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Trend Inflation Estimates for Thailand from Disaggregated Data

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Pym Manopimoke and Vorada Limjaroenrat

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Trend inflation estimates for Thailand from disaggregated data*

Pym Manopimoke Vorada Limjaroenrat

Puey Ungphakorn Institute for Economic Research
Bank of Thailand

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 (2016). Similar to core inflation, the MUCSVO produces an estimate of trend inflation utilizing information in disaggregated data, but also allows for time-varying weights that depend on the volatility, persistence and comovement of the underlying 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 help explain approximately 10 percent of MUCSVO trend inflation rate movements. Compared against other benchmark trend inflation measures, we show that the MUCSVO delivers trend estimates that are smoother, more precise, and are able to forecast average inflation over the 1-3 year horizon more accurately both in-sample and out-of-sample, especially since the year 2000.

Keywords: disaggregated 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 extract 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.

Changing inflation dynamics also complicates the task of trend inflation measurement. For Thailand, many authors report a sizable decline in the level, volatility, and persistence of CPI inflation since the year 2000, as well as a sustained divergence between actual and core inflation (Chantanahom et al., 2004; Khemangkorn et al., 2008). It has been suggested that these occurrences were a result of structural changes in the Thai economy, whether it be from the adoption of an inflation targeting framework by the Bank of Thailand (BOT), or globalization pressures that intensified during that time (Manopimoke and Direkudomsak, 2015). Furthermore, the underlying driving factors for Thai inflation appears to have evolved over time as well. Since the year 2000, Manopimoke and Direkudomsak (2015) find that a global output gap has replaced its domestic counterpart, while since the global financial crisis, oil price changes have become a more dominant driver of Thai CPI inflation.

In light of such issues, this paper investigates whether existing trend inflation measures for Thailand can be improved upon by utilizing a method that allows the 'data to speak' as much as possible. In doing so, we estimate a new trend inflation measure for Thailand based on the multivariate unobserved components model with stochastic volatility and outlier adjustments (MUCSVO) as proposed by Stock and Watson (2016). The key advantage of the model is that it distinguishes between common and sector-specific trend and transitory factors, and allows persistent movements in the disaggregated sectoral series to affect overall trend inflation rate movements through time-varying rather than fixed weights. Since these weights depend on fundamental changes in the volatility and persistence of the sectoral inflation series as well as the degree of co-movement among sectors, trend estimates from the MUCSVO should adapt to changing inflation dynamics more quickly and adequately than existing measures which are more rigid. Furthermore, the MUCSVO also incorporates a model-based treatment of outliers which, as mentioned by Stock and Watson (2016), makes the model particularly well-suited for the task of real-time trend estimation[1]. For a small open economy such as Thailand, this feature should be extremely helpful towards identifying the underlying trend amidst volatile price movements that often stem from external price shocks.

Throughout the empirical investigation, we focus on examining the following three questions that are central to the task of trend inflation measurement. First, we evaluate whether the use of disaggregated data in the MUCSVO 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 weights on sectoral components time-varying and how do they compare against their static expenditure share weights that are used to construct core inflation? To examine these two questions in further detail, we also conduct in-sample and out-of-sample forecasting exercises to evaluate how the resulting MUCSVO trend compares to other benchmark measures of trend inflation when it comes to forecasting headline inflation at horizons that are relevant to policymakers. Last, given that the estimated coefficients of the MUCSVO can provide information about the underlying characteristics of sectoral inflation series, we hope to gain improved insight about the changing nature of Thai inflation dynamics over past decades.

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 estimation error are roughly half of its univariate counterpart; (ii) the common trend component explains 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 MUCSVO 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 MUCSVO outperforms a variety of other benchmark trend inflation measures when forecasting average headline inflation both in-sample and out-of-sample at the

[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.

1-3 year horizon, 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 estimates for Thailand. Section 3 introduces the MUCSVO model of Stock and Watson (2016). Section 4 presents and discusses the estimation results and Section 5 conducts the forecasting exercise. Section 6 concludes.

2. Thai inflation dynamics and trend inflation measurement

Previous studies often recognize that Thai inflation dynamics underwent a significant change during the year 2000. From 1995 to 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 unprecedented success in lowering both the levels and volatility of Thai inflation[2]. Since then, 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 stabilizing or 'anchoring' long-term inflation expectations (Buddhari and Chensavasidja, 2003; Manopimoke and Direkudomsak, 2015).

In a country that adopts an inflation target such as Thailand, the issue of trend inflation measurement is truly central to monetary policymaking. To achieve and maintain low and stable inflation, an accurate measure of the trend 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 involves down-weighing or excluding the most volatile and nonpersistent sectors from aggregate inflation, which turn out to be components that are mostly influenced by supply-side shocks. Measures of core inflation that exclude 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

[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 changes 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.

underlying price dynamics from true market forces[3]. Against similar reasonings, underlying inflationary pressures are also often gauged from CPI inflation that excludes administered price items (CPI-xMeasure). 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 chosen set of excluded components are typically fixed, even when their influences can vary across time. In response, Bryan and Cecchetti (1994) introduced a trimmed mean or median measure, which is also based on an exclusion approach but 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 BOT often employs an asymmetric trimmed mean measure 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 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 can provide a good representation of the underlying trend. Some examples are the first-order integrated moving average (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 upon these models, Stock and Watson (2007) propose a univariate unobserved components model for inflation with stochastic volatility (UCSV) which treats the trend component of inflation as a latent state variable to be estimated within a framework of time-varying parameters and price shocks.

[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 also corresponds to approximately a fifth of Thailand's core inflation basket, thus exerting a sizable influence on inflation figures. Thus, removing rent prices from headline inflation can be a practical solution towards avoiding significant price distortions.

[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 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.

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 based on their variance-covariance structure. In comparison to the exclusion approach that always remove fixed components from the CPI basket, statistical approaches such as ones that are based on the PCA are favorable because they make no such restrictions. Therefore, while both the PCA and the exclusion approach both utilize cross-sectional data to arrive at an estimate for the trend, the PCA decides which sectors to include based on weights that are actually estimated, rather than specifying them in a manner that is relatively ad hoc.

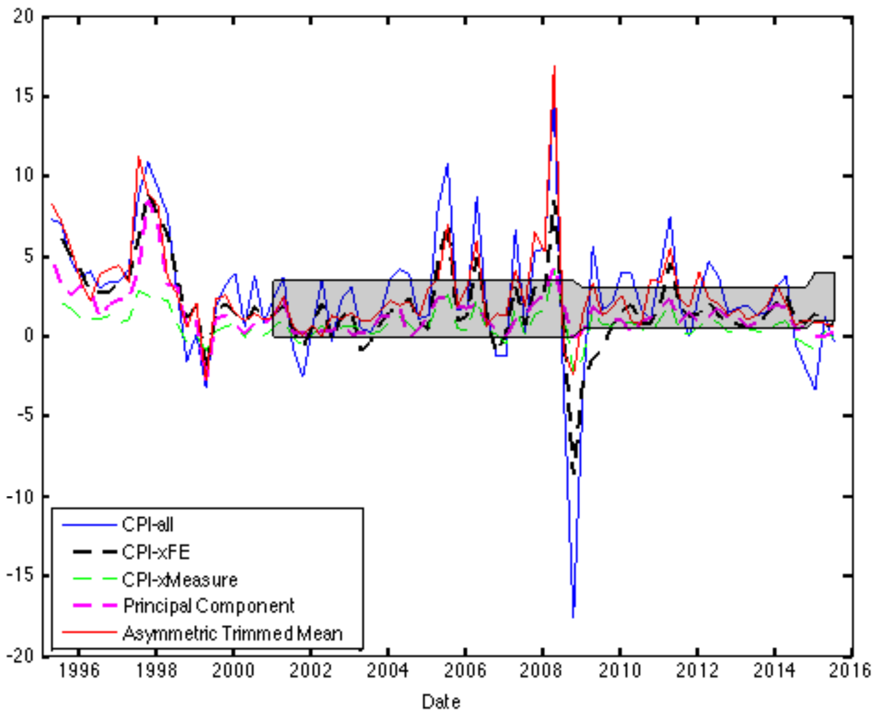
Figure 1 plots headline CPI inflation in Thailand against selected trend inflation measures that are closely monitored by the BOT, with the shaded region representing the BOT's inflation target band[5]. A few observations emerge. First, it is interesting to note the fundamental shift in the relationship 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 CPI-xMeasure. However, in the period thereafter, 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 relative to headline inflation rate movements, most likely due to the adoption of an inflation targeting framework in May 2000 which served to better anchor long-term inflation expectations.

Second, headline inflation remained consistently above 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. In light of such issues, the remainder of

[5]For monetary policy discussions, the BOT analyzes a wider range of trend inflation measures than those plotted in Figure 1. 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 analyzing trend inflation measures 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.

this paper is primarily devoted to constructing a new trend inflation estimate for Thailand and evaluating it against existing trend measures.

Figure 1: Headline and trend inflation measures for Thailand



Note: Displayed above are year-on-year quarterly inflation series computed from the Thai consumer price index. Trend inflation measures include: (1) headline inflation excluding raw food and energy components (fuel, gas, and electricity), denoted CPI-xFE; (2) CPI excluding administered price measures, denoted CPI-xMeasure; (3) trend inflation constructed from the principal components analysis; and (4) an asymmetric trimmed mean measure of trend inflation constructed by removing 12 and 6 percent of the items with the largest relative price changes from the lower and upper end of the price distribution respectively. The shaded region corresponds to the BOT's inflation target 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 (2016). 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 fundamental changes in the sectoral inflation 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 $(\eta_\varepsilon, \eta_\tau, \nu_\varepsilon, \nu_{\Delta\tau})$ is iid. N(0, I_4).

According to the above expression, Eq. (1) decomposes the current inflation rate π_t into a permanent component τ_t and a 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 process as specified by Eq (3). Innovations to both the trend and the transitory components, which are $\eta_{\tau,t}$ and $\eta_{\varepsilon,t}$ respectively, have time-varying variances that follow logarithmic random walk stochastic volatility processes (i.e. a random walk in logarithms) with scale parameters γ_ε and $\gamma_{\Delta\tau}$, as specified by Eqs. (4) and (5). Additionally, in Eq. (3), the transitory innovation ε_t is modeled as a mixture of normals via the i.i.d. variable s_t to accommodate for heavy tails, namely large infrequent spikes or outliers in the data. Following Stock and Watson (2016), the mixture model is specified in such a way that large one-time shifts in the price level are two to ten times as large in magnitude. That is, the outlier variable is distributed $s_t \sim U[2, 10]$ and occurs with probability p, while the case of no outliers or $s_t = 1$ occurs with probability $1 - p$.

To gain more intuition on the UCSVO, consider a simpler case of the model with no outliers and stochastic volatility, i.e. $\pi_t = \tau_t + \varepsilon_t$, $\tau_t = \tau_{t-1} + \eta_t$, where ε_t and η_t are serially uncorrelated innovations with means zero and variances σ^2_ε and σ^2_η respectively. In such a case, $\Delta\pi_t$ follows a time-varying IMA(1,1) process. In other words, inflation has a time-varying moving average representation in first differences[6]:

[6] To arrive at Eq. (6), we multiply both sides of the expression $\pi_t = \tau_t + \varepsilon_t$ by the operator $(1 - L)$. By recognizing that $(1 - L)\tau_t = \eta_t$, the expression becomes $\Delta\pi_t = \eta_t + \varepsilon_t - \varepsilon_{t-1}$. This sequence can then be mapped to the MA(1) process in Eq. (6) with parameters that satisfy the following two equations: $\sigma^2_\eta + 2\sigma^2_\varepsilon = \sigma^2_a(1 + \theta^2)$ and $-\sigma^2_\varepsilon = -\sigma^2_a\theta$, which are obtained from matching the variances and first autocovariances of the two MA(1) sequences respectively.

$$\Delta\pi_t = a_t - \theta a_{t-1}, E(a_t) = 0, Var(a_t) = \sigma_a^2, \tag{6}$$

where σ_a^2 and θ are functions of transitory and permanent disturbances, namely σ_η^2 and σ_ε^2. As explained in more detail by Stock and Watson (2007), the MA coefficient θ varies inversely with the ratio of permanent to transitory disturbances.

