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Trend Inflation Estimates for Thailand from Disaggregated Data*

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Abstract: This paper constructs a new trend inflation measure for Thailand based on the multivariate unobserved components model with stochastic volatility and outlier adjustments (MUCSVO) of Stock and Watson (2015). Similar to core inflation, the MUCSVO constructs a measure of the underlying trend based on disaggregated data, but with time-varying sectoral weights that vary with the volatility, persistence and comovement of the sectoral inflation series. Based on the empirical results, the majority of sectoral weights show significant time-variation, in contrast to their relatively stable expenditure shares. Volatile food and energy sectors that are typically excluded from core inflation measures also turn out to be less volatile, more persistent and explain approximately 10 percent of filtered trend inflation rate movements. Compared to various other trend inflation measures, we show that the MUCSVO delivers trend estimates that are smoother, has narrower confidence bands, and are able to forecast 8 quarter-ahead average inflation more accurately both in-sample and out-of-sample, especially in the post 2000 period.

Keywords: disaggregate prices, inflation, outlier adjustment, stochastic volatility, time-varying parameters, trend-cycle decomposition, unobserved components.

JEL Classifications: C33, E31.

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1. Introduction

Since May 2000, the Bank of Thailand (BOT) adopted an explicit inflation targeting framework, making the mandate of price stability an overriding objective for monetary policy. The task of trend inflation measurement, which provides a prediction of the general direction of future inflation, thus became particularly critical towards the BOT's policy assessment and decision-making process. However, being able to accurately gauge underlying inflationary pressures from overall inflation rate movements is no trivial task. Given that aggregate inflation is influenced by multiple sources of 'noise', it is a challenge to separate out long-term persistent movements that drive the 'signal' or trend, from transitory fluctuations in the data that influence the short-term cycle.

The measurement of trend inflation can also become complicated in the face of evolving inflation dynamics. In the year 2000, many authors report a sizable decline in the level, volatility, and persistence of Thai inflation rates alongside the beginning of a sustained divergence between actual inflation and traditional measures of the trend, such as core inflation (Chantanahom et al., 2004; Khemangkorn et al., 2008). During this time, the BOT adopted an inflation targeting framework, while Manopimoke and Direkudomsak (2015) also find that intensifying globalization pressures altered Thailand's price processes in significant ways. Such changes would undoubtedly have important implications on long-term inflation expectations as well as the price structure of shocks, thus a measurement approach that cannot adapt to such changes could result in biased or inferior estimates of the trend.

The goal of this paper is to improve upon existing trend inflation measures for Thailand by using a new approach that fully accounts for the evolving nature of Thailand's price dynamics. In doing so, we estimate a multivariate unobserved components model with stochastic volatility and outlier adjustments (MUCSVO) as proposed by Stock and Watson (2015). This approach is a trend-cycle decomposition for inflation that allows for both common persistent and transitory factors, time-varying factor loadings, and stochastic volatility in the common and sectoral components. As such, the MUCSVO utilizes information in disaggregated inflation data. However, in contrast to core inflation, it allows the influence of the various sectors to affect the trend through time-varying rather than fixed weights. As these weights depend on fundamental changes in the volatility and persistence of the sectoral inflation series as well as the degree of comovement among sectors, the MUCSVO allows the 'data to speak' as much as possible while estimating the trend. Another attractive feature of the MUCSVO is that it incorporates a model-based treatment of outliers, making it particularly well-suited for the task of real-time trend estimation[1].

Throughout the empirical investigation, we focus on examining the following four questions that are central to the task of trend inflation measurement. First, we evaluate whether the use of disaggregated data in the multivariate approach can help improve upon univariate estimates of trend inflation that are computed from headline inflation alone. Second, if there are gains to be had from the use of disaggregated data, are the implied sectoral weights time-varying and how do they compare against the static weights that are used to construct core inflation? In other words, do time-varying sectoral weights help improve overall measures of trend inflation? Third, we evaluate how the resulting MUCSVO trend compares to other conventional measures of underlying price pressures when it comes to forecasting headline inflation both in-sample and out-of-sample at horizons that are relevant to policymakers.

A preview of our main findings are as follows: (i) the MUCSVO trend estimates are smoother and substantially more precise than univariate measures of trend inflation. In particular, MUCSVO-based estimates of the root mean squared error are roughly half of its univariate counterpart; (ii) the trend component common to all sectors explain the majority of Thai inflation rate movements well up until the adoption of an inflation targeting regime in the year 2000, but its role became muted relative to transitory fluctuations in the data during the period thereafter; (iii) the implied weights of the sectoral series in the multivariate trend show substantial time-variation for the majority of sectors, despite their expenditure shares being relatively constant; (iv) food and energy price sectors that are often excluded from measures of core inflation are useful indicators for the MUCSVO trend, explaining approximately 10 percent of filtered trend inflation rate movements; (v) the 8 quarter-ahead in-sample and out-of-sample average inflation forecasts from the MUCSVO trend are substantially more precise when compared to a variety of other trend inflation measures that are typically considered by the BOT, particularly since the year 2000.

This paper is organized as follows. Section 2 provides a brief overview of Thai inflation dynamics and existing methods used to construct trend inflation in Thailand. Section 3 introduces the MUCSVO model of Stock and Watson (2015). Section 4 presents and discusses the estimation results and Section 5 conducts the forecasting exercise. Section 6 concludes.

[1]Econometricians typically rely on judgment-based and ex-ante adjustments of outliers prior to trend inflation estimation. However, this approach is not feasible for real-time trend estimation because it requires knowledge of whether a large change will mean-revert. Ignoring outliers altogether though is not recommended as it runs the the risk of mistaking a single large outlier as a systematic increase in the short-run volatility of inflation.

2. Trend Inflation Measurement

The broad nature of Thai inflation rate movements can be more or less characterized into two distinct periods. During 1995-1999, the average level of headline CPI inflation was as high as 4.2 percent. The adoption of an inflation targeting framework in May 2000 by the Bank of Thailand (BOT) however, has gained unprecendented success in bringing down both the levels and volatility of the inflation process in Thailand[2]. In the subsequent inflation targeting regime, the average inflation rate dropped to a low level of 2 percent. Based on various studies, the improved behavior of Thai inflation is in large part due to the BOT's success in anchoring long-term inflation expections (Buddhari and Chensavasidja, 2003; Manopimoke and Direkudomsak, 2015).

In a country that practices inflation targeting such as Thailand, the issue of trend inflation measurement is truly central to monetary policy making. To achieve and maintain low and stable inflation, an accurate measure of trend inflation is needed to gauge underlying inflationary pressures that will persist into the future. However, aggregate inflation is often affected by a myriad of temporary and volatile shocks, with complicated dynamics that change over time. Therefore, the problem of filtering out the transitory shocks or the 'noise' from the data to gain an estimate of the 'signal' that represents trend inflation, becomes a particular challenging task.

Overall, there are two main approaches to the signal extraction problem. The first approach is based on down-weighing or excluding the most volatile and non-persistent sectors from aggregate inflation, which turn out to be the components that are mostly influenced by supply-side shocks. Measures of core inflation that excludes food and energy prices are standard examples. For Thailand, a core inflation measure that excludes rent prices from CPI inflation is also often used as an operational guideline for trend inflation. This is because the Thai housing market can at times be heavily influenced by special government policy measures, divorcing underlying price dynamics from actual market forces[3]. Against similar reasonings, underlying inflationary pressures are also often gauged from core inflation that ex-

[2]At first, the BOT inflation targeting framework corresponded to maintaining core inflation within a range of 0-3.5 percent. This band was later narrowed to 0.5-3 percent in 2009. Then, to allow the target to better reflect the change in the cost of living, the BOT altered its inflation target in 2015 to correspond to headline CPI inflation at 2.5 percent with bands of plus and minus 1.5 percent.

[3]For example, during the early 2000s, tax incentives were implemented to boost recovery in the real estate market. As a result, consumers moved away from rental accommodation to home ownership, causing significant downward pressure on housing rent that was sustained throughout the 2002-2004 period. Note that the housing sector corresponds to approximately a fifth of Thailand's core inflation basket, thus exerting a sizable influence on inflation figures. This is another reason why rent prices are often removed from headline inflation numbers to avoid significant distortions.

cludes administered price items. Since 1998, administered price items accounted for more than 30 percent of Thailand's CPI basket - a sizable share that makes Thailand a country that imposes the highest degree of price controls in the world (Peerawattanachart, 2015)[4].

Core inflation is a widely used measure for trend inflation, particularly because it is straightforward to compute and transparent in the manner in which it can be communicated to the public. However, it has been criticized on the grounds that the set of excluded components are typically fixed, even when their influences change across time periods. In response, Bryan and Cecchetti (1994) introduced a trimmed mean or median measure, which is based on an exclusion approach that allows the set of removed components to change over time. Based on the distribution of price changes, the sectors excluded can be removed in a symmetrical or asymmetrical fashion. For Thailand, the asymmetric trimmed mean measure is most appropriate, removing 12 and 6 percent of the items with large relative price changes from the lower and upper end of the price distribution respectively.

The second signal extraction approach is based on times-series smoothing methods. According to various forecasting exercises, these time-series models have been shown to forecast inflation well, implying that they are a good representation of the underlying trend. Some examples are the IMA(1,1) model of Nelson and Schwert (1997) or the random walk model for four-quarter average inflation as proposed by Atkeson and Ohanian (2001). Building on these models, Stock and Watson (2007) propose an unobserved components model for inflation with stochastic volatility which serves as the basis for the MUCSVO model that will be the main focus of this paper. The unobserved components model treats the trend component of inflation as a latent state variable to be estimated within a framework of time-varying parameters and price shocks with stochastic volaility.

Another popular times-series approach for trend inflation measurement is based on the principal components analysis (PCA). The PCA is a data reduction method that estimates the trend by extracting price movements that are common to all sectors by their variance-covariance structure. In comparison to the exclusion approach that always removes the same volatile components from the CPI basket, statistical approaches such as ones that are based on the PCA are favorable because they

[4] Primarily, price controls are implemented by the Thai government to prevent large swings in inflation, such as by actively using oil fund levies and fuel excise taxes as instruments to stabilize domestic oil prices. In practice however, adjusting government instruments in response to global commodity price cycles in the past has resulted in large fluctuations in retail oil prices, as can be observed in July 2005 when the government suddenly increased its collection of oil funds to remove diesel price subsidies. Since the global financial crisis, the Thai government has attempted to restructure domestic fuel pricing by reducing price subsidies as well as by allowing energy prices to naturally respond to market forces.

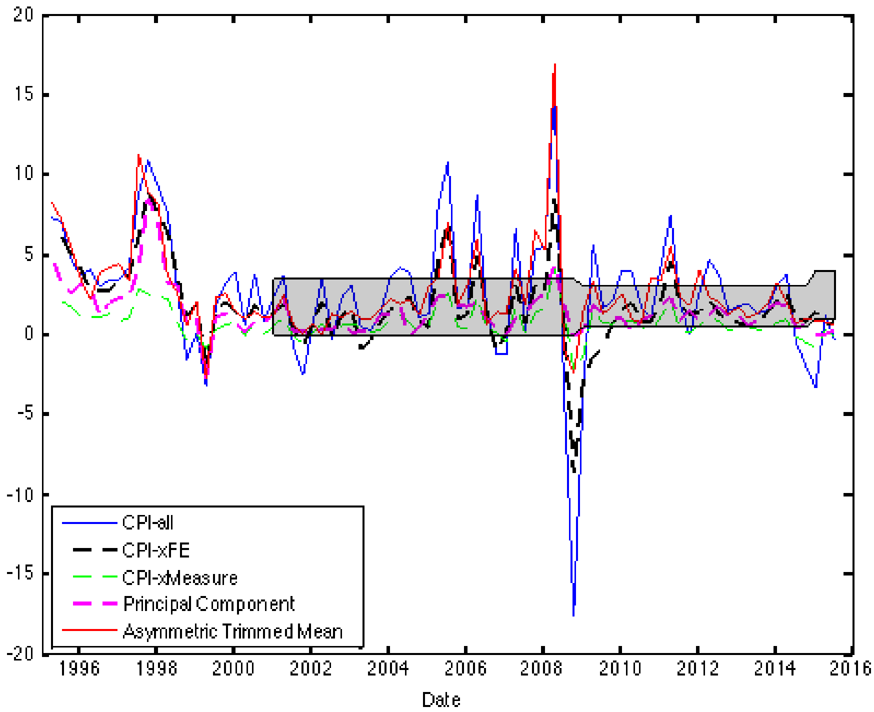
make no such restrictions and ‘let the data speak’ as much as possible. Therefore, while both the PCA and the exclusion approach both utilize cross-sectional data to arrive at an estimate for the trend, the PCA approach decides which sectors to include based on weights that are actually estimated, rather than specifying them in a manner that is relatively ad hoc.

