Trend Inflation Estimates for Thailand from Disaggregated Data*

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Abstract: This paper examines whether the multivariate unobserved components model with stochastic volatility and outlier adjustments (MUCSVO) of Stock and Watson (2015) can improve upon existing trend inflation measures for Thailand. Based on disaggregated data on sectoral inflation, the MUCSVO model explicitly accounts for common and sector-specific trends, and allows for time-varying sectoral weights which depend upon the comovement among sectors as well as the time-varying volatilities and persistence of the sectoral inflation series. The main findings are: (i) the resulting trend estimates from the MUCSVO model are smoother than univariate measures of trend inflation; (ii) the common trend component dominates Thai inflation rate movements up until the adoption of an inflation targeting framework in the year 2000, but since then the common transitory component plays a more prominent role; (iii) approximately half of the estimated sectoral weights are time-varying in contrast to their relatively stable expenditure shares; (iv) while raw food and energy components are noisy, persistence in these sectoral series are prominent enough to help explain approximately 10 percent of the filtered trend inflation movements; (v) the model-based filtering uncertainty about trend inflation is substantially reduced upon using disaggregated series in the MUCSVO model; and (vi) the MUCSVO model forecasts 8 quarter-ahead average inflation more accurately when compared to other benchmark inflation measures.

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

The issue of trend inflation measurement is a key task for central banks, particularly for a country like Thailand that implements an inflation-targeting framework. Trend inflation can be thought of as a long-term estimate of inflation that is rid of transitory fluctuations, making it one of the most important inputs for policymaking given that it provides a prediction of the general direction of future inflation. Estimating trend inflation however, is a challenging task. First of all, given that aggregate inflation is influenced by multiple sources of noise, it is difficult to extract the persistent movements that belong to trend inflation from the overall fluctuations in the data. Second, the process of estimating trend inflation is complicated in the face of changing inflation dynamics.

Inflation dynamics in Thailand has undergone fundamental changes during recent decades. For example, a number of authors such as Chantanahom et al. (2004) and Khemangkorn et al. (2008) report declining inflation persistence, while Manopimoke and Direkudomsak (2015) show that the sensitivity of Thai inflation to its traditional driving variables have undergone structural changes. Another peculiar behavior for Thai inflation is that since the year 2000, headline inflation no longer comoved with its corresponding core inflation series, which are typically used as measures of trend inflation. Given that trend inflation is defined as the underlying long-run rate in which headline inflation should return to after the dissipation of temporary shocks, the prolonged divergence between headline and core inflation in Thailand during the post-2000 era calls into question the validity of existing trend inflation measures.

The goal of this paper is to evaluate and improve upon existing measures of trend inflation for Thailand, which should also lead to a better understanding about the changing inflation process. Currently, the Bank of Thailand (BOT) combines judgment and the output from a structural econometric model to produce forecasts of long-term inflation, which is typically defined over a 8 quarter-ahead horizon. However, a structural econometric model lacks flexibility, while relying on judgments for long-term inflation forecasts calls for a more rigorous model-based measure.

Other trend inflation estimates for Thailand include standard core inflation measures that exclude certain volatile components such as food and energy from overall inflation (Clark, 2001; Wynne, 2008), and trimmed means or medians of sectoral inflation series (Bryan and Cechetti, 1994). However, while these measures have the advantage of being straightforward to compute, the importance of different price components in the overall trend are chosen in a manner that is relatively adhoc, rather than being based on weights that are actually estimated. In response to such criticisms, statistical approaches such as exponential smoothing can be employed, but producing trend inflation estimates in this way has the pitfall of relying on information in the aggregate inflation series alone. Consequently, it may overlook important information embedded in the dynamics of the underlying sectoral components, such as its time-varying contributions to core inflation, the existence of large outliers in certain sectors, as well as changes in the comovements across sectors.

To provide an estimate of trend inflation for Thailand that fully utilizes cross-sectional information while still being grounded in a solid statistical framework, this paper estimates the multivariate unobserved components model with stochastic volatility and outlier adjustment (MUCSVO) model as proposed by Stock and Watson (2015) with disaggregated sectoral data. An appealing feature of the model is that it allows for common persistent and transitory factors as well as stochastic volatility in the common and sectoral components. This feature allows for changing persistence in sectoral inflation innovations as well as sector-specific changes in volatility. Price dynamics in each sector are also allowed to affect the common components via time-varying factor loadings, which allows for changes in the comovements across sectors. Furthermore, the MUCSVO provides a method for model-based treatment of outliers, and therefore when combined with the flexibility of the model, the MUCSVO model becomes particularly well-suited for the task of real-time trend estimation[1].

Based on the empirical results, our main findings are as follows: (i) the multivariate trend estimates are smoother and substantially more precise than univariate measures of trend inflation that are based solely on headline inflation, as the model-based estimate of the root mean squared error of the MUCSVO trend is roughly half than that of univariate measures; (ii) the common trend component for Thailand dominates inflation rate movements up until the adoption of an inflation targeting framework in the year 2000, but since then trend inflation has become well-anchored and the common transitory component becomes the prominent driver of Thai inflation instead; (iii) the implied weights in the multivariate trend for most sectoral components show substantial time-variation despite their expenditure shares being relatively constant; (iv) the multivariate trend estimates are comprised of approximately 90 percent of traditional core inflation components, while the remaining 10 percent comes from the persistent dynamics in food and energy price sectors; (v) the 8 quarter-ahead out-of-sample average inflation forecasts from multivariate

[1]Typically, econometricians may have to rely on judgmental adjustments for outliers prior to model estimation, however this approach is not feasible for real-time trend estimation because it requires knowing whether a large change will mean-revert. Accounting for outliers is important because by ignoring them altogether runs the the risk of mistaking a single large outlier for a more systematic increase in the volatility of short-run inflation movements.

trend estimates are substantially more precise when compared to other benchmark trend inflation measures, particularly since the year 2000.

This paper is organized as follows. Section 2 provides a brief review of Thailand's existing measures of trend inflation. Section 3 introduces the MUCSVO model of Stock and Watson (2015). Section 4 presents and discusses the estimation results and Section 5 analyzes the forecasting performance of the MUCSVO model against other benchmark trend inflation measures. Section 6 concludes.

2. Trend Inflation Measurement

The adoption of an inflation targeting framework in May 2000 by the Bank of Thailand (BOT) has gained unprecendented success in bringing down both the levels and volatility of the inflation process in Thailand[2]. For example, during 1995-1999, the average level of headline CPI in Thailand was as high as 4.2 percent. In the subsequent inflation targeting regime during 2000-2015, the average inflation rate in Thailand 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).

The issue of trend or core inflation measurement is truly central to monetary policy making within an inflation targeting framework. 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, total 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 yet critical task.

Broadly speaking, there are two main approaches to the signal extraction problem. The first approach is based on downweighing or excluding the most volatile and non-persistent components from cross-sectional or sectoral inflation data, which are components that are mostly influenced by supply-side shocks. Measures of core inflation that excludes food and energy components are standard examples of this approach. Core inflation measures constructed in this way are closely monitored by central banks around the world, and is favored particularly because it is straightforward and transparent, both in terms of how it is computed as well as how it can

[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 again in 2015 to correspond to headline CPI inflation at 2.5 percent with bands of plus and minus 1.5 percent.

be communicated to the public.

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 in Thailand, the housing market can at times be influenced heavily by special government policy measures. For example, during the early 2000s, tax incentives were implemented to boost recovery in the real estate market. In the end, this caused significant downward pressure on housing rent that was sustained throughout the 2002-2004 period as consumers moved away from rental accomodation to home ownership. With the housing rent component accounting for approximately a fifth of the core inflation basket, rent prices are often removed from headline inflation to prevent any distortions in overall price analyses.

Due to similar reasons, another widely considered core inflation measure for Thailand is one that excludes adminstered price items. Since 1998, administered price items accounted for more than 30 percent of Thailand's CPI basket - a sizeable share that makes Thailand a country that imposes the highest degree of price controls in the world (Peerawattanachart, 2015). To prevent large swings in inflation, the Thai government actively manages the prices of administered items, such as using oil fund levies and fuel excise taxes as instruments to stabilize domestic oil prices[3]. However, the effect of such policies tend to distort underlying price dynamics as it divorces the movements of administered price items from their true underlying demand and supply forces.

Another prominent measure of core inflation that is based on the exclusion approach are trimmed means or medians of sectoral inflation rates as proposed by Bryan and Cecchetti (1994). These methods are in some ways preferred over simple core inflation measures as described above as the set of excluded components are allowed to change over time. Thailand uses a combination of both symmetric and asymmetric trimmed mean measures to analyze underlying long-term price pressures. Based on the distribution of price changes in Thailand, the asymmetric trimmed mean measure is constructed by 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 main signal extraction approach that disentagles "noise" from headline inflation is via the use of statistical methods. An estimate of trend inflation can

[3]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 government has attempted to restructure domestic fuel pricing by reducing price subsidies as well as allowing energy prices to better reflect their true costs.