We can arrive at an expression for the one-sided or filtered estimate of the trend by iterating Eq. (6) one period forward and taking expectations, yielding $\tau_{t|t} = \pi_t - \theta a_t$. The a_t term can then be solved out by using Eq. (6) in continual backward substitution, which gives the following expression for the filtered trend $\tau_{t|t}$:

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

In Eq. (7), the weights in front of the lagged inflation terms sum to one, and filtered trend inflation is simply a function of the distributed lags of past inflation. The equivalence of the observed components and IMA(1,1) model allows us to draw a link between the value */theta* and the dynamics of the filtered trend. Since θ varies inversely with the ratio of permanent to transitory disturbances, a smaller θ corresponds to more volatile trend innovations and the filtered trend depends more on recent observations. On the other hand, as θ approaches one, the filtered trend is simply the 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 transitory components of inflation, with remaining dynamics captured by sector-specific or idiosyncratic components. The MUCSVO model is outlined below:

$$\pi_{i,t} = \alpha_{i,\tau,t}\tau_{c,t} + \alpha_{i,\varepsilon,t}\varepsilon_{c,t} + \tau_{i,t} + \varepsilon_{i,t} \tag{8}$$

$$\tau_{c,t} = \tau_{c,t-1} + \sigma_{\Delta\tau,c,t} \times \eta_{\tau,c,t} \tag{9}$$

$$\varepsilon_{c,t} = \sigma_{\varepsilon,c,t} \times s_{c,t} \times \eta_{\varepsilon,c,t} \tag{10}$$

$$\tau_{i,t} = \tau_{i,t-1} + \sigma_{\Delta\tau,i,t} \times \eta_{\tau,i,t} \tag{11}$$

$$\varepsilon_{i,t} = \sigma_{\varepsilon,i,t} \times s_{i,t} \times \eta_{\varepsilon,i,t} \tag{12}$$

$$\alpha_{i,\tau,t} = \alpha_{i,\tau,t-1} + \lambda_{i,\tau}\zeta_{i,\tau,t} \text{ and } \alpha_{i,\varepsilon,t} = \alpha_{i,\varepsilon,t-1} + \lambda_{i,\varepsilon}\zeta_{i,\varepsilon,t} \tag{13}$$

$$\begin{aligned} \Delta ln(\sigma^2_{\varepsilon,c,t}) &= \gamma_{\varepsilon,c}\nu_{\varepsilon,c,t}, \qquad \Delta ln(\sigma^2_{\Delta\tau,c,t}) = \gamma_{\Delta\tau,c}\nu_{\Delta\tau,c,t}, \\ \Delta ln(\sigma^2_{\varepsilon,i,t}) &= \gamma_{\varepsilon,i}\nu_{\varepsilon,i,t}, \qquad \Delta ln(\sigma^2_{\Delta\tau,i,t}) = \gamma_{\Delta\tau,i}\nu_{\Delta\tau,i,t}, \end{aligned} \tag{14}$$

where the disturbance terms $\eta_{\tau,c,t}, \eta_{\varepsilon,c,t}, \eta_{\tau,i,t}, \eta_{\varepsilon,i,t}, \zeta_{i,\tau,t}, \zeta_{i,\varepsilon,t}, \nu_{\Delta\tau,c,t}, \nu_{\varepsilon,c,t}, \nu_{\Delta\tau,i,t}, \nu_{\varepsilon,i,t}$, are i.i.d. standard normal.

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 $\varepsilon_{c,t}$, and sector-specific trends and transient components, $\tau_{i,t}$ and $\varepsilon_{i,t}$. According to Eq. (13), the factor loadings on the common trend and transient components, $\alpha_{i,\tau,t}$ and $\alpha_{i,\varepsilon,t}$, evolve over time as random walks. Eqs. (9)-(12) allow stochastic volatility in the latent common and sector-specific components, where the stochastic volatility processes evolve according to a logarithmic random walk as in Eq. (14). Similar to the UCSVO, outliers in the transitory disturbances of the common and sector-specific components are accounted for through the random variables $s_{c,t}$ and $s_{i,t}$ in Eqs. (10) and (12), with corresponding outlier 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:

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

where n denotes the number of sectors, W_{it} is the expenditure share weight of sector i in total inflation, and $\alpha_{i,\tau,t}\tau_{c,t} + \tau_{i,t}$ represents the overall sectoral trend. From Eq. (15), note that in the extreme case where there is no common trend, trend inflation would just be the sum of the independent 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 availability. Headline inflation is denoted CPI-all, and is calculated as the year-on-year log changes in the quarterly consumer price index. More specifically, we compute inflation as $\pi_t = ln(CPI_t/CPI_{t-4}) \times 400$. 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 separated into raw food and food in core, and energy components can be separated from housing and transportation sectors. This gives us 10 components, which due to data limitations, is the lowest level of disaggregation for CPI-all inflation that we can achieve.

Table 1: Disaggregated components of CPI inflation

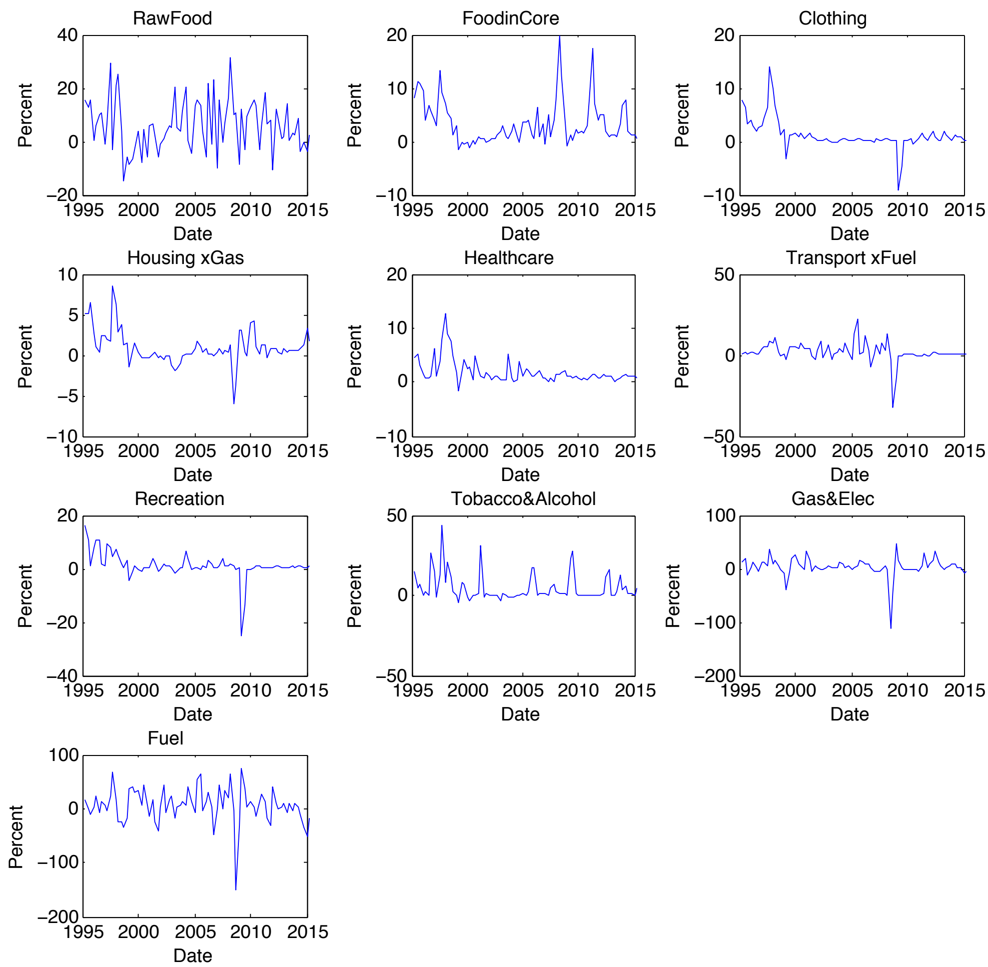
3 Components	7 Components	10 Components
1. Core Inflation	1. Food and Beverages	1. Raw food
2. Raw Food	2. Clothing	2. Food in Core
3. Fuel, Gas and Electricity	3. Housing	3. Clothing
	4. Healthcare	4. Housing excluding Gas and Electricity
	5. Transportation	5. Gas and Electricities
	6. Recreation and 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. A quick glance reveals that 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, during the recent crisis period, only about half of the sectors experienced a downward negative shock whereas the price series in other sectors remained stable

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

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 increased volatility towards the end of the sample.

Figure 2: Sectoral inflation series for Thailand



Note: The plot contains Thai CPI inflation disaggregated into 10 sectors based on their actual expenditure shares.

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 individual series over 5 year intervals based on monthly data[8]. Despite the expenditure shares of these sectoral inflation series being relatively constant (see Table 4), we find significant time variation in their volatility as well as their persistence, highlighting the importance of allowing for time-varying coefficients in the MUCSVO model.

Table 2: Standard deviation of sectoral inflation series

Sectoral Inflation	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 excluding Gas & Electricity	2.98	1.24	5.42	1.99
Healthcare	4.95	2.68	1.11	0.85
Transport excluding Fuel	5.25	7.25	15.40	1.05
Recreation & Education	9.24	4.28	15.15	1.07
Tobacco & Alcohol	19.69	12.02	16.85	7.74
Gas & 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 averaged over 5 year intervals.

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 exhibit the highest volatility across all subsamples, their persistence is not always necessarily the lowest. Therefore, simply excluding these volatile price sectors to arrive at a measure of core inflation may not be entirely appropriate, as the persistence contained in these series could also contain important information towards measurement of the trend. To account for this possibility, the MUCSVO leaves it up to the data to decide whether persistent price pressures of a particular sector should pass-through to the trend.

[8]There are different measures and estimation procedures to measure inflation persistence such as taking the sum of coefficients or the largest root in an autoregressive (AR) process, calculating the half-life defined as the number of periods in which inflation remains above 0.5 following a unit shock, or examining impulse response functions based on fitting a particular model (see Pivetta and Reis (2007), Kang et al. (2009) and references therein). We choose to measure persistence as the sum of coefficients in an AR process or order k i.e. $\gamma = \sum_{i=1}^{k} \theta_i$ where θ_i are the autoregressive coefficients. The rationale is that for a stationary inflation process, the cumulative effect of a shock on inflation is given by $1/(1-\gamma)$, and thus a larger γ corresponds to a higher level of persistence. To choose k, we use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which yielded a range of measures for k that are less than or equal to 4 depending on the subsample and sectoral series involved. To impose consistency across the subsamples and data series, we choose $k = 4$. Note that the results are robust to taking the largest autoregressive root of the AR(4) process as a measure of persistence as well.

Table 3: Persistence of sectoral inflation series

Sectoral Inflation	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 excluding Gas & Electricity	0.83	0.55	-0.21	0.46
Healthcare	0.83	0.42	0.81	0.89
Transport excluding Fuel	0.72	0.33	0.46	0.31
Recreation & 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 persistence of the annualized month-on-month sectoral inflation series estimated over five year intervals. Persistence is calculated as the sum of the coefficients in a fitted autoregressive model of order 4.

