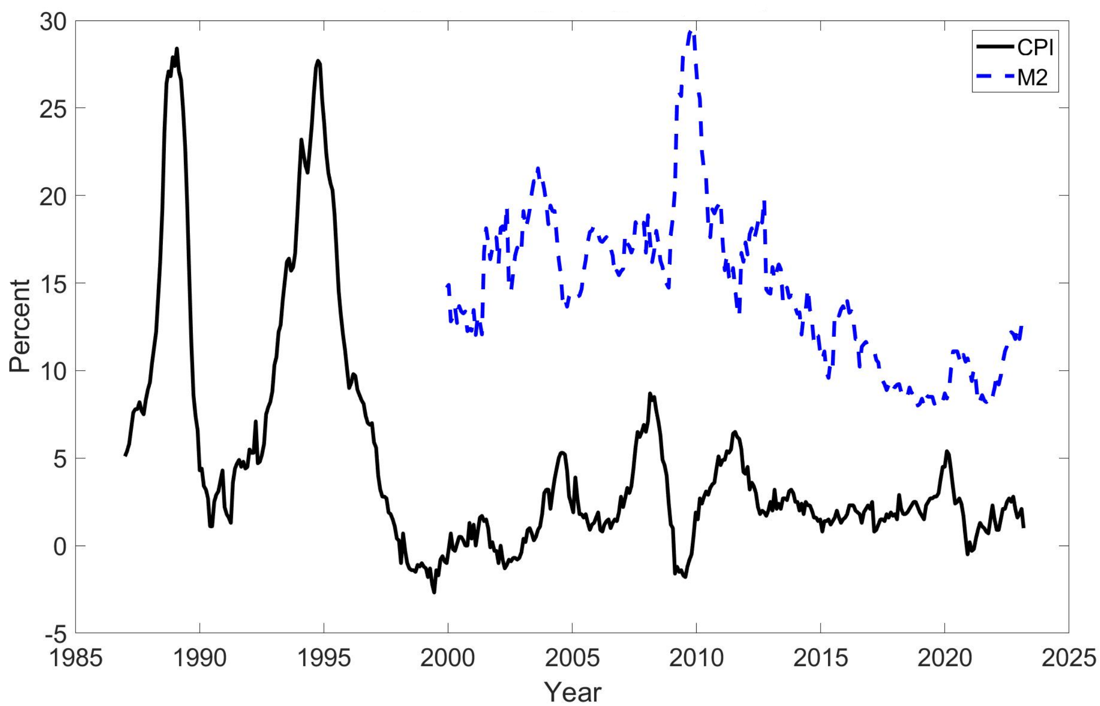

Figure 1: Year-on-year growth rate of Chinese M2 and CPI at the monthly frequency. Source: International Monetary Fund.

However, the link between money supply growth and the inflation rate seemed to break after 2015. Following the middle of 2015, while the money growth rate began to decrease, the inflation rate did not follow. In August 2017, the money supply growth rate slowed to a record low of 8.9 percent and remained low until now, while the inflation rate peaked in early 2018. In 2020 and 2023, to mitigate the impact of the COVID-19 pandemic on the economy, the People's Bank of China loosened its monetary policy again. The money supply growth rate rose while the inflation rate remained low.

The first goal of this paper is to revisit the link between Chinese money growth and inflation using a semi-parametric model. Our results indicate that money growth may no longer be a good predictor of Chinese inflation. We then formally assess the predictive ability of models with and without money growth. Among these, we consider two models that have not been evaluated in the Chinese inflation literature before—the univariate and multivariate unobserved components stochastic volatility models with outlier adjustment (UCSVO and MUCSVO) of Stock and Watson (2007). Following Stock and Watson (2007)'s argument for US inflation, our findings confirm that Chinese inflation predictability can be viewed as a measurement problem rather than forecasting—i.e. price data alone can be more helpful for its predictions than other macroeconomic variables, including money growth.

A large body of literature has documented several challenges and puzzles in inflation predictability, focusing primarily on the US and other OECD countries. A common puzzle is related to the poor performance of economic models encompassing macroeconomic variables: they outperform naive models, i.e., models based on past inflation, only occasionally. This includes a wide range of models such as the Phillips curve or dynamic stochastic general equilibrium models (See, e.g., Atkeson and Ohanian (2001), Stock and Watson (2007), Kabukçuoğlu and Martínez-García (2018), Edge and Gürkaynak (2011)).

As a strong alternative to existing models, Stock and Watson (2007) suggest that a univariate inflation model, an unobserved component trend-cycle model with stochastic volatility, may provide a good fit for US inflation.[1] This is equivalent to solving a signal extraction problem, where persistent variations in inflation need to be differentiated from those that are transitory. Mandalinci (2017) evaluates the predictive performance of various inflation models, including the univariate UCSV model, for nine emerging market economies (excluding China). Mandalinci (2017) finds models with stochastic volatility and time-varying parameters yield generally more accurate forecasts relative to an autoregressive (AR) benchmark. An extensive study of 14 EMEs including China by Duncan and Martínez-García (2019), find that a simple 4-quarter average of inflation in the spirit of Atkeson and Ohanian (2001) generally outperforms a rich set of models, including the Phillips curve models, BVARs, factor models, and standard time series models, some of which have proved successful in the context of the advanced country forecasting literature. However, they exclude UC models from their analysis. Our findings suggest

[1]While outside the scope of our paper, Faust and Wright (2013) document that judgemental forecasts perform remarkably well compared to several recently developed methods, including the UCSV model.

that the multivariate model of Stock and Watson (2007) provides superior performance, especially over shorter horizons.

Our initial assessment with the semi-parametric AR model helps uncover the nonlinear relationship between inflation and money growth. It shows that money growth has a sizeable effect on inflation when its level is high. This explains why most of the existing literature agrees that Chinese money growth is important for forecasting inflation. However, the money growth rate gained a lower and more stable path after 2015 and, as such, may have lost its forecasting ability afterwards.

We then turn to two unobserved component models that rely solely on price data, following Stock and Watson (2016). These models of core and trend inflation combine time series and cross-sectional smoothing techniques, and—to our knowledge—have not been used in the Chinese inflation forecasting literature.

We also evaluate the information content of money growth for inflation in a bivariate Bayesian Vector Autoregression (BVAR), which includes money growth and inflation, and a broader 7-variable BVAR model that includes key macroeconomic variables and money growth, in line with Higgins et al. (2016). In turn, we show that the link between M2 and inflation is not robust after 2015 and that the M2 growth rate may not be an efficient tool to forecast inflation.

In each forecasting exercise, we evaluate the performance of these models relative to the (driftless) random walk model of inflation, following Atkeson and Ohanian (2001). We conduct a similar evaluation for various simpler models, such as autoregressive models and the 12-month moving average relative to the random walk. Finally, we also consider a direct comparison between the forecast performance of BVARs and unobserved component models.

We summarize our contributions to the literature as follows. First, this paper provides the first use of the UCSV model, which has been proven useful in inflation forecasting since it combines two important technical methods (i.e., the UC method and stochastic volatility), to forecast Chinese inflation. Second, a one-sided seasonal adjustment method, as opposed to two-sided (see, e.g., He (2012)), is used to remove seasonal effects. As Rossi (2013) notes, a two-sided seasonal adjustment method may lead to the use of data that are not available to the econometrician at the time of the forecast, and a one-sided alternative should be preferred. Third, the semi-parametric method, which can be viewed as a relatively rare macroeconomic application, is used to uncover the nonlinear relationship between inflation and money growth. High money growth is accompanied by a high inflation rate, while low growth in the money supply has little effect on inflation. Fourth, we find that disaggregated Chinese inflation data is important for forecasting Chinese inflation. Fifth, while BVARs are an important policy tool for central banks and forecasting research, this paper provides a better forecasting tool for Chinese inflation.

Turning to the methodology and findings in the Chinese inflation literature, a commonly used model is the BVAR. Higgins et al. (2016) use a BVAR model with the Sims-Zha prior as their benchmark model. The model includes macroeconomic measures such as GDP growth, CPI inflation, M2 growth, and interest rates. Their forecasting result showed that the benchmark model and the BVAR model with the prior from Giannone et al. (2015) (GLP's prior) are competitive with other models (i.e., a random walk and univariate autoregression models), based on the root mean square error criterion. They also find that money supply (M2) growth is a key variable for forecasting macroeconomic variables. This conclusion is consistent with the empirical literature, which studies the relationship between the M2 growth rate and inflation (e.g. Su et al. (2016), He (2012), Sun and Ma (2004)). A similar paper from Amstad et al. (2014) developed an underlying inflation gauge (UIG) based on a broad dataset with 472 time series. They use the generalized factor model of Forni et al. (2000) to produce an inflation gauge that separates trend inflation from gap inflation, and found that the UIG for China outperforms traditional core inflation measures in forecasting headline inflation measured by the CPI. Although they also use the method of isolating trend values to forecast inflation, this paper differs by only using price data, and the models here include features of stochastic volatility, which is proven to be important for improving inflation forecasting accuracy (Cogley and Sargent (2001)). Further, Heaton et al. (2019) find that simple models can produce a more accurate forecast for the Chinese economy. Their study includes 19 forecasting models, ranging from simple models like the moving average to sophisticated models such as BVAR and factor models. Their results show that sophisticated models can provide superior 1-month-head forecasts of the producer price index when compared to simple models, but the evidence is weaker at longer horizons.

In addition, Chinese governmental and academic institutions provide inflation forecasts without publishing their model structures.[2] As a result, the forecasts by these institutions or universities are hard to evaluate. With this paper, we aim to provide a detailed analysis of Chinese inflation and its forecasts and provide an alternative source of information.

The rest of the paper is structured as follows. Section 2 explains the nonlinear relationship between money growth and inflation and why this relationship has led to the

[2]For example, see the China Annual Macroeconomic Model, developed jointly by the Chinese Academy of Social Science and the National Bureau of Statistics of China, and China's Quarterly Macroeconomic Model, developed by Xiamen University.

models from Stock and Watson (2016). Section 3 reviews two UC models from Stock and Watson (2016). Section 4 describes the Chinese inflation data used. Section 5 discusses the estimation results. Section 6 compares the forecast results from the different models. Finally, Section 7 concludes.

2 The nonlinear relationship between money growth and inflation

The quantity theory of money posits a one-for-one relationship between money growth and inflation. It has been a guiding principle for central banks in their efforts to keep inflation low. At the same time, money growth appears to have become less central in monetary policy discussions and standard monetary theory (Woodford, 2008), as more attention has been paid to other macroeconomic variables for price stability.

The theory, however, has not completely been dismissed. Some economists highlight a potential nonlinear relationship between money growth and inflation. For instance, Cecchetti et al. (2017) state that "... economists all agree that extreme rates of inflation are always accompanied by high rates of money growth. It does not follow, however, that when inflation is low and stable, changes in money growth are central to understanding movements in inflation." Hence, the empirical evidence for the link between money growth and inflation (or its lack, thereof) may be better detected in a nonlinear framework.[3]

To explore this nonlinear relationship for the Chinese economy, we consider a semi-parametric autoregressive model. Similar methods are used, for example, by Bachmeier et al. (2007).[4] As also indicated by Bachmeier et al. (2007), this method is prone to the curse of dimensionality. Hence, it is usually more easily applicable to parsimonious specifications rather than large models.

The model is specified by:

$$g(\mu) = \beta_0 + sp_1(\pi_{t-s}) + sp_2(\pi_{t-s-1}) + sp_3(\Delta m_{t-s}) + sp_4(\Delta m_{t-s-1})$$

where $g(\mu)$ is the conditional expectation of inflation and $g(\cdot)$ is a monotonic link function. π_t is the (monthly) inflation rate at month t and Δm_t is the (monthly) money growth rate at month t. $sp(\cdot)$ represents the smoothing functions of the independent variables.