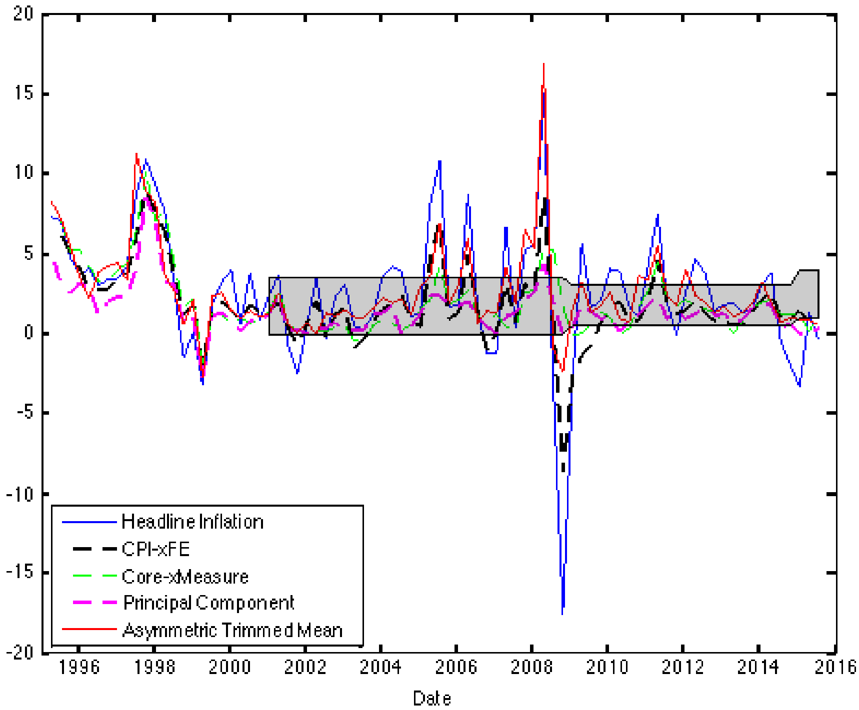
be filtered from overall movements in the price index by using univariate times-series smoothing methods such as the IMA(1,1) model of Nelson and Schwert (1997) or the four-quarter average of quarterly inflation (Atkeson and Ohanian, 2001). The unobserved components model for inflation with stochastic volatility as proposed by Stock and Watson (2007) is another signal extraction method that effectively decomposes inflation into trend and cycle based on the time-varying volatilies of shocks to persistent and non-persistent components of the univariate inflation process.

Among statistical approaches that are used to construct estimates of trend inflation, one widely used method by the BOT is based on the principal components analysis, which is a data reduction method for times series data. Based on disaggregated sectoral inflation series that excludes administered price items, the principal component analysis is employed to extract the common trend of movements that are embedded in the various price components based their variance-covariance structure. Comparing this approach to the exclusion method that simply removes pre-specified volatile price components, the advantage of the principal component method is that it selects price components to enter the overall trend 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 core inflation measures that are closely monitored by the BOT. First, it is interesting to note that around the year 2000, there has been a fundamental shift in the relationship between core and headline inflation. Prior to this period, core inflation moved closely with headline inflation, but the two series diverged to a significant extent in the period thereafter. In the latter period, headline inflation remained above core inflation for prolonged periods, only to fall below core inflation during the most recent period due to the persistent decline in world oil prices. In a way, this sustained divergence between headline and core inflation is somewhat disconcerting. This is because it implies that headline inflation is not reverting back to core inflation after temporary price shocks, which brings into question the validity of existing core inflation measures as a gauge for underlying price pressures.

Second, Figure 1 reveals significant variation among various core inflation measures themselves. During crises periods, these differences can become quite pronounced, especially in the post 2000 period. For monetary policy discussions, the BOT typically combines these core inflation measures with other estimates of trend inflation that incorporate information of economic activity, interest rates and terms of trade, such as those based on semi-structural economic and macro-finance models (Apaitan, 2015). At the same time, the BOT also relies on measures of long-term inflation expectations that are obtained from survey data for policy evaluations. Nevertheless, these additional trend inflation measures are highly disparate themselves, exacerbating the challenges that central bankers face in measuring the underlying inflationary trend. For a more detailed discussion of measurement issues and an evaluation of the various core inflation measures in Thailand, readers are referred to Griffiths and Poshyananda (2000).

Figure 1: Thailand headline and trend inflation measures



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 empirical models of Stock and Watson (2015). Their proposed multivariate unobserved components model with stochastic volatility and outlier adjustments (MUCSVO) combines the two common approaches for core inflation measurement as described in the previous section. More specifically, it utilizes statistical times-series methods to filter an estimate of trend inflation from cross-sectional inflation data. The key strengths of the model is that it allows for common persistent and transitory factors, time-variation in the factor loadings, stochastic volatility for the common and sectoral components, as well as a model-based treatment of outliers. Therefore, the resulting estimates of trend inflation will adjust on its own to changes in measurement methods as well as fundamental changes in the volatility and persistence of the component series. Since the MUCSVO model is based on a univariate unobserved components model that was developed in the authors' earlier work (Stock and Watson, 2007), this section first introduces the univariate framework before extending it to a multivariate one.

3.1 The Univariate Model

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

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

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

$$\varepsilon_t = \sigma_{\varepsilon,t} \times s_t \times \eta_{\varepsilon,t} \tag{3}$$

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

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

where the variance-covariance matrix $(\eta_\epsilon, \eta_\tau, \nu_\epsilon, \nu_{\Delta\tau})$ 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 of inflation, 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 intuition for the UCSVO model, note that without outliers, $\Delta\pi_t$ simply follows a time-varying IMA(1,1) process[4]:

[4]With explicit model-based treatment of outliers, the outlier distribution of the transitory innovation means that the estimate of τ_t in the UCSVO is not always well approximated by the linear exponential smoother associated with a local IMA(1,1).

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

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

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

where the weights in front of the lagged inflation terms sum to one. Setting aside time variation, filtered estimates of the inflation trend are therefore merely 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 trend inflation. Note that as θ_t approaches one, the estimated trend is simply an average of past inflation.

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 idiosyncratic components of inflation. The MUCSVO model is as shown below:

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

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. According to Eq. (13), the factor loadings on the latent common factors are allowed to be time-varying and evolve as 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 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.

The aggregate trend inflation from the MUCSVO model can be calculated 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 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 idiosyncratic 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 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 disaggregated inflation, the CPI inflation series is broken down into 3, 7, and 10 components based on expenditure share weights[5].

The 3, 7, and 10 components of CPI inflation 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 hous-

[5] While the main estimation results are based on 10 components, robustness checks are also performed for CPI inflation with 3 and 7 components. Due to space considerations, these robustness checks are not reported here in this paper, but are available upon request.

ing and transportation sectors. This gives us 10 components which, due to data limitations, is the lowest level of disaggregation for the CPI inflation series.

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

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 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.

The changing properties of sectoral inflation series are more succinctly summarized in Tables 2 and 3, which contain the standard deviation and persistence of the month-on-month sectoral inflation series calculated over 5 year intervals. In constrast to its expediture shares that remained relatively constant over the full sample (see Table 4), the individual sectors in CPI inflation exhibit significant time-variation in its volatility as well as its degree of persistence. These features thus indeed highlight the importance of time-varying weights in the MUCSVO model. Another interesting observation is that while sectors that are typically excluded from conventional core inflation measures (raw food, gas and electricity, and fuel) contain the highest volatility, the degree of persistence in these series are somewhat significant, especially during the first and last five years of the sample. Excluding these series altogether from measures of core inflation thus may not be entirely appropriate, as persistent movements in these components may have important bearings on the measurement of trend inflation, particularly in the form of pass-through of food and energy prices to core.

Figure 2: Sectoral inflation series in Thailand

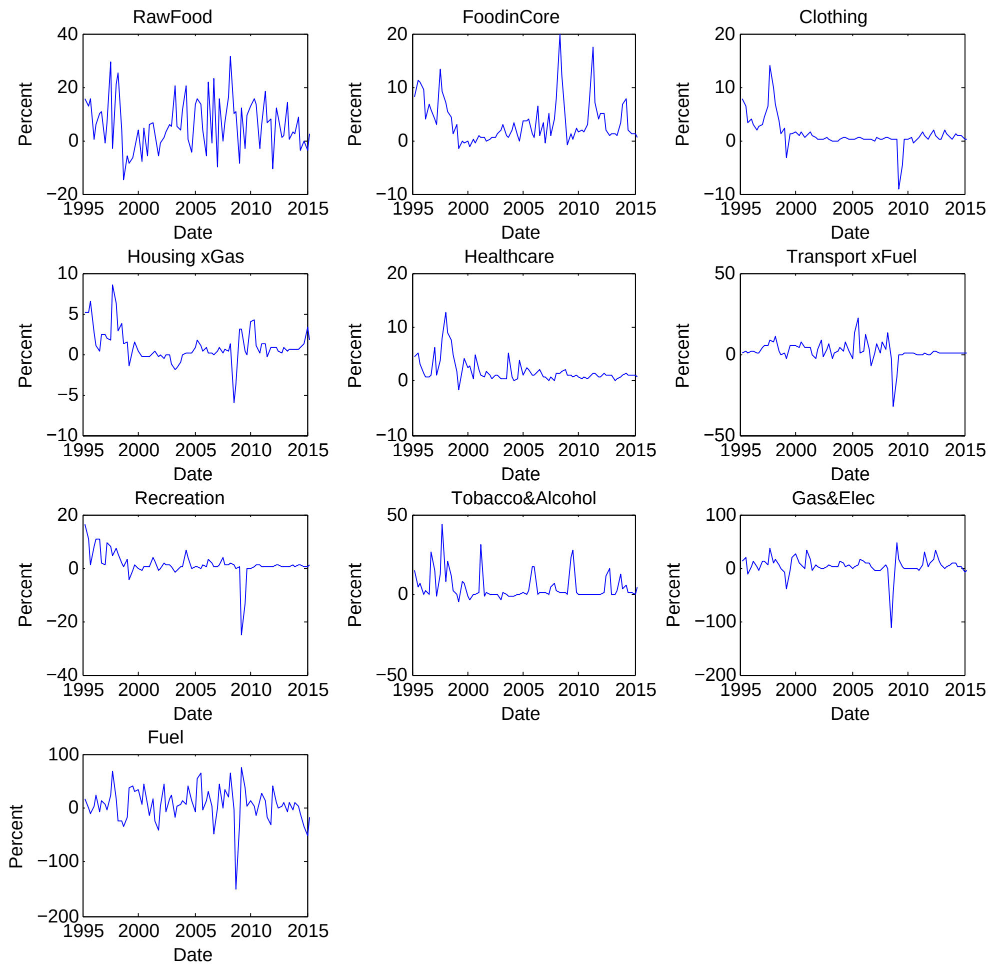


Table 2: Standard deviation of sectoral inflation series

	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 over 5 year intervals.