Table 4: Expenditure shares of sectoral inflation series

Sectoral Inflation	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 excluding Gas, & Electricity	27.10	25.04	21.86	20.27
Healthcare	7.26	7.39	6.89	6.48
Transport excluding Fuel	19.12	19.94	20.38	17.60
Recreation & 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 actual expenditure shares of sectoral inflation series in the consumer price index averaged over five year intervals.
Source: Thai Ministry of Commerce.

4.2 Estimation methodology

The estimation procedure for both the UCSVO and MUCSVO models is 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 (2016) 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 distibuted $U[0, 0.2]$. 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 in a sample of length 10 years with an outlier occurring once every 4 years. As for the initial values of τ_0, $ln(\sigma_{\varepsilon,0})$ and $ln(\sigma_{\Delta\tau,0})$, the priors are specified as independent diffuse normals[9].

In the MUCSVO model, the priors for the γ and p parameters as well as the sector specific components $\tau_{i,0}$, $ln(\sigma_{i,\varepsilon,0})$, 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 $ln(\sigma_{\varepsilon,c,0})$ 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, $\lambda_{i,\tau}$ and $\lambda_{i,\varepsilon}$, follow inverse gamma distributions.

Throughout this paper, we refer to smoothed estimates of an unobserved component at date t as the posterior mean of the component given the full dataset. The filtered estimate at date t on the other hand, is the conditional mean given only the data through date t, but with the parameters of the model evaluated using their posterior mean on the full dataset. We find it appropriate to use smoothed estimates for analyzing the dynamics of inflation ex-post, while filtered estimates are used to evaluate the accuracies and forecasting abilities of the unobserved components trend estimates.

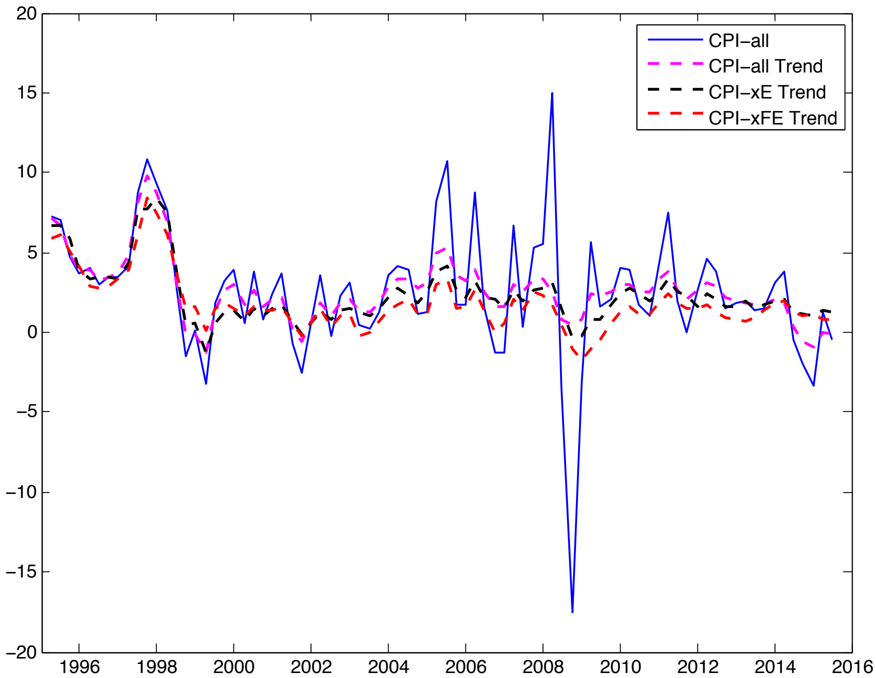
4.3 UCSVO results

Figure 3 plots CPI-all inflation and the full-sample posterior means of τ_t from the UCSVO model for headline (CPI-all) and core inflation measures which include CPI excluding energy (CPI-xE) and CPI excluding food and energy (CPI-xFE). 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 diverged in the period thereafter. In the post 2000 period, all trend estimates also became relatively smooth once compared to actual headline inflation. Interestingly, the CPI-all trend remains persistently above CPI-xE and CPI-xFE

[9]These specifications follow Stock and Watson (2016) which also seem reasonable for the Thai data sample. For robustness checks, we considered a range of different parameters for the prior distribution but this did not alter the posterior results in a significant way.

trend measures except for the most recent period due to falling oil prices.

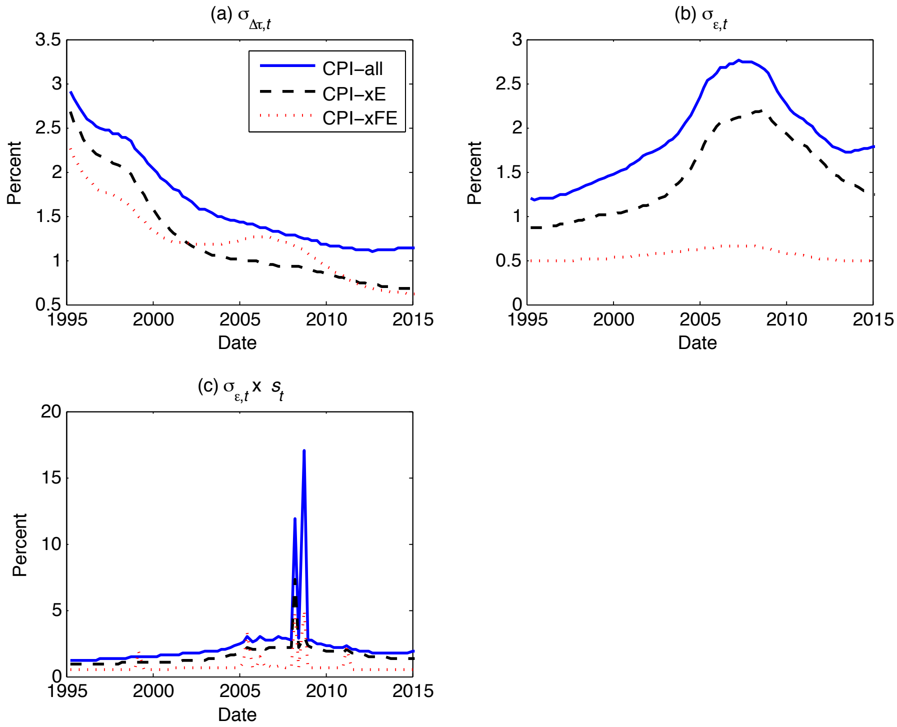
Figure 3: CPI inflation and smoothed UCSVO trends



Note: CPI-all is actual headline CPI inflation. CPI-all, CPI-xE and CPI-xFE trends are full-sample posterior mean estimates of trend inflation from the UCSVO based on CPI-all, CPI excluding energy (CPI-xE), and CPI excluding food and energy (CPI-xFE) data.

Figure 4 contains a plot of the full-sample posterior means of $\sigma_{\Delta\tau,t}$, $\sigma_{\varepsilon,t}$ and $\sigma_{\varepsilon,t} \times s_t$ obtained from the UCSVO, which reflect the variability of shocks to the trend and transitory components of inflation. 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 more stable around the year 2000. Since changes in monetary policy are known to have permanent effects on inflation, the adoption of an inflation targeting regime by the BOT in May 2000 most likely explains this result. Also, given that trend inflation shocks turn out to be more prominent in the earlier part of the sample, this finding explains why actual headline and core inflation moved closely in the pre 2000 period but diverged in the period thereafter.

Figure 4: Smoothed estimates of UCSVO permanent and transitory volatilities



Note: Panels (a)-(b) display the standard deviation estimates of shocks to the permanent and transitory components (without outliers) respectively. Panel (c) displays the standard deviation estimates of outliers in the transitory component of inflation. All estimates are full-sample posterior mean estimates based on applying the UCSVO to headline inflation (CPI-all) and core inflation (CPI-xE and CPI-xFE).

The second observation is that trend variability 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 if shocks to food and energy prices are largely transitory. The results here thus suggest that shocks to food and energy sectors are persistent, and contribute to the higher variability of permanent shocks in overall headline inflation[10]. Accordingly, the usual practice of discarding food and energy sectors altogether to arrive at a measure of core inflation may result in biased estimates of the trend.

The variability of the transitory components of CPI-all and core inflation measures also exhibit important differences, as shown in Panels (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 random variable s_t. As for CPI-xFE, it can be seen that

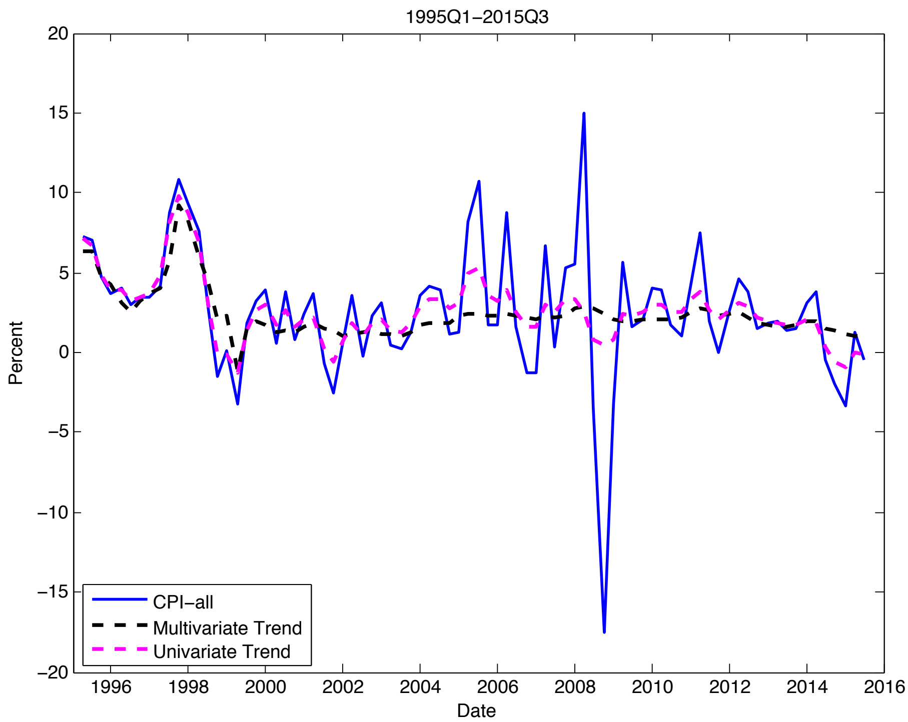
[10]Examining panel (a) further, some shocks from the global financial crisis show up in the trend component of CPI-xFE. However, based on the confidence bands associated with the trend estimates, this occurrence may merely be a reflection of sampling errors.

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 declined dramatically, especially during the global financial crisis. Therefore, we can infer that Thai inflation was largely driven by fluctuations in food and energy prices, particularly during the mid to late 2000s period.

4.4 MUCSVO results

The MUCSVO aggregate trend computed from 10 disaggregated sectors is plotted in Figure 5. For reference, we also plot headline inflation and the UCSVO trend from Figure 3. 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.