[3] In the standard New Keynesian framework, the quantity of money is even redundant as equilibrium output and inflation can be determined under an interest rate rule (Leeper and Roush, 2003).

[4] Their paper finds only a marginal improvement in inflation forecasts by the nonparametric model.

The lag length is given by $s = 1, 6, 12$ months. The error term follows a Gaussian distribution.[5]

The main data source for this exercise is China's Macroeconomy: Time Series Data from the Federal Reserve Bank of Atlanta, with the sample period from 1990 to 2018.[6] The money growth rate is based on the M2 measure from the Federal Reserve Bank of Atlanta. Figures A4-A6 show the results for lag lengths $s = 1, 6, 12$, respectively, with the marginal effects and the 95% confidence intervals from the semi-parametric model estimates.

Accordingly, the results are strongly in support of a nonlinear relationship between money growth and inflation. In Figure A4, inflation is explained mainly by its value from the previous month, presenting a strong short-term impact from inflation today to inflation a month later. In Figures A5-A6, the marginal response of inflation 12 or 24 months later from an increase in local money growth today is quite small when the growth rate is low, while the response is more drastic when the money growth rate is larger than 30%. The long(er) term response of inflation to its current values is relatively small when the current inflation rate is high. This implies that for long(er)-run inflation forecasting, the money growth rate can have important information content for inflation when it is high, while it may not be useful when its value is low.[7]

This result motivates us to consider a model using only price data for inflation forecasts when the Chinese money growth rate is relatively low, and it gains importance to follow the approach of Stock and Watson (2016). As Figure A1 in the Appendix shows, the monthly Chinese money growth was relatively high from 2010 to 2015, but it mostly remained below 30% during that period. We nevertheless consider models with money growth, following Higgins et al. (2016), to formally assess this claim.[8]

[5]The method for estimating this semi-parametric model and constructing the thin-plate regression splines is explained in Wood (2006). The mgcv package in R was used to estimate the model.

[6]See https://www.atlantafed.org/cqer/research/china-macroeconomy for the data and Higgins and Zha (2015) for further details on the data.

[7]Alternatively, we consider a global liquidity measure, following D'Agostino and Surico (2009) and Dur and Martínez-García (2020) that find global liquidity helps predict US inflation dynamics. For China, we construct a similar global liquidity measure as the average of the M2 growth rates for China and its five largest trading partners: the US, the Euro Area, Japan, South Korea, and Hong Kong. However, we did not detect (hence, did not report) a statistically significant relationship between Chinese inflation and global liquidity, even in the long run.

[8]We exclude the nonparametric approach from our analysis in the forecast exercises, since, as shown by Bachmeier et al. (2007) among others, this approach does not appear to yield a superior forecasting performance.

3 Unobserved Components Stochastic Volatility Models with Outlier Adjustment

In order to forecast Chinese inflation, we adopt two unobserved components stochastic volatility models with outlier adjustments studied in Stock and Watson (2016) for US inflation. The first model is a univariate model (UCSVO) that extracts measures of trend inflation via time series smoothing methods. The second model is a multivariate model (MUCSVO) proposed by Del Negro and Otrok (2008) that combines two distinct approaches to measure trend inflation. In particular, it utilizes disaggregated data at the sectoral level and time series smoothing methods.

3.1 The Univariate Model (UCSVO)

Consider the following univariate model from Stock and Watson (2016):

$$\pi_t = \tau_t + \epsilon_t \tag{1}$$

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau,t} \times \eta_{\tau,t} \tag{2}$$

$$\epsilon_t = \sigma_{\epsilon,t} \times s_t \times \eta_{\epsilon,t} \tag{3}$$

$$\Delta \ln(\sigma^2_{\epsilon,t}) = \gamma_\epsilon \nu_{\epsilon,t} \tag{4}$$

$$\Delta \ln(\sigma^2_{\Delta\tau,t}) = \gamma_{\Delta\tau} \nu_{\Delta\tau,t} \tag{5}$$

where the variance-covariance matrix $(\eta_\epsilon, \eta_\tau, \nu_\epsilon, \nu_{\Delta\tau}) \sim N(0, I_4)$, i.i.d.

This model expresses the inflation rate π_t as the sum of trend inflation τ_t (a permanent component) and gap inflation ϵ_t (a transitory component), which is specified by equation (1). Trend inflation τ_t follows a random walk according to equation (2), gap inflation ϵ_t is a serially uncorrelated process as specified by equation (3) and is modeled as a mixture of normals via the i.i.d. variable s_t, which is distributed $s_t = 1$ with probability $(1 - p)$ and $s_t \sim U[2, 10]$ with probability p. Innovations to both trend inflation and gap inflation, which are $\eta_{\tau,t}$ and $\eta_{\epsilon,t}$, respectively, follow logarithmic random walk stochastic volatility processes, equations (4) and (5). Scale parameters γ_ϵ and $\gamma_{\Delta\tau}$ control the scale of the innovation in equations (1) and (2).

3.2 The Multivariate Model (MUCSVO)

This multivariate model extends the UCSVO to include a common latent factor in trend and gap inflation. Remaining dynamics are captured by sector-specific components. The

MUCSVO model consists of:

$$\pi_{i,t} = \alpha_{i,\tau,t}\tau_{c,t} + \alpha_{i,\epsilon,t}\epsilon_{c,t} + \tau_{i,t} + \epsilon_{i,t} \tag{6}$$
$$\tau_{c,t} = \tau_{c,t-1} + \sigma_{\Delta\tau,c,t} \times \eta_{\tau,c,t} \tag{7}$$
$$\epsilon_{c,t} = \sigma_{\epsilon,c,t} \times s_{c,t} \times \eta_{\epsilon,c,t} \tag{8}$$
$$\tau_{i,t} = \tau_{i,t-1} + \sigma_{\Delta\tau,i,t} \times \eta_{\tau,i,t} \tag{9}$$
$$\epsilon_{i,t} = \sigma_{\epsilon,i,t} \times s_{i,t} \times \eta_{\epsilon,i,t} \tag{10}$$
$$\alpha_{i,\tau,t} = \alpha_{i,\tau,t-1} + \lambda_{i,\tau}\zeta_{i,\tau,t} \tag{11}$$
$$\alpha_{i,\epsilon,t} = \alpha_{i,\epsilon,t-1} + \lambda_{i,\epsilon}\zeta_{i,\epsilon,t} \tag{12}$$
$$\Delta \ln(\sigma^2_{\epsilon,c,t}) = \gamma_{\epsilon,c}\nu_{\epsilon,c,t} \tag{13}$$
$$\Delta \ln(\sigma^2_{\Delta\tau,c,t}) = \gamma_{\Delta\tau,c}\nu_{\Delta\tau,c,t} \tag{14}$$
$$\Delta \ln(\sigma^2_{\epsilon,i,t}) = \gamma_{\epsilon,i}\nu_{\epsilon,i,t} \tag{15}$$
$$\Delta \ln(\sigma^2_{\Delta\tau,i,t}) = \gamma_{\Delta\tau,i}\nu_{\Delta\tau,i,t} \tag{16}$$

where $(\eta_{\tau,c,t}, \eta_{\tau,i,t}, \eta_{\epsilon,c,t}, \eta_{\epsilon,i,t}, \zeta_{i,\tau,t}, \zeta_{i,\epsilon,t}, \nu_{\Delta\tau,c,t}, \nu_{\Delta\tau,i,t}, \nu_{\epsilon,i,t}, \nu_{\epsilon,c,t})$ are i.i.d standard normal.

Equation (6) decomposes sector i inflation into a latent common factor for trend inflation $\tau_{c,t}$, a latent common transient component $\epsilon_{c,t}$, and sector-specific trends and transient components, $\tau_{i,t}$ and $\epsilon_{i,t}$. Specified by equations (11) and (12), the factor loadings on the common trend and transient components, $\alpha_{i,\tau,t}$ and $\alpha_{i,\epsilon,t}$, evolve as random walks. Specified by equations (7) to (10), stochastic volatility is allowed for in the latent common and sector-specific components. The stochastic volatility processes evolve according to a logarithmic random walk from equations (13) to (16). The model allows for outliers in the transitory disturbances of the common and sectoral transitory components, which are accounted for through the random variables $s_{c,t}$ and $s_{i,t}$ in equations (8) and (10), where outlier probabilities are p_c and p_i. The measure of aggregate trend can be calculated by the sum of sectoral trends, weighted by the expenditure share weight w_{it} of sector i in total inflation:

$$\tau_t = \sum_{i=1}^{n} w_{it}(\alpha_{i,\tau,t}\tau_{c,t} + \tau_{i,t}) \tag{17}$$

where n denotes the number of sectors, $i = 1, \ldots, n$.

4 Data

The data set consists of monthly inflation data from 2006M12 to 2023M2 from the National Bureau of Statistics of China (NBS). Inflation is measured using annualized, monthly changes in the headline CPI given by: $\pi_t = 1200 \times ln(\frac{CPI_t}{CPI_{t-1}})$.

The disaggregated components of headline CPI are listed in Table 1. The eight components are food, tobacco and liquor, clothing, household facilities, health care, transportation and communication; recreation, education, and culture; and residence.[9]

The Chinese disaggregated inflation data have several distinct features. First, the food sector includes food services (e.g., restaurants), which are part of the core inflation, and grocery purchases, which are excluded from core inflation. The category of residence includes gas and electric utilities, which are not under core inflation. The NBS also computes the residence components as the imputed cost of housing, because the residence price index is affected by mortgage rates and property management fees.[10]

Next, the expenditure share weights of CPI, w_{it}, are needed to estimate the MUCSVO model. The NBS has changed the weights every five years since 2006, as presented in Table 2. In 2016, the NBS combined the food and tobacco sectors into one sector, food and tobacco, and stopped providing separate data. As a result, we also combine these two sectors' time series into one using their expenditure share weights. In our forecasts based on the MUCSVO model, we take into account the changes in CPI share weights in the data.

The seasonally adjusted aggregated and disaggregated inflation rates are plotted in the Appendix (Figure A3) (X-13ARIMA-SEATS software from the US Census Bureau was used to seasonally adjust raw data and to develop an algorithm to provide the seasonal-adjusted observations from future information. Details about seasonal adjustment can be found in the Appendix.) A quick glance reveals that the dynamics of each series are distinct. The volatility of the food and tobacco component is similar to the volatility of aggregate inflation. A simple explanation can be that the food and tobacco component occupies the largest weight and is the most volatile component. The health care and personal articles component is not volatile in most of the observations, though it saw a large increase at the end of 2014. The residence component is also not volatile compared to the other five components. However, one of the largest criticisms of the accuracy of Chinese inflation rates from the NBS is that the price index of the residence component is

[9]The description of these eight components is provided in Table 1, which is from the English version of the NBS website.

[10]The first two features prevent us from estimating a simpler three-sector MUCSVO model (core inflation, energy, and food) with Chinese inflation data since we cannot calculate core inflation based on this dataset.

not reflective of rapidly increasing Chinese housing prices. Although high housing prices do not directly affect the residence component (the NBS claims they use the standard 93SNA to measure residence prices, which is a common method that means the housing price should not be accounted for based on this standard), the low-volatility residence price index prompts speculation.

Table 1: Description of CPI Components

CPI Components	Description
1. Food	Food and drink including processed food, semi-finished, and unprocessed food. Does not include tobacco or substances used only as drugs.
2. Tobacco, Liquor, and Articles	Tobacco includes high, middle, and low grade cigarettes. Liquor refers to alcoholic beverages fermented by sorghum, barley, rice, grapes, or other fruits.
3. Clothing	Clothing refers to a variety of wearable goods, including clothing made by cotton, linen, silk, etc.
4. Household facilities	Furniture, bedding, household goods and services and maintenance services.
5. Health care	Health care includes medical instruments, traditional Chinese medicine, Western medicine, health care appliances, articles, and services.
6. Transportation and communication	Transportation includes transportation facilities, fuel and parts, fees for vehicles use and maintenance, and traffic fares. Communication includes communication facilities and communication services.
7. Recreation, education, and culture	Durable consumer goods for cultural and recreational use and services, education, cultural and recreational articles, touring and outings.
8. Residence	Building and building decoration materials, renting, private housing, water, electricity and fuels, etc.

