Monthly Trend Inflation Measurement at Sectoral Level*

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Abstract

The pandemic-era inflation surge raised questions about whether it was persistent or transitory and whether it was broad-based or confined to specific sectors. We estimate monthly trend inflation in the UK across 31 sectors using an Unobserved Components Stochastic Volatility and Outlier-adjusted (UCSVO) model, which separates persistent inflationary trends from transitory fluctuations. First, we find that aggregate headline inflation was low and stable until 2021 but grew more persistent due to lasting shocks and higher trend volatility. Goods inflation exhibited greater volatility and persistence, while services inflation remained stable, with moderate persistence from 2021. Second, by extending the model to a multivariate framework, we find that recent inflation persistence was mainly driven by macroeconomic shocks in the goods sector, along with some sector-specific shocks in services. The multivariate model improves the accuracy of trend inflation estimates by 50%, highlighting the value of incorporating sectoral dynamics in analysing inflation patterns.

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1 Introduction

The inflation surge starting in 2021 had ignited the debate about whether this rise is persistent or temporary, and whether it is broad-based or sector-specific. These questions are critical for monetary policymakers' role in controlling inflation. Better understanding of sectoral inflation dynamics also helps them make more informed judgment when forecasting inflation and setting monetary policy (Mann, 2024). However, the answers to these questions are nuanced, as each sub-sector of the consumer price index (CPI) has its own dynamics and driving forces.

To answer these questions and accurately measure underlying inflation, we distinguish the persistent component of inflation (trend) from the temporary, while simultaneously adjusting for seasonality, using the unobserved component stochastic volatility and outlier-adjusted (UCSVO) model. We build on Stock and Watson (2016, 2020) UCSVO model, a key methodology in the literature on modelling and forecasting trend inflation, extending it in two ways. One, while most applications focus on quarterly inflation (Li and Koopman, 2021; Stock and Watson, 2016), we estimate monthly trend inflation, allowing for more timely insights. Two, where previous studies primarily estimate headline inflation, we extend our analysis using the full sectoral composition of the CPI basket.

Measures of underlying inflation provide a means of looking beyond short-term volatility in price developments. There are at least two possible sources of short-term volatility – changes in seasonality and idiosyncratic price changes (henceforth "outliers"). The trend component from our estimated model smooths out fluctuations caused by transitory or seasonal factors in the data, capturing inflation persistence. Additionally, allowing for stochastic volatility of the trend directly influences how inflation persistence evolves over time. Periods of high stochastic volatility in the trend reflect increased uncertainty and longer-lasting inflationary pressures. In contrast, the volatility associated with transitory components reflects short-term, one-time shocks that do not have lasting effects on inflation. The USCVO model also automatically adjusts for outliers – this is helpful for data that shows large, infrequent spikes in inflation, particularly in sectoral components.

For our analysis, we estimate monthly aggregate and sectoral trend inflation using UK CPI data from the Office for National Statistics, covering 85 sub-sectors from January 2000 to December 2023. At the aggregate level, we examine headline inflation, as well as goods and services inflation. At the sectoral level, we aggregate the 85 sub-sectors into 31 broader categories representing goods and services sectors. Across sectors, we find that the UCSVO model performs well compared to the simple unobserved components model, i.e., one without stochastic volatility and outlier adjustments. By computing the trend signal-to-noise ratio, we observe that 93% of the 31 sectors in the CPI basket show improved signal extraction when including stochastic volatility in the trend. This indicates that the UCSVO model effectively captures the stochastic nature of inflation's mean, volatility, and persistence.

Our key results are in two-fold. First, we seek to answer whether the recent rise in inflation has mainly been persistent or temporary. Our analysis reveals that, up until 2021, UK headline inflation remained relatively low and stable, hovering around the 2% target with minimal persistence. This period was characterised by a steady trend and low volatility. However, post-2021, inflation exhibited a marked shift, becoming increasingly persistent. This change was driven by significant, persistent shocks coupled with heightened trend stochastic volatility, although short-term transitory shocks and outliers further amplified fluctuations during this period. Notably, aggregate headline inflation can mask the underlying dynamics, particularly during periods of elevated inflation. To uncover the sources of this persistence, we examine goods and services inflation separately. Trend inflation of goods rose sharply in late 2020 before declining in 2023, and shows higher trend volatility, reflecting greater inflation persistence in goods accompanied by more transitory shocks. In contrast, trend inflation of services sector are stable throughout the sample period, rising only from 2021 and with lower trend volatility, indicating that inflation persistence in services is moderate and more gradual compared to goods. The transitory component in services, however, has slightly increased, suggesting that short-term fluctuations are rising alongside moderate persistence.

Second, we further assess whether persistence in aggregate trend inflation is broad-based or sector-specific. Analysing 31 sectoral trends show varying levels of trends and volatilities, highlighting the importance of disentangling sectoral shocks from aggregate persistence to understand the underlying drivers of UK inflation during high-inflation periods. To explore the breadth of the inflation surge, we extend the univariate model analysis to a multivariate model (MUCSVO) to capture the joint dynamics of sectoral inflation in UK. This approach allows us to examine whether headline trend inflation was driven by a shock to specific sectors or by macroeconomic factors impacting all sectors. The multivariate trend consists of two components for each sector: a common trend and a unique trend. The common trend reflects broad-based price changes across all sectors, driven primarily by economy-wide shocks, while the unique trend captures sector-specific price movements arising from shocks to individual sectors. Accordingly, we construct multivariate trend inflation as the weighted sum of the common and sector-specific unique trends, with weights based on sector shares. The MUCSVO model improves the accuracy of trend inflation estimation by 50% compared to the posterior uncertainty intervals of headline trend estimates from the UCSVO model.[1]

We find that the persistence in aggregate trend inflation is largely driven by broad-based price changes across sectors facing economy-wide shocks. For the recent period, we find that the rise in aggregate trend was predominantly driven by macroeconomic shocks to goods and some sector-specific shocks to services. These widespread price movements can be attributed to a common component of the trend, driving co-movement across sectors. Key contributors to this persistence can include demand-supply imbalances, commodity price fluctuations or labour shortages, all of which create sustained inflationary pressures throughout the economy. However, when examining the persistence of inflation in goods and services inflation separately, distinct patterns emerge. The common component of trend exerts greater influence on inflation

[1] The accuracy of MUCSVO trend estimates improves by 80% when compared to 'bottom-up' aggregated sectoral trend estimates from UCSVO.

in goods, where shared drivers such as input costs, transportation constraints, or trade dynamics result in synchronised price changes. In contrast, the unique component of trend, representing sector-specific price movements, plays a larger role in driving inflation persistence in services. This may be linked to factors like labour market frictions or wage growth in service industries. One of the key tasks of a policymaker is to address the macroeconomic drivers that contribute to broad-based inflation persistence, as reflected in the common component. At the same time, it is also crucial to monitor pressures in specific sectors, particularly services in the UK, which may at times contribute to inflation persistence.[2]

Additionally, while the focus of this paper is on estimating trend inflation and understanding their sources, one of the motivations of producing a more accurate trend is to improve forecasting accuracy. We ran out-of-sample forecasts based on the UCSVO model on aggregate and sectoral inflation series. The forecast performance based on root mean squared errors (RMSE) reveals several key trends. First, forecast accuracy decreases as the horizon lengthens, with short-term predictions generally more precise than longer-term ones. Periods prior to Covid shows lower forecast errors, indicating higher forecast reliability in stable economic conditions. Moreover, when comparing forecast performance of different aggregate inflation, headline inflation performance lies between that for goods and services, with goods exhibiting the highest RMSE – likely due to the volatility inherent in goods prices. Additionally, the CPI sectors exhibit varying RMSE values, with some parts showing greater fluctuations in forecast accuracy over time, while others demonstrate a shift in behaviour before and after the Covid-19 pandemic. For instance, while pre-Covid forecasts for household goods and packaged holidays showed distinct performance differences at 3- and 6-month horizons, these discrepancies diminish in post-Covid forecasts. Together, these observations provide insights into how forecast accuracy can fluctuate across time horizons and sectors, highlighting areas where the model performs reliably and where adjustments might be necessary for better forecast performance.