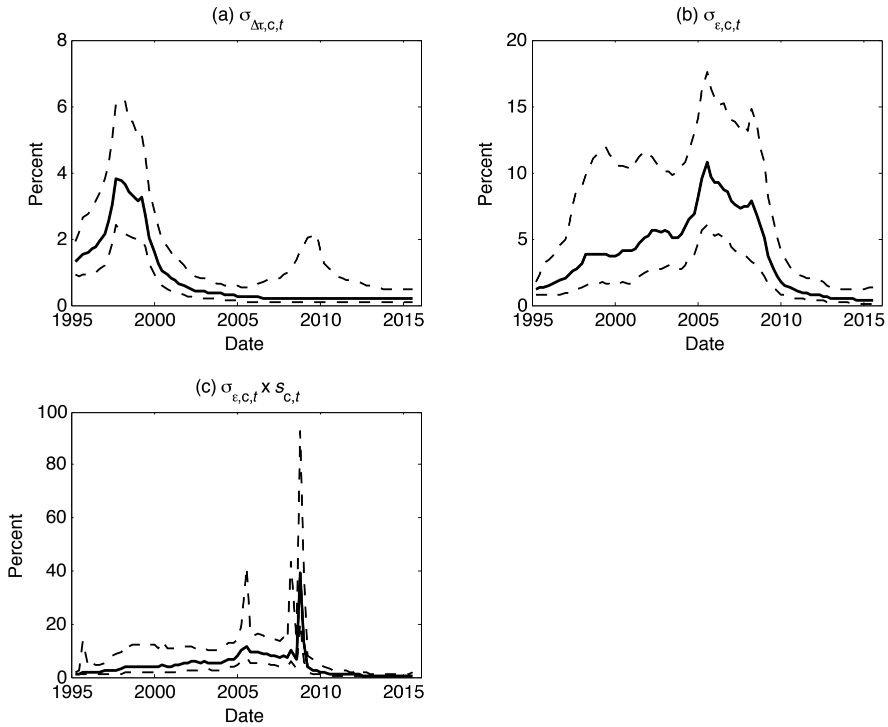
Figure 5: CPI Inflation and smoothed UCSVO and MUCSVO trends



Note: CPI-all is actual headline inflation. The UCSVO and MUCSVO trends are the full-sample posterior mean estimates computed from the CPI-all UCSVO and the 10-component MUCSVO.

Differences between the univariate and multivariate models can be discerned more closely by comparing Figure 4 with Figure 6. The latter figure plots the estimated posterior means of permanent and transitory volatilities of shocks from the MUCSVO model that are common to all 10 sectoral series. 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, whilst 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 variability in Thai inflation leading up to the Asian financial crisis may have been sector-specific, before delivering persistent macroeconomic-wide effects.

Figure 6: Smoothed estimates of MUCSVO permanent and transitory volatilities



Note: Panels (a)-(b) display the standard deviation estimates of shocks to the permanent and transitory components (without outliers) that are common to all sectors respectively. Panel (c) displays the standard deviation estimates of outliers to the common transitory component of inflation. All estimates are full-sample posterior mean estimates based on applying the MUCSVO to data on 10 disaggregated sectoral inflation series.

A second observation is that compared to the UCSVO model, the multivariate model detects a sharper decline in trend inflation variability around the year 2000. Furthermore, the volatility of MUCSVO trend innovations are also much lower and more stable during the post 2000 period, highlighting the effectiveness of the inflation targeting framework towards anchoring long-term inflation expectations.

Turning to examine the variability of the common transitory component ($\sigma_{\varepsilon,c,t}$) in Panel (b) of Figure 6, both univariate and multivariate models suggest 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. The MUCSVO, on the other hand, attributes this volatility to sector-specific rather than common transitory shocks. Last, Panel (c) suggests that the behavior of large outliers as captured by the univariate and multivariate models are more or less similar.

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 $(\alpha_{i,\tau,t}, \alpha_{i,\varepsilon,t}, \sigma_{\Delta\tau,c,t}, \sigma_{\varepsilon,c,t}, \sigma_{\Delta\tau,i,t}, \sigma_{\varepsilon,i,t})$ fixed at their full-sample posterior means. Then, we can compute the filtered MUCSVO trend for each sector as:

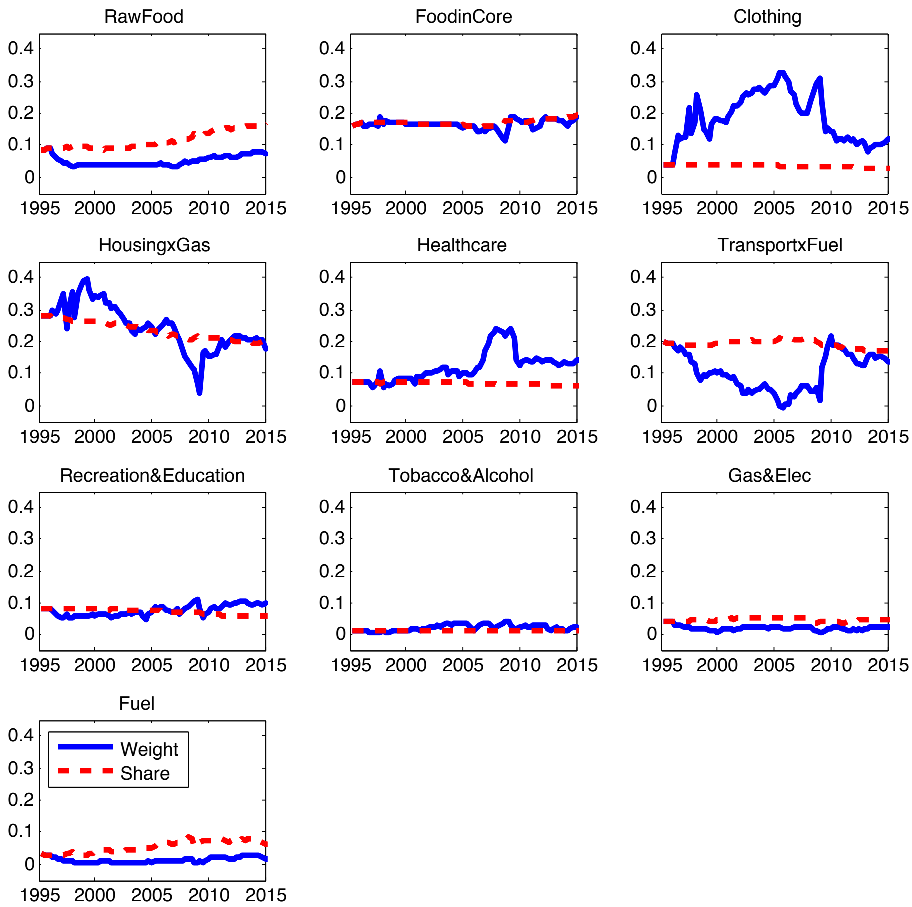
$$\tau_{i,t|t} = \sum_{j=0}^{t-1} \omega_{ij,t} \pi_{i,t-j} \tag{16}$$

where $\omega_{ij,t}$ are the implied time-varying weights for each sector.

Figure 7 plots the actual expenditure shares of each sector in CPI inflation against their approximate linear weights as implied by the MUCSVO trend estimate. We follow Stock and Watson (2016) and calculate the linear weight as the sum of the weights on the current and first three lagged values of the component inflation series over the sum of all component weights across the 10 sectors, i.e. $\bar{\omega}_{i,t} = \sum_{j=0}^{3} \omega_{ij,t} / \sum_{i=1}^{10} \sum_{j=0}^{3} \omega_{ij,t}$ where $\omega_{ij,t}$ follows the definition in Eq. (16). Note that the sum of all approximated linear weights in Figure 7 sum to one, and when we compare the approximate linear weights $\bar{\omega}_{i,t}$ to their expenditure shares, the linear weight for each sector shows whether the sector is getting more or less weight in the MUCSVO trend than in CPI-all.

The importance of allowing for time-varying sectoral weights in the MUCSVO cannot be understated. 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. 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 liquefied petroleum gas (LPG) prices in 2013.

Figure 7: Approximate weights for MUCSVO trend estimates and actual expenditure shares



Note: The solid lines are the approximate linear weights on the 10 components implied by the MUCSVO filtered trend and the dashed line are actual expenditure shares.
Source: Authors' calculations and the Ministry of Commerce.

To gain more intuition on the underlying factors that drive time-variation in the sectoral weights, we plot the full-sample posterior mean estimates of the trends, volatilities, factor loadings, and outliers belonging to each sector in Figures 12-21, which are placed in the Appendix due to space considerations. For all sectors, we observe that estimates of the idiosyncratic factor loadings and the standard deviations of trend components ($\alpha_{i,\tau,t}$ and $\sigma_{\Delta\tau,i,t}$) are relatively stable over the entire sample. This finding implies that the decline in the variability of the overall 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. As we discussed earlier, this occurrence can most likely be attributed to the adoption of an inflation targeting framework by the BOT during that time.

Next, we analyze selected sectors that display relatively high time-variation in their sectoral weights, 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 its exceptionally low volatility of transitory shocks as shown in Panel (d) of Figure 14, particularly when compared to the estimates of $\sigma_{\varepsilon,i,t}$ in other sectors.

Second, the implied sectoral weight for the housing excluding gas and electricities sector is large, in line with its importance in the CPI basket. However, compared to its expenditure share, its implied weight 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 ($\alpha_{i,\varepsilon,t}$), whereas in the latter period this sector was affected by a large number of sector-specific outliers.

Next, while the estimated weight for the healthcare sector was comparable to its actual expenditure share in the pre 2005 period, it gained dominance in the period thereafter. According to Figure 16, this can be explained by the decline in the volatility and magnitude of the factor loading on the transitory component in the healthcare sector which took place in the mid 2000s. Last, for the transportation excluding fuel sector, the sectoral weight was comparable to its expenditure share in the post 2010 period, but declined 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 during the same period.

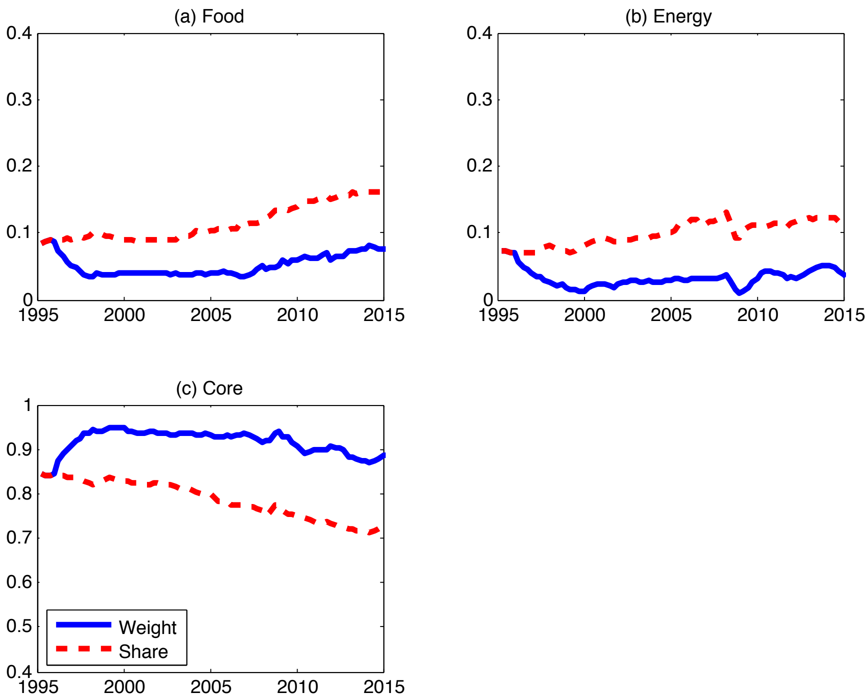
Three sector results

Traditional core inflation measures typically exclude raw food and energy sectors due to high volatility in these components. A quick glance at $\sigma_{\varepsilon,i,t}$ as plotted in Figures 12, 20, and 21 supports this line of reasoning. For Thailand, the fuel sector exhibits the highest degree of volatility in the transitory component, while the gas and electricity sector contains many outliers. Transitory shocks to the raw food sector is also volatile to a considerable degree.

Upon closer inspection of Figure 7 however, the filtered weights for these sectors 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 estimates of the overall trend, and this information should not be overlooked particularly because of the substantive roles that these sectors play in Thailand's consumer price basket.