Table 3: Persistence of the 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 over five year intervals. Persistence is defined as the sum of the coefficients in a fitted autoregressive model of order 4.

Table 4: Average expenditure share in the consumer price index

	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

4.2 Estimation Method

The estimation procedure for both the UCSVO and MUCSVO models are based on Bayesian methods. The Markov Chain Monte Carlo (MCMC) approach is used to estimate the posterior, and stochastic volatility is handled following Kim et al. (1998), modified to use the Omori et al. (2007) 10-component Gaussian mixture approximation for the log-chi squared error. 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. Nevertheless, a few details are highlighted here.

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.

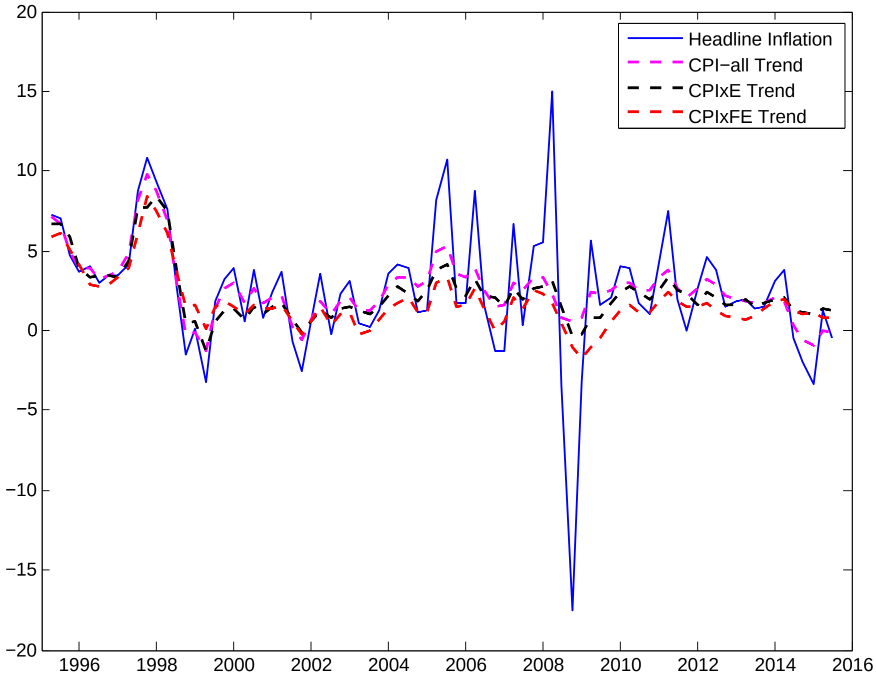
4.3 UCSVO Results

Figure 3 plots CPI-all inflation and the full-sample posterior means of τ_t from the UCSVO model for headline and core inflation measures. The behavior of headline and core inflation trends reflect the previously discussed relationship between actual headline and core inflation. More specifically, all trend estimates closely track one another up until the end of the 1990s but the series diverge after the year 2000.

Throughout the sample, trend estimates for CPI-all is a smoothed version of overall headline inflation. It tracks the overall movements in headline inflation well and remains persistently above other univariate trend inflation measures during most of the sample. Notable differences between the univariate trend estimates occur during the mid 2000s and the global financial crisis in 2008, as well as during the most recent years where the estimated trend of CPI-all drops below its core inflation counterparts due to falling oil prices.

Figure 4 contains a plot of the posterior means of $\sigma_{\Delta\tau,t}$, $\sigma_{\epsilon,t}$ and $\sigma_{\epsilon,t} \times s_t$ for the common components of headline and core CPI inflation. The volatility of trend and transitory components are significantly higher for headline inflation. While this result is not surprising for the transitory component, substantive differences in the variability of the common low frequency components of the univariate trends run counter to our typical assumption that the effects of food and energy price shocks are largely transitory.

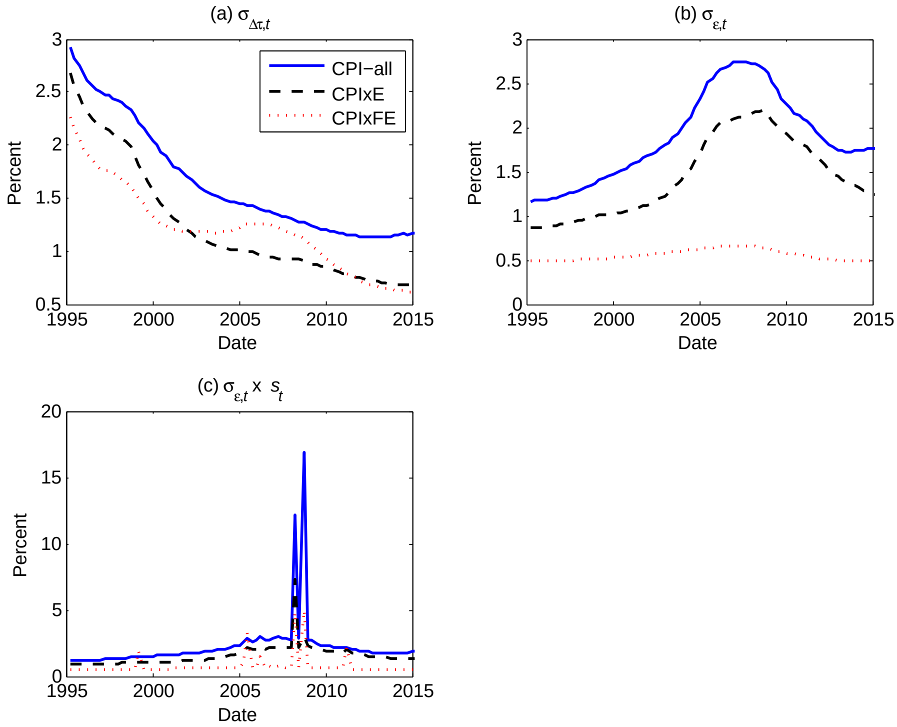
Figure 3: CPI inflation and filtered univariate trends



Examining the estimates of $\sigma_{\Delta\tau,t}$ in Panel (a) of Figure 4 further, trend variation was substantially more volatile for all inflation series during the first part of the sample, but became well "anchored" after the adoption of an inflation targeting framework in the year 2000. However, an interesting observation is that around the mid 2000s, the variability of trend inflation for CPIxFE increases for a brief period. By examining the confidence bands associated with univariate trend estimates, this occurrence may merely be a reflection of sampling errors for the filtered trend.

In Panel (b) of Figure 4, estimates of $\sigma_{\epsilon,t}$ show important differences among the various trend inflation measures. For CPI-all and CPI-xE, a marked increase in the volatility of the high frequency component occurred during the global financial crisis even though outliers have been captured to a great extent by the variable s_t as shown in Panel (c) of Figure 4. Neverthless, once food and energy components have been completely removed from the CPI, the variability of the transitory component declines dramatically and there hardly remains any important variation in the CPIxFE series that can be detected over time. According to this result, the variability of the transitory component in Thai inflation is mostly driven by the dynamics of food and energy prices.

Figure 4: Smoothed estimates of UCSVO permanent and transitory volatilities



The results thus far can shed some light on the observed divergence between headline and core inflation measures since the year 2000. According to the UCSVO results, inflation dynamics in Thailand were mostly driven by large low frequency shocks to the trend prior to the year 2000. Transitory shocks by contrast were relatively low, thus the differences between actual headline and core inflation appeared small.

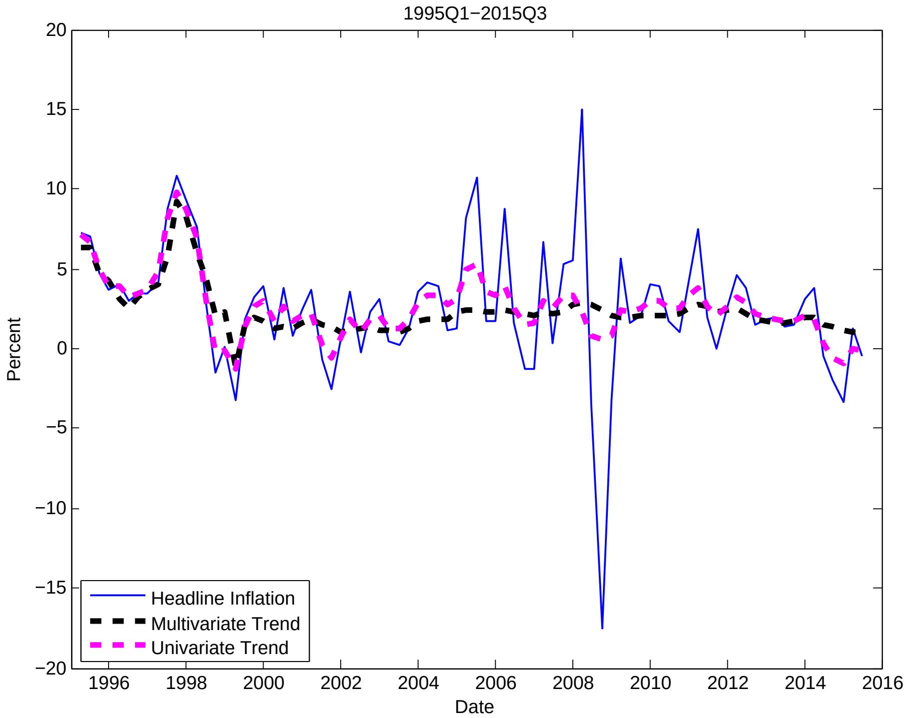
However, after the adoption of an inflation targeting framework, trend inflation variability declined significantly due to better anchoring of long-term inflation expectations. The volatility of the transitory component nevertheless, picked up to a great extent, peaking at the height of the global financial crisis. With the transitory component of CPIxFE being exceptionally stable, we can infer that high frequency shocks affecting the Thai inflation process during this second half of the sample largely stem from global food and commodity price swings that occurred during that time. Therefore, the wedge that we observe between actual headline and core inflation since 2000 appears to be driven in large part by volatile shocks in food and oil markets.