This paper is related to two strands of literature. First, we contribute to the estimation of trend inflation. The UC model extended with stochastic volatility for both the permanent and transitory shocks has gained much interest in the literature and central banking application on the modelling and forecasting of inflation. There are a number of papers that have applied the UC model including Chan et al. (2013), Clark and Doh (2014), Li and Koopman (2021) and Eo et al. (2023) devise univariate, bi-variate and multivariate UCSV methods to model and forecast US quarterly inflation. We follow the methodology of Stock and Watson (2016), who estimated the quarterly trend inflation of the US for PCE inflation. They also estimated *quarterly* trend for Euro Area for HICP inflation in Stock and Watson (2020), where they additionally model seasonal component in the UCSVO model as HICP inflation is published non-seasonally adjusted. In the UK, the data we receive from ONS is not seasonally adjusted. We contribute to the existing literature by incorporating a *monthly* seasonal component into

[2]A couple of Monetary Policy Reports by the Bank of England, for example the February 2024 MPR, considers services inflation to be an indicator of inflation persistence because it is primarily driven by domestic cost pressures, which tends to be sticky and slow to adjust.

the UCSVO model, representing a significant advancement in the accurate capture and analysis of inflation dynamics. This feature of the model is particularly important across sectors as the seasonality patterns exhibit substantial variation over time.

Second, there is a growing body of literature addressing focusing on disaggregated approach, and our work contributes to this expanding field of research. Barkan et al. (2023) use disaggregated inflation series for US to forecast inflation. They apply a Hierarchical Neural network model to forecast disaggregated inflation that can help policy makers understand aggregate dynamics. Bermingham and D'Agostino (2011) test the empirical performance of various statistical models on US and Euro area desegregated price data and argue that it is better to aggregate forecast rather than forecasting headline, similar to Duarte and Rua (2007) who find the same for Portuguese CPI disaggregates using factor models. Ibarra (2012) use a mix of macro and disaggregated CPI series to forecast Mexican inflation to find that dynamic factor models that input disaggregated series outperform a simple AR process. Disaggregated approaches remain relatively under-explored for the UK, with the exception of Joseph et al. (2024) who uses monthly disaggregated price data but with a focus on forecasting, employing a range of models from linear principal component analysis to more advanced machine learning tools. Our paper builds on these findings by introducing a multivariate UCSVO (MUCSVO) model, which explicitly accounts for sectoral co-movements in inflation persistence.

The rest of the paper is structured as follows. Section 2 describes the aggregated and disaggregated UK CPI data series. Section 3 briefly describes the univariate and multivariate method. In Section 4, we discuss key findings on inflation persistence and its contributors. Section 5 integrates results from the different methodologies and data disaggregation levels, comparing their accuracy and effectiveness to achieve more nuanced insights. The final section 6 concludes.

2 Data

We use the price indices for Consumer Price Inflation (CPI) components obtained from the Office for National Statistics (ONS). The complete set of CPI disaggregates consists of 85 series that contribute to the calculation of headline CPI inflation. For our analysis, we aggregate these 85 indices using CPI weights, also provided by the ONS, into 31 sectors, distinguishing between goods and services.[3] To build intuition on UK inflation, we start our analysis on three aggregate measures: headline, goods and services. Inflation is measured monthly in percentage points at an annualised rate. Our sample period spans from January 2000 until December 2023.[4]

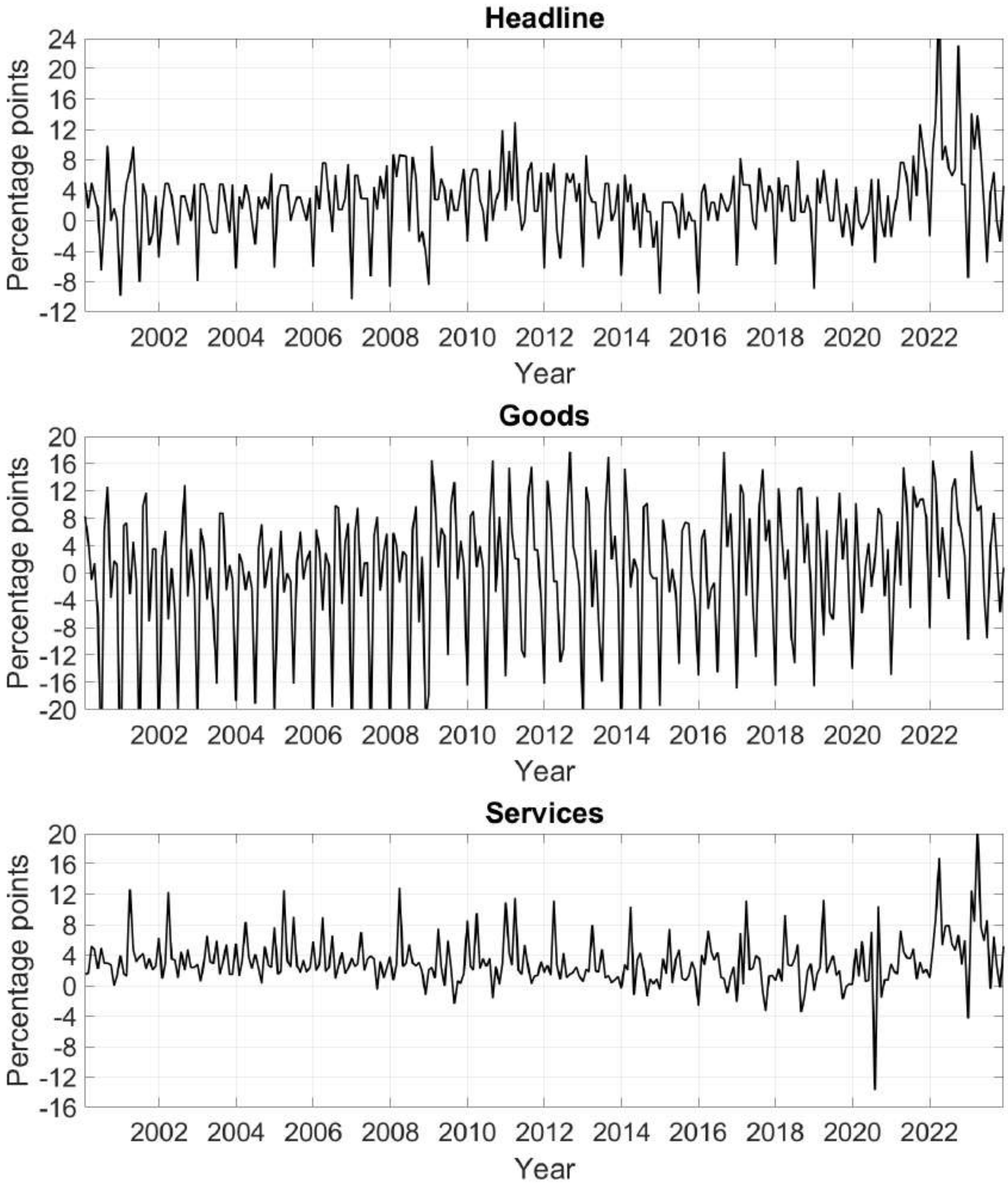
Figure 1 presents the monthly annualised headline inflation rate for the UK, with an average of 2.54 percent and a standard deviation of 4.86 percent. Aggregate goods inflation has a lower average of 0.31 percent but is more volatile, with a standard deviation of 10.06 percent. Services,

[3]A full list of these components, along with summary statistics, is provided in Table 2 in the Appendix.