Table 2: Weights of CPI Components

Year	2006-2010	2011-2015	2016-2020	2021-2023
Food and Tobacco	0.30	0.30	0.30	0.30
Clothing	0.09	0.09	0.08	0.07
Household facilities, articles, and services	0.06	0.06	0.05	0.05
Health care and personal articles	0.10	0.09	0.10	0.11
Transportation and communication	0.10	0.09	0.10	0.11
Recreation, education, and cultural articles	0.14	0.14	0.14	0.13
Residence	0.13	0.17	0.20	0.22

5 Estimation methodology and results

Our estimation methodology closely follows Stock and Watson (2016), where both the UCSVO model and the MUCSVO model are estimated using Bayesian methods. While the key points are highlighted here, a detailed description of the priors and the numerical methods involved in approximating the posteriors can be found in the work of Stock and Watson (2016).

In these models, the goal is to estimate the trend inflation along with the other components. For the UCSVO model, priors for the stochastic volatility parameter γ_ϵ and $\gamma_{\Delta\tau}$ are independent uniform priors distributed U[0,0.15], which control the scale of the standard deviations of annual changes in the values of $\ln(\sigma_{\epsilon,t})$ and $\ln(\sigma_{\Delta\tau,t})$. We set the value of the hyperparameter here as 0.15 instead of 0.2 in Stock and Watson (2016) because the latter will lead to no changes in $\ln(\sigma_{\epsilon,t})$. The prior for parameter p, which controls the probability of outliers occurring in each period, is $Beta(\alpha, \beta)$, where α and β are calibrated to reflect our belief that an outlier occurs once every 30 months. The priors for the MUCSVO model follow the priors used in the UCSVO model.

Estimation of the posterior proceeds involves Markov chain Monte Carlo (MCMC) methods with a burn-in period of 10,000 iterations. Then 50,000 iterations are carried out, saving one draw per ten, yielding 5,000 draws. These 5,000 draws form the posterior distributions of the two models Stock and Watson (2016).

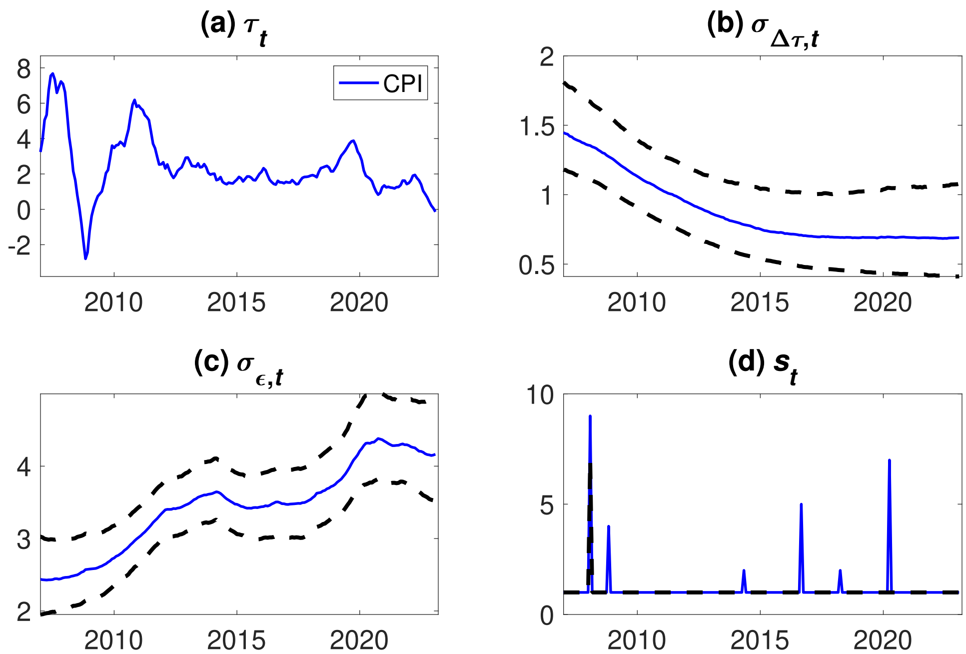

Figure 2: Posterior medians and 68% intervals from the UCSVO model

Figure 2 plots the full-sample posterior means for τ_t, $\sigma_{\Delta\tau,t}$, $\sigma_{\epsilon,t}$, and s_t from the UCSVO model. Figure 2a plots τ_t. Trend inflation peaks at around 8% in late 2007 and then troughs during the global financial crisis. It peaks again in 2011 following the expansionary monetary policy of the People's Bank of China. It then remains stable from 2012 to 2019. It spikes again during the COVID-19 pandemic. Figure 2b shows estimates of $\sigma_{\Delta\tau,t}$. The stochastic volatility of trend inflation fell during the estimation sample, which reflects the trend variation decreasing over time. Figure 2c plots $\sigma_{\epsilon,t}$, which generally increases in the whole trial period but decreases after 2020. Finally, Figure 2d shows estimates of the outlier scale factors s_t. This figure shows that the UCSVO model captures the large fall in Chinese inflation in 2008 because of the global financial crisis, the jump in 2009 that occurred because of the expansionary monetary policy, and the supply-side revolution in 2017 (when the Chinese government shut down some small private companies to increase the price of goods and the profit of government-owned companies). In 2020, the outbreak of the COVID-19 pandemic caused supply chain disruptions and led to a rise in the cost of living, and therefore, inflation.

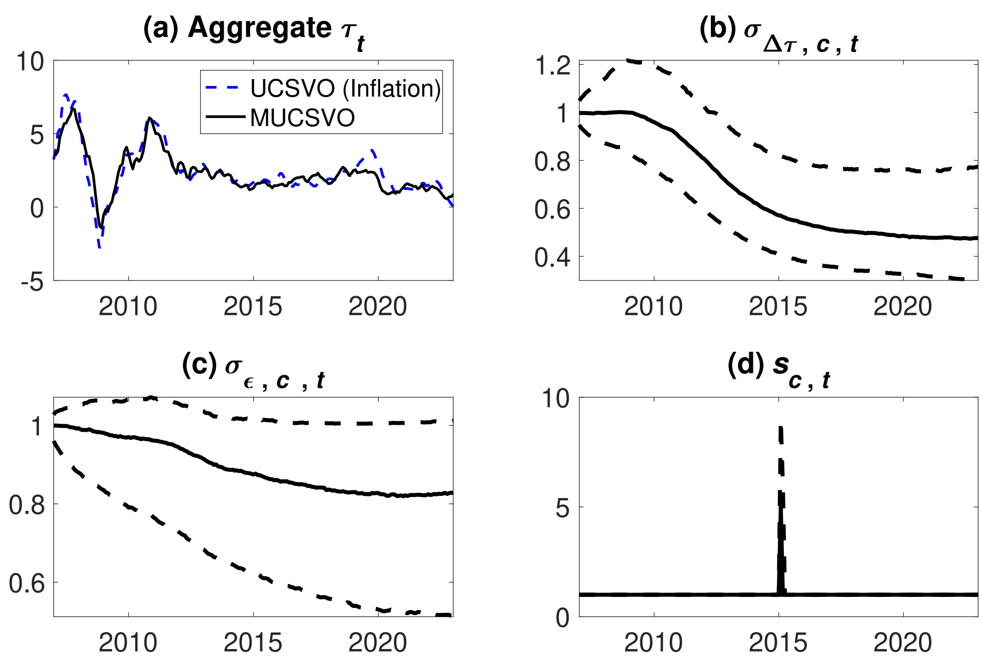

Figure 3: Posterior medians and 68% intervals from the Multivariate UCSVO model

Figure 3 displays the MUCSVO model's full sample estimates for the aggregate inflation trend and the UCSVO estimate. Broadly speaking, the trend component of the MUCSVO model (Figure 3a) is smoother than that of the UCSVO model. The time series of volatility for the common trend factor, $\sigma_{\Delta\tau,c,t}$, in the MUCSVO model (Figure 3b) is different from that in the UCSVO model. It increases before 2010 and then decreases over the second half of the sample period. The time series of volatility for the common transient factor $\sigma_{\epsilon,c,t}$ is stable (Figure 3c). Its posterior median gently decreases over ten years. The outlier detected by the MUCSVO model is less than the UCSVO model. Some outliers are found in sectoral transitory components instead of common transitory components. In the process of recursive forecasting, the priors for the MUCSVO model is slightly different from those in the UCSVO model. The priors, which control the probability of outliers occurring in each period, are calibrated to reflect estimation results that an outlier occurs once every 120 months.

6 Pseudo Out-of-Sample Forecasting Methodology and Results

In this section, we assess the pseudo out-of-sample predictive ability of the UCSVO model and the MUCSVO model. The benchmark model for comparison is the driftless random walk model, which is a commonly used benchmark in the inflation forecasting literature. We consider other models that have proved useful in the literature as well:

(i) Random walk: $\pi_{t+h} = \pi_t + u_{t+h}$

(ii) 12-month moving average (MA): $\pi_{t+h} = \frac{1}{12}[\pi_{t-1} + \pi_{t-2} + ... + \pi_{t-12}]$

(iii) Univariate AR models, with or without trend:

$\pi_{t+h} = \alpha + \beta_0 t + \sum_{l=1}^{L} \beta_l \pi_{t-l} + u_{t+h}$, where L=1, 6 and $\beta_0 = 0$ whenever a trend is not used.

(iv) BVAR models (presented in reduced form because we are interested in forecasting):

$y'_{t+h} = c' + \sum_{l=1}^{p} y'_{t-l} B_l + u'_{t+h}$, with $p = 2$ and $y_t = (M2_t,\ CPI_t,\ )'$ and $p = 5$ and $y_t = (GDP_t,\ Consumption_t,\ Investment_t,\ M2_t,\ CPI_t,\ Export_t, Repo_t)'$. The data for real GDP growth rate, real consumption growth rate, real investment growth rate, M2 growth rate, inflation rate, net exports (as a percent of GDP), the 7-day repo rate in the national interbank market, and the one-year benchmark deposit rate are from the China's Macroeconomy: Time Series Data from Federal Reserve Bank of Atlanta database. The 5-variable BVAR model follows Higgins et al. (2016). Higgins et al. (2016) and Higgins and Zha (2015) who discuss how they seasonally adjust and interpolate their data, and the prior is from Giannone et al. (2015)'s paper. They treat priors as additional parameters and use a hierarchical modeling method to find the best choice. Since we would like to evaluate the predictive performance of M2 growth alone, we consider a simple bivariate BVAR model as well.

All forecasts were computed using the pseudo-out-of-sample forecast methodology. So for a sample that starts in t_0 and ends in t_1, the estimation sample starts at t_0 and ends in t, with $t_0 < t < t_1$ and, the forecasting sample begins in $t + h$ and ends in t_1. We consider a recursive scheme. Hence, we estimate a model using all data up to date t to forecast inflation at date $t + h$. We keep adding data to the estimation sample to estimate the parameters of the model, which continues until period $t_1 - h$.

Our metric of forecast evaluation is the mean squared forecast error (MSFE):

$$MSFE = \frac{1}{F}\sum_{i=0}^{F}(\pi_{t+i+h} - \hat{\pi}_{t+i+h})^2,$$

where h is the horizon and F is the length of the forecast window, which starts in January 2015 and ends in February 2023.[11] A relative MSFE metric for a model and the random walk that is less than or equal to one, $MSFE/MSFE_{RW} \leq 1$, which suggests that the forecast of the model is at least as accurate as that of the random walk, and less accurate otherwise. We focus on forecasts at the one- to thirty-month horizon.