4.4 MUCSVO Results

Figure 5 contains a plot of the MUCSVO aggregate trend based on 10 sectors, and for comparison also plots the CPI-all UCSVO trend and headline inflation.

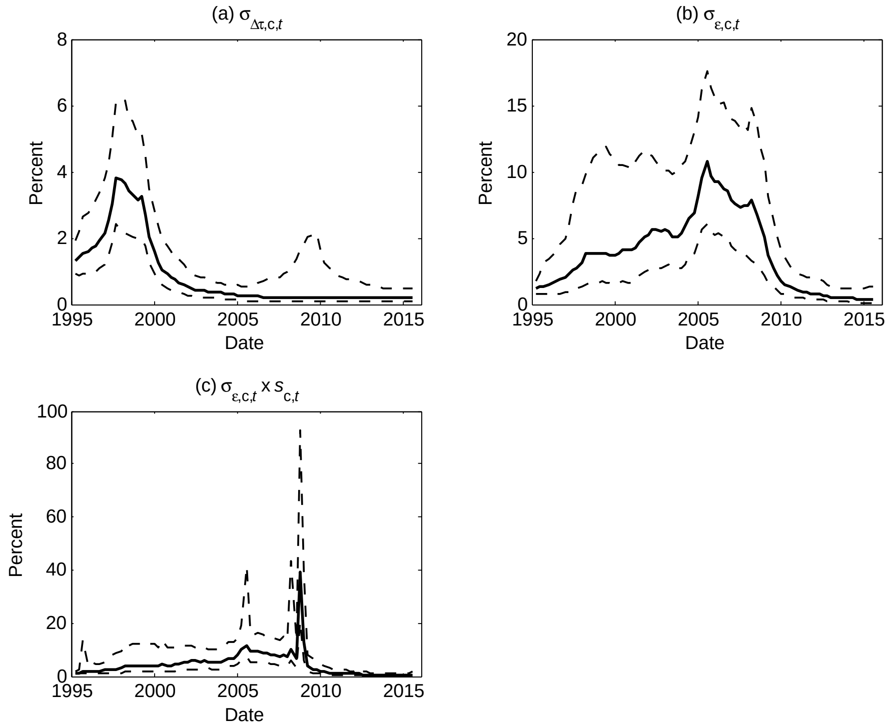
Generally speaking, the multivariate trend is a smoother version of the univariate trend. Examining the plots closely, both trend estimates are similar in the pre 2000 period, but diverged notably at a number of dates during the second part of the sample, particularly around 2005-2006, 2008-2009 and 2014-2015. The first two dates correspond to large changes in retail oil prices that resulted from changes in the Thai government's policy on the collection of oil funds in response to large global commodity price swings. The final date is associated with large persistent declines in world oil prices. Accordingly, differences between the UCSVO and MUCSVO estimates of the trend largely stem from the multivariate model not treating large changes in energy prices as persistent sector-specific shocks.

Figure 5: Multivariate trend inflation



The more subtle differences between the univariate and multivariate models can be discerned from the posterior means of $\sigma_{\Delta\tau,c,t}$, $\sigma_{\epsilon,c,t}$ and $\sigma_{\epsilon,c,t} \times s_t$. The posterior means for the common components of the MUCSVO model alongside its 90 percent confidence bands are plotted in Figure 6 and are compared against the univariate results in Figure 4. Two observations stand out. First, comparing Panels (a) of both Figures which contain estimates for the volatility of the trend component, the variability of trend inflation did not peak for the MUCSVO model until the Asian Financial crisis. This finding implies that high trend volatility prior to 1997 as captured by the univariate model stemmed from sector-specific persistence that was not neccesarily common to all of the 10 sectors.

Figure 6: Smoothed estimates of MUCSVO permanent and transitory volatilities



Second, both models suggest a significant decline in trend inflation volatility since the year 2000 although the decline as captured by the MUCSVO model was much more abrupt. Furthermore, trend inflation volatility in the multivariate model remained exceptionally low with levels close to zero after the year 2000, suggesting that the adoption of an inflation targeting framework was successful in lowering and stabilizing the common trend component. The success of Thailand's explicit inflation targeting framework in anchoring long-term inflation expectations is highlighted by the fact that trend inflation remained remarkably stable during the recent global financial crisis, in stark contrast to volatile trend inflation movements that characterized the 1997 Asian financial crisis.

Panel (b) of Figure 6 contains estimates of $\sigma_{\epsilon,c,t}$. Overall, the variability of the common transitory component is similar to those implied by the univariate model. In particular, both models show a substantial increase in high frequency volatility to inflation during 2005-2010. However, one important difference between the two models that occur towards the end of the sample is that in the UCSVO model, the volatility of the transitory factor remains high and is even slightly on the rise for the CPI-all measure. On the other hand, by allowing for idiosyncratic components, the variability of the common transitory factor is almost non-existent in the MUCSVO model. Finally, examining the nature of outliers in Panel (c), the behavior of large one-time shocks as captured by both univariate and multivariate models are broadly similar. A minor difference is that the existence of outliers for the common transitory component in the multivariate model is essentially zero towards the end of the sample.

Differences between the estimated trend in the MUCSVO and the UCSVO begs the question of what are the time-varying weights implicitly used in the multivariate trend. In calculating these weights, 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 inflation rates. The weights on each sectoral series evolve over time according to times series smoothing implied by the model that are complicated functions of the volatilities, persistence, and correlations among the permanent and transitory components of sectoral inflation series.

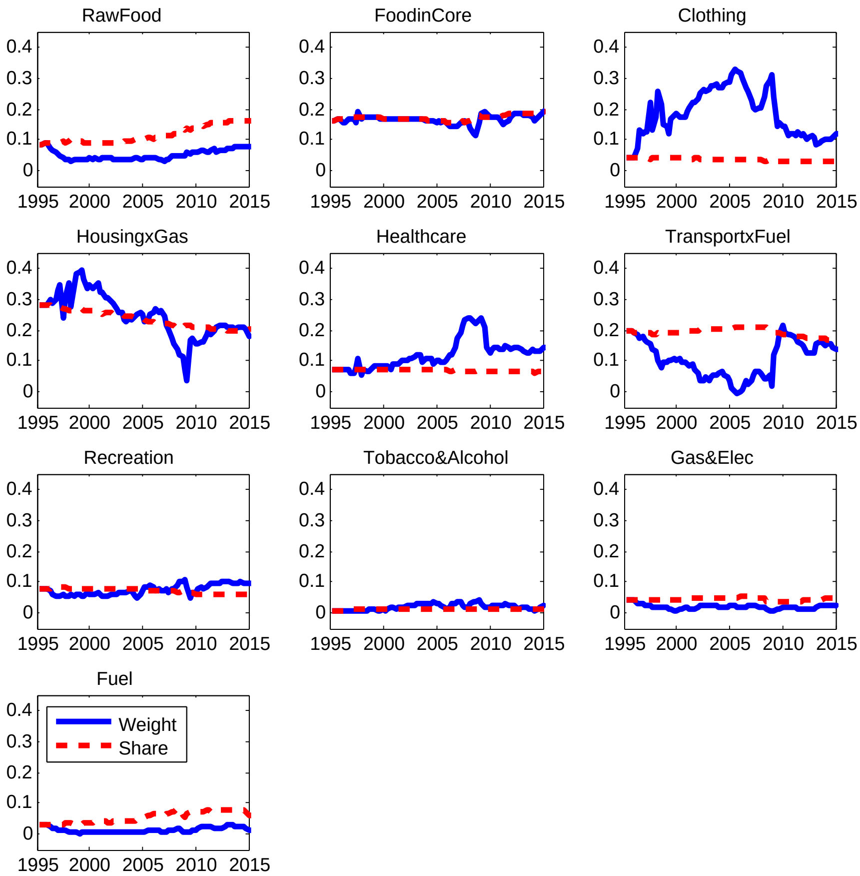
Due to the existence of an outlier variable, an exact representation for the time-varying weights in terms of a linear weighted average is not feasible. Therefore, to provide an approximation of time-varying weights, we follow the approach of Stock and Watson (2015) to first obtain a linear approximation to the one-sided trend estimates using a Kalman filter based on Eqs. (8)-(12). In doing so, we hold fixed the values of the time-varying factor loadings and volatilies $(\alpha_{i,c,t}, \alpha_{i,\tau,t}, \Delta ln(\sigma^2_{\Delta\tau,c,t}), \Delta ln(\sigma^2_{\epsilon,i,t}))$ at their full-sample posterior mean values at that date and ignore outliers by setting $s_{c,t} = s_{i,t} = 1$. Then, in the same spirit as Eq. (7), the filtered trend for each sector in the multivariate model can be written 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. Then, the approximated linear weights for each sector can be defined as the sum of the weights on the current and first three lagged values of the component inflation series, i.e. $\bar{\omega}_{i,t} = \sum_{j=0}^{3} \omega_{i,j,t} / \sum_{i=1}^{10} \sum_{j=0}^{3} \omega_{i,j,t}$. With $\bar{\omega}_{i,t}$ calculated as the time-varying share, the approximated linear weights of all 10 sectors sum to one.