Figure 1 plots headline CPI inflation in Thailand against selected trend inflation measures that are closely monitored by the BOT, with the shaded region representing the BOT’s inflation targeting band. A few observations emerge. First, it is interesting to note the fundamental shift in the relationship between headline and the various trend inflation measures around the year 2000. In the earlier period, headline generally moved in line with trend inflation, with the exception of core inflation that excludes administered items (CPI-xMeasure). However, in the period thereafter, the differences between headline and trend became more pronounced, especially during crises periods. At the same time, trend inflation estimates in the post 2000 period are more smooth compared to headline inflation rate movements, most likely due to the adoption of the inflation targeting framework in May 2000 which served to better anchor long-term inflation expectations.

Second, headline inflation remained consistently above the core measures for prolonged periods after the year 2000, except for brief periods of sharp downturns. Given that core inflation is supposed to represent the underlying long-run rate in which headline inflation reverts to after the effects of temporary price shocks dissipate, the sustained divergence between headline and core is somewhat disconcerting and raises concerns about using the core as a representative measure of trend inflation. Finally, there is significant variation among the various trend inflation measures themselves, particularly in the post 2000 period, making it difficult to gauge ‘true’ underlying price pressures[5]. In light of such issues, the remainder of this paper is primarily devoted to an evaluation of competing trend inflation measures in Thailand and a more rigorous study on how to appropriately capture underlying price pressures.

[5]For monetary policy discussions, the BOT typically analyzes a wide range of trend inflation measures. These include measures of trend inflation obtained from semi-structural economic and macro-finance models that utilize information on real economic activity, interest rates and terms of trade (Apaitan, 2015; Manopimoke and Direkudomsak, 2015). The BOT also relies on measures of long-term inflation expectations that are obtained from survey data to gauge underlying price pressures. To confine our scope, this paper focuses on measures of trend inflation that are constructed from information within the price series alone. Readers are referred to Griffiths and Poshyananda (2000) for a more detailed discussion of the various trend inflation measures that are being considered at the BOT.

Figure 1: Thailand Headline and Trend Inflation



Note: The inflation series are calculated as quarter-on-quarter changes in the consumer price index. Trend inflation measures include: (1) headline inflation excluding raw food and energy components (fuel, gas, and electricity), denoted CPIxFE; (2) CPIxFE excluding administered price measures, denoted Core-xMeasure; (3) trend inflation constructed from the principal components analysis; and (4) an asymmetric trimmed mean measure of trend inflation. The shaded region represents the BOT's inflation targeting band.

3. The Unobserved Components Model for Inflation

This section introduces the multivariate unobserved components model with stochastic volatility and outlier adjustments (MUCSVO) as proposed by Stock and Watson (2015). The model combines the two common approaches to measuring trend inflation as discussed in the previous section. That is, it utilizes disaggregated data at the sectoral level similar to core and trimmed-mean approaches, but extracts measures of the underlying trend via times series smoothing methods. In this way, the resulting trend estimate will be a statistical one that adjusts on its own to changes in measurement methods as well as fundamental changes in the sectoral series. Since the MUCSVO model is built upon a univariate unobserved components model that was developed in the authors' earlier work (Stock and Watson, 2007), we will first introduce the univariate version before extending it to the multivariate case.

3.1 The Univariate Model

Consider the following univariate unobserved components model with stochastic volatility and outlier-adjustments (UCSVO):

$$\begin{aligned}
\pi_t &= \tau_t + \varepsilon_t && (1)\\
\tau_t &= \tau_{t-1} + \sigma_{\Delta\tau,t} \times \eta_{\tau,t} && (2)\\
\varepsilon_t &= \sigma_{\varepsilon,t} \times s_t \times \eta_{\varepsilon,t} && (3)\\
\Delta ln(\sigma^2_{\varepsilon,t}) &= \gamma_\varepsilon \nu_{\varepsilon,t} && (4)\\
\Delta ln(\sigma^2_{\Delta\tau,t}) &= \gamma_{\Delta\tau} \nu_{\Delta\tau,t} && (5)
\end{aligned}$$

where the variance-covariance matrix $(\eta_\epsilon, \eta_\tau, \nu_\epsilon, \nu_{\Delta\tau})$ is iid. N(0, I$_4$).

The above expression decomposes the current inflation rate π_t into a permanent component τ_t and transitory component ϵ_t. The trend component τ_t follows a martingale process according to Eq. (2), and the transitory component ϵ_t is a serially uncorrelated mixture of normals as specified by Eq (3). To capture outliers in the transitory component, the mixture is a function of the i.i.d. variable s_t, which allows for large one-time shifts in the price level that occurs with probability p. Last, the innovations to both trend and transitory components have variances that evolve over time according to logarithmic random walk stochastic volatility processes with scale parameters γ_ϵ and $\gamma_{\Delta\tau}$ as specified by Eqs. (4) and (5).

To gain more intuition on the UCSVO, note that without outliers, $\Delta\pi_t$ simply follows a time-varying IMA(1,1) process:

$$\Delta\pi_t = a_t - \theta_t a_{t-1}, E(a_t) = 0, Var(a_t) = \sigma^2_{a,t}, \quad (6)$$

where $\sigma^2_{a,t}$ and θ_t are functions of transitory and permanent disturbances, namely $\sigma^2_{\epsilon,t}$ and $\sigma^2_{\eta,t}$. Accordingly, the one-sided or filtered estimate of τ_t follows exponential smoothing, and can be written as[6]:

$$\tau_{t|t} = (1 - \theta_t) \sum_{i=0}^{\infty} \theta_t^i \pi_{t-i}, \quad (7)$$

where the weights in front of the lagged inflation terms sum to one. Therefore, by setting aside time variation, filtered estimates of the inflation trend are merely

[6] However, with explicit model-based treatment of outliers, the resulting estimate of τ_t that belongs to the UCSVO model is not always well approximated by the linear exponential smoother associated with a local IMA(1,1).

a distributed lag of past inflation. Since θ_t varies with the ratio of transitory to permanent disturbances, the more volatile is the trend, the smaller is θ_t, and the more weight is placed on recent observations for filtered estimates. Note that as θ_t approaches one, the filtered trend simply represents the average of past inflation rate movements.

3.2 The Multivariate Model

The multivariate unobserved components model with stochastic volatility and outlier-adjustments (MUCSVO) extends the UCSVO to include a common latent factor in both trend and transitory components of inflation, with remaining dynamics captured by sector-specific or idiosyncratic components. The MUCSVO model is as shown below:

$$\begin{aligned}
\pi_{i,t} &= \alpha_{i,\tau,t}\tau_{c,t} + \alpha_{i,\varepsilon,t}\varepsilon_{c,t} + \tau_{i,t} + \varepsilon_{i,t} && (8)\\
\tau_{c,t} &= \tau_{c,t-1} + \sigma_{\Delta\tau,c,t} \times \eta_{\tau,c,t} && (9)\\
\varepsilon_{c,t} &= \sigma_{\varepsilon,c,t} \times s_{c,t} \times \eta_{\varepsilon,c,t} && (10)\\
\tau_{i,t} &= \tau_{i,t-1} + \sigma_{\Delta\tau,i,t} \times \eta_{\tau,i,t} && (11)\\
\varepsilon_{i,t} &= \sigma_{\epsilon,i,t} \times s_{i,t} \times \eta_{\varepsilon,i,t} && (12)\\
\alpha_{i,\tau,t} &= \alpha_{i,\tau,t-1} + \lambda_i\zeta_{i,\tau,t} \text{ and } \alpha_{i,\varepsilon,t} = \alpha_{i,\varepsilon,t-1} + \lambda_{i,\varepsilon}\zeta_{i,\varepsilon,t} && (13)\\
\Delta ln(\sigma^2_{\epsilon,c,t}) &= \gamma_{\epsilon,c}\nu_{\epsilon,c,t}, \qquad \Delta ln(\sigma^2_{\Delta\tau,c,t}) = \gamma_{\Delta\tau,c}\nu_{\Delta\tau,c,t}, \\
\Delta ln(\sigma^2_{\epsilon,i,t}) &= \gamma_{\epsilon,i}\nu_{\epsilon,i,t}, \qquad \Delta ln(\sigma^2_{\Delta\tau,i,t}) = \gamma_{\Delta\tau,c}\nu_{\Delta\tau,i,t}, && (14)
\end{aligned}$$

where the disturbances $(\epsilon_{c,t}, \epsilon_{i,t}, \eta_{c,t}, \eta_{i,t}, \zeta_{c,t}, \zeta_{i,t}, \nu_{\epsilon,c,t}, \nu_{\Delta\tau,i,t}, \nu_{\varepsilon,i,t})$ are i.i.d. $N(0, I_9)$.

In the above specification, Eq. (8) 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 $\epsilon_{i,t}$. Eqs. (9)-(12) capture stochastic volatility in the latent common and sector-specific components, whereas Eq. (13) allows the factor loadings on the latent common factors to be time-varying according to a random walk process. Similar to the UCSVO, the stochastic volatility processes evolve according to a logarithmic random walk as specified by Eq. (14). Furthermore, outliers in the transitory disturbances of the common and sector-specific components are accounted for through the independent multinomial variables $s_{c,t}$ and $s_{i,t}$ in Eq. (10) and Eq. (12), which occur with probabilities p_c and p_i respectively.

An implied measure of the aggregate trend can be obtained from the estimates of the common and sector-specific trend components as follows:

$$\tau_{t|t} = \sum_{i=1}^{n} w_{it}(\alpha_{i,\tau,t}\tau_{c,t|t} + \tau_{i,t|t}) \tag{15}$$

where n denotes the number of sectors, w_{it} is the expenditure share weight of sector i in total inflation, and $\alpha_{i,\tau,t}\tau_{c,t|t} + \tau_{i,t|t}$ is the overall sectoral trend. From the above expression, note that in the extreme case where there is no common trend, trend inflation would just be the sum of the sector-specific trends, weighted by the sectoral share weights. On the other extreme, should all sectoral trends share common movements, there will be $n-1$ cointegrating vectors among the n sectors.

4. Data and Estimation Results

4.1 Data Description and Analysis

The dataset for estimation consists of quarterly data for the sample 1995Q1-2015Q3 obtained from the Thai Ministry of Commerce, with the length of the time series chosen based on data availability. Headline inflation is denoted CPI-all, and is calculated as the log changes in the quarterly consumer price index. For the sectoral series that are used to estimate the MUCSVO, CPI-all inflation is disaggregated into 3, 7, and 10 components based on actual expenditure share weights[7].

The disaggregated components of CPI-all are listed in Table 1. The 3 components disaggregates CPI inflation into core, raw food, and energy sectors. The 7 components consists of food and beverages, clothing, housing, healthcare, transportation, recreation and education, and tobacco and alcohol. By disaggregating the 7 components dataset down further, food and beverages can be seperated into raw food and food in core, and energy components can be extracted out from housing and transportation sectors. This gives us 10 components, which due to data limitations, is the lowest level of disaggregation we can achieve for CPI-all inflation.

Figure 2 contains a plot of the 10 sectoral series. As shown, the dynamics of each series are quite distinct, whether it be its persistence, its volatility, or the nature of its outliers. For example, the volatility of the raw food component is substantially more volatile when compared to clothing or healthcare sectors. Also, only about half of the sectors experienced a downward negative shock during 2008 and 2009, whereas the price series in other sectors remained stable or even experienced positive shocks, such as food in core. The behavior of each sector-specific inflation series also vary over time. For example, transport excluding fuel and recreation and education

[7]The main estimation results are based on 10 components series. However, robustness checks are performed for CPI inflation with 3 and 7 components as well. Due to space considerations, the robustness check results are not included here but are available upon request.

components were volatile before 2010, but became persistently stable in the period thereafter. Food in core, on the other hand, exhibited more volatility towards the end of the sample.

Table 1: Dissaggregated components of CPI inflation

3 Components	7 Components	10 Components
1. Core Inflation	1. Food and Beverages	1. Raw food
2. Raw Food	2. Clothing	2. Food in Core
3. Fuel, Gas and Electricities	3. Housing	3. Clothing
	4. Healthcare	4. Housing excluding Gas and Electricities
	5. Transportation	5. Gas and Electricities
	6. Recreation and Education	6. Healthcare
	7. Tobacco and Alcohol	7. Transportation excluding Fuel
		8. Fuel
		9. Recreation and Education
		10. Tobacco and Alcohol

The changing properties of sectoral inflation series are more succinctly summarized in Tables 2 and 3, where we calculate the standard deviation and persistence of each sectoral series over 5 year intervals based on monthly data series. In contrast to expenditure shares of each sector that remained relatively constant over similar sub-samples (see Table 4), significant time-varying volatility as well as persistence can be observed at the disaggregated level for CPI inflation. These features thus highlight the importance of allowing for time-varying weights for the influence of sectoral inflation series on trend inflation in the MUCSVO model.