For a formal forecast evaluation, we consider a one-sided Diebold-Mariano (Diebold and Mariano, 2002), or DM test, which can be applicable to non-nested models like ours. The null hypothesis captures a loss function based on the (squared) forecast error differences from Model 1 and Model 2 (the random walk), testing the null that "the random walk is better than Model 1". We use the bias correction to the DM test by Harvey et al. (1997) for small samples, and the resulting statistic is then compared with a standard normal distribution. Finally, we use this test in the forecast evaluation of other non-nested model pairs, excluding the random walk, in a subsequent exercise.

Table 3 and Table 4 summarize the forecasting competition results. Five main results stand out. First, all models produce more accurate forecasts than the random-walk model based on the relative MSFE metric. Further, the modified Diebold and Mariano (DM) test results suggest that these results are largely statistically significant. Second, the MUCSVO model yields a better forecast in every horizon compared with all of the models, except for the 12-month MA. Although the 12-month MA provides a qualified forecast result like the one from the MUCSVO model, the MUCSVO model becomes a better choice for horizons up to three months. When the horizon is longer, the MUCSVO model is as accurate as the MA model. Third, the comparison between the MUCSVO model and the UCSVO model shows that disaggregated inflation data is important for forecasting Chinese inflation. The MSFE from the MUCSVO model is much lower than that from the UCSVO model, showing that the information from sectoral inflation is essential. Fourth, the MUCSVO model and the UCSVO model show better forecast ability than BVAR models at all horizons. On average, the MUCSVO model has 7% lower MSFE than BVAR models, which is a significant improvement. Fifth, the bivarate BVAR model has a fore-

[11] The comparison between UC models and BVAR is based on the forecasting evaluation period from January 2015 to February 2022 because of missing GDP data. In Table A1 in the Appendix, we provide a comparison between UC models and other models except for the BVAR in this period of time and report similar results.

casting ability comparable to that of the seven-variable BVAR model, which implies that the information content of key macroeconomic variables other than money growth may be low.

7 Conclusion

In this paper, we explore different ways to explain and forecast Chinese inflation. In light of the discussions in the literature, the first question we address is whether money growth as a key macroeconomic fundamental is a good predictor of Chinese inflation. Our initial assessment with a parsimonious semiparametric AR model concludes that the information content of money growth for inflation is confined to the high inflation era of pre-2015. We then estimate and forecast Chinese inflation using the two UC models from Stock and Watson (2016), that is, models based solely on price data. We evaluate these forecasts from different models that have been widely used in the literature, documenting the superior performance of the UC models.

The multivariate UC model provides the best forecasts for the inflation rate, and both UC models perform better than the BVAR model and various time series models according to the relative MSFE metric. An additional advantage of the UC models is that they rely only on CPI data, which are published at a monthly frequency, as opposed to models that rely on macroeconomic fundamentals such as real GDP, consumption or investment, which are available at a quarterly frequency and thus rely on interpolation to forecast at the monthly frequency (see, e.g. Higgins et al. (2016)).

This paper presents a thorough analysis of Chinese inflation models for forecasting, highlighting the predictive performance and practical importance of the UC models. The literature has yet to explore the performance of these models, especially the multivariate UC model, for emerging markets where money growth rates have been lower and less volatile compared to the past. Our work may suggest a future path for inflation modeling and forecasting in emerging market economies where the Atkeson and Ohanian (2001) inflation puzzle is ubiquitous, i.e., inflation has become less responsive to macroeconomic factors and can be better predicted with models using exclusively price data.

Table 3: Pseudo-Out-of-Sample Forecasting Performance for CPI Inflation: MSFE Relative to the Random Walk

Horizon	MUCSVO	UCSVO	12-month MA	AR(1) without trend	AR(6) without trend	AR(1) with trend	AR(6) with trend
h=1	0.61**	0.68**	0.69*	0.62***	0.66**	0.98	0.69**
	(0.01)	(0.04)	(0.05)	(0.01)	(0.03)	(0.85)	(0.03)
h=2	0.45***	0.49***	0.47***	0.44***	0.47***	0.85***	0.51***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
h=3	0.49***	0.53***	0.53***	0.51***	0.55***	0.81*	0.57***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)
h=6	0.61***	0.63**	0.59**	0.58**	0.58*	0.81	0.66
	(0.01)	(0.01)	(0.02)	(0.04)	(0.08)	(0.73)	(0.11)
h=9	0.50***	0.53***	0.53**	0.48***	0.48***	0.84	0.59***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.12)	(0.01)
h=12	0.48***	0.51***	0.48***	0.45**	0.45**	0.88	0.54**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.17)	(0.02)
h=15	0.59***	0.59***	0.61***	0.59**	0.59**	0.86	0.65**
	(0.00)	(0.00)	(0.00)	(0.02)	(0.04)	(0.64)	(0.04)
h=18	0.51**	0.53**	0.50**	0.47**	0.47**	0.98	0.61**
	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)	(0.13)	(0.03)
h=21	0.65***	0.67***	0.64***	0.67	0.67	1.00	0.74
	(0.00)	(0.00)	(0.00)	(0.19)	(0.28)	(0.90)	(0.30)
h=24	0.59	0.62	0.58	0.59**	0.59**	1.00	0.71**
	(0.27)	(0.31)	(0.29)	(0.03)	(0.04)	(0.35)	(0.03)
h=27	0.54**	0.57**	0.53*	0.55*	0.55	0.95	0.59
	(0.05)	(0.05)	(0.06)	(0.09)	(0.15)	(0.50)	(0.15)
h=30	0.69	0.75	0.74	0.76	0.75	0.94	0.74
	(0.29)	(0.24)	(0.22)	(0.14)	(0.21)	(0.86)	(0.29)

Notes: This table reports the relative MSFE of h-month-ahead pseudo out-of-sample forecasts of inflation between the pairs of models indicated in each column. *, **, *** denote that the MSFE of the former model is significantly different from the latter at 10, 5, and 1 percent significance levels, respectively. P-values are reported in parentheses. These results are based on the modified version of the one-sided DM test from Harvey et al. (1997), which corrects for the size property of the original test statistic in a small sample. The out-of-sample forecasting period is from January 2015 to February 2023 for various monthly horizons from $h = 1, 2, ..., 30$.

Table 4: Pseudo-Out-of-Sample Forecasting Performance for CPI Inflation: MSFE Relative to Alternative Benchmark Models: Moving Average (MA), Bivariate BVAR (2-BVAR) and 7-variable BVAR (7-BVAR) (From January 2015 to February 2022)

Horizon	MUCSVO vs. 12-month MA	UCSVO vs. 12-month MA	MUCSVO vs. 2-BVAR	UCSVO vs. 2-BVAR	MUCSVO vs. 7-BVAR	UCSVO vs. 7-BVAR
h=1	0.90	1.00	0.91	1.02	0.89	1.00
	(0.20)	(0.59)	(0.20)	(0.64)	(0.30)	(0.99)
h=2	0.96	1.04	0.96	1.04	1.00	1.08
	(0.42)	(0.65)	(0.73)	(0.49)	(0.93)	(0.64)
h=3	0.93	1.00	0.93	1.00	0.80**	0.86
	(0.68)	(0.89)	(0.29)	(0.83)	(0.01)	(0.14)
h=6	1.03	1.06	1.03	1.06	0.93	0.95
	(0.78)	(0.99)	(0.69)	(0.55)	(0.55)	(0.67)
h=9	0.95	1.00	1.00	1.05	1.01	1.06
	(0.60)	(0.78)	(0.77)	(0.47)	(0.70)	(0.43)
h=12	1.00	1.06	1.10	1.17	1.03	1.10
	(0.69)	(0.84)	(0.34)	(0.15)	(0.71)	(0.40)
h=15	0.97	0.97	0.99	0.99	0.88	0.88
	(0.72)	(0.83)	(0.87)	(0.95)	(0.20)	(0.14)
h=18	1.01	1.06	1.09	1.15	1.01	1.06
	(0.55)	(0.68)	(0.21)	(0.12)	(0.86)	(0.56)
h=21	1.02	1.05	0.92	1.00	0.86	0.93
	(0.88)	(1.00)	(0.78)	(0.47)	(0.36)	(0.84)
h=24	1.02	1.07	0.99	1.08	0.92	1.00
	(0.86)	(0.97)	(0.88)	(0.19)	(0.44)	(0.91)
h=27	1.02	1.07	1.04	1.07	0.96	0.99
	(0.87)	(0.99)	(0.65)	(0.50)	(0.86)	(0.96)
h=30	0.94	1.01	0.93	0.94	0.87	0.88
	(0.64)	(0.74)	(0.50)	(0.60)	(0.35)	(0.41)

Notes: This table reports the relative MSFE of h-month-ahead pseudo out-of-sample forecasts of inflation between the pairs of models indicated in each column. *, **, *** denote that the MSFE of the former model is significantly different from the latter at 10, 5, and 1 percent significance levels, respectively. P-values are reported in parentheses. These results are based on the modified version of the one-sided DM test from Harvey et al. (1997), which corrects for the size property of the original test statistic in a small sample. The out-of-sample forecasting period is from January 2015 to February 2023 for various monthly horizons from $h = 1, 2, ..., 30$.

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8 Appendix

8.1 Figures and Tables

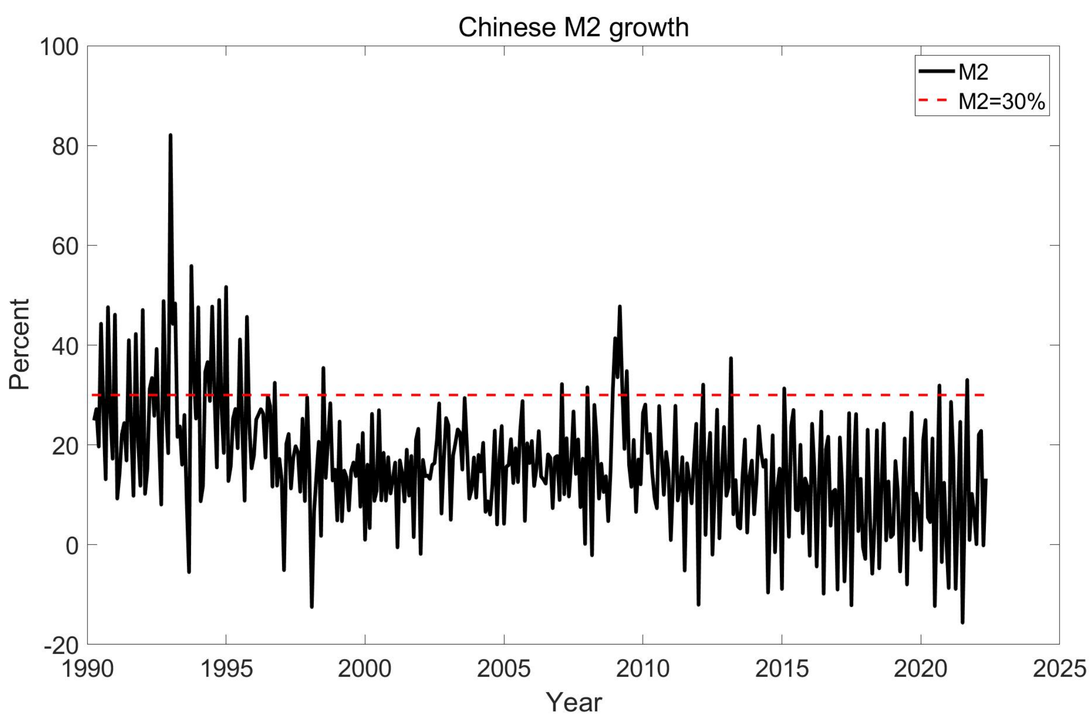

Figure A1: Month-on-month growth rate of Chinese M2 (seasonally adjusted).