Figure 7 plots the approximate linear weights of the 10 components in the MUCSVO estimate of the trend against the weight of its expenditure share in the overall CPI. In comparison to the weight of the expenditure share, the approximate linear weight shows whether the sector is getting more or less weight in the MUCSVO trend than it does in CPI-all. Components that more or less track expenditure share includes food in core, recreation and education, tobacco and alcohol, and gas and electricity. However, even though the approximate weights of these components are generally stable, the approximate weights in some of these components such as food in core and recreation and education become slightly more time-varying towards the second half of the sample.

Figure 7: Implied weights in the filtered MUCSVO trend estimate and actual expenditure shares



An interesting observation is that while expenditure shares for all 10 components are relatively stable, almost half of the components have approximate weights that are time-varying. To gain intuition on the time-variation present in the estimated weights of specific sectors, we plot the filtered trend estimates as well as the sector-specific volatilities, factor loadings, and outliers for permanent and transitory components of all sectors in Figures 10-19, which are placed in the Appendix due to space considerations. An observation from all these plots is that in general, the sector-specific time-varying factor loadings and volatilities of the permanent components, $\alpha_{i,\tau,t}$ and $\sigma_{\Delta\tau,i,t}$, remain relatively stable, whether it be across time or across sectors. In contrast, the factor loadings and volatilities for the transitory components, $\alpha_{i,\epsilon,t}$ and $\sigma_{\epsilon,i,t}$ exhibit considerable variation across both dimensions.

This finding however, does not suggest that the permanent component of inflation does not change over time, but instead implies that changes to the trend component occurs only at the aggregate level due to macroeconomic-wide events such as an adoption of an inflation targeting regime.

Sectors that exhibit considerable time-varying filtered trend weights include clothing, housing excluding gas, healthcare, and transport excluding fuel[6]. These sectors are analyzed in turn. First, for the clothing sector, despite a relatively low expenditure share weight, clothing receives considerable weight in the MUCSVO trend, especially during 1997-2010 where the weight is more than quadruple times its expenditure share. Based on Panel (d) of Figure 12, the MUCSVO model imparts high weight to the clothing sector due to relatively low volatility in its transitory component during this time.

Next, the weight for the housing excluding gas and electricity sector is also time-varying. It receives higher weight compared to its expenditure share in the pre 2002 period, but a lower weight during 2008-2010. During the former period, price dynamics in the housing sector was largely driven by Thai government policies such as tax benefits that were employed to boost the real estate sector. Based on Figure 13, the lower trend weight during the latter period is due to the large existence of outliers as well as exceptionally high sectoral volatility that also increased $\alpha_{i,\epsilon,t}$, which is the loading factor on the common transitory component.

The importance of the healthcare sector to trend inflation on the other hand, becomes more important during the global financial crisis. From Figure 14, this is because the volatility of the sector's transitory component is low compared to other sectors during this time. Furthermore, its reduced volatility since the mid 2000s stands in stark contrast to its high volatility towards the beginning of the sample. Last, for the transport excluding fuel sector, Figure 15 shows that this sector is highly volatile, especially as reflected by the dynamics of the transitory component during the pre 2010 period. Increased volatility during this time is in large part due to the removal of the Thai government diesel subsidy in July 2005 as well as other government measures enacted in response to large commodity price swings in 2008. For this reason, its filtered weights for trend inflation are much lower than its expenditure share during this time.

Three Sector Results

Traditional core inflation measures typically exclude raw food, gas and electricity

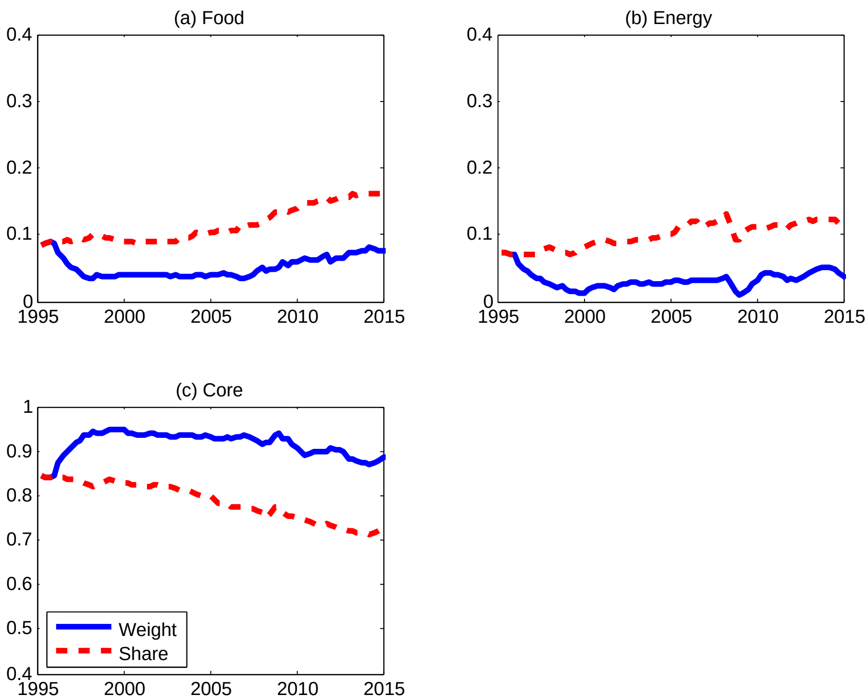
[6]While the magnitude is relatively small, food in core also displays enhanced time-variation in its filtered trend weight in the post global financial crisis period. This is due to sharp rises in global food prices in 2008, increases in food prices due to the swine disease epidemic in 2011, and changes in government policy measures that affected household LPG prices in 2013.

and fuel sectors from measures of trend inflation due to high volatility in these components. According to Figures 10, 18, and 19, the MUCSVO estimation results confirm that the transitory components of these series are indeed volatile. The fuel sector exhibits the highest degree of volatility in the transitory component. The degree of variability in the raw food and gas and electricity components are high as well, while the latter sector contains many outliers.

What is interesting to note is that that while the filtered trend weights for these three components are small, they are not exactly zero. Furthermore, estimates of the factor loading on the common trend component $\alpha_{i,\tau,t}$ and the volatility of shocks to the sector-specific trend $\sigma_{\Delta\tau,i,t}$ are by no means smaller in magnitude when compared to other sectors. Accordingly, these sectors contain persistence that contribute to the measurement of the mlutivariate trend, 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 these sectors towards multivariate trend estimation, we group the results from the 10 sector model into 3 sectors as shown in Figure 8. Here, the raw food sector is labelled as the food component, and both the gas and electricity and fuel components are aggregated into an energy component. The remaining sectors are grouped into a core inflation component.

Figure 8: Implied weights in the filtered MUCSVO trend estimate and actual expenditure shares for food, energy and core sectors



Panel (a) of Figure 8 displays the implied weights for the food sector. As shown, the filtered weight increases slightly since 2007 and reaches a level of nearly 0.1 by the end of the sample. In part, this may be due to the corresponding increase in the actual expenditure share of raw food items. On the other hand, Figure 10 depicts a sizeable fall in the volatility of the transitory component of the raw food series since 2007, which may have enhanced the role of the raw food sector towards measurement of the overall trend.

Panel (b) of Figure 8 shows that despite a slight but gradual increase in the expenditure share of the energy sector, its corresponding filtered weight remains relatively constant. Only a slight dip in the filtered weight occurred during 2008-2009, which according to Figures 18 and 19, reflects the increase in the volatility of the transitory component due to global oil price swings. Nevertheless, despite the energy sector being highly volatile, the filtered weight for the energy sector is non-zero, implying that there exhibits some form of pass-through from energy prices to the overall CPI.

Analyzing the dynamics of the energy component further, the factor loading on the transitory component for fuel in Panel (c) of Figure 19 or $\alpha_{\epsilon,i,t}$, is largest both in terms of its magnitude as well as changes that it experienced through time when compared to other sectors. This observation is interesting at least along two dimensions. First, the sizeable 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. Given that fuel by far exhibits the highest degree of short-term volatility, this finding in a way loosely suggests that common short-run price movements among different sectors are influenced to a significant degree by fuel price changes. Based on the estimates of $\alpha_{\epsilon,i,t}$ which are the sectoral factor loadings for the transitory component, sectors that share common transitory fluctuations with fuel to a large extent include raw food, clothing in the pre 2000 period, housing in the post 2005 period, transportation, recreation and education, and gas and electricity.

Another intriguing finding is that $\alpha_{\epsilon,i,t}$ in the fuel sector more than doubles in magnitude around the year 2000. This result implies that influence of the fuel sector on short-run inflation dynamics in Thailand has intensified, which is in line with the findings of Manopimoke and Direkudomsak (2015). Based on an open economy New Keynesian Phillips curve for Thailand, the 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 in part captures the effects of oil price changes through the direct import price channel. While it is not clear within the framework of this paper what forces are responsible for the changes in $\alpha_{\epsilon,i,t}$, the growing importance of this factor loading is interesting insofar as it can explain the increase in the variability of the transitory component of inflation from year 2000 onwards. With headline inflation becoming increasingly influenced by volatile fuel price dynamics in the post 2000 period, it is not surprising that the divergences between headline and traditional core inflation measures started to become more pronounced since then.