Finally, another interesting observation that can be drawn from the results in Tables 2 and 3 is that while sectors that are typically excluded from conventional core inflation measures (raw food, gas and electricity, and fuel) do maintain the highest volatility over all subsamples, its persistence is not necessarily the lowest. This observation becomes particularly apparent during the last subsample. Therefore, the traditional approach of simply excluding volatile price sectors to arrive at a measure of core inflation thus may not be entirely appropriate. The MUCSVO becomes appealing in this regard because it leaves it up to the data to decide upon whether a particular sector contains useful information for the trend. In other words, the MUCSVO allows persistent price pressures to pass-through to filtered trend estimates through time-varying sectoral weights, which depend on the dynamic nature of underlying shocks to trend and transitory components of the price series.

Figure 2: Thailand Sectoral Inflation Series

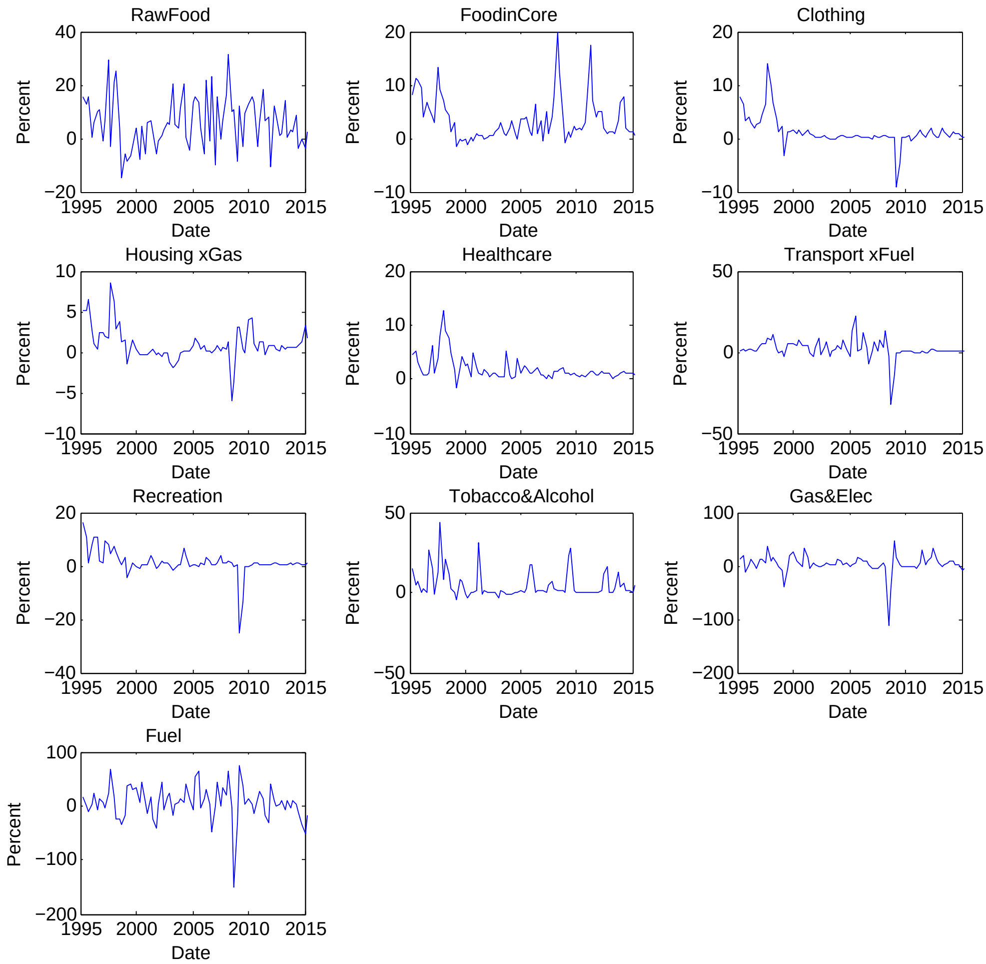


Table 2: Standard Deviation of Sectoral Inflation Series

	1995M1-1999M12	2000M1-2004M12	2005M1-2009M12	2010M1-2015M12
Raw Food	21.76	16.11	21.65	13.07
Food in Core	6.65	2.04	6.07	5.00
Clothing	5.56	0.89	5.61	1.14
Housing x Gas, Elect	2.98	1.24	5.42	1.99
Healthcare	4.95	2.68	1.11	0.85
Transport x Fuel	5.25	7.25	15.40	1.05
Recreation and Education	9.24	4.28	15.15	1.07
Tobacco and Alcohol	19.69	12.02	16.85	7.74
Gas and Electricity	33.26	25.85	71.43	20.21
Fuel	38.48	46.87	71.87	32.99

Note: Reported are the standard deviations of the annualized month-on-month sectoral inflation series calculated over 5 year intervals.

Table 3: Persistence of Sectoral Inflation Series

	1995M1-1999M12	2000M1-2004M12	2005M1-2009M12	2010M1-2015M12
Raw Food	0.31	0.17	0.07	0.27
Food in Core	0.78	0.53	0.77	0.82
Clothing	0.82	0.71	-0.04	0.58
Housing x Gas, Elect	0.83	0.55	-0.21	0.46
Healthcare	0.83	0.42	0.81	0.89
Transport x Fuel	0.72	0.33	0.46	0.31
Recreation and Education	0.61	0.14	0.01	0.55
Tobacco & Alcohol	0.43	0.05	0.34	0.45
Gas & Electricity	0.22	-0.06	0.01	0.35
Fuel	0.43	0.05	0.41	0.30

Note: Reported are the estimated persistence of the annualized month-on-month sectoral inflation series calculated over five year intervals. Persistence is defined as the sum of the coefficients in a fitted autoregressive model of order 4.

Table 4: Expenditure Shares of Sectoral Inflation Series

	1995M1-1999M12	2000M1-2004M12	2005M1-2009M12	2010M1-2015M12
Raw Food	9.18	9.22	11.69	15.55
Food in Core	16.96	16.53	16.35	18.31
Clothing	3.97	3.88	3.42	3.03
Housing x Gas, Elect	27.10	25.04	21.86	20.27
Healthcare	7.26	7.39	6.89	6.48
Transport x Fuel	19.12	19.94	20.38	17.60
Recreation and Education	8.04	7.73	7.01	5.93
Tobacco & Alcohol	1.00	1.14	1.13	1.25
Gas & Electricity	4.20	4.85	4.69	4.21
Fuel	3.11	4.24	6.52	7.32

Note: Reported are the average expenditure shares of the relevant sectors in the consumer price index.
Source: Thai Ministry of Commerce.

4.2 Estimation Methodology

The estimation procedure for both the UCSVO and MUCSVO models are based on Bayesian methods. To estimate the posterior, we use the Markov Chain Monte Carlo (MCMC) approach and stochastic volatility is handled by following the method outlined in Kim et al. (1998), modified to use the Omori et al. (2007) 10-component Gaussian mixture approximation for the log-chi squared error. While a few details are highlighted here, readers are referred to the online appendix of Stock and Watson (2015) for a detailed description of the priors and numerical methods involved to approximate the posteriors.

For the UCSVO model, priors for the stochastic volatility parameters γ_ϵ and $\gamma_{\Delta\tau}$ are independent uniform priors that are calibrated so that the standard deviation of annual changes in $ln(\sigma_{\epsilon,t})$ and $ln(\sigma_{\Delta\tau,t})$ are distributed $U[0, 0.2]$. The variable s_t that controls for outliers takes on the value $s_t = 1$ with probability p, which has a prior distributed Beta(α, β). The prior parameters α and β are calibrated to reflect information that an outlier will occur every 4 years in a sample of length 10 years. As for the initial values of τ_0, $ln(\sigma_{\epsilon,0})$ and $ln(\sigma_{\Delta\tau,0})$, their priors are specified as independent diffuse normals.

In the MUCSVO model, the priors for the γ and p parameters as well as the sector specific components $\tau_{i,0}$, $ln(\sigma_{i,\epsilon,0})$, and $ln(\sigma_{i,\Delta\tau,0})$ are the same as the univariate model. The initial values of $\tau_{c,0}$, $\tau_{i,0}$, $ln(\sigma_{\Delta\tau,c,0})$, and $ln(\sigma_{\epsilon,c,0})$ are set to zero. An informative prior for the intitial value of α_τ which is the factor loading on $\tau_{c,t}$ follows $\alpha_\tau \sim N(0, \kappa_1^2 ll' + \kappa_2^2 I_n)$ where n is the number of sectors and l is a $n \times 1$ vector of 1's. The parameter κ_1 governs the prior uncertainty about the average value of factor loadings and is set to 10 for a relatively uninformative prior. The parameter κ_2 governs the variability of each factor loading from the average value and is set to 0.4 to ensure shrinkage towards average values. The prior for α_ϵ is as before, and the priors for the parameters that govern time-variation in the factor loadings, $(\lambda_{i,\tau}, \lambda_{i,\epsilon})$ follow an inverse gamma distribution.

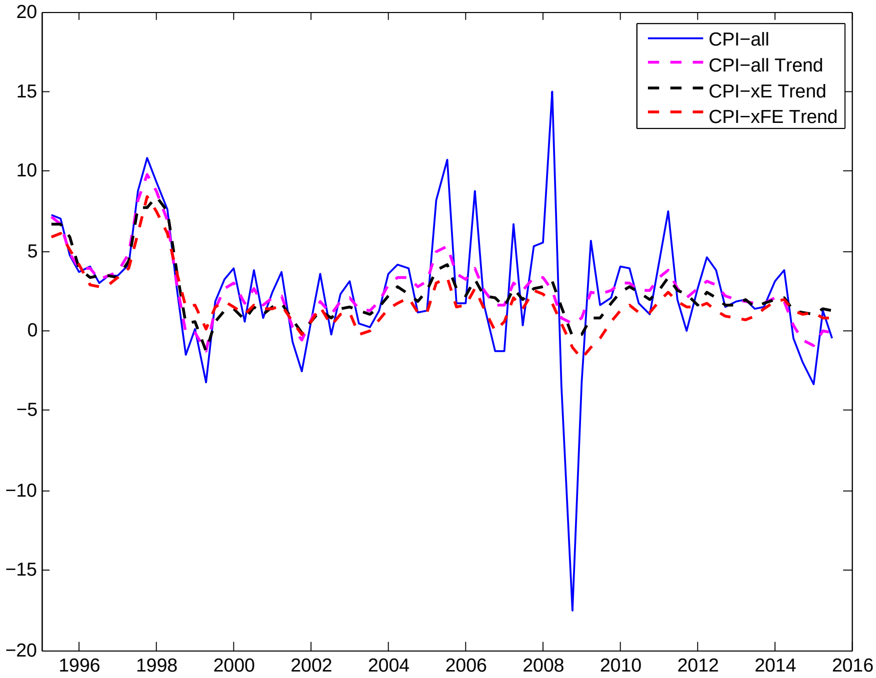
4.3 UCSVO Results

Figure 3 plots CPI-all inflation and the full-sample posterior means of τ_t from the UCSVO model for headline and core inflation. The behavior of the estimated trends reflect the previously discussed relationship between actual headline and core inflation. More specifically, all trend estimates move closely with headline inflation up until the beginning of the year 2000, but the series diverge in the period thereafter. Furthermore, in the post 2000 period, all trend estimates are a smoothed version of overall headline inflation. Interestingly, the CPI-all trend remains persistently above other core inflation measures except for the most recent period due to falling oil prices.

Figure 4 contains a plot of the posterior means of $\sigma_{\Delta\tau,t}$, $\sigma_{\epsilon,t}$ and $\sigma_{\epsilon,t} \times s_t$ from the UCSVO. Focusing on panel (a), two observations of interest emerge. First, trend variation for all inflation series were substantially more volatile during the first part of the sample, but became well "anchored" and stable after the adoption of an inflation targeting framework in the year 2000. Given that trend inflation shocks were prominent in the earlier part of the sample, this finding explains why actual headline and core inflation moved closely in the pre 2000 period. Second, the variability of the trend component of CPI-all is significantly higher than its core inflation counterparts. This is a surprising result since we expect the trend of

CPI-all to be more or less in line with those of the core inflation measures given that shocks to food and energy price sectors are largely transitory. The results here thus suggest that food and energy price shocks have a persistent component and the usual practice of discarding these sectors altogether from core inflation measures may lead to biased estimates of the trend.