To gain a better understanding about the role of food and energy prices shocks in the MUCSVO trend, the results from the 10 sector model in Figure 7 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.

Figure 8: Approximate weights for MUCSVO trend estimates and expenditure shares for food, energy and core components



Note: The solid line is the approximate share of each component's contribution to the overall filtered trend computed from the 10 component MUCSVO, and the dashed line is its actual expenditure share. The food component denotes the raw food sector, the energy component denotes gas, electricity and fuel sectors and the remaining sectors make up the core component.
Source: Authors' calculations and the Ministry of Commerce.

Panel (a) of Figure 8 displays the approximate 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 partly explain this result, according to estimates of $\sigma_{\varepsilon,i,t}$ in Figure 12, the food sector could have also become more important in the MUCSVO trend due to the fall in the volatility of its sector-specific transitory component since 2007. The finding that the food sector has become more persistent during the more recent period and should receive more weight in the overall trend inflation measure is similar to the findings for the US as reported by Stock and Watson (2016).

In contrast, the approximate weight on the energy component as shown in Panel (b) of Figure 8 appears relatively stable, despite the gradual rise in its expenditure share. Only a slight dip in its 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 seings in world oil price. The approximate weight for the energy sector is lower than the food component, implying that if one had to choose between CPI-xE and CPI-xFE, the former should be the preferred core measure for Thailand. However, the weight on the energy sector is still non-zero, implying that persistent movements in this component nonetheless contain useful information towards measurement of the overall CPI trend.

To further analyze why the energy component does not receive more weight in overall trend inflation, Panel (c) of Figure 21 shows that the factor loading on the transitory component of fuel or $\alpha_{\varepsilon,i,t}$ 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 to a considerable degree, lowering its persistence and as a result dampening the degree of energy 'pass-through' to the trend[11]. While it is not clear within the framework of this paper what structural forces are responsible for this result, the pick-up in $\alpha_{\varepsilon,i,t}$ for fuel is interesting insofar as it also suggests that since the year 2000, common transitory shocks in Thai inflation ($\varepsilon_{c,t}$) has become increasingly correlated with fuel price dynamics.

Finally, Panel (c) of Figure 8 plots the approximate weights for all remaining CPI sectors excluding food and energy components. In contrast to its declining expenditure share, the influence of core components on the estimated MUCSVO trend appears 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. In sum, the results in this section show that while traditional core inflation measures places no weight on food and energy price components, the MUCSVO recognizes that persistent movements from these sectors actually 'pass-through' to the overall trend with an approximate weight of 10 percent, which is a non-negligible contribution of half their expenditure share

[11] 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 co-moved closely with fluctuations in oil prices after the year 2007.

weights.

Accuracy of trend estimates

Due to differences in UCSVO and MUCSVO trend estimates, we ask whether the multivariate model measures trend inflation more precisely than its univariate counterpart. If so, we can infer that the use of sectoral data helps improve the precision of trend estimates. We evaluate this question based on the root mean squared estimation errors (RMSE) of MUCSVO and UCSVO trend estimators for headline (CPI-all) and core (CPI-xE and CPI-xFE) inflation. More specifically, we use the Kalman filter and the parameter paths of the 10 component MUCSVO model evaluated at their posterior means to compute the variances of the trend estimates associated with the UCSVO and 3 and 10 component MUCSVO models. Then, using relevant expenditure share weights (W_{it}), uncertainty surrounding these trend inflation estimates can be treated as a measure of accuracy for the trend of headline, CPI-xE and CPI-xFE core inflation.

Table 5 reports the RMSEs computed over three intervals, 1995Q2-1999Q4, 2000Q1-2008Q4, and 2009Q1-2015Q3, which is use to examine how the accuracy of trend estimates may have evolved over time[12]. The findings suggest that MUCSVO trend estimates are superior to those of the UCSVO as they are associated with lower RMSEs. Furthermore, the RMSEs associated with the 10 component MUCSVO model for all inflation measures are approximately half the magnitude when compared to those of the UCSVO during similar time periods. Accordingly, we can infer that additional information in disaggregated inflation series appears to have helped reduce trend inflation uncertainty, even at the cost of additional complexity. This observation is further confirmed by comparing the results of the 3 and 10 component multivariate model. While the 3 component model in general performs well, the 10 component model MUCSVO significantly outperforms the 3 component model for all inflation series and time periods, except for CPI-xE and CPI-xFE in the pre 2000 period.

[12] As a robustness check, the RMSEs are also computed by excluding the high volatility period during the global financial crisis, but we find that doing so does not affect the empirical results.

Table 5: Root mean squared estimation errors of UCSVO and MUCSVO trend estimates

Trend Estimator	1995Q2-1999Q4	2001Q1-2008Q4	2009Q1-2015Q3
UCSVO			
CPI-all	3.91	4.92	3.98
CPI-xE	2.99	3.77	3.09
CPI-xFE	2.01	2.50	1.63
MUCSVO (3 components)			
CPI-all	2.98	3.05	2.83
CPI-xE	1.55	1.72	2.16
CPI-xFE	1.07	1.29	1.60
MUCSVO (10 components)			
CPI-all	1.98	1.73	1.93
CPI-xE	1.77	1.36	1.40
CPI-xFE	1.39	1.03	0.77

Note: Reported are the RMSE of the trend estimator for the UCSVO and 3 and 10 components MUCSVO models, treated as an estimate of the trend for headline (CPI-all) and core (CPI-xE and CPI-xFE) inflation. All RMSEs are computed using the posterior means of the 10 component MUCSVO.

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 both the in-sample and out-of-sample predictive abilities of filtered UCSVO and MUCSVO trends against other benchmark measures that are commonly considered by the BOT.

All competing forecasts are evaluated based on their ability to predict the average value of future headline CPI-all inflation. More specifically, for both the in-sample and out-of-sample forecasting exercises, we are interested in computing the h-period-ahead forecast errors, $e_{t+h|t} = \bar{\pi}_{t+1:t+h} - \tau_{t|t}$ where $\bar{\pi}_{t+1:t+h} = h^{-1}\sum_{i=1}^{h}\pi_{t+i}$ is the average value of future headline inflation and $\tau_{t|t}$ is the current period trend estimate computed from all information available at time t. The forecasting horizons are $h = 4, 8$ and 12, which are typically the horizons considered for monetary policy analysis. Note that for the unobserved components models, the filtered trend $\tau_{t|t}$ for the in-sample analysis is slightly different from the out-of-sample one. The in-sample analysis uses data on the full data set to estimate all parameters, but

$\tau_{t|t}$ is the posterior mean of the trend that is estimated using data only up through date t. On the other hand, the out-of-sample analysis is based on a fixed rolling estimation window where the model parameters and the posterior mean of the trend $\tau_{t|t}$ are computed conditional on all data up to date t, where t marks the end of the rolling estimation window.

5.1 In-Sample Results

We first evaluate the in-sample predictability of UCSVO and MUCSVO filtered trend estimates, core inflation measures (CPI-xE and CPI-xFE), and trend inflation calculated from the asymmetric trimmed mean and PCA approaches. The accuracy of forecasts are evaluated based on its root mean squared forecast errors (RMSFE) averaged over the full sample, as well as over the following five-year subsamples: 1995Q2-1999Q4, 2001Q1-2004Q4, 2005Q1-2009Q4 and 2010Q1-2015Q3 to investigate whether the forecasting abilities of the various trend inflation measures changed over time.

Table 6 displays the average RMSFEs for various trend measures relative to those of the UCSVO trend. Overall, the MUCSVO outperforms the UCSVO at all forecast horizons since the reported statistics are less than one for the majority of samples. Other trend measures generate forecasts of future average inflation that are not cnstantly better than the UCSVO. Regarding the horizon of forecast, there is no conclusive evidence as to how shorter term forecasts ($h = 4$) fare when compared to longer term ones ($h = 12$).

To get a sense of the magnitude of RMSFEs, Figure 9 plots the 5-year rolling average RMSFEs associated with 8 quarter-ahead inflation forecasts, calculated from t=1995Q2 up until the end of sample[13]. Based on the plot, an interesting observation is that prior to the year 2000, average RMSFEs associated with all trend measures are more or less comparable. During this period, the UCSVO trend performed worst while the 3 component MUCSVO and the PCA measures outperformed others, but only by a modest margin.

After the early 2000s however, the RMSFEs associated with core and asymmetric trimmed mean measures increased significantly. The performance of the PCA measure is more or less in line with the UCSVO, with RMSFEs that are relatively low. Overall, the MUCSVO models are able to forecast inflation well, with the 10-sector MUCSVO model in the lead, followed by the 7 and 3 sector MUCSVO models respectively. Based on these results, additional information in sectoral inflation data appears to help forecast inflation, as the MUCSVO is able to deliver

[13]Rolling forecasts at other horizons look similar and are not reported here due to space considerations.

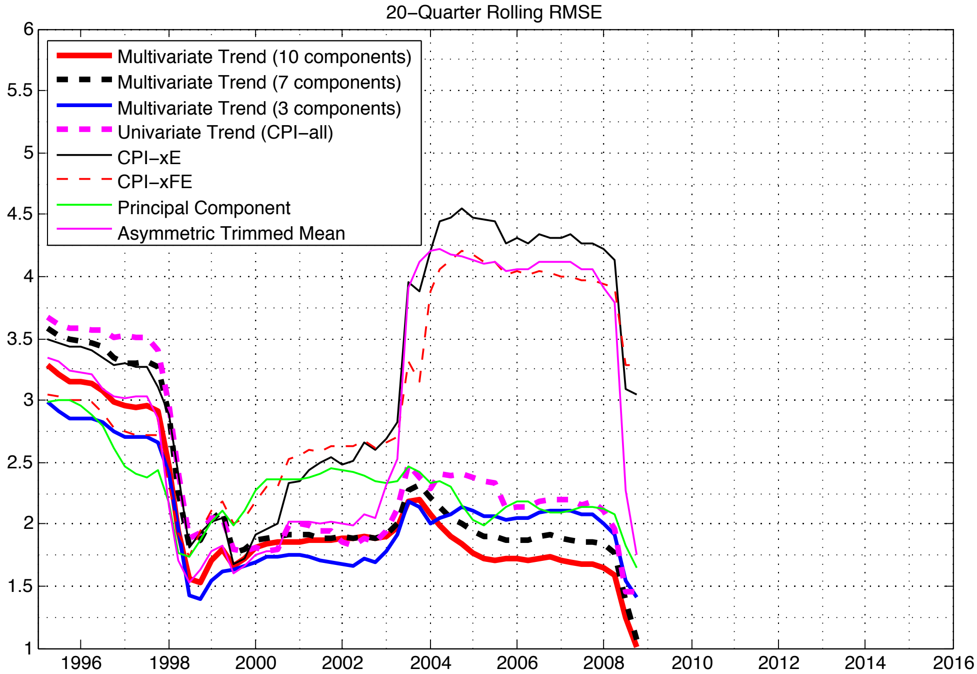
superior forecasts when compared to its univariate counterpart. However, given that core inflation also utilizes cross-sectional data but fares rather poorly suggests that the use of sectoral data alone cannot guarantee reliable forecasts for headline inflation. Rather, time-variation in sectoral weights is also an important feature for models of trend inflation.