Finally, Panel (c) of Figure 8 plots the filtered weights attributed to all CPI components that exclude food and energy as well as its corresponding expenditure share. The expenditure share of core components fell continuously since the beginning of the sample, and currently accounts for only about 0.7 of the CPI basket. The importance of core components in trend inflation however, did not necessarily follow this decline in expenditure share. It increased by about 10 percent in the late 1990s, remained quite stable at levels slightly higher than 0.9 through to the mid 2000s, then started to fall only slightly after the global financial crisis. Currently the importance of core components in the estimated MUCSVO trend is slightly less than 0.9, while food and energy takes up the remaining share. This finding thus suggests that food and energy components while volatile still contains persistent movements that are pertinent to the measurement of the multivariate trend.

Accuracy of trend estimates

Taking a step back to analyze the results from the UCSVO and MUCSVO models, we ask whether using sectoral inflation data has helped improve the precision of CPI trend estimates. This is a difficult question to answer given that trend inflation is in itself an unobserved variable. However, we can still evaluate model-based accuracy measures based on the width of posterior uncertainty intervals, as well as an out-of-sample forecasting exercises which will be carried out in the next section.

First, we point out that the width of posterior intervals reflects two sources of uncertainty, which are, 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 smaller in the MUCSVO model. However, the MUCSVO model involves many more parameters to be estimated, 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 calculated from the UCSVO and MUCSVO with 3 and 10 components for headline and core inflation series over three intervals, 1995Q2-2000Q1, 2000Q1-

2008Q4, and 2009Q1-2015Q2. As a robustness check, the posterior intervals are also computed by excluding high volatility crises periods in the sample, but the results are qualitatively similar. For all inflation series, the multivariate models display narrower bands in comparision to the univariate model, suggesting a substantial reduction in uncertainty based on the additional information used in the multivariate model, even at the cost of additional complexity.

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

Note: The table shows the average width of full-sample posterior intervals for the inflation trends listed in the first column.

In general, the full-sample posterior intervals associated with the 10 component MUCSVO model for CPI-all trend is approximately half as narrow when compared to the corresponding intervals for the univariate model. For core inflation measures, the relative improvements in accuracy of the 10 component model are less than twofold in the pre 2000 period, but the improvements in the period thereafter more than doubles.

Comparing the 3 and 10 component MUCSVO intervals for all inflation series, the average width shows that the 10 component model is superior except for CPIxE and CPIxFE during 1995Q2-2000Q1. The gains in accuracy from the 3 to 10 components for CPI-all is around 35 percent, with slightly larger improvements to be had in the pre 2000 period compared to the period that follows. Improvements for the 10 component multivariate model based on core inflation measures during 2000Q1-2008Q2 are around 20 percent and are higher at around 35 percent for CPIxE and 50 percent for CPIxFE during the final period. Therefore, the overall results suggest that significant gains in accuracy are to be had when more information in the disaggregated sectoral inflation series are used to calculate measures of trend inflation.

5. Inflation forecasting

Trend inflation is defined as long-horizon forecasts of inflation, thus it is natural to use a forecasting exercise to evaluate candidate estimates of trend inflation. This section evaluates the forecasting performance of trend inflation estimates from the UCSVO and MUCSVO models against other benchmark univariate trend inflation measures that are often used by the BOT. Following the literature, we focus on forecasts at the 1-3 year horizon. Due to space considerations, the results reported in this section are only based on the 2 year horizon (8 quarter-ahead) inflation forecasts. Forecasting results at other horizons are qualitatively similar and are available upon request.

Trend inflation is measured by the one-sided posterior mean estimates of $\tau_{t|t}$ and are used to forecast 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 $h = 8$. $\bar{\pi}$ is the average of headline inflation even when it is being forecasted by core trend estimates. Forecasts are based on $\tau_{t|t}$ estimates that are constructed from the UCSVO and the MUCSVO models with 3, 7, and 10 components. Other benchmark inflation forecasts are based on CPIxE, CPIxFE, and trend inflation estimates calculated from the principal components and trimmed mean approaches.

The performance of the various trend estimates are evaluated based on the average of its root mean squared errors (RMSE) over a five year horizon, calculated as:

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

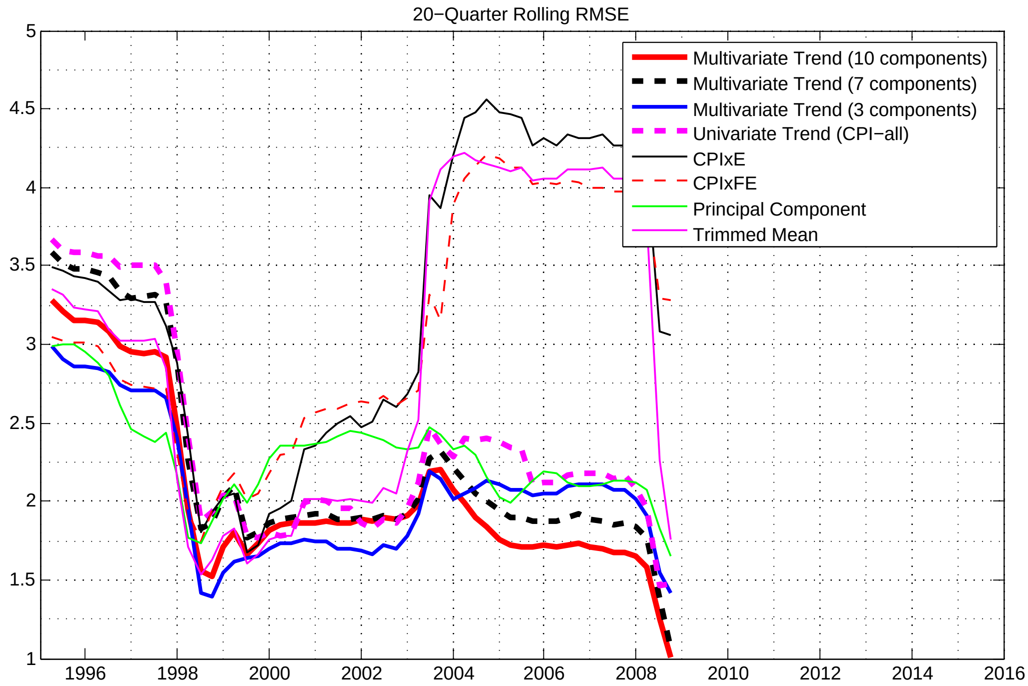
where the model-based forecast errors for $h = 8$ are defined as:

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

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 inflation measures are relatively similar, with the UCSVO trend performing worst and the 10 component multivariate trend not showing any significant improvements over other trend series.

After the early 2000s however, it is clear that the UCSVO and MUCSVO trends produce markedly more accurate forecasts when compared to existing core and trimmed meaned measures.

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.

During the most recent period, the performance of the 10-sector MUCSVO model becomes noticeably superior. The improved forecasting performance of the 10-sector model is followed closely by the 7 components MUCSVO trend, trend estimates produced by a principal component approach, the 3 components MUCSVO trend, and the UCSVO trend. Core and trimmed mean forecasts on the other hand, clearly display large RMSEs. This finding suggests that additional information in sectoral data can help improve inflation forecasts. However, given that the principal components approach also utilizes no less information than the 10 component multivariate trend while the UCSVO trend still performs relatively well, allowing for time-varying sectoral weights also appear as an important feature towards accurate measurement of the trend. Finally, the poor performance of traditional core inflation measures imply that for Thailand, the exclusion of food and energy sectors may downgrade forecasts of headline inflation, especially in the post 2000 period.

According to Figure 9, the RMSEs are close for a number of trend inflation estimates. In the post 2000 period, the differences between the RMSEs for the univariate and multivariate models may not be statistically significant, it cannot be said with much confidence that the multivariate models offer a significant improvement over the UCSVO trend. To assess whether the differences in the out-of-sample predictive accuracies of the trend inflation estimates are statistically significant, Table 6 reports the modified Diebold-Mariano test statistic and their corresponding p-values in parentheses for the forecast errors[7]. The test statistics are calculated based on the following null hypothesis:

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

where the forecast errors of each trend inflation measure is compared against the one produced from the UCSVO model.

Table 6: Tests of equal predictive accuracy

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)
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 Diebod Mariano test statistic and corresponding p-values (in parenthesis) for the null of equal predictive accuracy between different trend inflation measures and the UCSVO trend. The modified Diebold Mariano test statistic is based on an absolute loss function.

Column 2 of Table 6 contains the predictive accuracy test results for the full sample. As shown, trend inflation estimates from the multivariate models all outperform the UCSVO trend at the 10 percent significant level. On the other hand, the test results reveal that trend estimates belonging to the principal components approach does not outperform the UCSVO results despite utilizing cross-sectional information in inflation data. Similarly, the UCSVO offers equal predictive accuracy when compared to trimmed mean and CPIxFE measures, although it does offer a significant improvement over CPIxE core inflation.

We also perform tests of predictive accuracies over the two subsamples: (i) 2000Q1-2015Q2, which marks the inflation targeting regime; and (ii) 2005Q1-2015Q2,

[7]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.

which is associated with a significant divergence in RMSEs of the competing models as displayed in Figure 9. During both subsamples, the test results indicate that the MUCSVO trends offer a significant improvement in out-of-sample forecasting accuracy when compared to its univariate counterpart, with the exception of the 7-component MUCSVO model during the 2000-2015 period. In line with the full sample results, the performance of the UCSVO model is on par with the principal components approach. However, in contrast to the full sample results, there is now clear cut evidence in the subsamples that trend inflation estimates from the UCSVO offer a significant improvement over trimmed mean and core inflation measures. Thus overall, both UCSVO and MUCSVO models are superior to existing core inflation measures being used by the BOT, with information in disaggregated sectoral inflation data helping improve overall trend inflation measurements.