[4]CPI data is published from January 1996 but Healthcare Services price data starts in January 2000. For a balanced panel of data, particularly when we turn to the Multivariate UCSVO in Section 4.3, we use data from 2000 onwards.

in contrast, exhibit less volatility, with a mean of 3.12 percent and a standard deviation of 3.38 percent.

Figure 1. Monthly Annualised Aggregate Inflation Series for the UK



Note: This figure plots the monthly inflation rate on an annualised basis from January 2000 to December 2023 for three aggregate measures: Headline, Goods, and Services.

The monthly annualised inflation for 31 sectors (see Appendix, Figure 15) reveals significant variation in the time series properties across these sectors. For instance, seasonal fluctuations appear in categories such as Airfares, Clothing and Footwear, while distinct upward and downward trends emerge in Audio-Visual Goods and Household Services, respectively.

3 Methodology

Our methodology builds on the Stock and Watson (2016, 2020) unobserved component model with stochastic volatility and outlier adjustment (UCSVO), extended in two ways. First, while most UCSV applications focus on quarterly inflation, we estimate monthly trend inflation of UK CPI inflation, allowing for more timely insights. This version of the UC model seasonally adjusts inflation and estimates its trend—particularly useful for analysing different categories of the CPI basket. Additionally, we extend the model to capture the joint dynamics of sectoral inflation using a multivariate UCSVO framework (MUCSVO), which allows us to address our second question regarding the drivers of persistence in inflation: are they broad-based or sector-specific?

3.1 UCSVO model

Unobserved component models decompose inflation into persistent (trend), seasonal and transitory components, with innovations to those components following variances that evolve over time according to independent stochastic volatility processes. The innovation to the transitory component is allowed to have heavy tails to account for potential outliers in the data, which helps adjust for outliers in the data in real time, particularly during periods of inflation surges.

Inflation at time t, denoted by π_t, is expressed as the sum of a trend component τ_t, a seasonal component s_t and a transitory component ε_t:

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

Each component follow a distinct stochastic processes. The trend component τ_t follows a random walk (martingale process):

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

The seasonal component s_t follows a monthly process:

$$s_t = s_{12} - \cdots - s_1 + \eta_{s,t} \tag{3}$$

The transitory component ε_t is unforecastable:

$$\varepsilon_t = \eta_{\varepsilon,t} \tag{4}$$

Time-varying variances are introduced by modelling the shocks $\eta_{\tau,t}, \eta_{s,t}$ and $\eta_{\varepsilon,t}$ to follow stochastic volatility:

$$\eta_{\tau,t} = \sigma_{\tau,t} e_{\tau,t}; \eta_{s,t} = \sigma_{s,t} e_{s,t}; \eta_{\varepsilon,t} = o_t \sigma_{\varepsilon,t} e_{\varepsilon,t} \tag{5}$$

where $e_{\tau,t}, e_{s,t}, e_{\varepsilon,t} \sim$ i.i.d $N(0,1)$ and $\sigma^2_{\tau,t}, \sigma^2_{s,t}, \sigma^2_{\varepsilon,t}$ evolves through time as a logarithmic random walk with $\nu_t \sim$ i.i.d $N(0, \sigma^2_\nu)$. Outliers are captured through the variable o_t, which follows a mixture of normals. With probability $(1-p)$, $o_t = 1$ (no outlier) and with probability p, o_t

is drawn from $U(2, 10)$ there is an outlier with a standard deviation that is between 2 and 10 times larger than a case of no outlier.

In the non-seasonal UC model, the forecast of future inflation rate is the estimate of τ_t, based on past observations of π_t:

$$\mathbb{E}\left(\pi_{t+h}|\{\pi_i\}_{i=1}^t\right) = \mathbb{E}\left(\tau_{t+h} + \varepsilon_{t+h}|\{\pi_i\}_{i=1}^t\right) = \mathbb{E}\left(\tau_t|\{\pi_i\}_{i=1}^t\right) = \tau_{t|t} \tag{6}$$

where the final equality follows from the random walk model for τ_t and the unpredictability of ε_t.[5]

The UC model with seasonal component is structured to ensure that the long-run trend remains the primary long-term forecast for annual averages. The seasonal process is a time-series process with predicted values that (i) repeat seasonally where $S_{T'+j|T} = S_{T'+j+12|T}$ and (ii) it sums to zero over a one-year period $\sum_{j=1}^{12} S_{T'+j|T} = 0$, where $S_{r|T}$ is the predicted value of S_r made using data through time T, for any $T' \geq T$. Therefore, the seasonal model yields a similar interpretation of the $\tau_{t|t}$ as in the non-seasonal version of the model, but for the annual averages of future values of inflation $\bar{\pi}$:

$$\mathbb{E}\left(\bar{\pi}_{t+j:t+j+11}|\{\pi_k\}_{k=1}^t\right) = \mathbb{E}\left(\bar{\tau}_{t+j:t+j+11} + +\bar{\varepsilon}_{t+j:t+j+11}|\{\pi_k\}_{k=1}^t\right) = \mathbb{E}\left(\tau_t|\{\pi_k\}_{k=1}^t\right) = \tau_{t|t} \tag{7}$$

for $j > 0$, where the final equality follows from the random walk model for τ_t, the seasonal model that sums to zero over a one-year period $\sum_{j=1}^{12} S_{T'+j|T} = 0$ and the unpredictability of ε_t.

3.2 Multivariate UCSVO

The multivariate model extends the UCSVO model where it estimates a common latent factor along with the sector-specific unobserved components. Each sector i has its own trend, seasonal, and transitory components, and now also shares common components across sectors.

For each sector i, inflation $\pi_{i,t}$ is modelled as:

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

where $\tau_{c,t}, s_{c,t}, \varepsilon_{c,t}$ are common components, $\tau_{i,t}, s_{i,t}, \varepsilon_{i,t}$ are sector-specific and $\alpha_{i,\tau}, \alpha_{i,s}, \alpha_{i,\varepsilon}$ are time-invariant factor loadings. The multivariate model also allows outliers in each of the sector specific component and in the common component. The aggregate trend inflation is the

[5] The model is estimated using Bayesian method, adapting the approach from Stock and Watson (2020), with Kalman filtering applied at a monthly frequency. Stock and Watson (2020) use the setup in Kim et al. (1998) to incorporate stochastic volatility model that is estimated using Gibbs sampling methods using a mixture of normal densities to approximate the log - χ_t^2 density together with Kalman smoothing recursions.

weighted sum of the sectoral trend:

$$\tau_t = \sum_{i=1}^{n} w_{i,t} \left(\alpha_{i,\tau} \tau_{c,t} + \tau_{i,t} \right) \tag{9}$$

where $w_{i,t}$ denotes the CPI weight of each sector i in total inflation and n is the number of sectors.