Table 6: Root mean squared forecast errors of in-sample trend inflation forecasts of future average CPI inflation, relative to UCSVO trend forecasts

Trend Measure	1995Q2-2015Q3	1995Q2-1999Q4	2001Q1-2004Q4	2005Q1-2009Q4	2010Q1-2015Q3
Forecasts of headline inflation over the next 4 quarters ($h = 4$)					
MUCSVO (10 components)	0.862	0.892	0.962	0.791	0.962
MUCSVO (7 components)	0.933	0.982	0.965	0.876	0.930
MUCSVO (3 components)	0.879	0.830	0.817	0.913	1.039
CPI-xE	1.540	0.949	1.341	2.152	1.734
CPI-xFE	1.322	0.777	1.378	1.873	1.282
Principal components	1.015	0.877	1.649	0.966	1.313
Asymmetric trimmed mean	1.380	0.801	0.932	2.091	1.254
Forecasts of headline inflation over the next 8 quarters ($h = 8$)					
MUCSVO (10 components)	0.771	0.816	0.996	0.547	0.709
MUCSVO (7 components)	0.904	0.972	1.054	0.665	0.866
MUCSVO (3 components)	0.735	0.675	0.875	0.787	0.777
CPI-xE	1.659	0.925	1.120	3.539	2.386
CPI-xFE	1.406	0.704	1.436	3.081	1.085
Principal components	0.851	0.676	1.568	0.726	1.444
Asymmetric trimmed mean	1.402	0.848	0.931	3.003	1.208
Forecasts of headline inflation over the next 12 quarters ($h = 12$)					
MUCSVO (10 components)	0.699	0.784	0.942	0.386	0.655
MUCSVO (7 components)	0.859	0.955	1.038	0.570	0.795
MUCSVO (3 components)	0.693	0.643	0.861	0.665	0.802
CPI-xE	1.647	0.895	1.139	3.366	2.117
CPI-xFE	1.401	0.633	1.467	3.014	0.772
Principal components	0.749	0.564	1.557	0.560	0.977
Asymmetric trimmed mean	1.362	0.842	0.924	2.693	1.265

Note: The results are in-sample RMSFEs generated from trend estimates in the first column relative to those associated with the CPI-all UCSVO. Forecasts are computed for the 4, 8 and 12 quarter ahead horizons and are averaged over various sample periods as listed in the first row.

Figure 9: Rolling five-year average RMSFEs for 8-quarter ahead in-sample inflation forecasts



Note: Reported are the in-sample RMSFEs for various trend inflation measures averaged over a five-year rolling window starting in 1995Q2. The end point of 2008Q3 in the plot represents the five-year average of RMSFEs that are associated with forecast errors calculated as the difference between the average value of CPI-all inflation over the next 8-quarters (2010Q3-2015Q3) and filtered trend inflation estimates (2008Q3-2013Q3). Trend measures are generated from the MUCSVO model using CPI-all data disaggregated into 10, 7, and 3 components; the UCSVO model using CPI-all; core inflation measures including CPI-all excluding energy (CPI-xE) and CPI excluding food and energy (CPI-xFE), and trend measures constructed from the principal component analysis and the asymmetric trimmed mean.

One particular concern from the previously discussed forecasting results is that the RMSFEs 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 employ the modified Diebold-Mariano test statistic which is based on the following null hypothesis[14]:

$$H_0 : E(|e_{i,t+h|t}| - |e_{UCSVO,t+h|t})|) = 0. \tag{17}$$

[14]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.

As shown in Eq. (17), the test statistic formally evaluates the difference between the forecast errors associated with a particular model i against those produced from the benchmark UCSVO model.

The calculated test-statistics along with their associated p-values are reported in Table 7. The predictive accuracy test results are evaluated for the full 1995Q2-2015Q3 sample, as well as over two subsamples after the year 2000 when the forecasting performances of the various models diverged. From the full-sample results in the second column, all MUCSVO models outperform the UCSVO at the 10 percent confidence level. The PCA, asymmetric trimmed mean, and core inflation measures on the other hand, do not offer significant improvements over the UCSVO.

Table 7: Tests of equal predictive accuracy for in-sample inflation forecasts

Inflation Trend	1995Q2-2015Q3	2000Q1-2015Q3	2005Q1-2015Q3
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)
CPI-xE	2.357 (0.011)	3.061 (0.002)	2.632 (0.001)
CPI-xFE	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 in the first column and the UCSVO trend.

The third column of Table 7 contains the predictive accuracy test results for the 2000Q1-2015Q3 period, which corresponds to Thailand's inflation targeting regime. The MUCSVO trends again offer significant improvements over its univariate counterpart. Similar to the full sample results, trend inflation from the PCA does not outperform the UCSVO, implying that utilizing information in the correlation structure of disaggregated inflation series alone cannot guarantee good estimates for trend inflation in Thailand.

Finally, similar conclusions can be drawn from the 2005Q1-2015Q3 period, which according to Figure 9, is the period in which in-sample inflation forecasts diverged most. All multivariate models are now superior to the UCSVO while the UCSVO continues to deliver 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. These results then imply that information in disaggregated sectoral inflation data and allowing for 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

One puzzle in the inflation forecasting literature, especially for advanced economies such as 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 based on 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 an unobserved components model with stochastic volatility (UCSV) can offer significant gains in inflation forecasting over traditional Phillips curve models.

In this section, we assess the out-of-sample predictive ability of the 3, 7 and 10 component filtered MUCSVO trends, against trend estimates computed from benchmark univariate models that are known to forecast inflation well in the literature, namely the UCSV and the Atkeson and Ohanian (AO) model. However, to be consistent with the in-sample forecasting exercise, we use the UCSVO instead of the UCSV, which is the UCSV extended to include model-based adjustments for outliers. As for the AO forecast, average h-quarter-ahead inflation is compared to the average rate of inflation over the previous year. The UCSVO utilizes CPI-all inflation whereas the AO model is computed using both CPI and core inflation measures.

Based on the previous in-sample forecasting results, recall that there was not much difference in the predictive accuracies of competing trend inflation measures in the pre 2000 period. For this reason, we only focus on the post inflation targeting regime for our out-of-sample forecasting exercise. We compute the first h-quarter-ahead out-of-sample forecast for average inflation starting in 2005Q1, using 2000Q1-2004Q4 data, then extend our analysis based on a fixed estimation window to the end of the sample. Note that the reason why we did not use data prior to the year 2000 for our first out-of-sample forecast to avoid any parameter instability issues that could have occurred from the switch to the inflation targeting regime during that time.

Table 8 reports the RMSFEs computed from competing trend inflation measures relative to those of the UCSVO trend for various forecasting horizons, averaged over different subsamples. The three subsamples correspond to the pre crisis, crisis, and post-crisis periods respectively. Surprisingly, all trend measures outperform the UCSVO trend by a considerable margin across all sample periods. Also, the gains over the UCSVO are most pronounced prior to the year 2010 implying that the performance of the UCSVO was substantially inferior to others during the crisis period. In contrast to the in-sample forecasting results, we can also observe from Table 8 that the out-of-sample forecasting results generally improve as the horizon h increases.

Table 8: Root mean squared forecast errors of out-of-sample trend inflation forecasts of future average CPI inflation, relative to UCSVO trend forecasts

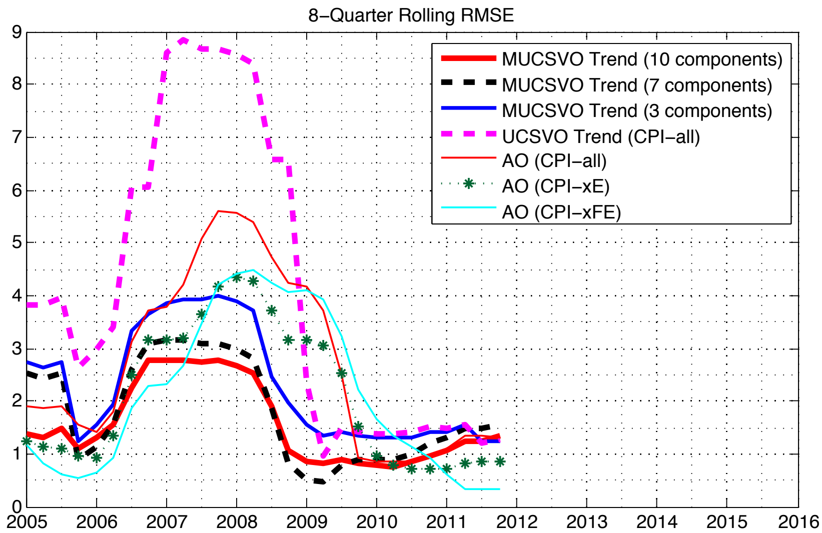
Trend Measure	2005Q1-2007Q2	2007Q3-2009Q4	2010Q1-2015Q3
Forecasts of headline inflation over the next 4 quarters ($h = 4$)			
MUCSVO (10 components)	0.285	0.241	0.998
MUCSVO (7 components)	0.541	0.276	0.938
MUCSVO (3 components)	0.626	0.361	1.083
AO (CPI-all)	0.403	0.372	0.602
AO (CPI-xE)	0.494	0.351	0.944
AO (CPI-xFE)	0.568	0.525	0.679
Forecasts of headline inflation over the next 8 quarters ($h = 8$)			
MUCSVO (10 components)	0.141	0.104	0.694
MUCSVO (7 components)	0.377	0.129	0.900
MUCSVO (3 components)	0.456	0.217	0.900
AO (CPI-all)	0.095	0.255	0.425
AO (CPI-xE)	0.075	0.264	0.841
AO (CPI-xFE)	0.204	0.421	0.677
Forecasts of headline inflation over the next 12 quarters ($h = 12$)			
MUCSVO (10 components)	0.157	0.056	0.673
MUCSVO (7 components)	0.400	0.075	0.852
MUCSVO (3 components)	0.512	0.152	0.935
AO (CPI-all)	0.213	0.202	0.465
AO (CPI-xE)	0.180	0.233	0.707
AO (CPI-xFE)	0.438	0.367	0.520

Note: The results are out-of-sample RMSFE that belong to trend estimates in the first column relative to those associated with the CPI-all UCSVO. Forecast errors are computed for the $4, 8$ and 12 quarter ahead horizons and are averaged over the various sample periods as listed in the first row. The MUCSVO trend is computed based on 10, 7 and 3 disaggregated series, and the Atkeson and Ohanian (AO) model is applied to CPI-all, CPI excluding energy (CPI-xE) and CPI excluding food and energy (CPI-xFE) data.

The poor out-of-sample forecasting performance of the UCSVO is confirmed in Figure 10, where we plot the RMSFEs for 8-quarter-ahead out-of-sample inflation forecasts for various trend measures, averaged over a fixed two-year window due to the shorter sample. First, ignoring the fact that the RMSFEs associated with

UCSVO out-of-sample inflation forecasts are exceptionally high, we observe that similar to the in-sample forecasting results, the MUCSVO RMSFEs are again the lowest RMSFEs for all inflation measures. 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 price shocks that occurred during that time.

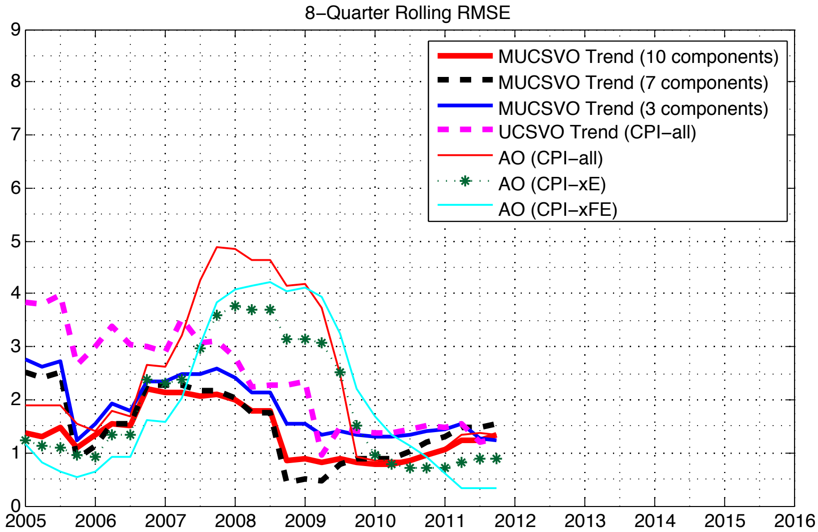
Figure 10: Rolling two-year root mean squared forecast errors for 8-quarter ahead out-of-sample inflation forecasts



Note: Reported are the out-of-sample RMSFEs for various trend inflation measures averaged over a two-year rolling window starting in 1995Q2. The end point of 2011Q3 in the plot represents the two-year average of RMSFEs that are associated with forecast errors calculated as the difference between the average value of CPI-all inflation over the next 8-quarters (2013Q3-2015Q3) and filtered trend inflation estimates (2011Q3-2013Q3). Trend measures are computed from the MUCSVO model using CPI-all data disaggregated into 10, 7, and 3 components; the UCSVO model using CPI-all data; and the Atkeson and Ohanian (AO) model applied to CPI-all, CPI excluding energy (CPI-xE) and CPI excluding food and energy (CPI-xFE) data.