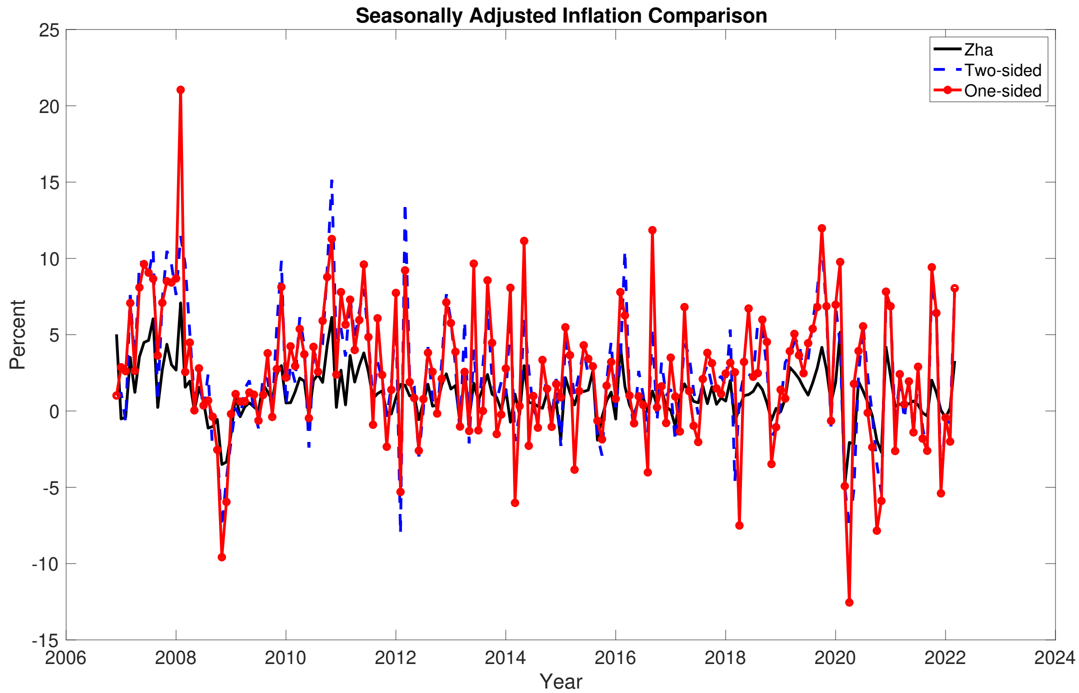

Figure A2: Chinese month-on-month CPI inflation: (i) Zha's data (ii) Inflation based on a two-sided seasonal adjustment filter and (iii) Inflation based on a one-sided seasonal adjustment filter

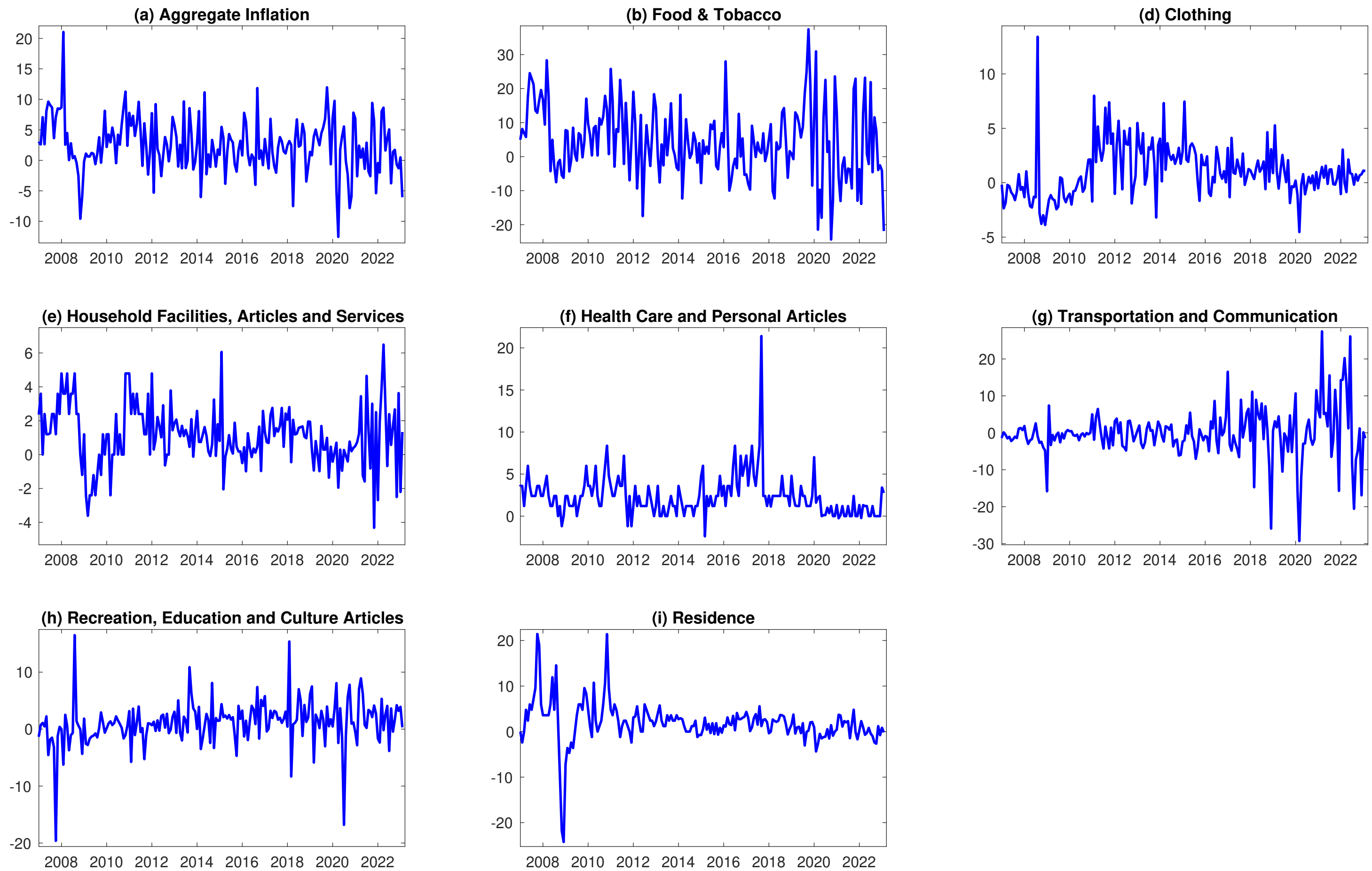

Figure A3: Monthly aggregated and disaggregated Chinese inflation rate (annualized percentage change in CPI, seasonally adjusted)

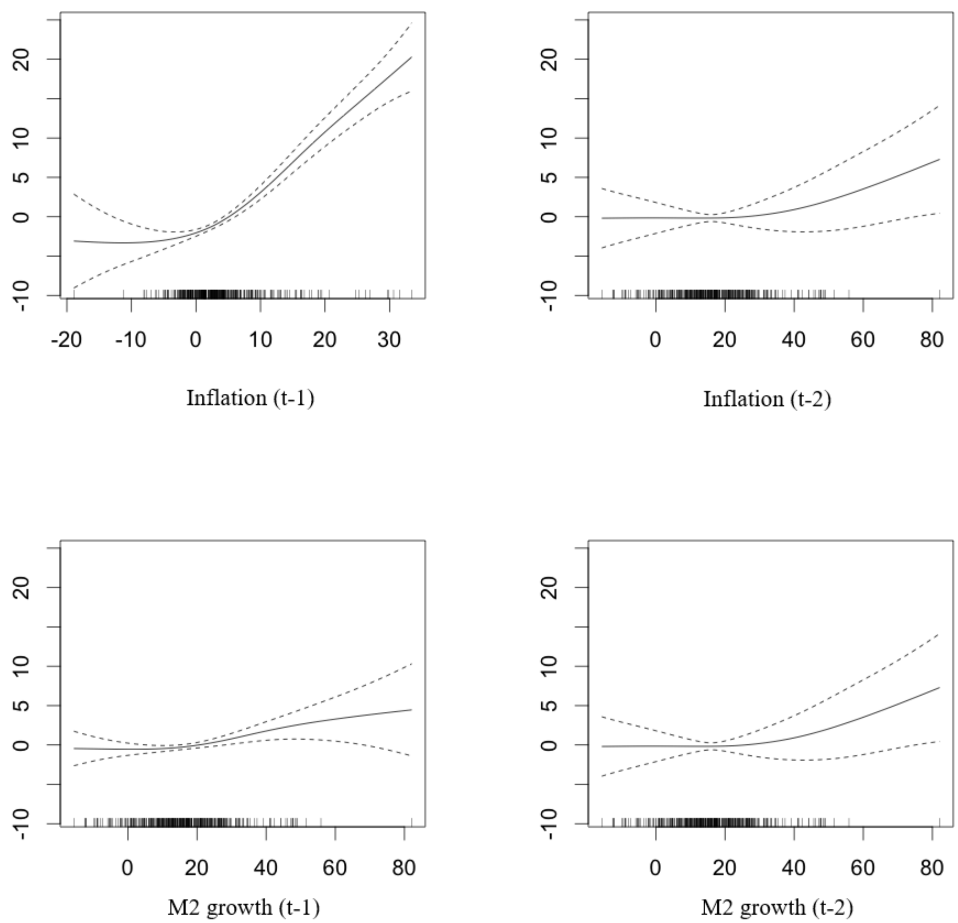

Figure A4: Semi-parametric AR model marginal effects M2 growth and s=1

Notes: This figure reports the marginal effects and 95% confidence intervals of inflation and M2 growth on inflation 1 and 2 months ahead, estimated from the semi-parametric AR model described in Section 2.

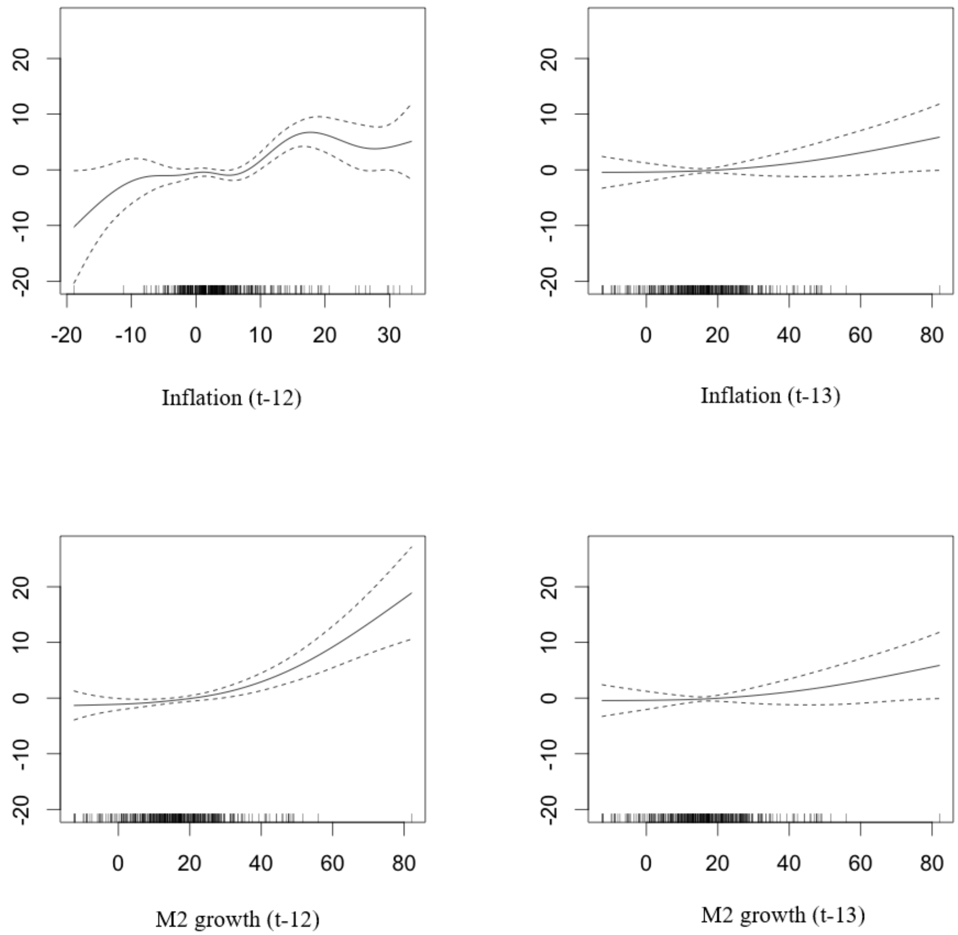

Figure A5: Semi-parametric AR model marginal effects: Local liquidity and *s*=12

Notes: This figure reports the marginal effects and 95% confidence intervals of inflation and M2 growth on inflation 12 and 13 months ahead, estimated from the semi-parametric AR model described in Section 2.