4 Results

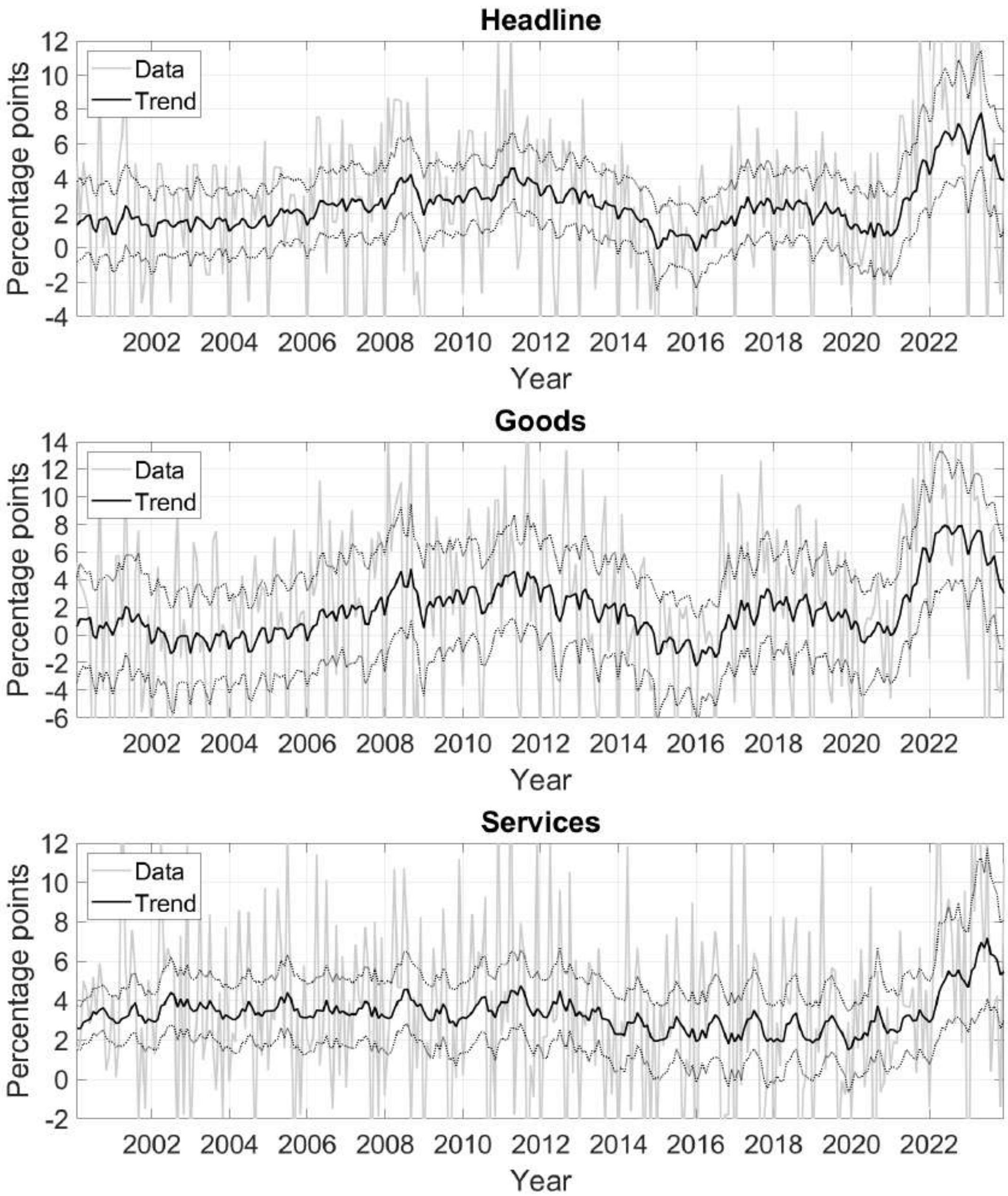
In this section, we discuss the estimated persistent (trend), seasonal and transitory components from the model. The first subsection focuses on the estimated components from the UCSVO model applied to the aggregate (headline, goods and services) inflation series. We then explore the 31 sectors to better understand the dynamics in the entire inflation basket. Lastly, we present findings from the multivariate (MUCSVO) model to see how broad based inflationary shocks were.

4.1 Analysing Aggregate Inflation: Persistent and Transitory Components

The UCSVO model facilitates the differentiation between the persistent and transitory components of inflation, while also adjusting for outliers. By smoothing fluctuations from transitory and seasonal factors, the trend component largely captures inflation persistence. In Figure 2 plots the (filtered) estimates of trend inflation τ_t posterior mean and 68% credible interval from the UCSVO model for three inflation aggregate series: Headline, Goods, and Services. Aggregate headline inflation can obscure underlying dynamics so we investigate goods and services trend as well to better understand their contributions to overall persistence. The trend in headline inflation hovered around 2%, averaging 2.1% prior to the significant increase in 2021. Meanwhile, trend inflation for goods and services averaged at 1.2% and 3.1%, respectively. The recent rise in headline inflation trend can be attributed to increases in both goods and services inflation. In 2022, driven by surges in energy and food prices, trend goods inflation soared to 7.9%. Services inflation also reached a historical high and remained persistently high, in contrast to trend of goods inflation, which has gradually returned to its pre-Covid levels.

The stochastic volatility feature of the model effectively captures the volatilities of trend component, aiding in the identification of persistence in the trends. This volatility significantly influences the evolution of inflation persistence, thus playing a key role in its development. Figure 4 (a) plots the estimated standard deviations of the innovations in trend σ_{τ_t} for inflation aggregates. In a constant volatility UC model, these variances would reflect the average over the sample period. Instead, our estimates indicate that the volatilities of aggregate inflation have been increasing over the years, albeit at different speed and magnitude. Periods of elevated stochastic volatility indicate heightened uncertainty and prolonged inflationary pressures. In early 2000s, the level of volatility in goods trend inflation was approximately twice that of headline inflation; however, it picks up at a faster rate and at the end of 2023, goods trend inflation is about 3.5 times more volatile than headline.[6]

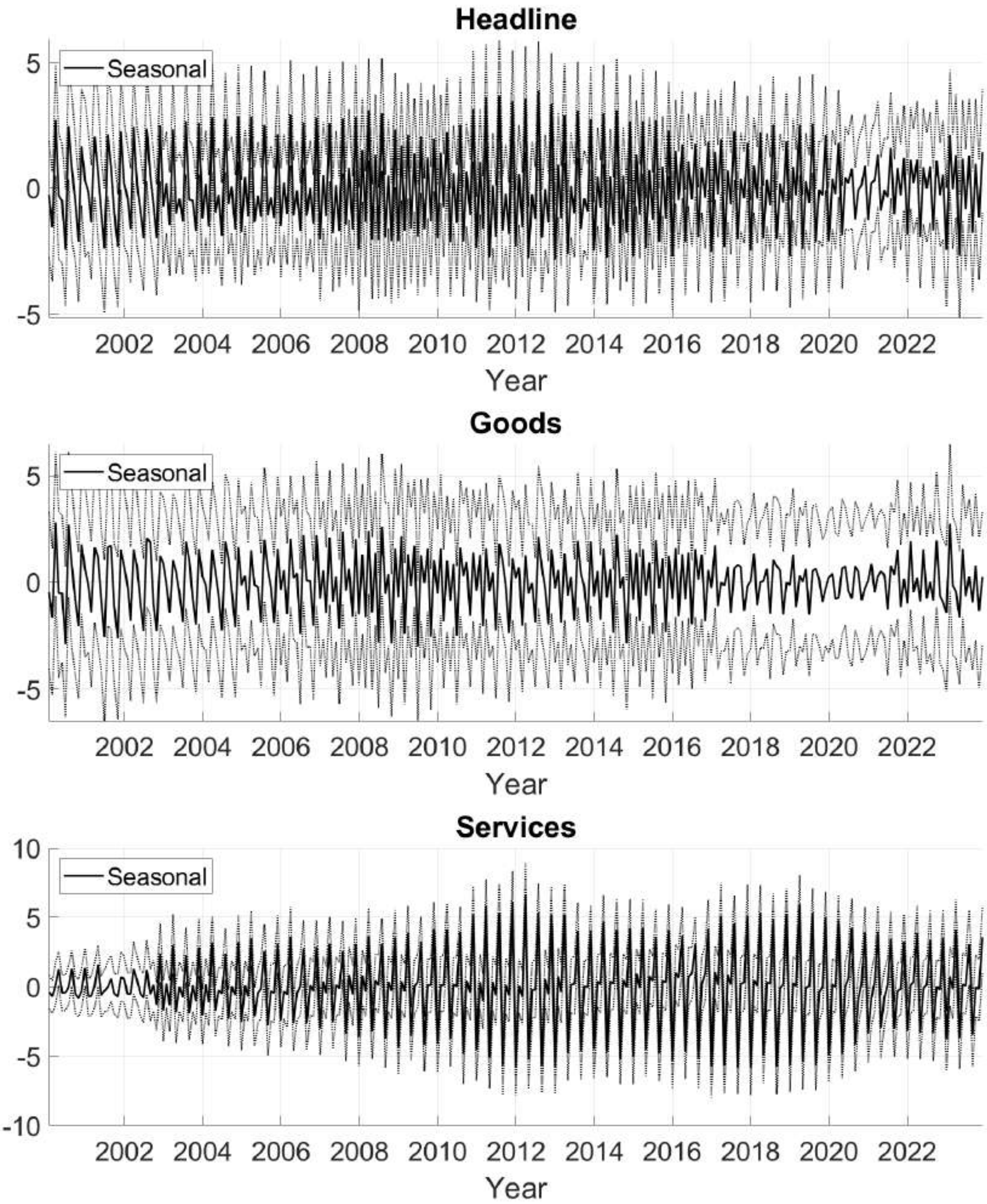
Figure 2. Estimated Trend Component of Aggregate Inflation