Next, to explain the exceptionally poor out-of-sample forecasting performance of the UCSVO model, we investigated further and found that this result stems from exceptionally high forecast errors in 2008Q2 and 2008Q4. Unlike the MUCSVO, the univariate model was unable to adequately detect outliers at these dates, implying that the use of disaggregated data and separating common from sector-specific components helps the unobserved components model identify outliers to a considerable degree. As shown in Figure 11, once the forecast errors in 2008Q2 and 2008Q4 are removed, the average RMSFEs for the UCSVO model improves dramatically.

Figure 11: Rolling two-year root mean squared forecast errors for 8-quarter ahead out-of-sample inflation forecasts with outliers in 2008 removed



Note: Reported are the out-of-sample RMSFEs for various trend inflation measures averaged over a two-year rolling window starting in 1995Q2. The forecast errors are identical to those plotted in Figure 10, except that the forecast errors in 2008Q2 and 2008Q4 are removed before applying the average rolling window.

Finally, with the forecast errors associated with some competing trend measures in Figure 11 being fairly close, we compute the modified Diebold-Mariano test-statistics for equal predictive accuracy between the MUCSVO and AO trend measures relative to the UCSVO trend, with forecast errors in 2008Q2 and 2008Q4 removed. As shown in Table 9, the MUCSVO models clearly outperforms the UCSVO, whilst the AO model does not offer significant improvements. Therefore, the in-sample and out-of-sample forecasting results in this section both provide strong evidence that trend estimates constructed from the MUCSVO offers significant gains in forecasting when compared to other benchmark trend inflation measures in Thailand.

Table 9: 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 (CPI-all)	-0.379 (0.353)
AO (CPI-xE)	1.397 (0.085)
AO (CPI-xFE)	-0.992 (0.164)

Note: Reported are the modified Diebold Mariano test-statistic and corresponding p-values for the null of equal predictive accuracy between competing trend inflation measures in the first column against the CPI-all UCSVO trend. Forecast errors in 2008Q2 and 2008Q4 are removed before computing the test statistics.

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 (2016), we deliver new estimates of trend inflation for Thailand that improves upon conventional measures.

The empirical findings highlight at least two features that are important towards trend inflation measurement in Thailand. First, the MUCSVO utilizes sectoral inflation data which allows the model to better differentiate between system-wide and sector-specific shocks, as well as identify outliers. As a result, the uncertainty associated with MUCSVO trend estimates are approximately half the size of its univariate counterpart. When forecasting average future inflation at the 1-3 year horizon, the MUCSVO also delivers significantly lower inflation forecast errors than other benchmark trend inflation. Second, the MUCSVO allows persistent price shocks at the sectoral level to pass-through to trend inflation with weights that vary over time. By doing so, 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 rate movements for Thailand.

Our results help shed light on the drivers behind changing inflation dynamics in Thailand. During the pre 2000 period, inflation was mainly driven by common permanent shocks. These shocks however, became muted to a significant degree in the period thereafter due to the adoption of an inflation targeting framework. In the post 2000 period, fuel price movements became an important driver behind common transitory movements for Thai inflation, and therefore its weight in the estimated trend while positive, was relatively low. On the other hand, the raw food component became more persistent since the global financial crisis, giving it more weight in the overall estimate of the trend inflation. Together, these findings suggest that the core inflation measure that policymakers should pay more attention to should be CPI that excludes energy (CPIxE) rather than CPI that excludes food and energy (CPIxFE).

Finally, further refinements and extensions of the MUCSVO model in future research work would be beneficial, particularly for the tasks of real-time trend measurement and inflation forecasting. Towards this purpose, the results in this paper are already encouraging. A robust result is that the MUCSVO trend is able to outperform a wide range of benchmark trend inflation measures at various forecasting horizons, both in-sample and out-of-sample. Furthermore, the MUCSVO is able to detect and adapt to outliers more effectively than other models, which is an inarguably important feature for any real-time forecasting model. Nevertheless, a good real-time model for trend measurement and forecasting should work well with monthly data, but our current experiments find that the MUCSVO when directly applied to monthly data yielded inferior forecasts than those at the quarterly frequency. Future studies that investigate alternative specifications for trend and cycle innovations that are more well-suited to monthly data would therefore be particularly promising towards future developments in the inflation forecasting literature.

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Appendix

Figure 12: Raw food

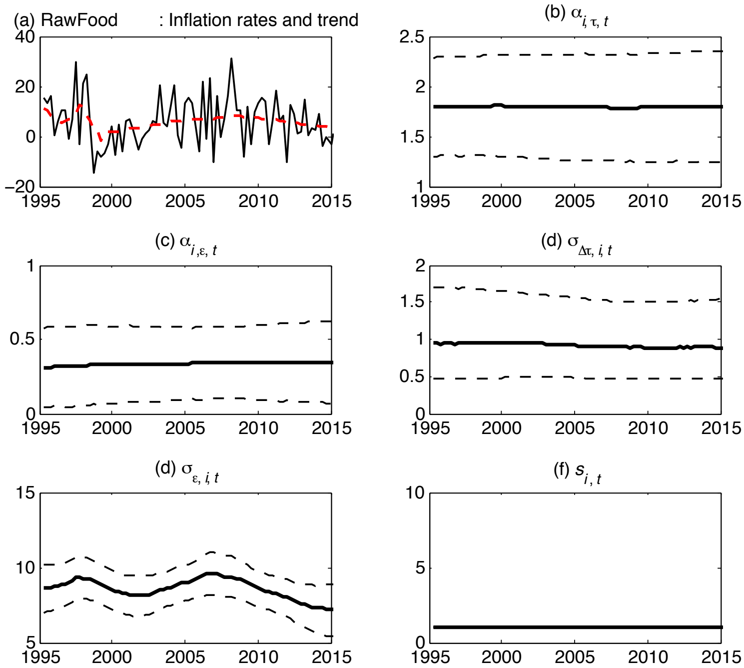
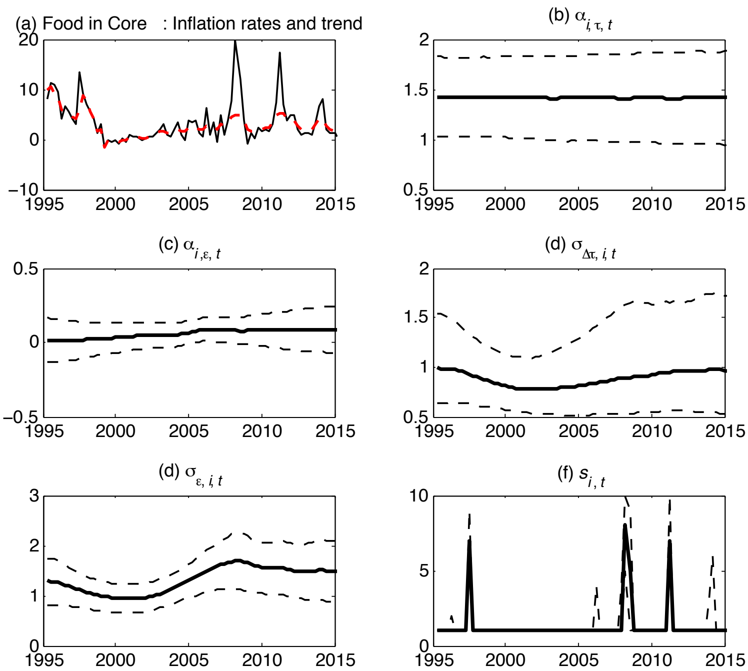


Figure 13: Food in core



Note: Panel (a) contains the sectoral series (solid line) and full-sample posterior means of the sectoral trend (dashed line). Panels (b)-(f) contain full-sample posterior medians (solid line) and 67% intervals (dashed line) for the sectoral factor loading on the common trend; factor loading on the common transitory component; standard deviation of the sector-specific permanent component; standard deviation of the sector-specific transitory component; and outliers in the transitory component respectively.

Figure 14: Clothing

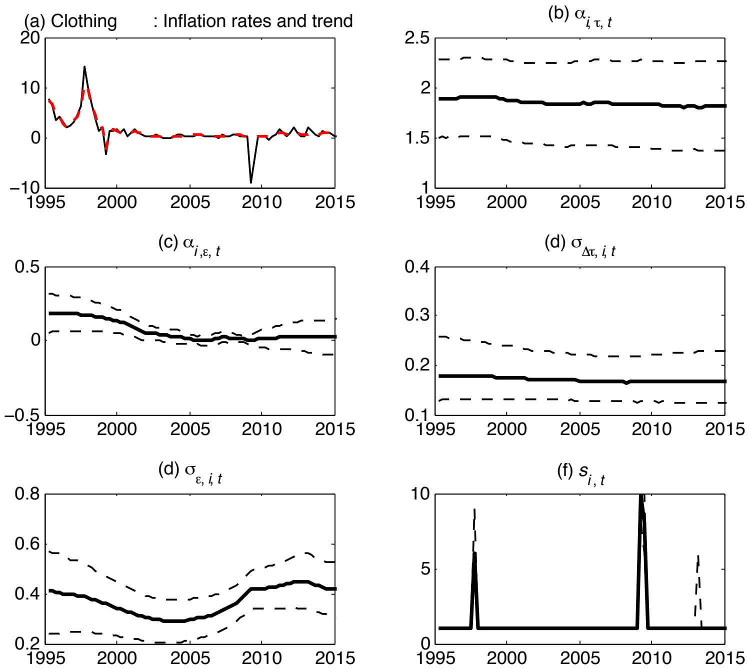
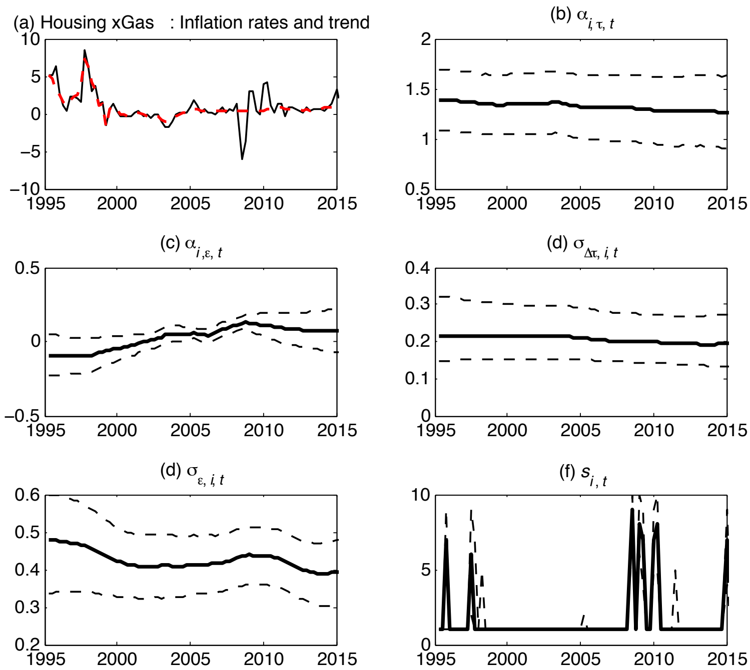


Figure 15: Housing excluding gas and electricity



Note: Panel (a) contains the sectoral series (solid line) and full-sample posterior means of the sectoral trend (dashed line). Panels (b)-(f) contain full-sample posterior medians (solid line) and 67% intervals (dashed line) for the sectoral factor loading on the common trend; factor loading on the common transitory component; standard deviation of the sector-specific permanent component; standard deviation of the sector-specific transitory component; and outliers in the transitory component respectively.