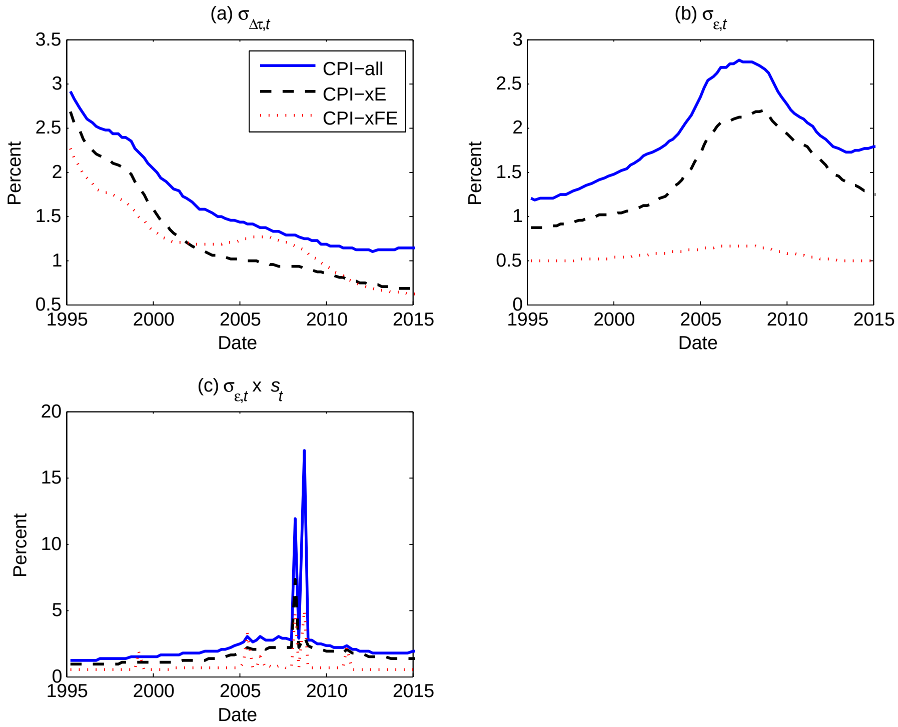
Figure 3: CPI Inflation and Filtered Univariate Trends



The variability of the transitory components of CPI-all and core measures also exhibit important differences, as shown in Panel (b) and (c) of Figure 4. For CPI-all and CPI-xE, the volatility of the high frequency component peaked during the height of the global financial crisis despite significant outliers already being captured by the variable s_t. For the CPI-xFE series, it can be seen that once food and energy components have been completely removed from CPI-all, the variability of the transitory component as well as the existence of outliers decline dramatically, particularly during the global financial crisis[8]. Therefore, based on the estimated volatilities of the transitory shocks in the UCSVO, we can infer that Thai inflation was largely driven by fluctuations in food and energy prices, particularly during the mid to late 2000 period.

[8]Examining panel (a) further, some of the variation from the global financial crisis show up in the trend component of CPI-xFE. However, based on the confidence bands associated with filtered trend estimates, this occurrence may merely be a reflection of sampling errors.

Figure 4: Smoothed Estimates of UCSVO Permanent and Transitory Volatilities

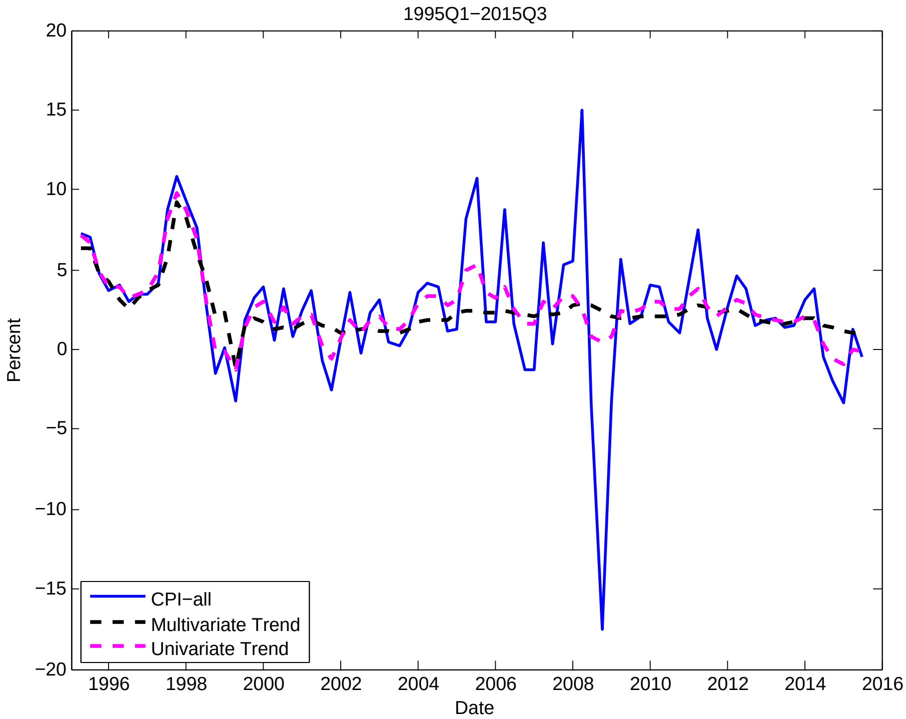


4.4 MUCSVO Results

The MUCSVO aggregate trend based on 10 sectors is plotted in Figure 5 alongside the estimated UCSVO trend from CPI-all and actual headline inflation. As shown, the multivariate trend is a smoother version of the univariate trend, particularly during the post 2000 period. Examining the plots more closely, the univariate and multivariate trends diverged most during times of large oil price changes in 2005, 2008 and 2015 where the MUCSVO trend remained relatively stable compared to its univariate counterpart.

Differences between the univariate and multivariate models can be discerned more closely from the estimated posterior means of $\sigma_{\Delta\tau,c,t}$, $\sigma_{\epsilon,c,t}$ and $\sigma_{\epsilon,c,t} \times s_t$, which are plotted alongside their 90 percent confidence bands in Figure 6. Compared with the univariate results in Figure 4, two observations stand out. First, the variability of the common permanent shocks to trend inflation ($\sigma_{\Delta\tau,c,t}$) did not peak for the MUCSVO until the Asian Financial crisis, while the variability of permanent shocks to trend inflation in the UCSVO model was high from the beginning of the sample. As the UCSVO does not differentiate between common and sector-specific shocks, this finding implies that persistent shocks to the trend leading up to the Asian financial crisis may have been sector-specific, before delivering persistent macroeconomic-wide effects.

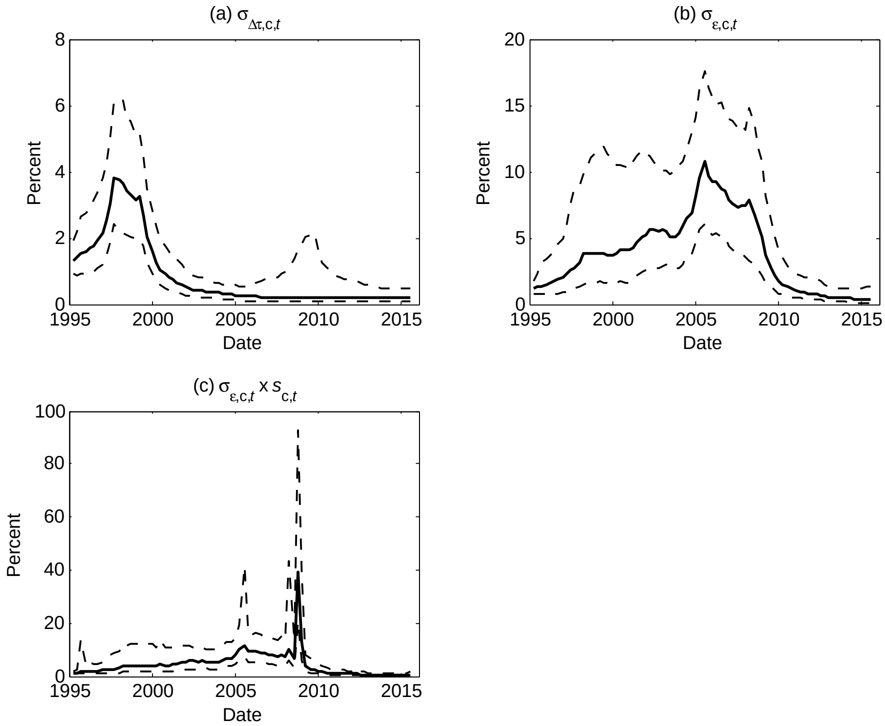
Figure 5: Multivariate Trend Inflation



A second observation is that both models detect a significant decline in trend inflation variability since the year 2000. Since changes in monetary policy are known to have permanent effects on inflation, the adoption of an inflation targeting framework by the BOT in May 2000 most likely explains this result. However, the decline in trend inflation variability during the year 2000 as suggested by the MUCSVO model was much more abrupt. Furthermore, MUCSVO trend estimates are also much lower and more stable during the post 2000 period, highlighting the effectiveness of the inflation targeting framework in anchoring long-term inflation expectations.

Turning to examine the variability of the common transitory component ($\sigma_{\epsilon,c,t}$) in Panel (b) of Figure 6, both univariate and multivariate models show a substantial increase in the volatility of the high frequency component during 2005-2010. However, unlike the MUCSVO, the volatility of the transitory factor for CPI-all as captured by the UCSVO model remains high and is even slightly on the rise towards the end of the sample. Finally, as shown in Panel (c), the behavior of large one-time shocks to the transitory components as captured by the univariate and multivariate models are more or less similar.

Figure 6: Smoothed Estimates of MUCSVO Permanent and Transitory Volatilities



Next, we analyze the time-varying weights that are implicitly used to construct the multivariate trend. To compute these weights, first recall that at any given point in time, the one-sided estimates of the multivariate trend is a nonlinear function of current and past values of the 10 sectoral series, making the weights become complicated time-varying functions of the volatilities, persistence, and correlations across sectors. Due to the existence of outliers however, obtaining an exact representation for the time-varying weights in terms of a linear weighted average is not feasible. Therefore, we resort to an approximation by computing the one-sided trend from applying a Kalman filter to Eqs. (8)-(12). In doing so, we ignore outliers by setting $s_{c,t} = s_{i,t} = 1$ and hold the time-varying factor loadings and volatilities $(\alpha_{i,c,t}, \alpha_{i,\tau,t}, \Delta ln(\sigma^2_{\Delta\tau,c,t}), \Delta ln(\sigma^2_{\epsilon,i,t}))$ fixed at their full-sample posterior means. Then, we compute the filtered trend for each sector in the multivariate model as:

$$\tau_{i,t|t} = \sum_{j=0}^{\infty} \omega_{i,j,t}\pi_{i,t-j} \tag{16}$$

where $\omega_{i,j,t}$ are the implied time-varying weights.

Figure 7 plots the approximated linear weight for each sector alongside its corresponding expenditure share in headline CPI inflation. Following Stock and Watson

(2015), the linear weights for each sector is defined as a time-varying share, computed as $\bar{\omega}_{i,t} = \sum_{j=0}^{3} \omega_{i,j,t} / \sum_{i=1}^{10} \sum_{j=0}^{3} \omega_{i,j,t}$. Note that the sum of all approximated linear weights will sum to one and that when we compare the approximate linear weights to its expenditure share, the linear weight for each sector shows whether the sector is getting more or less weight in the MUCSVO trend than it does in CPI-all.