Note: The figure plots the estimated trend inflation from the UCSVO model from January 2000 to December 2023 for the aggregates: Headline, Goods, and Services. The dotted line represents the 68% credible intervals, and the light grey lines show monthly annualised inflation data.

[6]This is a different dynamic to the US quarterly series, where Eo et al. (2023) finds a sharp drop in the volatility of trend inflation for goods in the recent years, resulting in a decline in aggregate trend inflation volatility.

Figure 3. Estimated Seasonal Component of Aggregate Inflation



Note: The figure plots the estimated seasonal component of inflation from the UCSVO model from January 2000 to December 2023 for the aggregates: Headline, Goods, and Services. The dotted line represents the 68% credible intervals.

The task of measuring trend inflation is further complicated by substantial seasonal fluctuations in many sectoral prices. In the UK, the CPI data published by the ONS is not seasonally adjusted. Figure 3 shows that the changes of aggregate inflation series exhibit seasonal changes, albeit mild. The estimated monthly seasonal components goods inflation display similar pattern and magnitude with headline inflation, while there is relatively more variation in the seasonality of services. Figure 4 (b) captures this volatility in the seasonal components clearly. The seasonality of headline and goods hover around 0.38 and 0.45 percent, respectively, but the volatility of services inflation seasonality vary more significantly over the sample period.

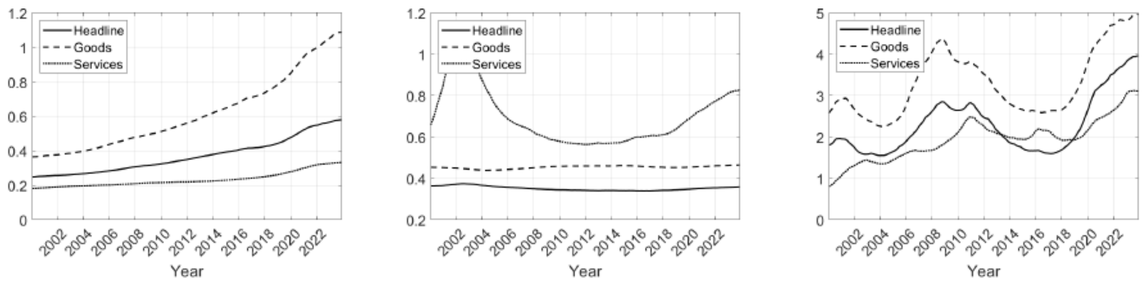
Notably, the volatility of services seasonality increases at the beginning and the end of sample period but was relatively low around the Great Moderation period. This illustrates that the behaviour of different parts of the inflation basket could only be unmasked by modelling the sectors individually – a point we revisit in the next subsection.

In contrast to trend volatility, the stochastic volatility linked to the transitory component indicates temporary, one-time shocks that do not have a prolonged impact on inflation. Examining the estimates of the volatility of the transitory component in Figure 4 (c), we find that the time variation of the transitory component among the three aggregate inflation measures co-moves, with the first peak during the global financial crisis and a more recent elevation since the onset of the Covid-19 pandemic. Goods inflation exhibits greater volatility in the irregular component than services and headline inflation, which is not surprising given that goods include more volatile items, such as food and energy, while services comprises of items that tend to have stickier prices.

Moreover, the UCSVO model setup enables the transitory components' innovations to have heavy tails which aids in adjusting automatically for data outliers, especially during significant inflation surges. Figure 5 plots the estimates of the outlier. Across the three inflation aggregates, while the specific quarters in which outliers occur differ, they cluster around the mid-2000s, the global financial crisis and the recent inflationary surge. Owing to their unexpected and one-off nature, in practice, outliers are often mechanically incorporated when updating the short-term inflation forecast path – keeping the month-on-month profile for subsequent months unchanged compared with the previous forecast. This bears the risk of overlooking that the outlier might be a first step in a change in trend, or that it might unwind very quickly via a counter movement. For example, the UCSV model in Stock and Watson (2007) handled outliers through preliminary judgment-based adjustments, before model estimation. However, this is impractical for real-time trend estimation, as it requires determining whether a large fluctuation will revert to the mean. This is particularly challenging when looking into the sectoral inflation. The automatic detection in the UCSVO model set up helps forecaster to disentangle short-lived shocks from long-term trends.

Figure 4. Stochastic Volatilities of Aggregate Inflation

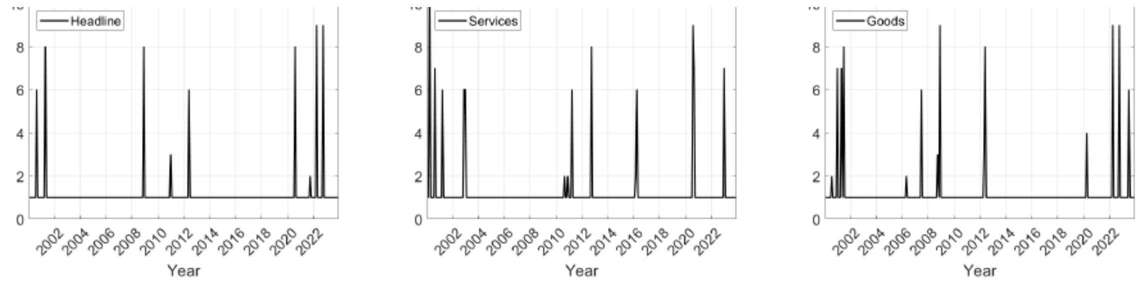
(a) Trend (b) Seasonal (c) Transitory



Note: The figure plots the estimates of stochastic volatility from January 2000 to December 2023 for the three components of the UCSVO model: trend, seasonal, and transitory. Headline volatility (solid line), Goods(dashed line), and Services (dotted line).