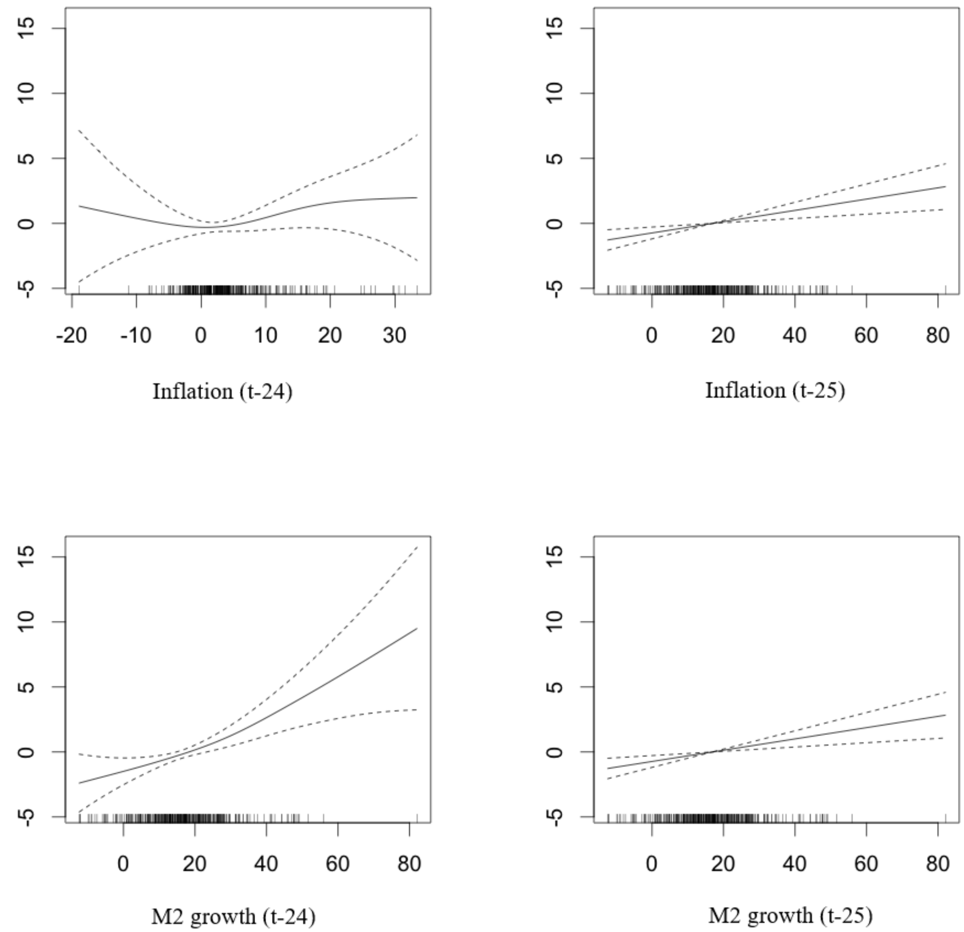

Figure A6: Semi-parametric AR model marginal effects: Local liquidity and s=24

Notes: This figure reports the marginal effects and 95% confidence intervals of inflation and M2 growth on inflation 24 and 25 months ahead, estimated from the semi-parametric AR model described in Section 2.

Table A1: Forecast performance relative to the random walk for the January 2015-February 2022 period

Horizon	MUCSVO	UCSVO	12-month mov. avg.	AR(1) without trend	AR(6) without trend	AR(1) with trend	AR(6) with trend
h=1	0.61**	0.68*	0.68*	0.63	0.67	1.01	0.70
h=2	0.44***	0.48***	0.45***	0.44***	0.47***	0.88***	0.51***
h=3	0.48***	0.52***	0.52***	0.51***	0.56***	0.85*	0.59***
h=6	0.62**	0.63**	0.59**	0.60***	0.59***	0.82	0.67***
h=9	0.52**	0.54**	0.53**	0.51***	0.51***	0.84*	0.62***
h=12	0.47***	0.49***	0.45***	0.43***	0.44***	0.88***	0.55***
h=15	0.59***	0.58***	0.58***	0.59***	0.58***	0.83	0.65***
h=18	0.52**	0.55***	0.52**	0.48*	0.49*	1.06	0.65*
h=21	0.67***	0.73***	0.70***	0.70	0.70	1.01	0.79
h=24	0.78	0.85	0.81	0.79**	0.79***	1.30	0.96**
h=27	0.65**	0.67***	0.62**	0.63*	0.63	0.98	0.70*
h=30	0.86	0.87	0.84	0.92	0.92	0.89	0.86

Notes: This table reports the relative MSFE of h-month-ahead pseudo out-of-sample forecasts of inflation between the pairs of models indicated in each column. *, **, *** denote that the MSFE of the former model is significantly different from the latter at 10, 5, and 1 percent significance levels, respectively. These results are based on the modified version of the one-sided DM test from Harvey et al. (1997), which corrects for the size property of the original test statistic in a small sample. The out-of-sample forecasting period is from January 2015 to February 2022 for various monthly horizons from $h = 1, 2, ..., 30$.

8.2 Seasonal adjustment

To perform seasonal adjustment, we convert growth series into levels with an initial value set at 1, and use X-13ARIMA-SEATS. The algorithm for this can be found in Caporello et al. (2004). One of the most critical problems for Chinese inflation data is the effect of the Chinese New Year, also called the Spring Festival. It can fall in January or February or across both. The X-13-ARIMA-SEATS program provides methods to deal with this problem Lin and Liu (2002). By doing this, the inflation time series in this paper becomes similar to that in Higgins et al. (2016). Using a two-sided filter may result in spurious forecasts. To improve forecasting results, we use the concurrent seasonal adjustment of observations. The concurrent seasonal adjustment of the observation at time t in the X-13ARIMA-SEATS reference manual is defined as the seasonal adjustment of the original data using only the sample before time t. The X-13ARIMA-SEATS only provides part of concurrent observations. We developed an algorithm to gain all of them. The steps are as follows: First, seasonally adjust the first fifty observations. Then, seasonally adjust the first fifty-one observations to obtain the fifty-first seasonally-adjusted observation and accompany it with other fifty seasonally-adjusted observations. This loop continues until we seasonally adjust all of the raw observations. From Figure A2, compares the inflation series from one-sided and two-sided seasonal adjustment. The differences appear to be prominent on occasion.

8.3 Estimation results for the multivariate UCSVO model

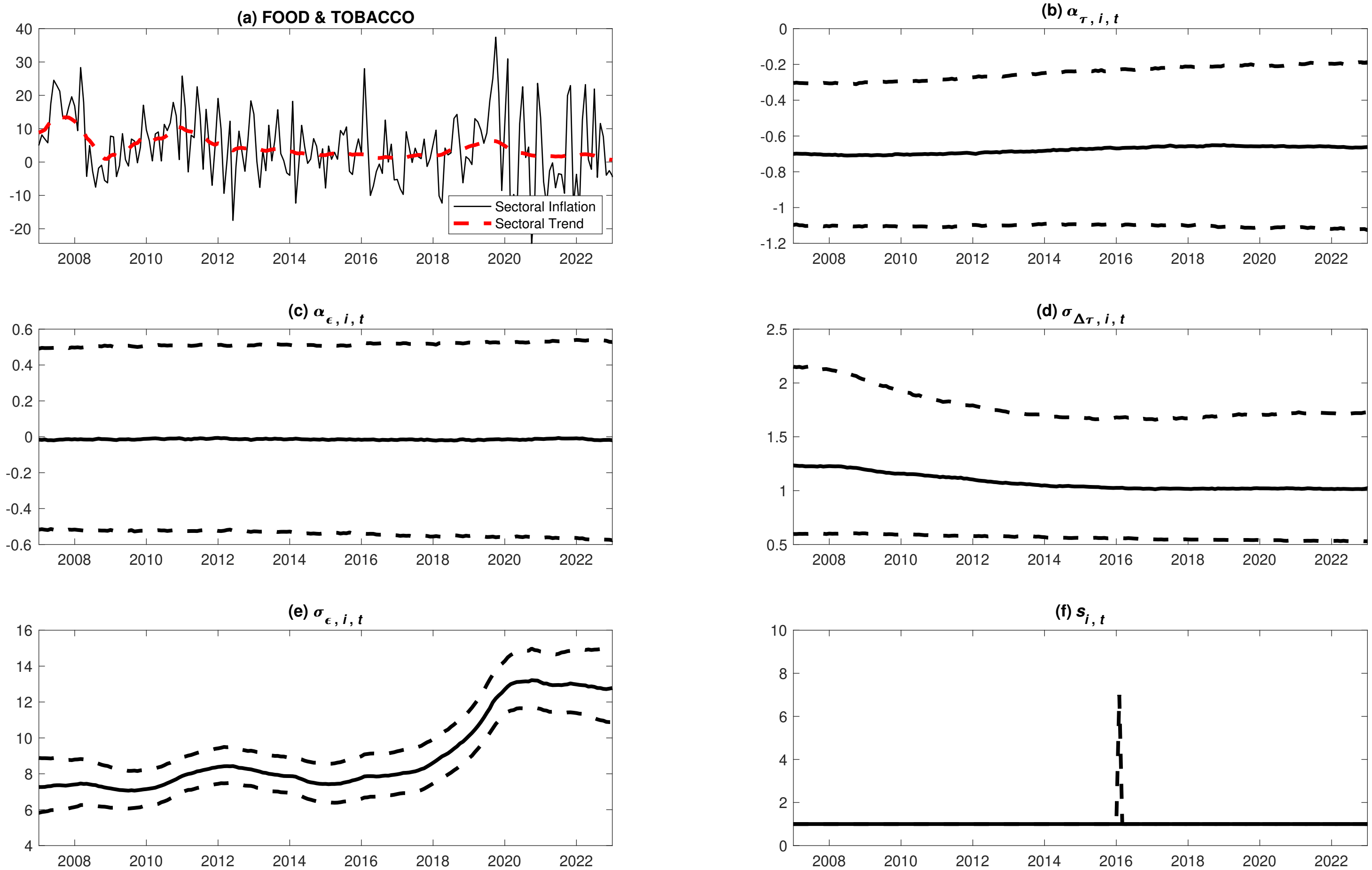

Figure A7: Posterior medians and 68% intervals from the Multivariate UCSVO model: food and tobacco sector