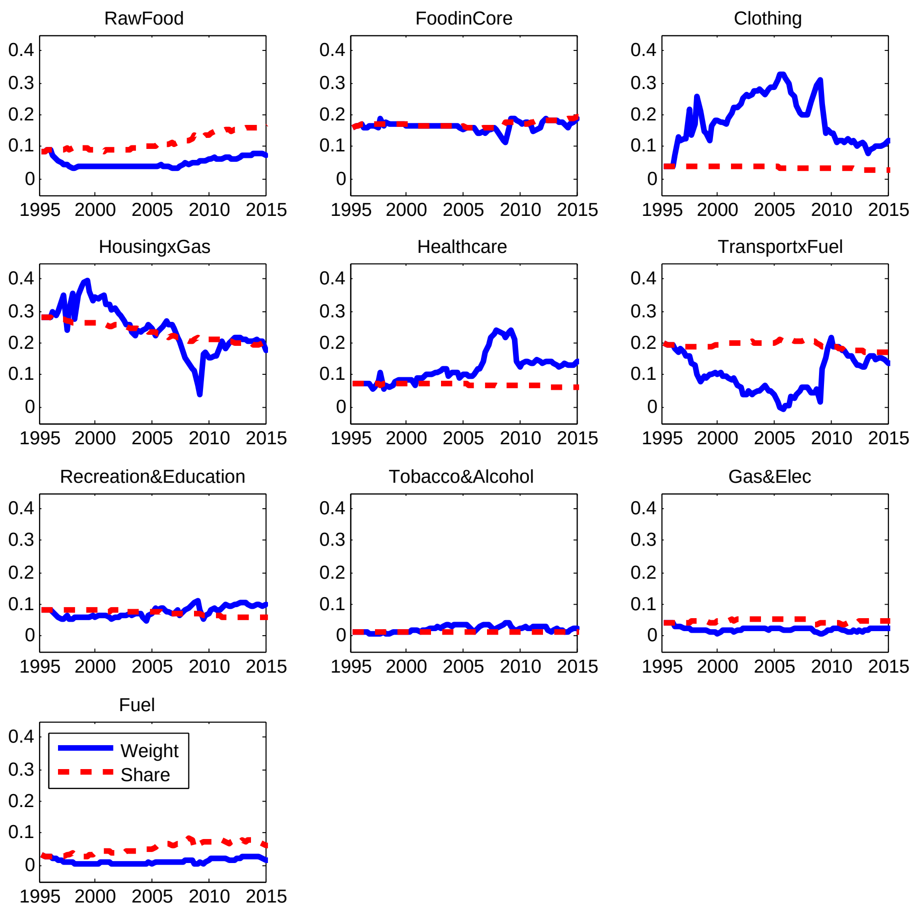
The importance of allowing for time-varying sectoral weights in the MUCSVO cannot be understated. A quick glance at Figure 7 reveals that more than half of the sectoral weights show significant time-variation throughout the sample despite their expenditure shares being relatively constant. The nature of time variation in each sectoral series also changed over time. For example, since the global financial crisis, the variability of the weight on food in core picked up to some extent, most likely due to events such as sharp rises in global food prices in 2008, increases in food prices due to the swine disease epidemic in 2011, and changes in government policy measures that affected household LPG prices in 2013.

To gain more intuition on the underlying factors that drive time-variation in the sectoral weights, we plot estimates of the sector-specific filtered trends, volatilities, factor loadings, and outliers for both permanent and transitory components in Figures 12-21, which are placed in the Appendix due to space considerations. For all sectors, we observe that estimates of the factor loadings and the volatilities of the sector-specific trend components ($\alpha_{i,\tau,t}$ and $\sigma_{\Delta\tau,i,t}$) remain relatively stable. This finding implies that the decline in the aggregate MUCSVO trend during the year 2000 that we observed in Figure 5 must have mainly stemmed from changes in common rather than sector-specific persistent shocks. In other words, the driving factor must have been a macroeconomic-wide shock, making the adoption of an inflation targeting framework by the BOT a leading explanation.

Next, we focus on analyzing the sectors that display more time-variation in the sectoral weights than others, namely clothing, housing excluding gas, healthcare, and transportation excluding fuel. First, for the clothing sector, despite having a relatively low expenditure share in CPI-all, it commands considerable weight in the MUCSVO trend, especially during the 1997-2010 period. This sizable share can be explained by the volatility of transitory shocks to the clothing sector as shown in Panel (d) of Figure 14, which is considered to be exceptionally low particularly when compared to the estimates of $\sigma_{\epsilon,i,t}$ of other sectors.

Second, the implied sectoral weight for the housing excluding gas and electricities sector is sizable, in line with its importance in the CPI basket. However, compared to its expenditure share, the implied weight for the housing sector was higher in the pre 2002 period but lower during 2008-2010. According to Figure 15, this is because the earlier period corresponded to a low factor-loading estimate for the transitory component ($\alpha_{i,\epsilon,t}$), whereas the latter period was affected by a large number of sector-specific outliers.

Figure 7: Implied Weights in the Filtered MUCSVO Trend and Actual Expenditure Shares



Next, while the estimated weight for the healthcare sector was comparable to its actual expenditure share in the pre 2005 period, it became increasingly important in the period thereafter. According to Figure 16, this is because transitory shocks to the healthcare sector in the mid 2000s became less volatile. Last, for the transportation excluding fuel sector, the sectoral weight was comparable to its expenditure share in the post 2010 period, but was lower during 1997-2010. Based on panel (c) of Figure 17, this result is not surprising given the rising influence of the factor loading on the common transitory component prior to 2010.

Three Sector Results

Traditional core inflation measures typically exclude raw food and energy sectors from measures of trend inflation due to high volatility in these components. This is confirmed by estimates of $\sigma_{\epsilon,i,t}$, as plotted in Figures 12, 20, and 21. For Thailand, the fuel sector in particular exhibits the highest degree of volatility, while gas and electricity sector contains many outliers.

While these sectors certainly exhibit substantial volatility, the filtered weights for these sectors in Figure 7 are not exactly zero, implying that they should not be excluded from measures of trend inflation altogether. In other words, these sectors contain persistence that can serve as useful indicators for trend inflation, which is especially important to account for given the substantive role that food and energy components play in Thailand's consumer price basket.

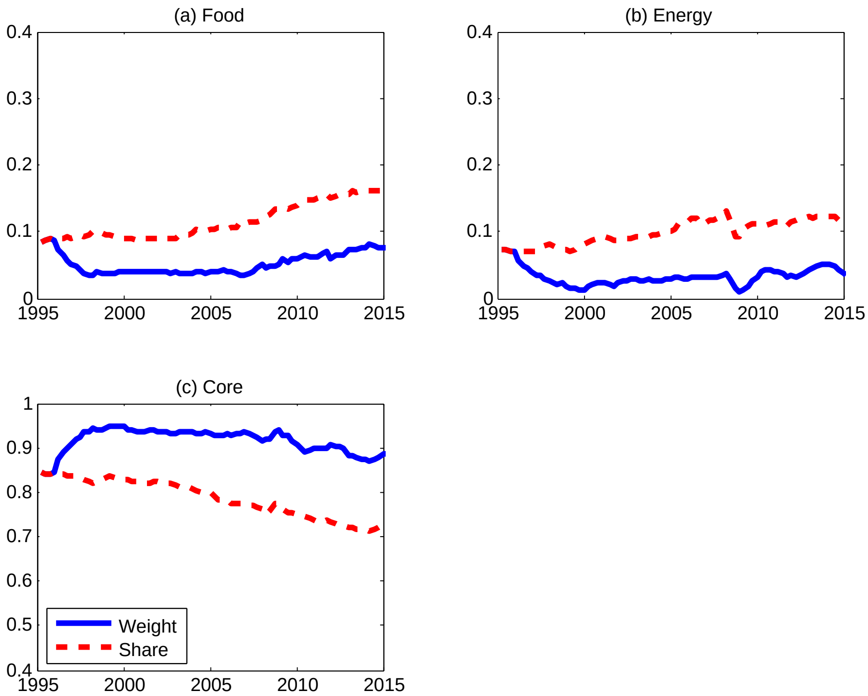
To gain intuition on the role of food and energy price sectors towards trend inflation measurement, the results from the 10 sector model are grouped into 3 sectors as shown in Figure 8. Here, the raw food sector is relabelled as the food component, both the gas and electricity and fuel components are aggregated as an energy component, and the remaining sectors make up the core component.

Panel (a) of Figure 8 displays the implied weight on the food sector. As shown, the filtered weight gradually increases from year 2007 onwards and reaches a level of nearly 0.1 by the end of the sample. While the rising expenditure share of actual raw food items could explain this result, according to estimates of $\sigma_{\epsilon,i,t}$ in Figure 12, the food sector could have also become more important in the MUCSVO trend due to the sizable fall in the volatility of its transitory component since 2007.

In contrast, the implied weight on the energy component as shown in Panel (b) of Figure 8 appears relatively stable, especially when compared to the gradual rise in its expenditure share. Only a slight dip in the filtered weight occurred during 2008-2009, which according to Figures 20 and 21, corresponded to an increase in the variability of the transitory component due to large oil price swings. Nevertheless, despite the energy sector being highly volatile, the filtered weight for the energy sector is non-zero, implying that energy components have persistent movements that contain useful information towards measurement of the overall CPI trend.

Analyzing the dynamics of the energy component further, the factor loading on the transitory component for fuel ($\alpha_{\epsilon,i,t}$) in Panel (c) of Figure 21 is largest both in terms of its magnitude as well as its variability across time once compared to other sectors. This observation is interesting along at least two dimensions. First, the sizable factor loading on fuel implies that the dynamics of the common transitory component for Thai inflation or $\sigma_{\epsilon,c,t}$ is correlated with fuel price changes to a large extent. This implies that short-run volatility in fuel price dynamics spillover to other sectors to a significant degree. As gauged by the magnitude of the factor loading on the transitory common component ($\alpha_{\epsilon,i,t}$), sectors that are heavily influenced by fuel price fluctuations include raw food, clothing in the pre 2000 period, housing in the post 2005 period, transportation, recreation and education, and gas and electricity.

Figure 8: Implied Weights and Actual Expenditure Shares of Food, Energy and Core Sectors in the Filtered MUCSVO Trend



Another interesting observation is that the magnitude of the factor loading on the transitory component of fuel or $\alpha_{\epsilon,i,t}$ more than doubles around the year 2000. This result implies that the influence for fuel price changes on short-run inflation dynamics in Thailand intensified during that time[9]. While it is not clear within the framework of this paper what structural forces are responsible for this result, its growing importance is interesting insofar as it can explain the increase in the variability of the overall transitory component in headline inflation that picked up during the second part of the sample.

Finally, Panel (c) of Figure 8 plots the filtered weights attributed to all remaining CPI components excluding food and energy price sectors. In contrast to its corresponding actual expenditure share, the influence of core components on the estimated MUCSVO trend remains relatively stable. For the most recent period, the weight of core components in the filtered trend is around 90 percent, while food and energy takes up the remaining 10 percent share. Thus an important way in which

[9]A similar finding is reported by Manopimoke and Direkudomsak (2015). Based on an open economy New Keynesian Phillips curve for Thailand, these authors show that due to the effects of globalization, short-run fluctuations in Thai inflation has become increasingly driven by a global output gap, which moved closely with fluctuations in oil prices after the year 2007.

the MUCSVO trend differs from traditional core inflation measures is that while the latter places no weight on food and energy price components, the MUCSVO allows persistent movement in these prices to 'pass-through' to measurements of the trend.

Accuracy of Trend Estimates

Due to differences in the UCSVO and MUCSVO results, we ask whether the multivariate model can measure trend inflation more precisely than its univariate counterpart. In other words, can the use of sectoral data help reduce the uncertainty surrounding trend inflation measures? We evaluate this question based on the width of posterior uncertainty intervals that are associated with the filtered trend.

The width of posterior intervals reflect two sources of uncertainty - the signal extraction uncertainty conditional on values of the model parameters, and uncertainty about the model parameter themselves. The information set for the multivariate model is larger than the univariate model, thus signal extraction uncertainty will be by default smaller in the MUCSVO model. However, there are many more parameters to estimate in the MUCSVO model which may increase parameter uncertainty, and therefore we cannot say a priori whether the posterior intervals will be larger or smaller for the MUCSVO model when compared to its univariate counterpart.

Table 5 reports the average width of the 90 percent posterior intervals for trend inflation as computed from the UCSVO and MUCSVO filtered trends. We consider the performance of both headline and core inflation series and evaluate the MUCSVO trend based on both 3 and 10 components. The estimation is done over three intervals, 1995Q2-2000Q1, 2000Q1-2008Q4, and 2009Q1-2015Q2 to examine how the degree of accuracy may have changed over time. As a robustness check, the posterior intervals are also computed by excluding high volatility crises periods during the sample, but we find that doing so does not affect the estimation results.

For all inflation series, the multivariate model is superior, as it displays narrower bands in comparison to the univariate model, suggesting that additional information in disaggregated series can result in a substantial reduction in filtered trend uncertainty, even at the cost of additional complexity. While the 3 component multivariate model generally performs well, the 10 component model results are even more impressive. First of all, the 10 component MUCSVO outperforms the 3 component model for all inflation series except for CPIxE and CPIxFE in the pre 2000 period. Second, the posterior intervals associated with the 10 component MUCSVO model for CPI-all trend is approximately half as narrow when compared to the UCSVO corresponding intervals. For CPIxE and CPIxFE, the relative improvements in accuracy of the 10 component model over its univariate counterpart more than doubles in the post 2000 period.