Figure 5. Outlier of Aggregate Inflation

(a) Headline (b) Goods (c) Services



Note: The plot shows the outliers from the UCSVO model from January 2000 to December 2023 for three aggregate measures: Headline, Goods, and Services. An outlier is defined as a standard deviation that is between 2 and 10 times larger than the non-outlier case.

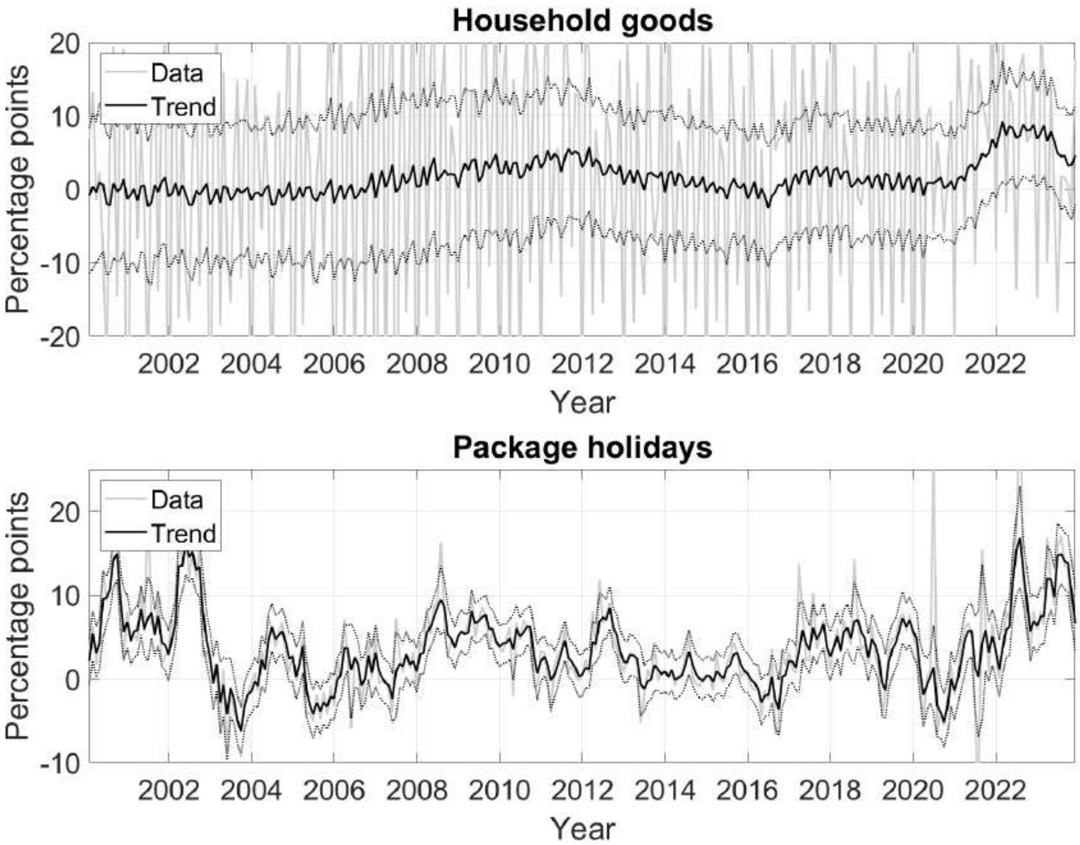
4.2 Dissecting Sectoral Inflation: Persistent and Transitory Components

Policymakers are often tasked with explaining movements in headline CPI, and to help provide a more detailed narrative, they rely on sectoral inflation data to understand which items of the inflation basket are contributing to inflation dynamics. However, this is challenging, as inflation dynamics in each sectors vary significantly and differ from the aggregated series. Additionally, it is complex to discern whether these sectoral inflation changes are persistent or transitory. To address these challenges, we estimate the trend, seasonal and transitory components – and their respective volatilities – for all 31 sectors. For illustration, in this section, we focus on two sectors: Household Goods (one of the sectors that is a part of aggregate goods) and Packaged Holidays (part of aggregate services). Figures 6 and 7 present the estimated trend and seasonal components, respectively, and Figure 8 shows the estimated stochastic volatility and outlier for these sectors.

The Household Goods data shows significant fluctuations over the years and its estimated trend resembles a smoothed version of the raw data. This indicates that fluctuations are likely driven by seasonal factors, which we discuss below. The trend component for Package Holidays is less volatile compared to household goods. There is a pronounced spike in prices during the summer of 2020, corresponding to the easing of the first round of pandemic restrictions, which may have led to an increase in holiday travel. These observations underscore the importance of accurately estimating sector-specific trends and behaviours.

Turning to seasonal component, Figure 7 shows the seasonal components of Household Goods and Packaged Holidays. Figures 18, 19 in Appendix B plots the full sectors. Deviations from the usual seasonal pattern can have a strong impact on annual inflation. The key advantage of allowing for time variation in the seasonal component is demonstrated by the significant sectoral differences, underscoring the importance of accurate seasonality estimation. Using year-on-year data or seasonally adjusted figures (such as X-13) can address seasonality in univariate models. For headline or other aggregate inflation, where seasonality do not vary much over time, those methods may be sufficient. However, for sectoral inflation, this adjustment may not be as effective as for headline inflation, which exhibits only moderate seasonal variation.

Figure 6. Estimated Trend Component of Sectoral Inflation

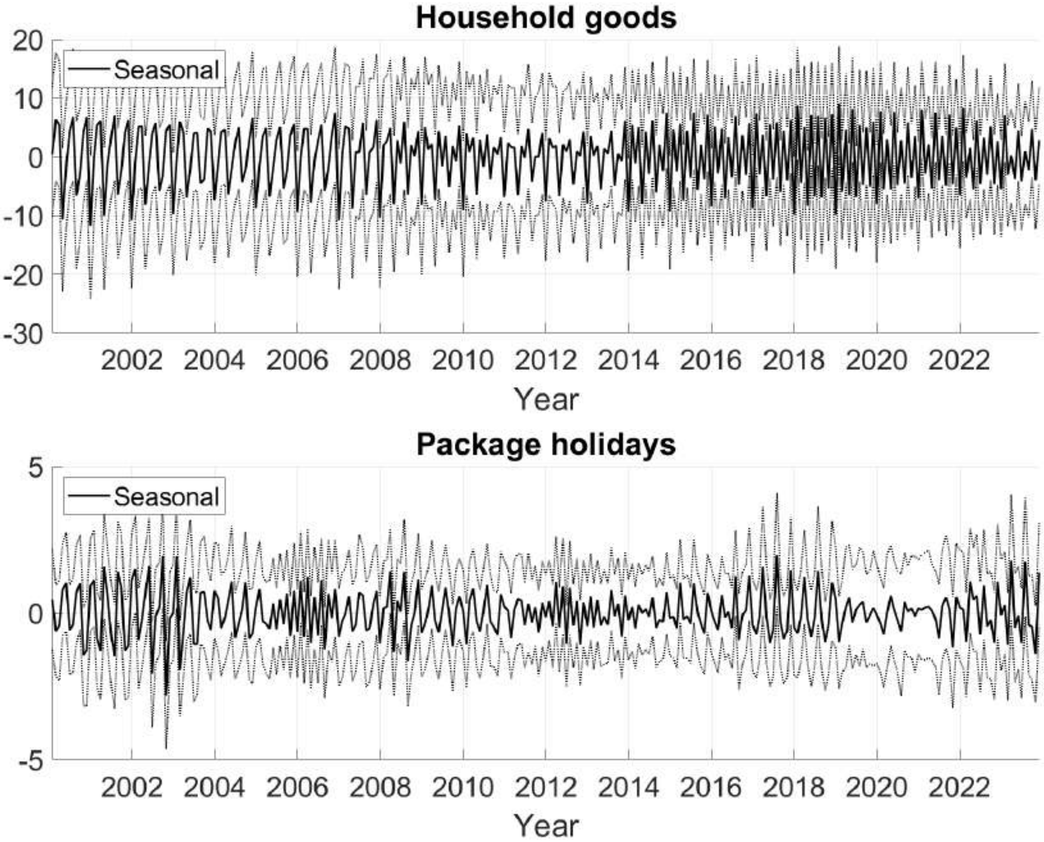


Note: The figure plots the estimated trend inflation from the UCSVO model from January 2000 to December 2023 for two sectors: Household Goods (a subset of Goods) and Package Holidays (a subset of Services). The dotted line represents the 68% credible intervals, and the light grey lines display the annualised sectoral inflation data.