Figure 16: Healthcare

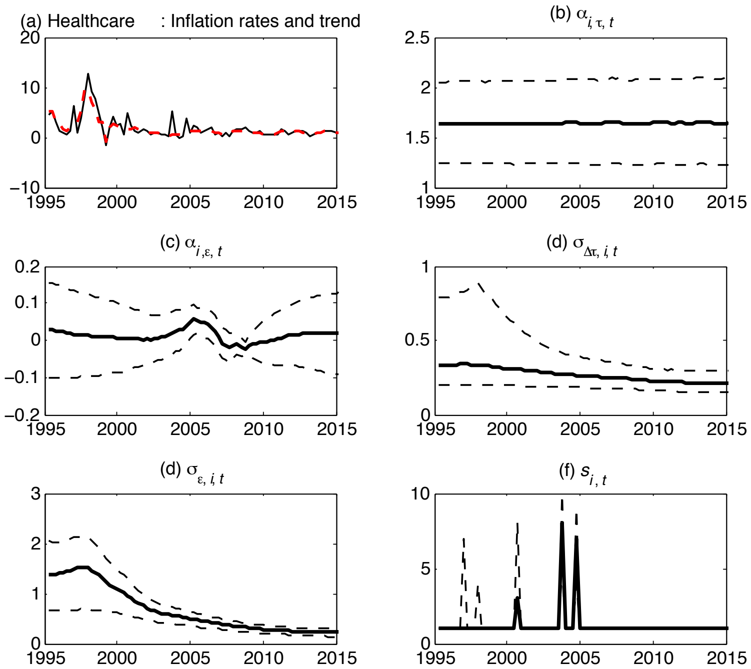
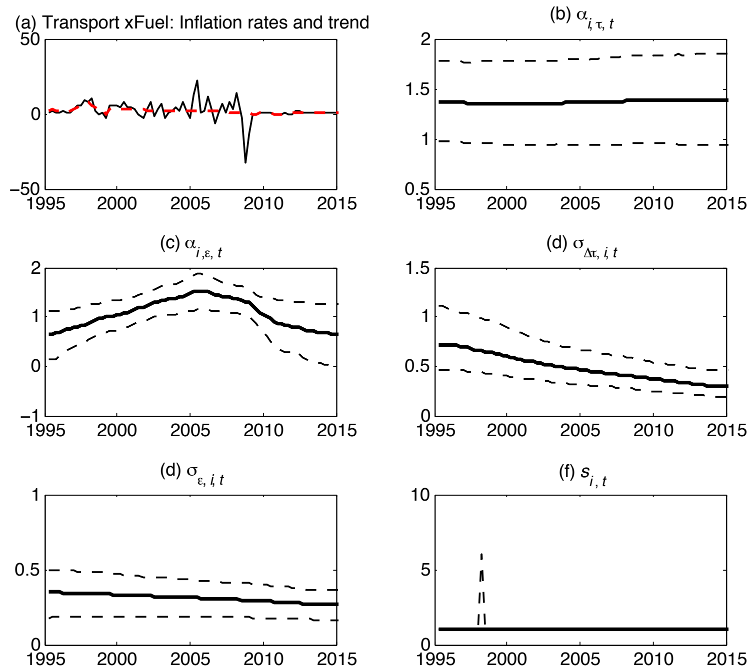


Figure 17: Transportation excluding fuel



Note: Panel (a) contains the sectoral series (solid line) and full-sample posterior means of the sectoral trend (dashed line). Panels (b)-(f) contain full-sample posterior medians (solid line) and 67% intervals (dashed line) for the sectoral factor loading on the common trend; factor loading on the common transitory component; standard deviation of the sector-specific permanent component; standard deviation of the sector-specific transitory component; and outliers in the transitory component respectively.

Figure 18: Recreation and education

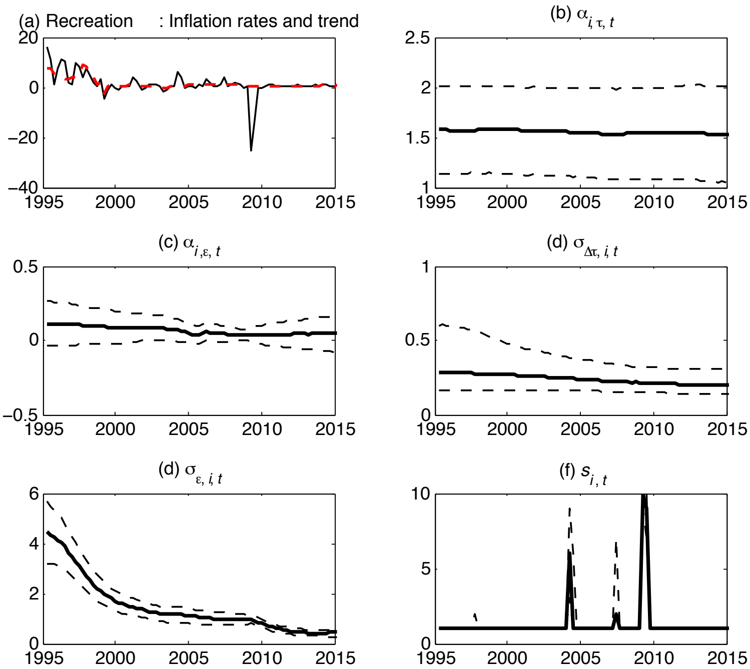
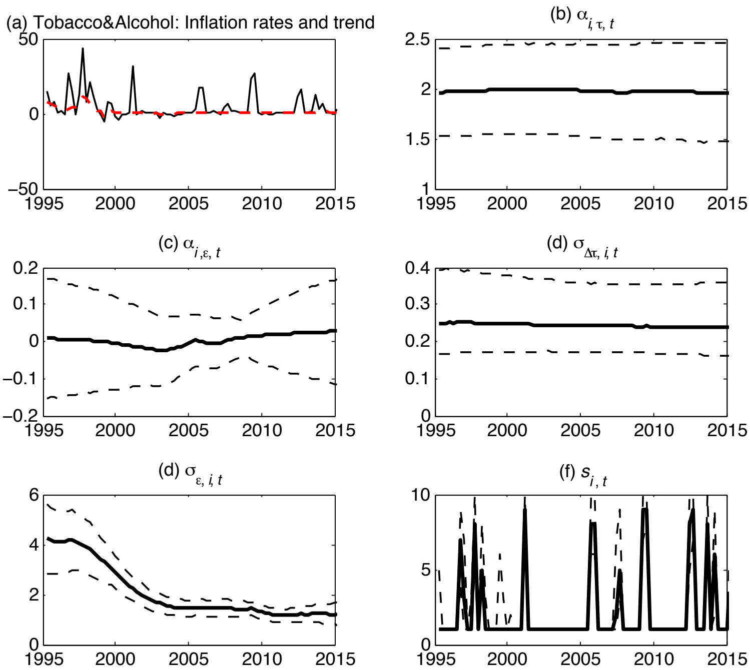


Figure 19: Tobacco and alcohol



Note: Panel (a) contains the sectoral series (solid line) and full-sample posterior means of the sectoral trend (dashed line). Panels (b)-(f) contain full-sample posterior medians (solid line) and 67% intervals (dashed line) for the sectoral factor loading on the common trend; factor loading on the common transitory component; standard deviation of the sector-specific permanent component; standard deviation of the sector-specific transitory component; and outliers in the transitory component respectively.

Figure 20: Gas and electricity

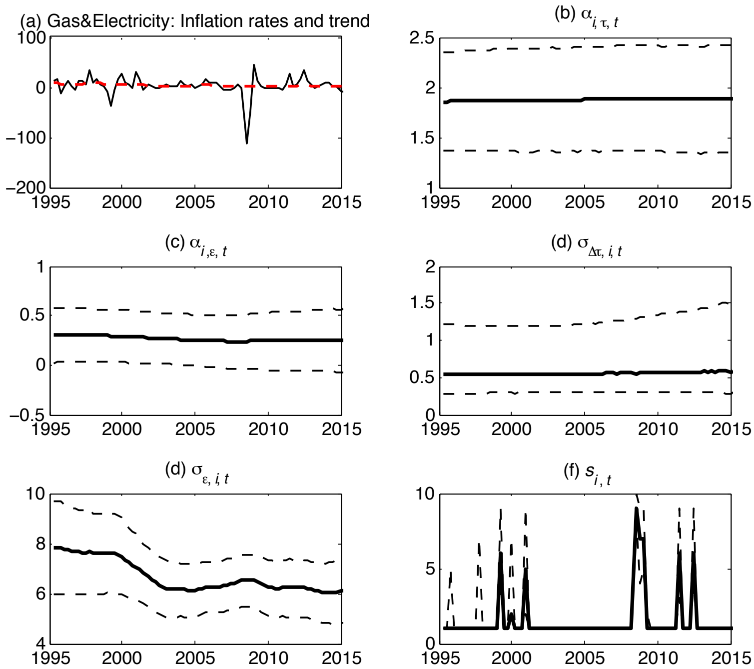
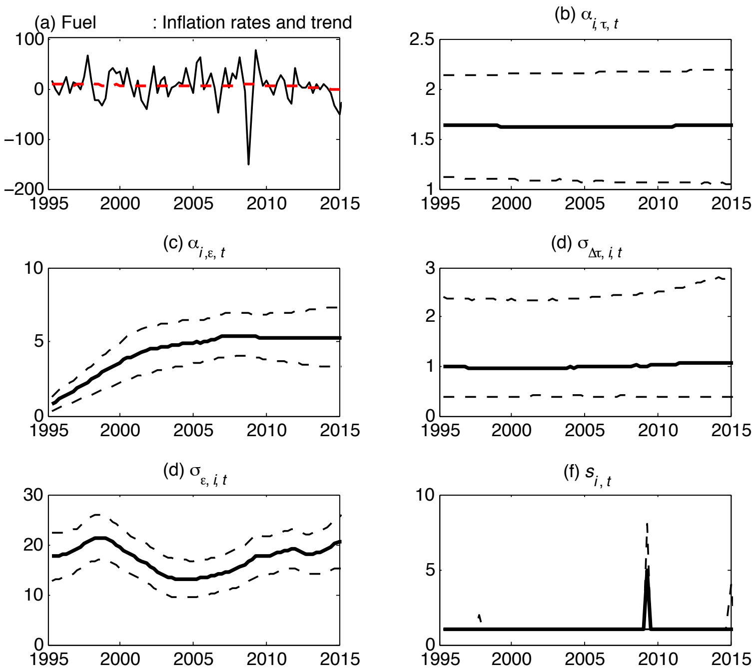


Figure 21: Fuel



Note: Panel (a) contains the sectoral series (solid line) and full-sample posterior means of the sectoral trend (dashed line). Panels (b)-(f) contain full-sample posterior medians (solid line) and 67% intervals (dashed line) for the sectoral factor loading on the common trend; factor loading on the common transitory component; standard deviation of the sector-specific permanent component; standard deviation of the sector-specific transitory component; and outliers in the transitory component respectively.