Table 5: Average Width of 90 Percent Posterior Intervals for Trend Inflation

Inflation Series	1995Q2-1999Q4	2001Q1-2006Q4	2009Q1-2015Q2
Univariate			
CPI-all	3.91	4.92	3.98
CPIxE	2.99	3.77	3.09
CPIxFE	2.01	2.50	1.63
Multivariate (3 components)			
CPI-all	2.98	3.05	2.83
CPIxE	1.55	1.72	2.16
CPIxFE	1.07	1.29	1.60
Multivariate (10 components)			
CPI-all	1.98	1.73	1.93
CPIxE	1.77	1.36	1.40
CPIxFE	1.39	1.03	0.77

5. Inflation Forecasting

Trend inflation is defined as long-horizon forecasts of inflation. Therefore, whether a certain trend measure is a good indicator of underlying price pressures can be evaluated by their ability to forecast headline inflation. In this section, we analyze the predictive abilities of filtered UCSVO and MUCSVO trends against other benchmark trend measures that are commonly used by the BOT. Following the literature, we focus on forecasts at the 1-3 year horizon, which is typically the horizon used for monetary policy analysis. Due to space considerations, the results reported here are only based on the 2 year horizon (8 quarter-ahead) while others are available upon request.

5.1 In-Sample Results

We first evaluate the in-sample predictability of UCSVO and MUCSVO filtered trend estimates against CPIxE and CPIxFE core inflation measures, the asymmetric trimmed mean, and trend inflation calculated from the principal components approach. All competing forecasts are evaluated based on their ability to predict the average value of inflation over the next 8 quarters i.e. $\bar{\pi}_{t+1:t+h} = h^{-1}\sum_{i=1}^{h}\pi_{t+i}$ where $h = 8$. To evaluate how the forecasting performance of the various trend measures change over time, we evaluate the accuracy of forecasts based on the average of its root mean squared errors (RMSE) over a five year horizon, calculated as:

$$\sqrt{\frac{1}{20}\sum_{\tau=t}^{\tau+19} e^2_{\tau+h|\tau}},$$

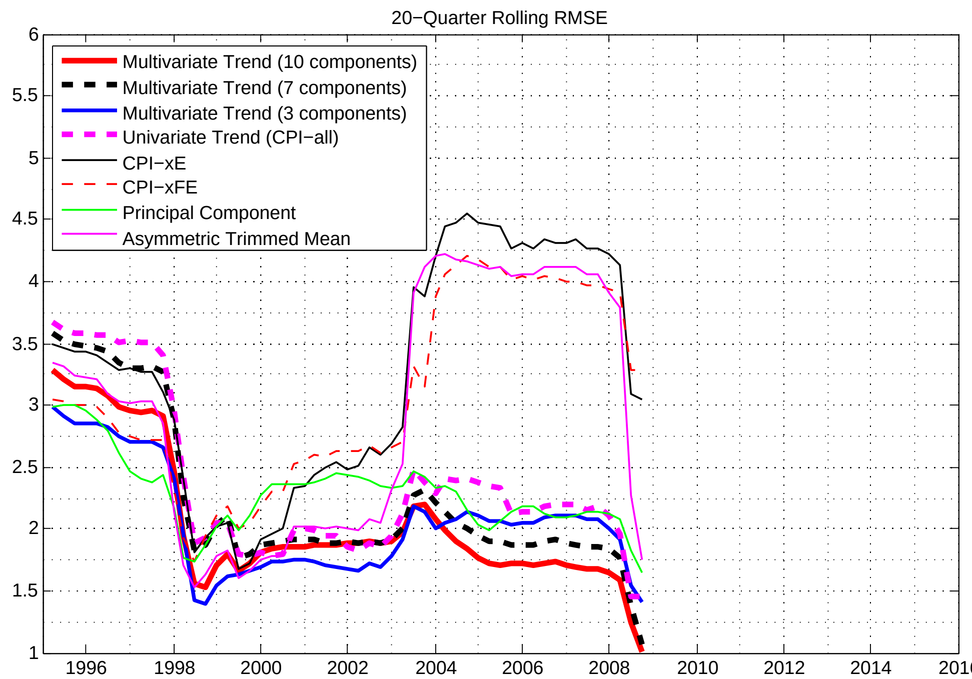
where the model-based forecast errors for $h = 8$ is defined as:

$$e_{t+h|t} = \frac{1}{h}\sum_{t=1}^{h} \pi_{t+i} - \tau_{t|t}.$$

and $\tau_{t|t}$ represents the current period trend estimate computed from all available information available at time t. For the UCSVO and MUCSVO, $\tau_{t|t}$ is the one-sided posterior mean.

Figure 9 plots the 5 year rolling RMSEs for 8 quarter-ahead inflation forecasts, calculated from t=1995Q1 until the end of sample. An interesting observation is that prior to the year 2000, the RMSEs from all trend measures are more or less comparable. During this period, the UCSVO trend performed worst while the 10 component and principal component trend outperformed others by only a modest margin.

Figure 9: Rolling Five-Year RMSEs for 8-Quarter Ahead Inflation Forecasts



Note: Reported are the averages of the RMSEs for various trend inflation measures based on a rolling five-year estimation window beginning in 1995Q1.

After the early 2000s period however, the RMSEs associated with core and asymmetric trimmed mean measures increased significantly. On the other hand, RMSEs of other trend estimates remained low, with the 10-sector MUCSVO forecasts containing the smallest RMSEs, followed by the 7 and 3 sector multivariate and UCSVO models respectively. The performance of the principal components trend is more or less in line with the UCSVO. Based on these results, additional information in sectoral inflation data appears to help forecast inflation, as the MUCSVO is able to deliver superior forecasts when compared to its univariate counterpart. However, given that core inflation also utilizes cross-sectional data but fares rather poorly suggests that the use of sectoral data alone cannot guarantee reliable forecasts for headline inflation. Rather, time-variation in sectoral weights is also an important feature needed for trend inflation measurement in Thailand.

One concern from the forecasting results above is that the RMSEs of the UCSVO are fairly close to its multivariate counterpart. To assess whether the differences in forecast errors from the competing models are statistically significant, we resort to the modified Diebold-Mariano test statistic[10]. The test-statistic is calculated based on the following null hypothesis:

$$H_0 : E(|e_{i,t+h|t})| - (|e_{UCSVO,t+h|t})|) = 0,$$

where all competing trend measures are evaluated against the UCSVO.

The calculated test-statistics along with their associated p-values are reported in Table 6. The predictive accuracy test results are evaluated within the full 1995Q2-2015Q2 sample, as well as over two subsamples after the year 2000. First, the full-sample results suggest that all multivariate models based on 10, 7 and 3 components outperform the UCSVO at the 10 percent confidence level. The remaining measures for trend inflation based on the PCA, asymmetric trimmed mean, and core inflation measures however, do not offer significant improvements in predictive ability over the UCSVO.

The next column of Table 6 contains the predictive accuracy test results for the 2000Q1-2015Q2 period, which corresponds to Thailand's inflation targeting regime. The MUCSVO trends again offer significant improvements over its univariate counterpart, with the exception of the 7-component MUCSVO model. Similar to the full sample results, the PCA does not outperform the UCSVO, implying that information in the correlation structure alone cannot guarantee good estimates of the trend.

[10]The original Diebold-Mariano test statistic is a t-statistic associated with the null hypothesis that the mean squared errors of the two forecasts being compared is zero (Diebold and Mariano, 1995). The modified version as derived by Harvey et al. (1997) attempts to correct for the poor size property of the original test statistic in small samples.

Table 6: Tests of Equal Predictive Accuracy for In-Sample Inflation Forecasts

Inflation Trend	1995Q2-2015Q2	2000Q1-2015Q2	2005Q1-2015Q2
Multivariate (10 components)	-2.162 (0.017)	-1.401 (0.083)	-3.542 (0.001)
Multivariate (7 components)	-1.450 (0.075)	-1.074 (0.144)	-2.541 (0.079)
Multivariate (3 components)	-2.428 (0.009)	-1.365 (0.089)	-2.701 (0.005)
Principal Components	-0.178 (0.429)	0.748 (0.229)	-0.200 (0.421)
Asymmetric Trimmed Mean	0.552 (0.291)	1.248 (0.109)	1.419 (0.082)
CPIxE	2.357 (0.011)	3.061 (0.002)	2.632 (0.001)
CPIxFE	1.094 (0.139)	2.227 (0.015)	1.906 (0.033)

Note: The table shows the modified Diebold Mariano test-statistic and their corresponding p-values in parenthesis for the null of equal predictive accuracy between competing trend inflation measures against the UCSVO trend.

Last, similar conclusions can be drawn from the 2005Q1-2015Q2 period. All multivariate models are now superior to the UCSVO while the UCSVO still delivers more accurate forecasts over traditional core and trimmed mean measures. Based on these findings, we can therefore conclude that the MUCSVO offers significant gains to inflation forecasting over its univariate counterpart as well as other trend inflation measures such as core inflation. This results imply that disaggregated sectoral inflation data and time-varying sectoral weights are attractive features that can help improve the overall predictive ability of trend inflation constructs.

5.2 Out-of-Sample Results

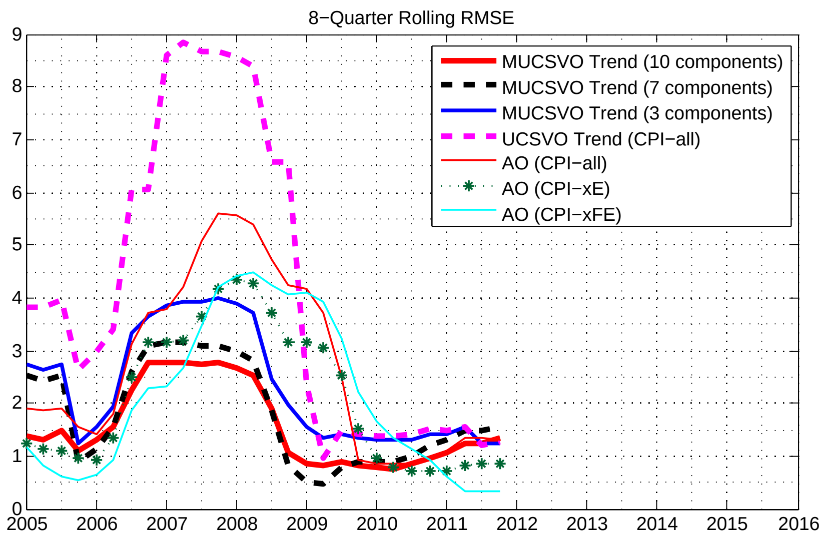
A puzzle in the inflation forecasting literature for the US is that while inflation has become more stable and subdued in the post 1980s period, it has become harder to forecast out-of-sample. Atkeson and Ohanian (2001) show that during this period, backward-looking Phillips curve forecasts in the US are not able to outperform a naïve forecast of 12 month inflation by its average rate over the previous 12 months. This result implies that information about real economic activity in the Phillips curve offers no predictive information over univariate measures of inflation. The same conclusion is reached by Stock and Watson (2007), where they show that the an unobserved components model with stochastic volatility (UCSV) can offer significant gains in inflation forecasting over traditional Phillip curve models.

In this section, we assess the out-of-sample predictive ability of the MUCSVO against benchmark univariate models that are known to forecast inflation well, namely the UCSV and the AO model. However, instead of the UCSV, we use the UCSVO in this forecasting exercise with model-based adjustments for outliers. We follow Stock and Watson (2007) and compute the AO forecast as the average of 8-quarters-ahead inflation based on the 8-quarter-average of inflation today. As before, we evaluate 8-quarter-ahead inflation forecasts, except that now we perform an out-of-sample inflation forecasting exercise based on a rolling estimation window of 5 years.

Based on the previous in-sample forecasting results, there is not much difference in predictive accuracies across competing trend inflation measures in the pre 2000 period. For this reason, we focus only on the post inflation targeting regime for our out-of-sample forecasting exercise. In particular, we compute our first 8-quarter-ahead out-of-sample forecast of 2005Q2 using the 2000Q1-2004Q4 sample. The reason why we did not start our sample earlier to forecast 2000Q1 inflation is to avoid any parameter instability issues that could occur from the switch to the inflation targeting framework in the year 2000.

The five-year rolling RMSEs associated with the 8-quarter-ahead inflation forecasts are displayed in Figure 10. Similar to the in-sample forecasting results, the MUCSVO trend delivers forecasts with the lowest RMSEs. The AO model also performs relatively well except for a brief period during the global financial crisis. We conjecture that since the AO model does not have a built-in approach to deal with outliers like the MUCSVO, the naïve random walk process may not be able to adapt quickly enough to large changes in prices that occurred during the crisis.