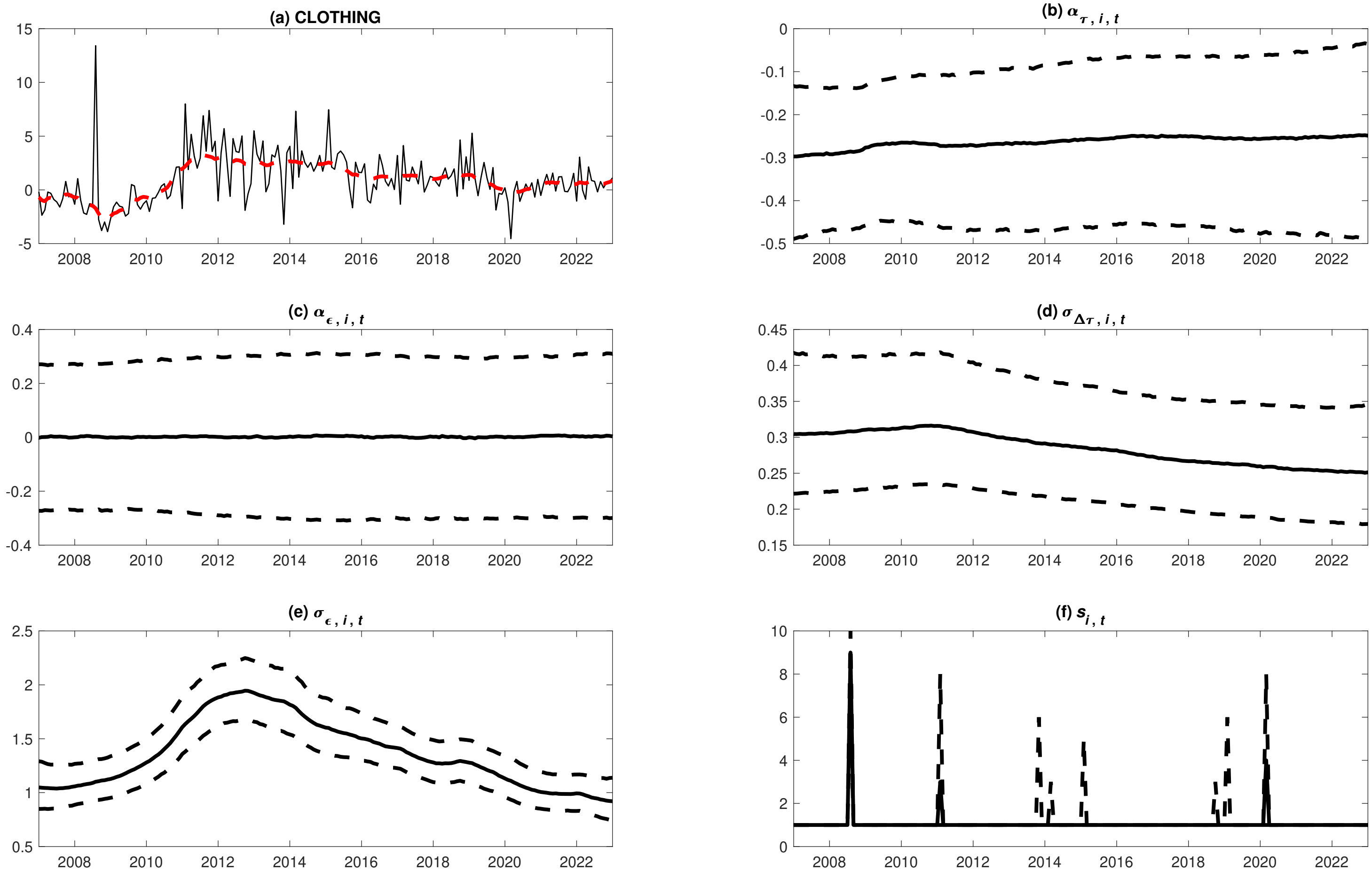

Figure A8: Posterior medians and 68% intervals from the Multivariate UCSVO model: clothing sector

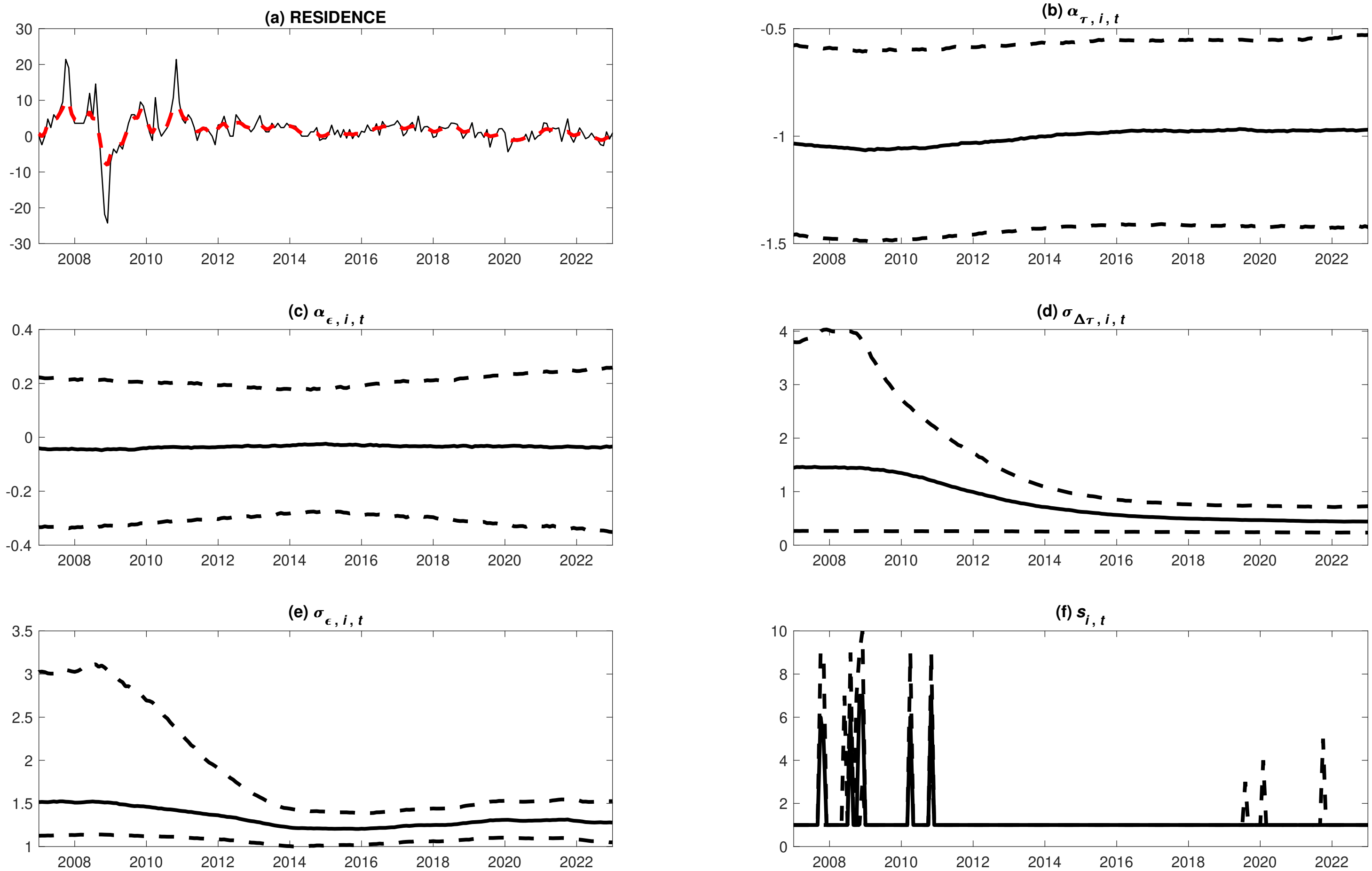

Figure A9: Posterior medians and 68% intervals from the Multivariate UCSVO model: residence sector

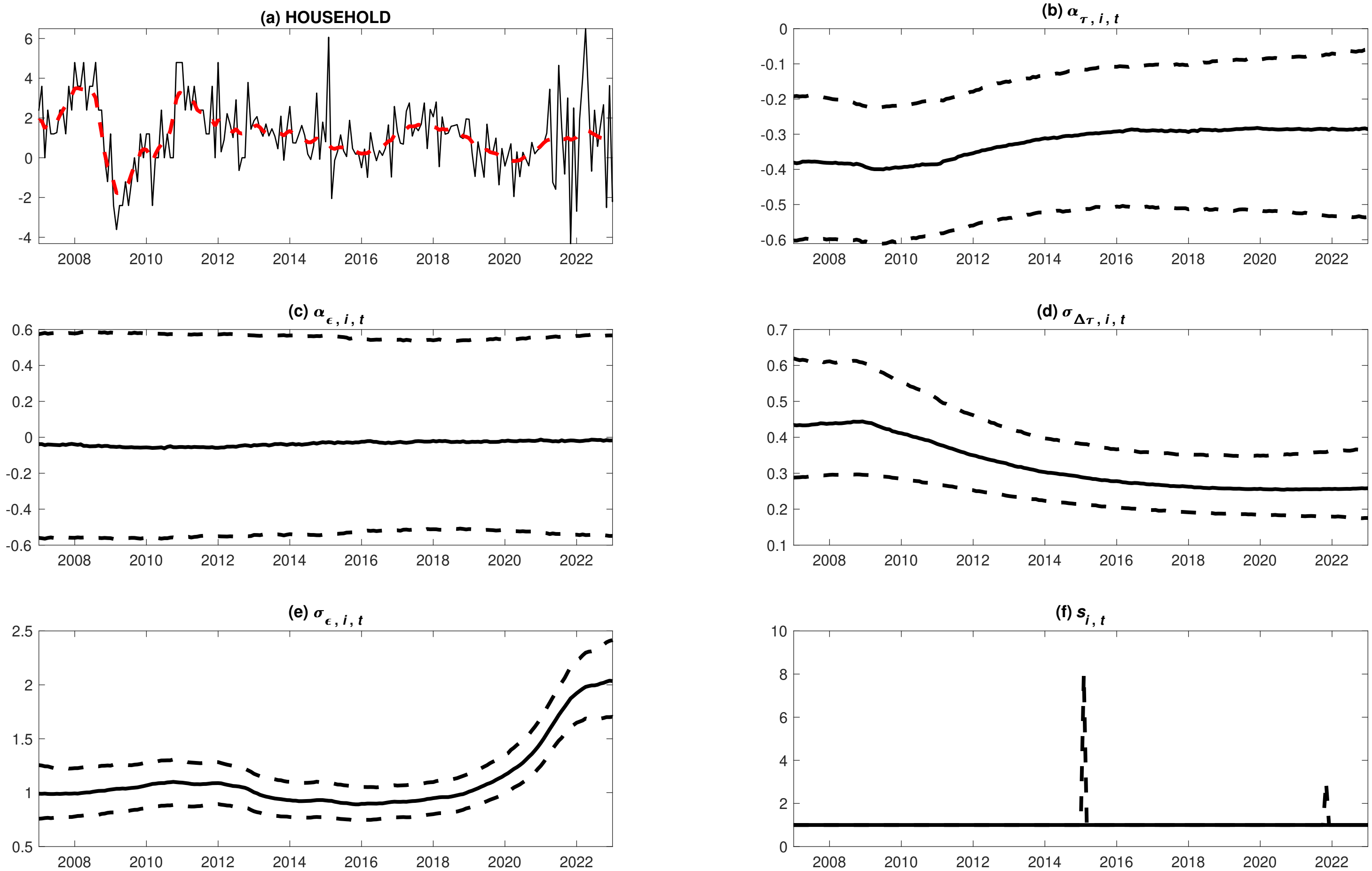

Figure A10: Posterior medians and 68% intervals from the Multivariate UCSVO model: household facilities sector