6. Conclusion

This paper provides a new estimate of trend inflation based on the multivariate unobserved components model with stochastic volatility and outlier adjustments as proposed by Stock and Watson (2015). The empirical results show that there are substantial gains to be had from the use of disaggregated sectoral data in the measurement of trend inflation, particularly by allowing for time-varying persistence, volatilities, as well as comovement among the permanent and transitory components of sectoral inflation series. The multivariate trend estimates are much smoother and substantially more precise when compared against univariate measures of trend inflation which are only based on headline inflation. Furthermore, the out-of-sample forecasting performance of the multivariate trend is significantly more accurate when compared to univariate measures of the trend or existing core inflation series, especially since the year 2000. Given the merits of the multivariate model, finer disaggregation of price components are encouraged to gain an improved measure of the trend, as well as towards developing a model that can be used for real-time trend measurement.

The empirical results in this paper also sheds light on the changing inflation process in Thailand. Prior to the adoption of an inflation targeting framework, Thai inflation rate movements were largely driven by volatile trend inflation shocks that affected all sectors. However, the implementation of an explicit inflation target served to stabilize trend inflation to a large extent, and since then, movements in overall headline inflation became mostly dominated by volatile transitory shocks. Global commodity price swings during the past decade appeared to play a significant role in driving short-run inflation rate movements in Thailand, while price dynamics in the fuel sector in particular, explains a large portion of common transitory movements in Thai inflation. Finally, the multivariate model suggests that there are persistent movements in food and energy price components that contribute to approximately 10 percent of multivariate trend dynamics. This finding implies that trying to gauge future persistent movements of inflation from core components that exclude food and energy sectors may not give an accurate representation of underlying trend inflation movements, especially given that price dynamics in Thailand are influenced by food and energy price sectors to a large extent.

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Appendix

Figure 10: Raw Food

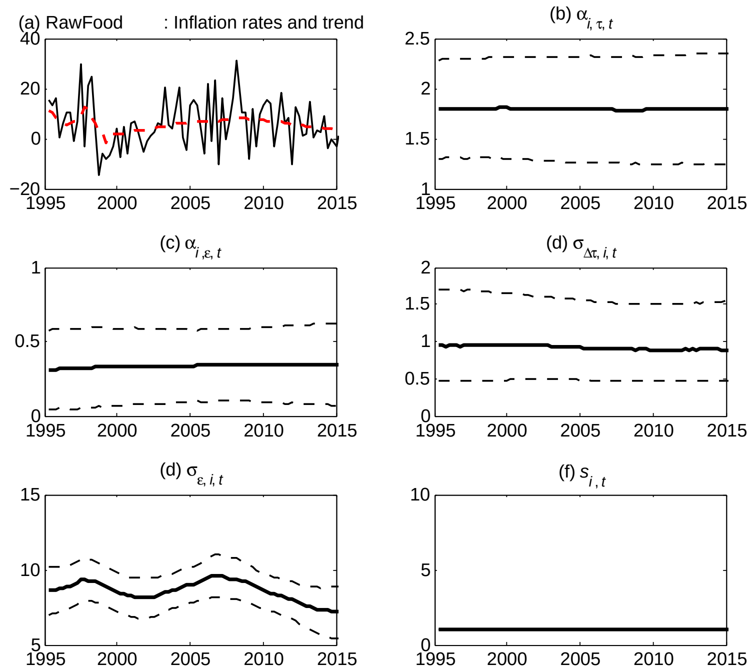
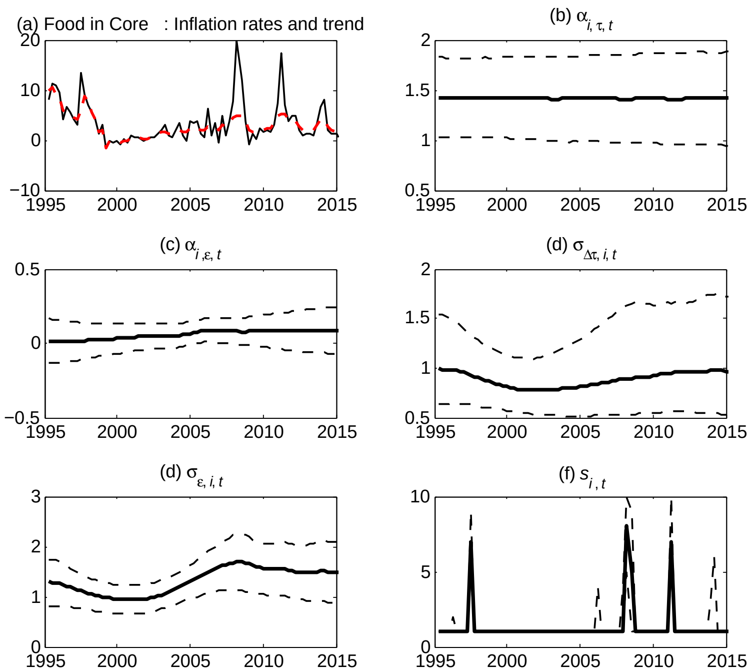


Figure 11: Food in Core



(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 12: Clothing

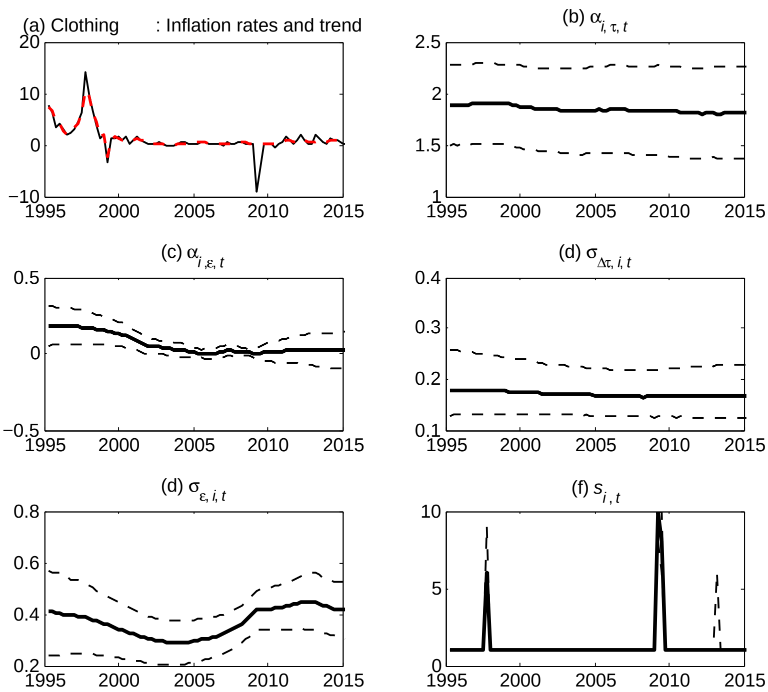
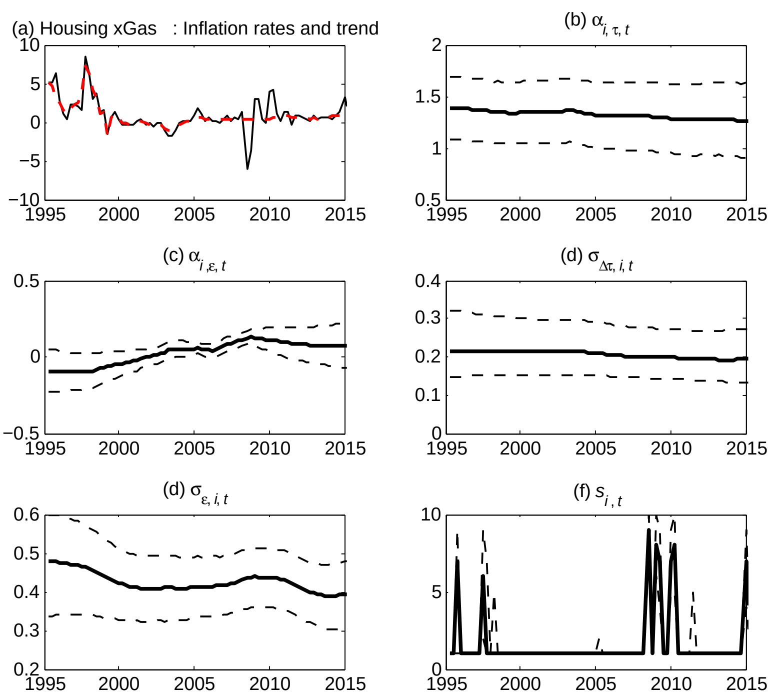