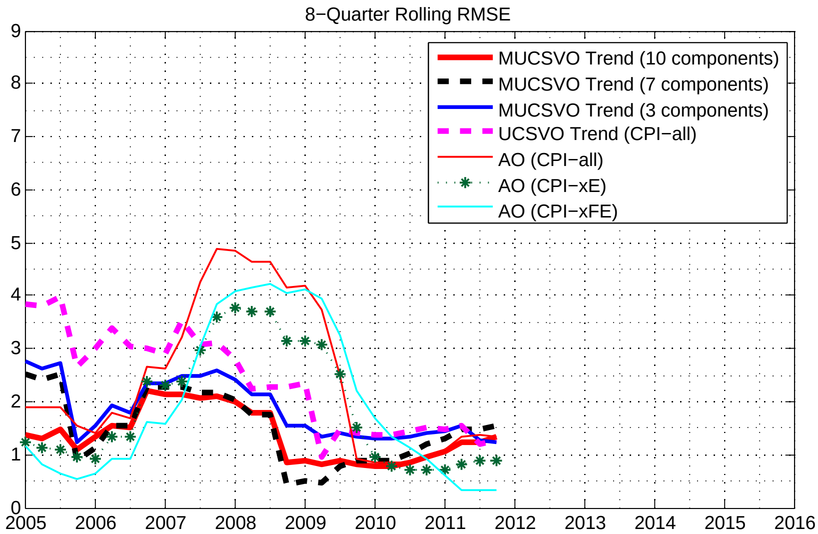
Figure 10: Rolling Five-Year RMSEs for 8-Quarter Ahead Out-of-Sample Inflation Forecasts



Note: Reported are the averages of the RMSEs associated with 8-quarter-ahead out-of-sample inflation forecasting based on a five-year rolling estimation window beginning in 2000Q1.

One surprising observation from the out-of-sample inflation forecasting results is that the RMSEs associated with the UCSVO forecast errors are exceptionally high. Investigating further, we found that the poor performance of the UCSVO model stems from the inability of the model to detect outliers in 2008Q2 and 2008Q4, leading to inferior inflation forecasts. Removing these two data points from the sample significantly improved the ability of the UCSVO to forecast headline inflation, as shown in Figure 11. Since the MUCSVO does not have a similar problem, this finding implies that separating common from sector-specific components can help the unobserved components model identify outliers.

Figure 11: Rolling five-year RMSEs for 8-quarter ahead out-of-sample inflation forecasts with outliers removed



Note: Reported are the averages of the RMSEs associated with 8-quarter-ahead out-of-sample inflation forecasting based on a five-year rolling estimation window beginning in 2000Q1 with the outliers in 2008Q2 and 2008Q4 removed.

Finally, similar to the in-sample forecasting results, the forecast errors associated with some competing trend measures in Figure 11 are fairly close. Table 7 contains the modified Diebold-Mariano test-statistic results and its corresponding p-values for the null of equal predictive accuracy. As shown, there is strong evidence that the multivariate models outperform the UCSVO. The AO model on the other hand, does not offer improved forecasts for inflation when compared to the UCSVO. Therefore, the out-of-sample forecasting results reported here thus strengthens the case that trend inflation measures constructed from the MUCSVO can offer significant improvements over univariate and existing trend inflation measures in Thailand.

Table 7: Tests of Equal Predictive Accuracy for Out-of-Sample Inflation Forecasts

Inflation Trend	Test-statistic (p-value)
Multivariate (10 components)	-4.373 (0.000)
Multivariate (7 components)	-3.147 (0.001)
Multivariate (3 components)	-2.112 (0.021)
AO (Headline)	-0.379 (0.353)
AO (CPI-xE)	1.397 (0.085)
AO (CPI-xFE)	-0.992 (0.164)

Note: The table shows the modified Diebold Mariano test-statistic and corresponding p-values for the null of equal predictive accuracy between competing trend inflation measures against the UCSVO trend.

6. Conclusion

During past decades, inflation dynamics in Thailand has undergone a number of key changes. This paper highlights the importance of accounting for such changes when constructing measures of trend inflation. Based on the multivariate unobserved components model with stochastic volatility and outlier adjustments (MUCSVO) as proposed by Stock and Watson (2015), we deliver estimates of trend inflation for Thailand that improves upon conventional measures.

The empirical findings highlight at least two important features that are important towards trend inflation measurement. First, the MUCSVO utilizes disaggregated sectoral inflation data, which contains a richer set of information when compared to the univariate series of inflation alone. This enables the MUCSVO to better differentiate between system-wide and sector-specific shocks as well as identify outliers, leading to more accurate measures of the trend. We find that when compared to its univariate counterpart, the posterior intervals associated with the MUCSVO filtered trend is approximately half as narrow. Furthermore, the forecast errors associated with the MUCSVO trend when forecasting 8-quarter-ahead inflation both in-sample and out-of-sample are significantly smaller than its univariate counterpart, as well as other existing measures of trend inflation for Thailand.

The second attractive feature of the MUCSVO is that through time-varying sectoral weights, the influence of sectoral price shocks is allowed to pass-through to trend inflation as well as change over time. This is different from the conventional approach used to construct core inflation, which uses fixed weights and completely removes certain volatile sectors such as food and energy for all time periods. The estimation results show that time-variation in sectoral weights is important, as more than half of the sectoral weights contain significant time variation due to changes in its persistence or its underlying structure of shocks. We find that food and energy price sectors that are typically excluded from measures of core inflation in fact have persistent dynamics that drive approximately 10 percent of trend inflation movements for Thailand.

The empirical findings also help shed light on why traditional measures of the trend such as core inflation diverged significantly from headline for sustained periods since the year 2000. In the pre 2000 period, inflation dynamics in Thailand was mainly driven by permanent shocks, causing headline inflation to move more or less in line with its core. However, after the adoption of an inflation targeting regime, trend inflation became exceptionally low and stable, while transitory shocks which mainly originated from fuel price changes became the more prominent driver behind inflation rate fluctuations. Since measures of core inflation typically exclude these volatile sectors altogether, it is not surprising that headline and core differed to a significant degree. Nevertheless, the fact that the two series diverged for sustained periods imply that the components that are excluded from core inflation may contain persistent price movements that should enter into estimates of the trend. These are food and energy price components, which according to the MUCSVO, account for approximately 10 percent of fluctuations in the overall trend.

In sum, this paper highlights the importance of allowing for persistent movements in the sectoral inflation series to 'pass-through' to trend inflation according to the changing nature of its underlying price shocks. So far, disaggregated data based on 10 components have given us improved insight on key issues that are important to trend inflation measurement in Thailand. Future studies that utilize disaggregated price components on a much finer level are highly encouraged, and would undoubtedly be beneficial towards helping us navigate through the challenges of real-time trend measurement.

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Appendix

Figure 12: Raw Food

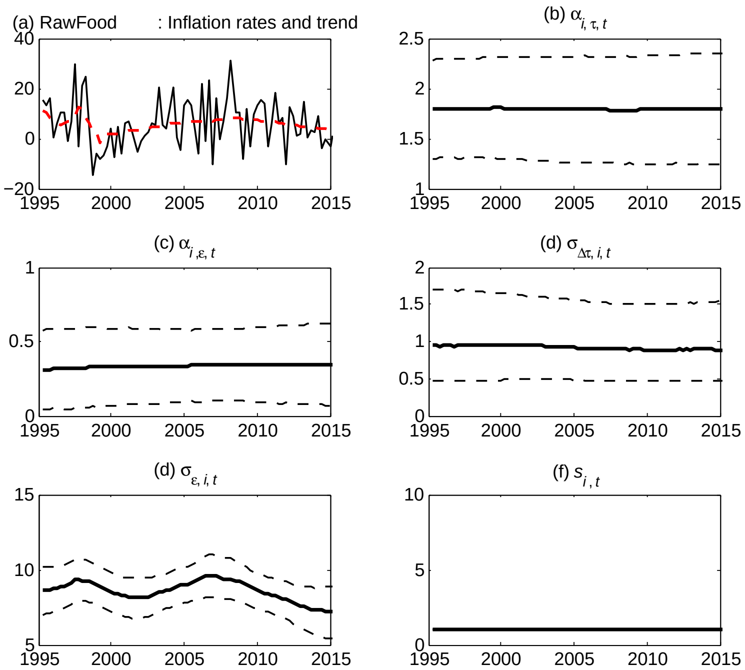
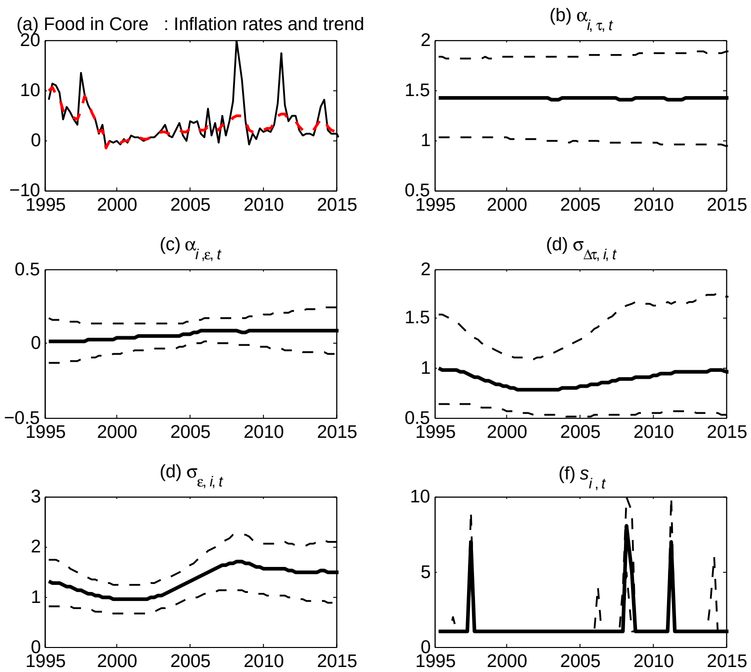


Figure 13: Food in Core



(a) Series (solid), trend (dashed red) (b) factor loadings of common trend (c) factor loading on common transitory component (d) standard deviation of sector-specific permanent component (e) standard deviation on sector-specific transitory component (f) outlier in the transitory component.

Figure 14: Clothing

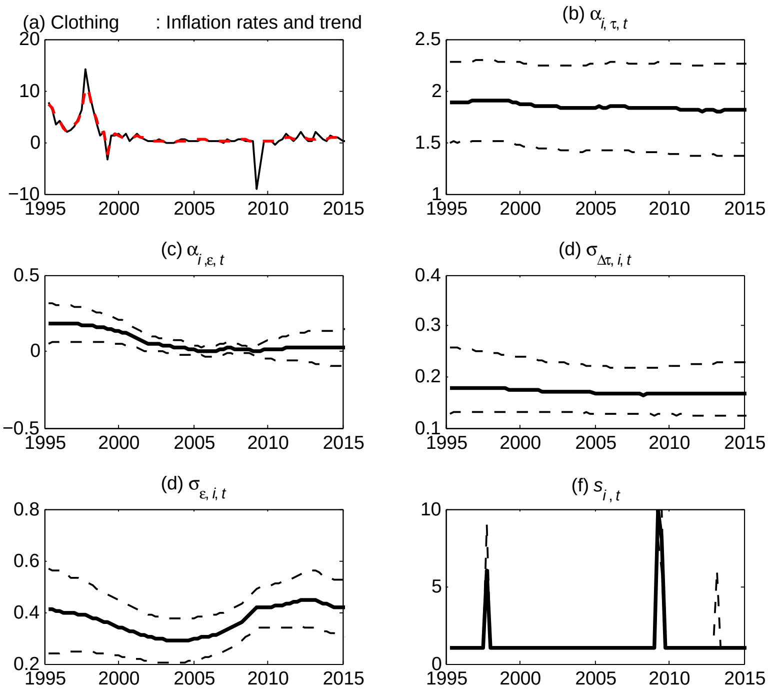
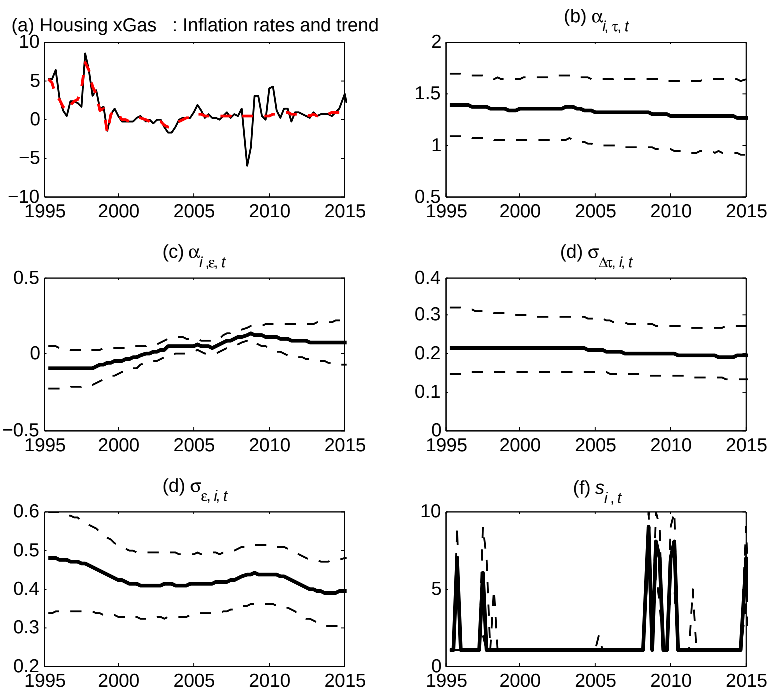


Figure 15: Housing excluding gas and electricity



(a) Series (solid), trend (dashed red) (b) factor loadings of common trend (c) factor loading on common transitory component (d) standard deviation of sector-specific permanent component (e) standard deviation on sector-specific transitory component (f) outlier in the transitory component.