The figures show that the seasonality of these sectors becomes more varied across time. Seasonal sales of Household Goods typically occur in the winter months of January and February and in the summer months of July and August, but this may have changed in the more recent years. An earlier (later) start to the sales period can imply a stronger (weaker) month-on-month price change than in the previous year and therefore a strong, temporary decrease (increase) in the annual inflation rate. The seasonality impact on Household Goods prices has become substantially larger since 2014, possibly due to enhanced price collection or improvements in methods for compiling price changes in winter and summer sales. In contrast, the seasonality component in Package Holidays have more distinct seasonal patterns. Comparing the two, there is a stark difference in the seasonal pattern and magnitude. This is reflected in Figure 8 (b) where the estimated standard deviation of seasonal components of Household goods is higher than Packaged holidays.

Given the varying levels of trends, seasonality, and volatilities across sectors, we next assess whether the persistence in inflation trend is broad-based or sector-specific, and incorporate sectoral co-movements in the estimation of aggregate trend inflation.[7]

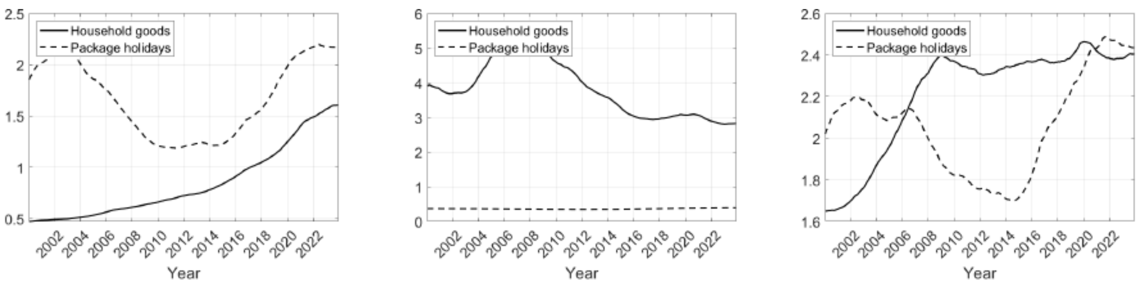
Figure 7. Estimated Seasonal Component of Aggregate Inflation



Note: The figure plots the estimated seasonal component of inflation from the UCSVO model from January 2000 to December 2023 for two sectors: Household Goods (a subset of aggregate goods) and Package Holidays (a subset of aggregate services). The dotted line represents the 68% credible intervals.

Figure 8. Stochastic Volatility of Sectoral Inflation

(a) Trend (b) Seasonal (c) Transitory

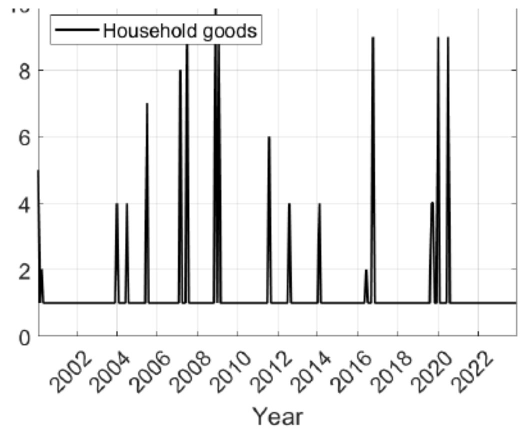


Note: This figure plots the estimates of stochastic volatility from January 2000 to December 2023 for the three components of the UCSVO model: trend, seasonal, and transitory. Household goods volatility (solid line) and Package holidays (dashed line).

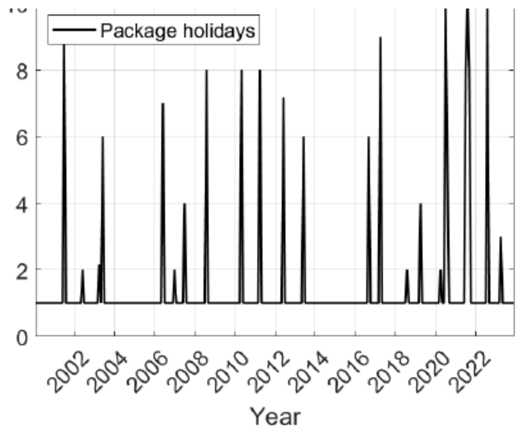
[7]The varying levels of trends, seasonality, and volatilities across sectors are also evident for US CPI (see Barkan et al. (2023)) and for Euro Area HICP (see Stock and Watson (2020)).

Figure 9. Outlier of Sectoral Inflation

(a) Households Goods



(b) Packaged Holidays



Note: This figure shows the outliers from the UCSVO model for two sectors: Household goods and Package holidays. An outlier is defined as a standard deviation that is between 2 and 10 times larger than the non-outlier case.

4.3 Incorporating Sectoral Dynamics in Trend Inflation: Macroeconomic and Sector-Specific factors

In this section, using a multivariate UCSVO model, we study sectoral co-movements in the estimation of aggregate trend inflation. The model captures the sectoral variation as in the univariate model while also modelling for sectoral covariance. This approach allows us to examine whether a shock to specific sectors, or by macroeconomic factors impacting all sectors, contributes to movement in headline trend inflation. The multivariate trend is composed of two components for each sector: a common and a unique trend. We construct multivariate trend as the sum of common and sector specific unique trends, weighted by sector shares. The common trend captures broad price changes across all sectors, driven primarily by economy wide shocks. Whereas the unique trend represents sector-specific price movements induced by shocks to individual sectors.

Figure 10 plots the contribution of the common and unique components to aggregate trend, highlighting key economic events. One, during the period of global financial crisis, the increase in aggregate inflation trend was driven by macroeconomic shocks that elevated the common component. This period saw significant fiscal and monetary policy easing to support the UK economy that faced turmoil from the credit crunch. Two, following the 2016 Brexit referendum, headline inflation trends picked up, with both common and unique components rising due to new trade barriers, heightened uncertainty, and shifts in consumer sentiment, reversing the low inflation period of 2014–2016. Lastly, since the Covid pandemic in 2020, the elevation in aggregate trend inflation was due to supply chain disruptions and rising energy costs. While in the surface it might be categorised as sector-specific shocks, these sectors are used as input in many other sectors, hence the first chart in Figure 10 shows that the price pressures was driven by common macroeconomic shocks coming. By early 2023, both the common and sector-specific factors began to decline, bringing inflation closer to 2 percent as the economy stabilises and shocks eased.