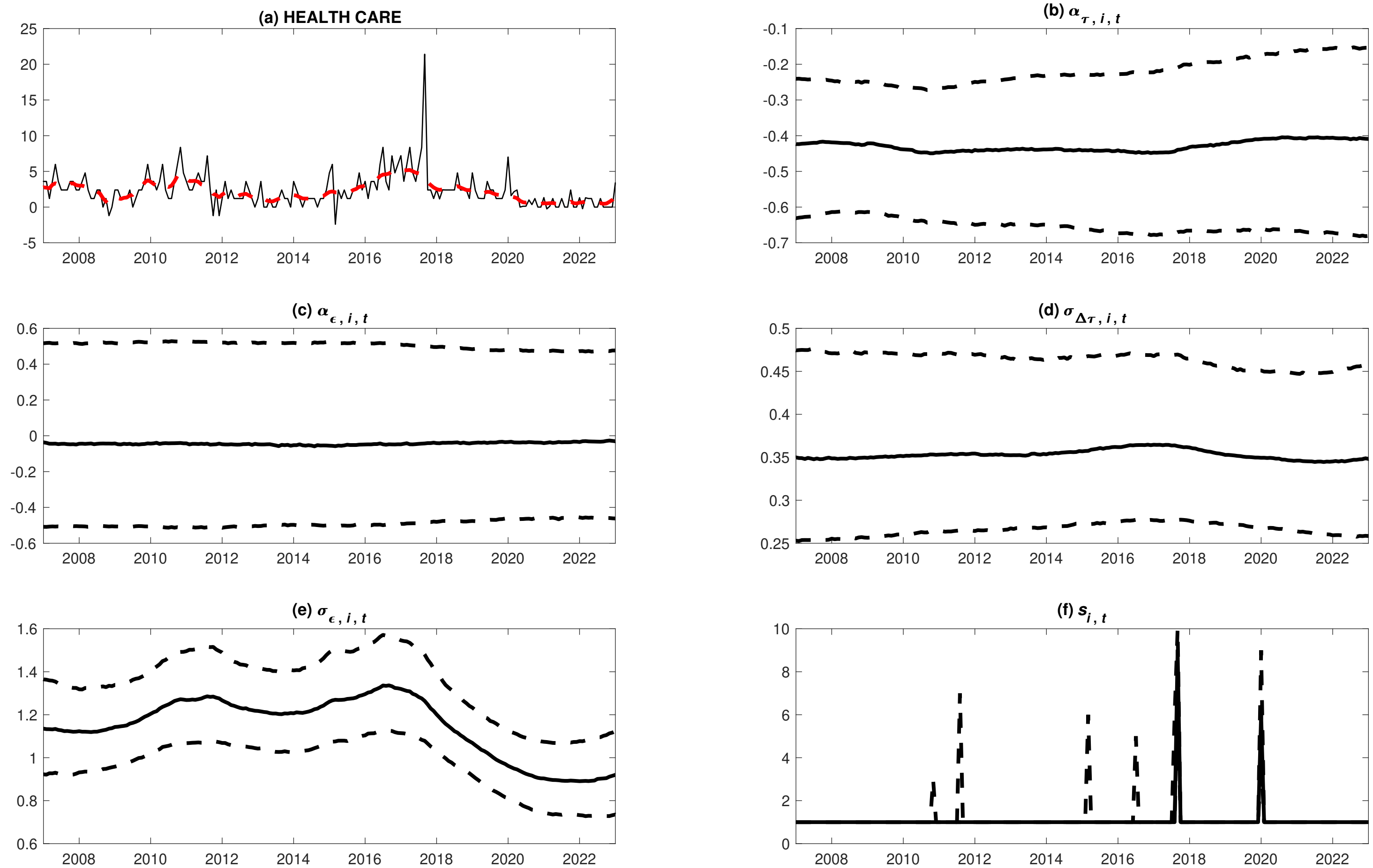

Figure A11: Posterior medians and 68% intervals from the Multivariate UCSVO model: health care sector

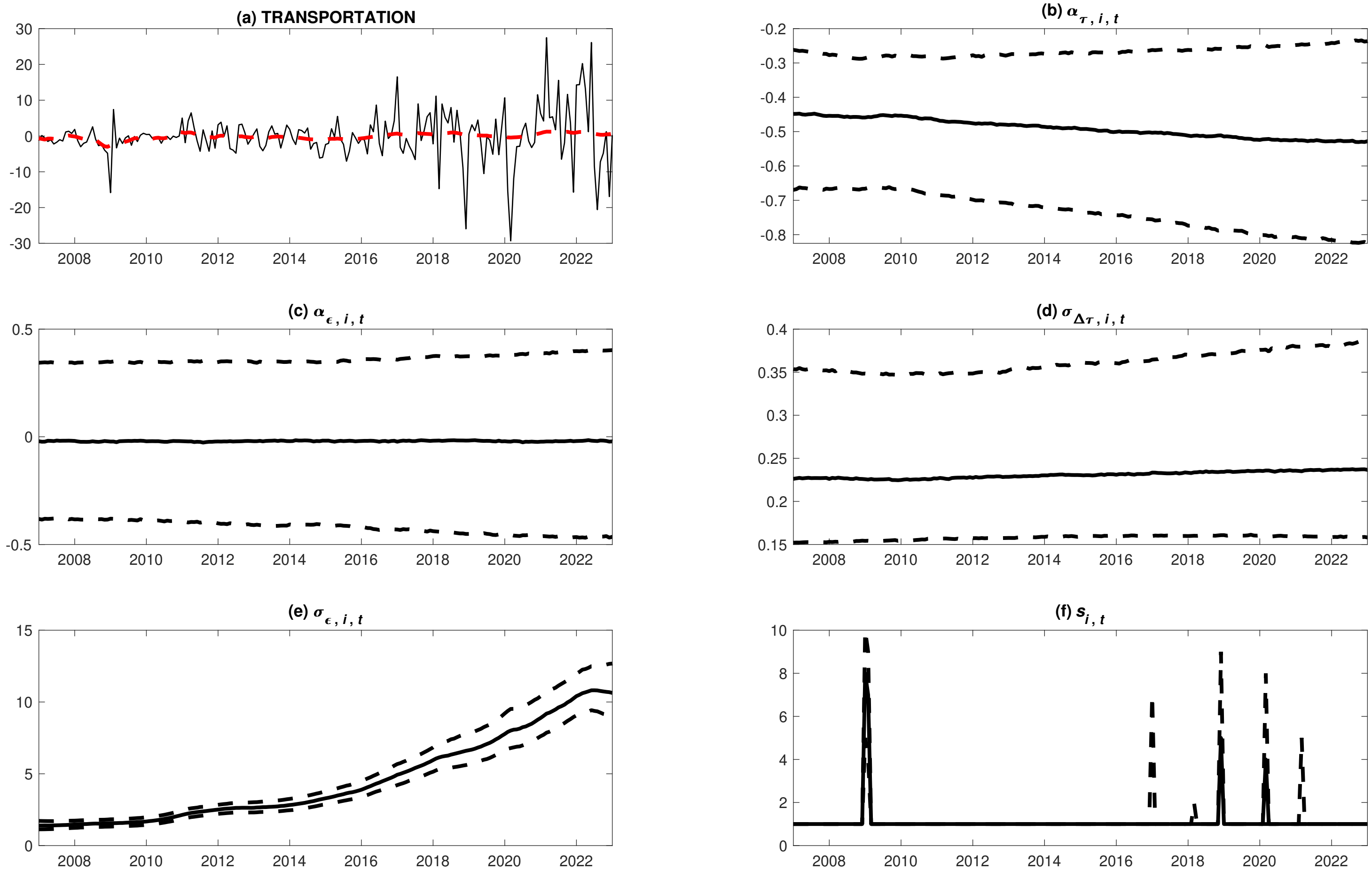

Figure A12: Posterior medians and 68% intervals from the Multivariate UCSVO model: transportation and communication sector

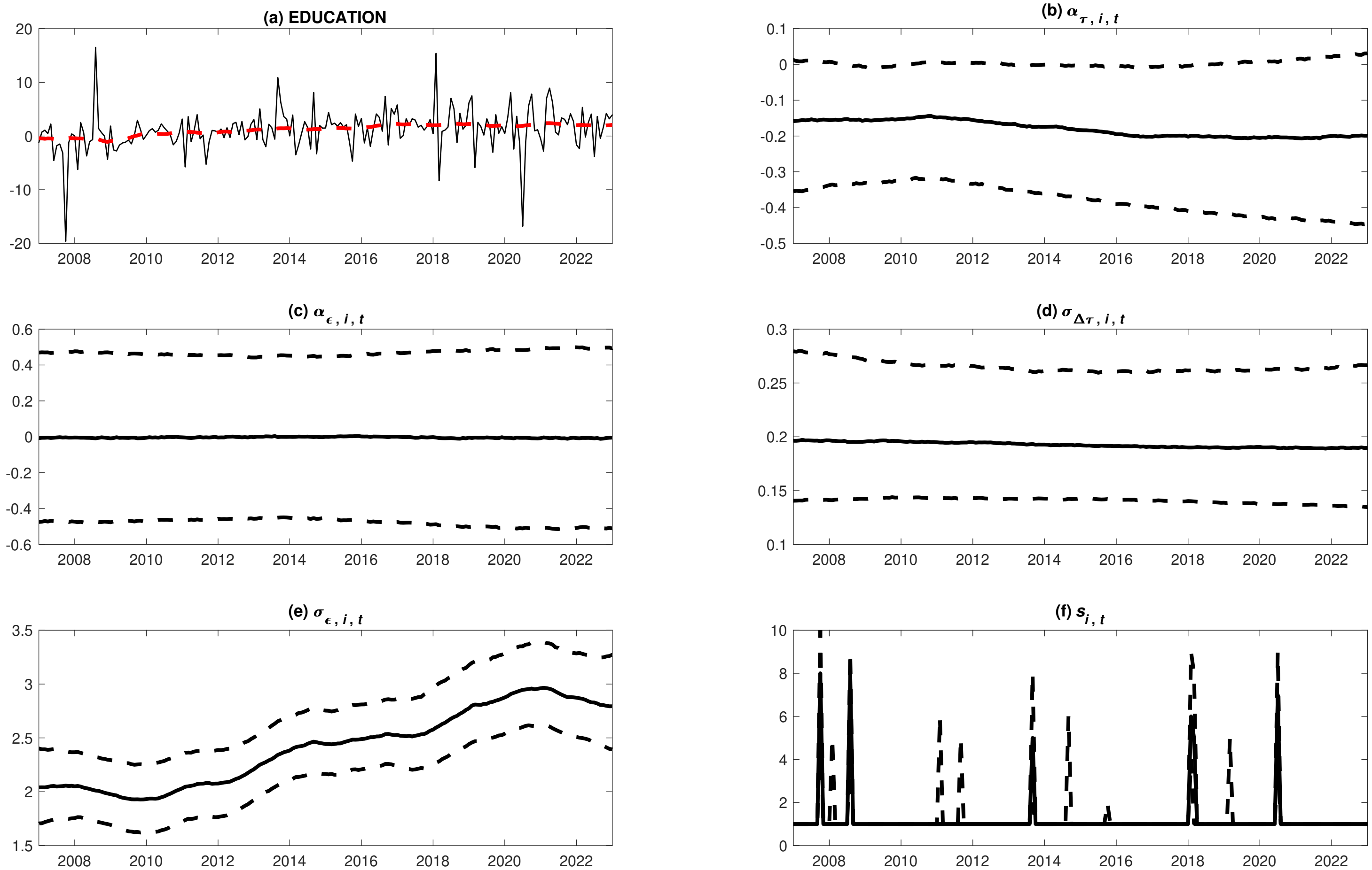

Figure A13: Posterior medians and 68% intervals from the Multivariate UCSVO model: recreation, education and culture sector