Figure 16: Healthcare

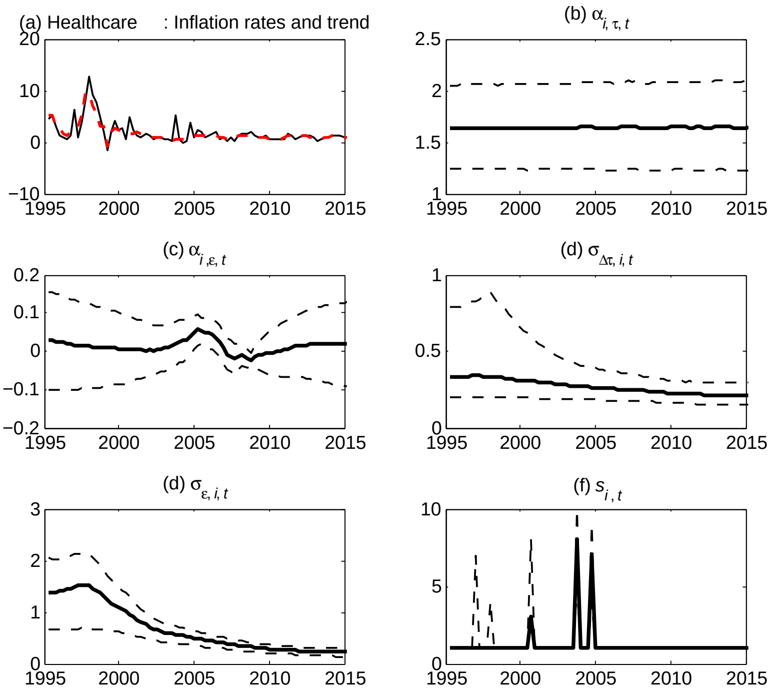
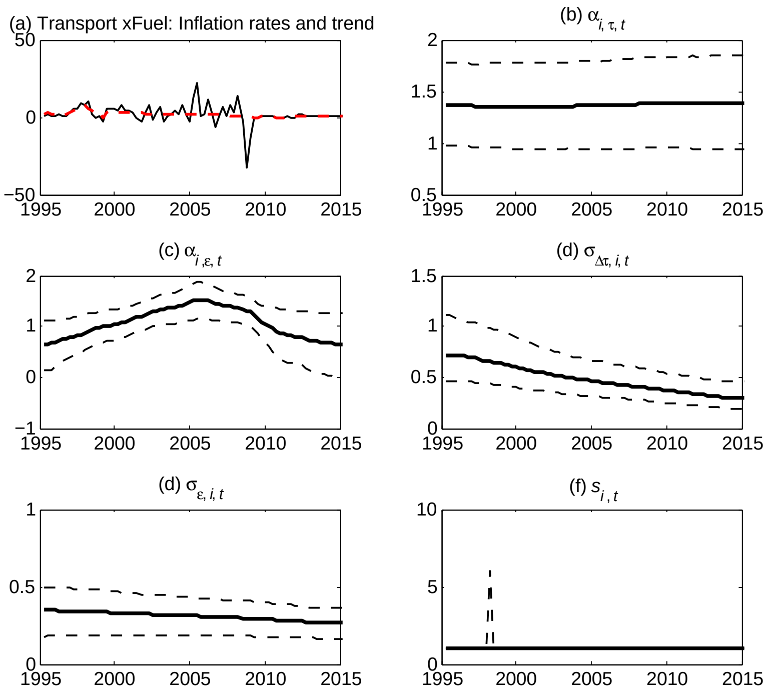


Figure 17: Transporation exclude fuel



(a) Series (solid), trend (dashed red) (b) factor loadings of common trend (c) factor loading on common transitory component (d) standard deviation of sector-specific permanent component (e) standard deviation on sector-specific transitory component (f) outlier in the transitory component.

Figure 18: Recreation and education

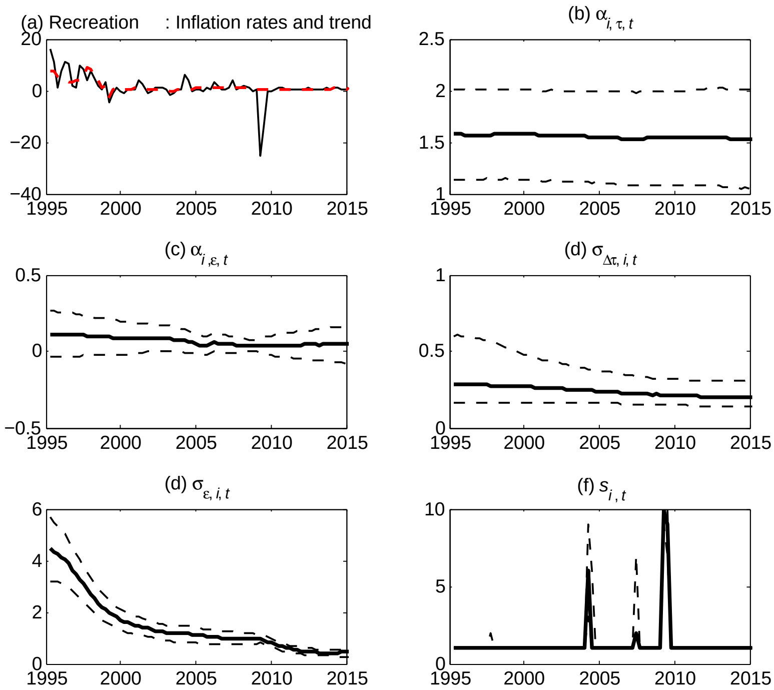
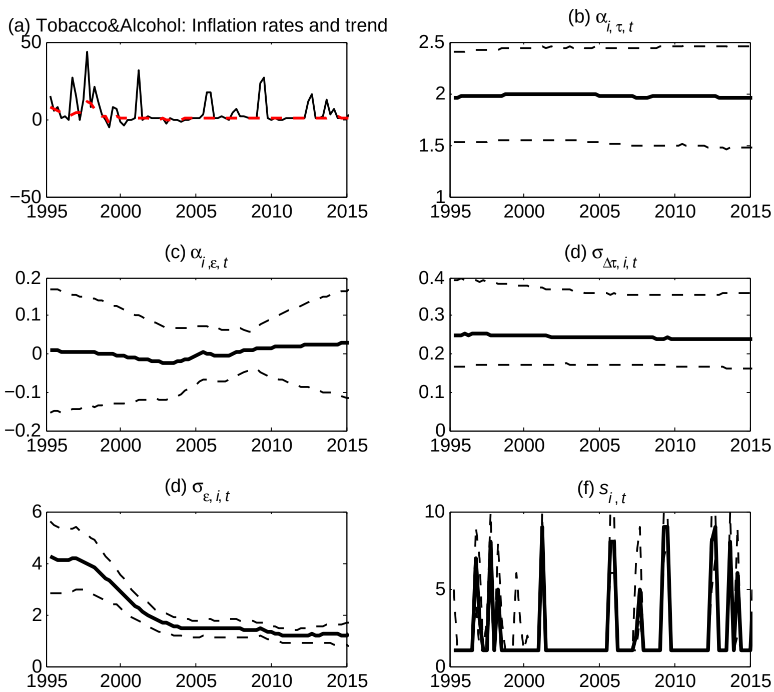


Figure 19: Tobacco and alcohol



(a) Series (solid), trend (dashed red) (b) factor loadings of common trend (c) factor loading on common transitory component (d) standard deviation of sector-specific permanent component (e) standard deviation on sector-specific transitory component (f) outlier in the transitory component.

Figure 20: Gas and electricity

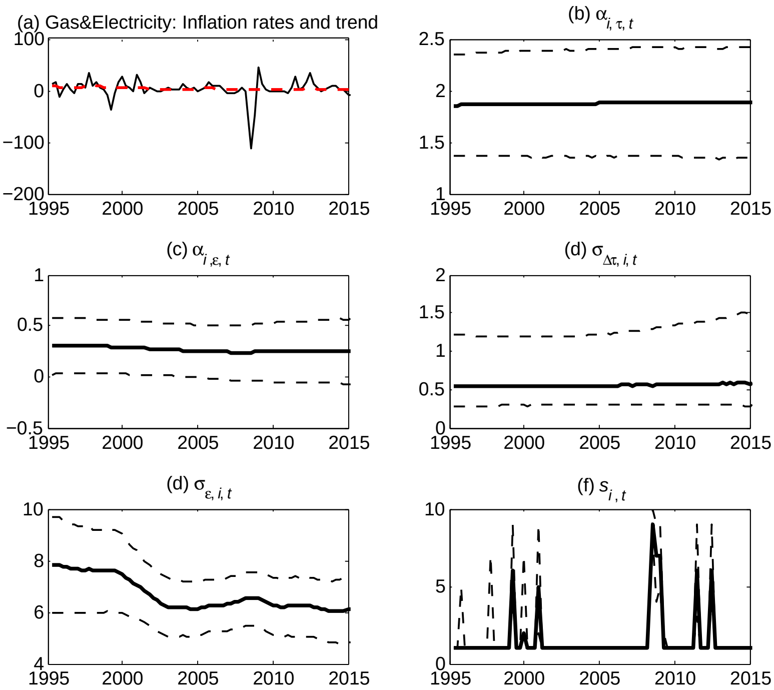
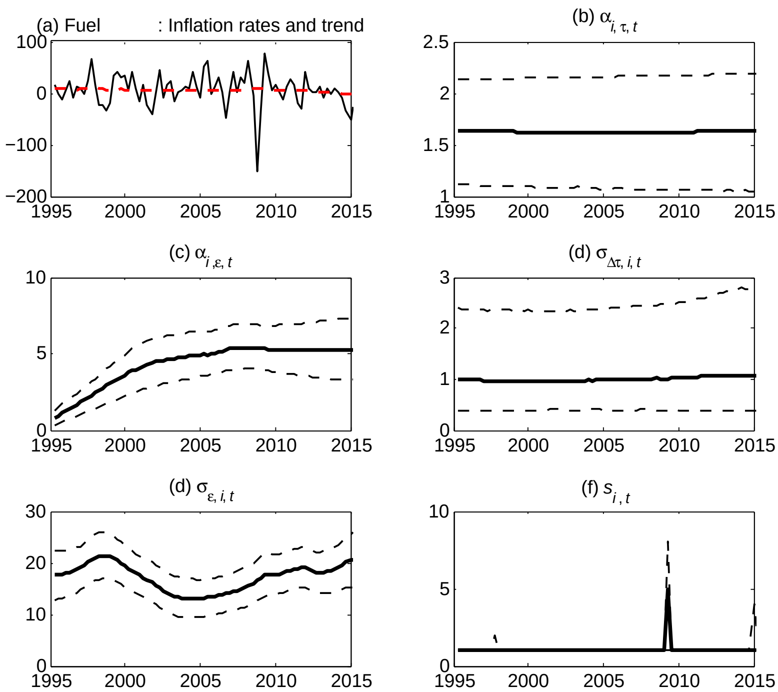


Figure 21: Fuel



(a) Series (solid), trend (dashed red) (b) factor loadings of common trend (c) factor loading on common transitory component (d) standard deviation of sector-specific permanent component (e) standard deviation on sector-specific transitory component (f) outlier in the transitory component.