Figure 13: Housing excluding gas and electricity



(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 14: Healthcare

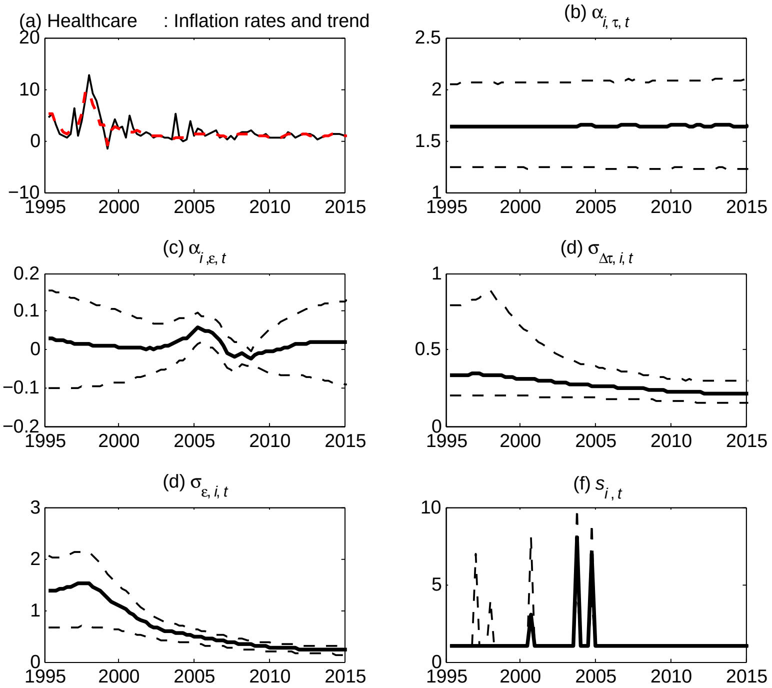
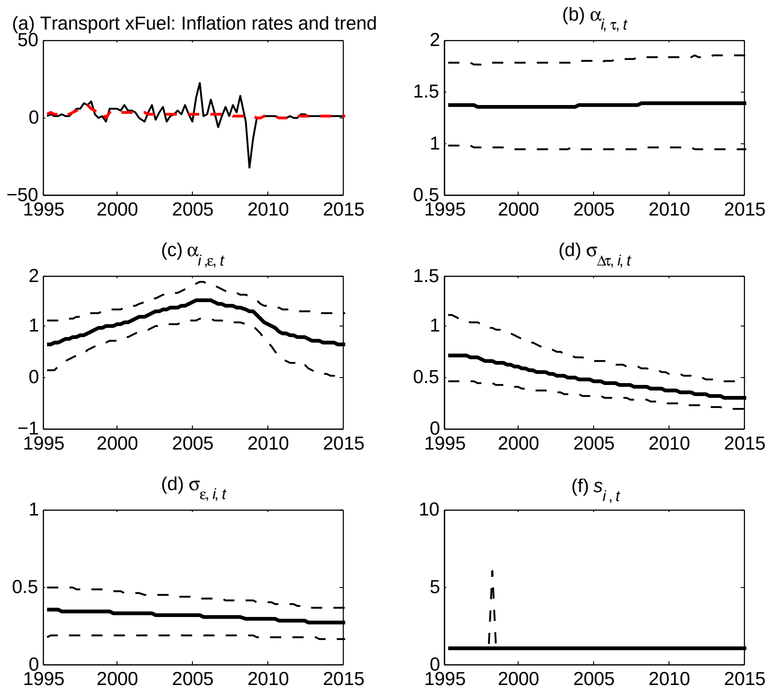


Figure 15: Transporation exclude fuel



(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 16: Recreation and education

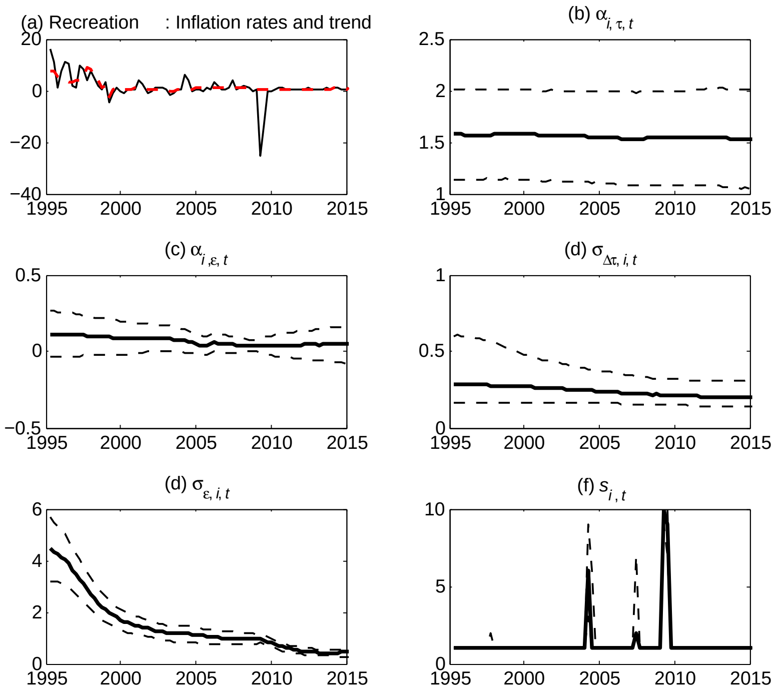
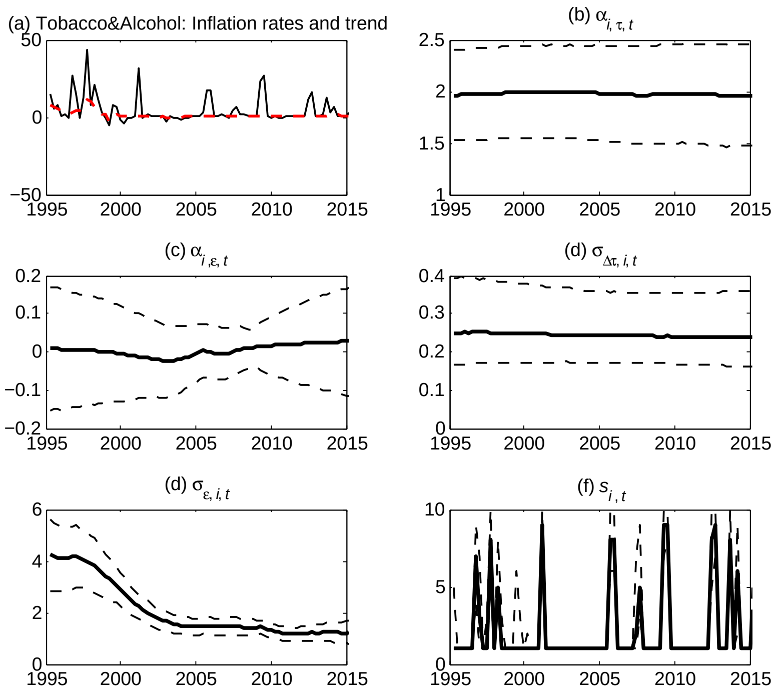


Figure 17: Tobacco and alcohol



(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 18: Gas and electricity

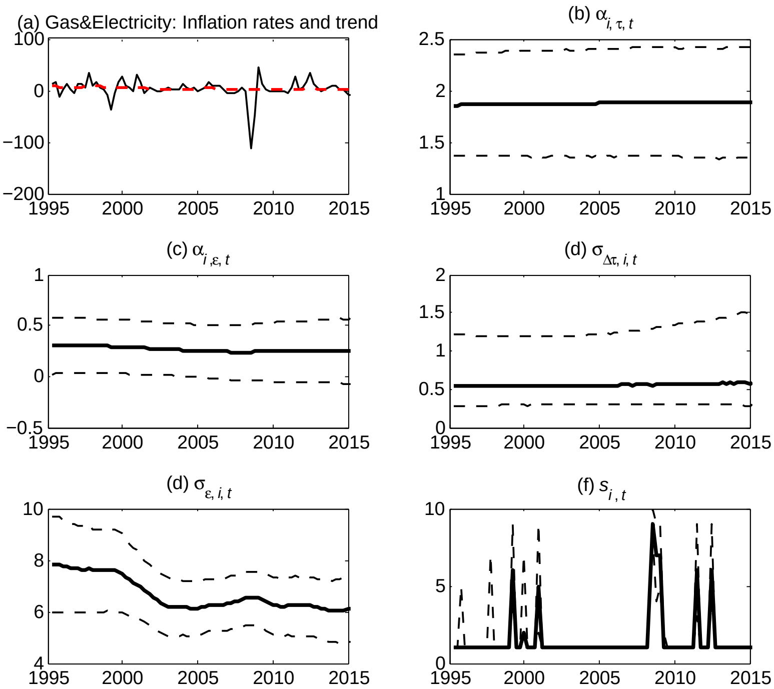
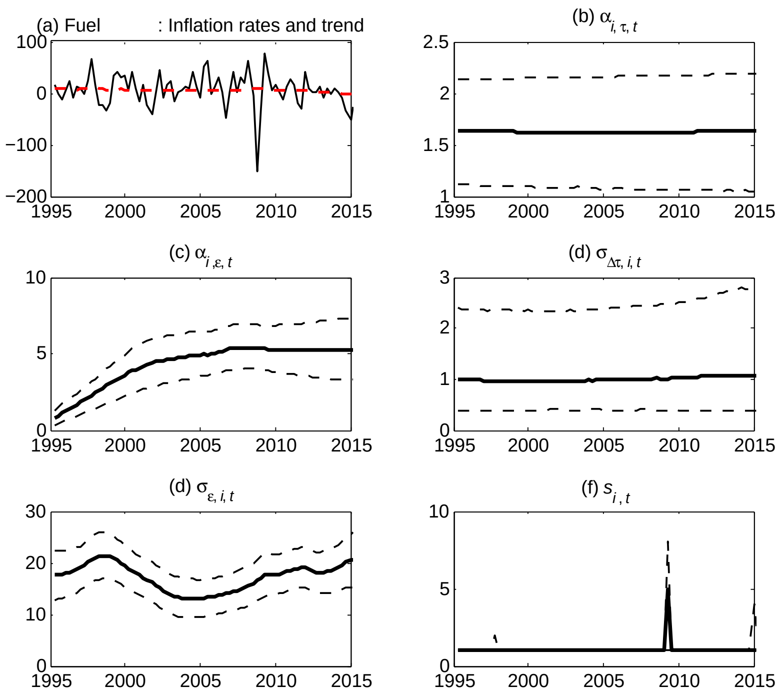


Figure 19: Fuel



(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.