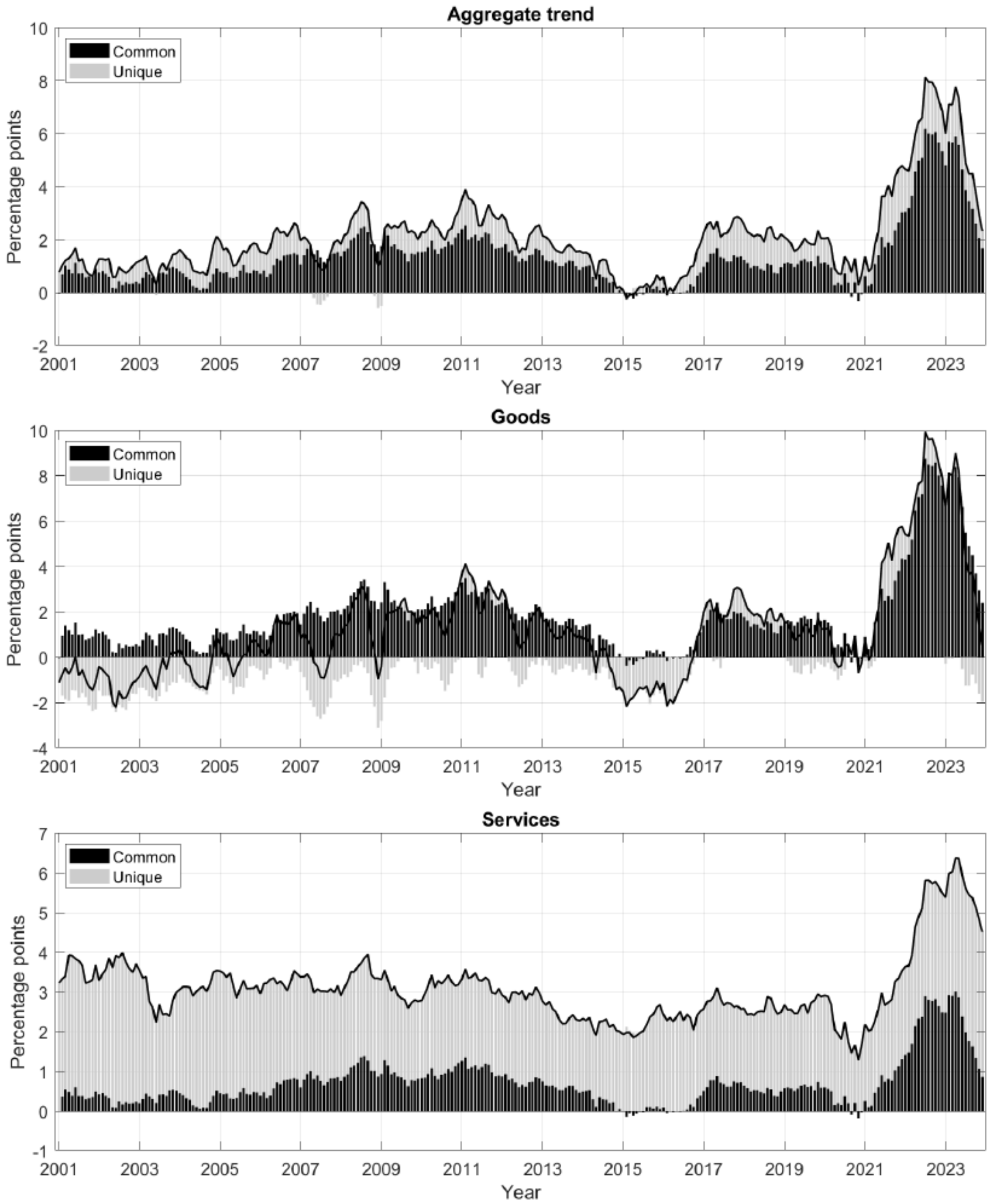
How did pandemic related shocks affect goods and services trend?

To explore the impact of the 2020 pandemic on inflation trends in goods and services, we re-calculate the trend, without re-estimating the model, by aggregating the trend using the same calculation as in Equation 9. For central banks, a key responsibility is responding to macroeconomic shocks that impact the common component of the economy, rather than sector-specific shocks that affect the unique component. The multivariate approach is crucial for distinguishing between the common and unique factors driving trend inflation. It also helps identify whether these factors originate from the goods or services sectors, providing a clearer understanding of inflation dynamics and informing more effective policy decisions, particularly during high inflationary periods.

As discussed, the rise in aggregate headline trend is driven from shocks to common components. This is reflected in the common component of goods trend inflation, particularly in sectors like seasonal and non-seasonal food, non-alcoholic beverages, and household goods, which surged beyond 10% during the pandemic. Meanwhile, services inflation—though influenced by similar macroeconomic factors—has risen at a comparatively lower pace, with notable increases in sectors such as airfares, catering, and accommodation services. Additionally, in Figure 11 (a), the stochastic volatility of the common trend component increased during the pandemic, indicating greater persistence in inflation trends. In contrast, the volatility of the common irregular component, associated with one-time shocks, remained relatively subdued.

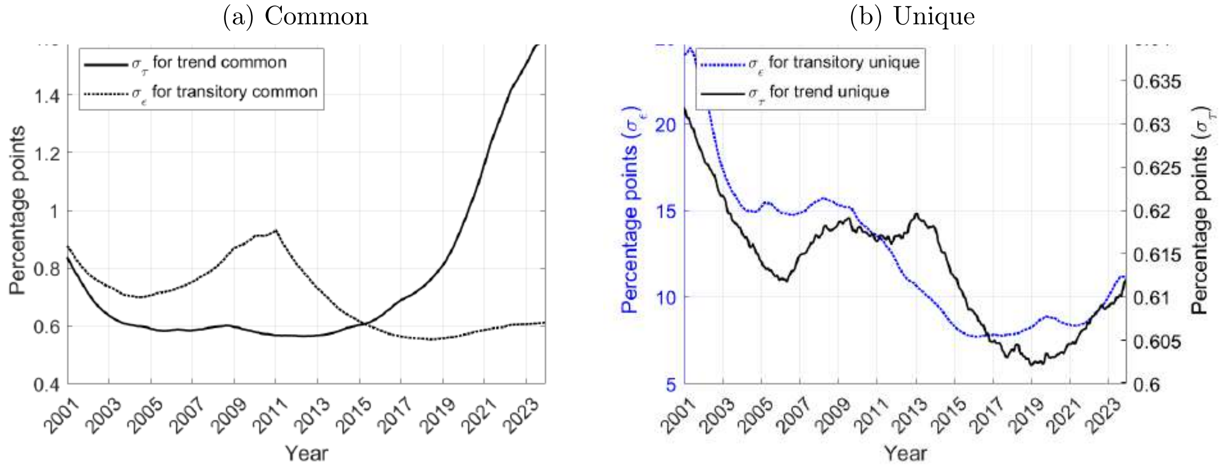
Sector-specific (unique) movements have primarily driven services inflation, particularly disruptions in sectors such as package holidays and housing rents. On the goods side, the unique component was largely influenced by fuels and lubricants, personal transport, and recreational goods. The unique components stochastic volatility for trend rose in 2021, reaching 0.6 percentage points (Figure 11 (b) RHS y-axis in black). However, it remained lower than the volatility of the irregular component, which surged to 11 percentage points in the same year (Figure 11 (b) LHS y-axis in blue). This suggests that sector-specific movements in services inflation were mostly driven by one-time shocks rather than persistent trends.

Figure 10. Common and Unique Component for Aggregate, Goods and Services Trend



Note: The first panel plots the aggregate multivariate trend (solid line), the contribution of the common component (dark grey bars) and the unique or sector-specific component (light grey bars). The second and third panels follow the same structure, but are recalculated for Goods and Services trend inflation. The sample is from January 2001 to December 2023.

Figure 11. Stochastic Volatilities for the Components of MUCSVO Aggregate Trend



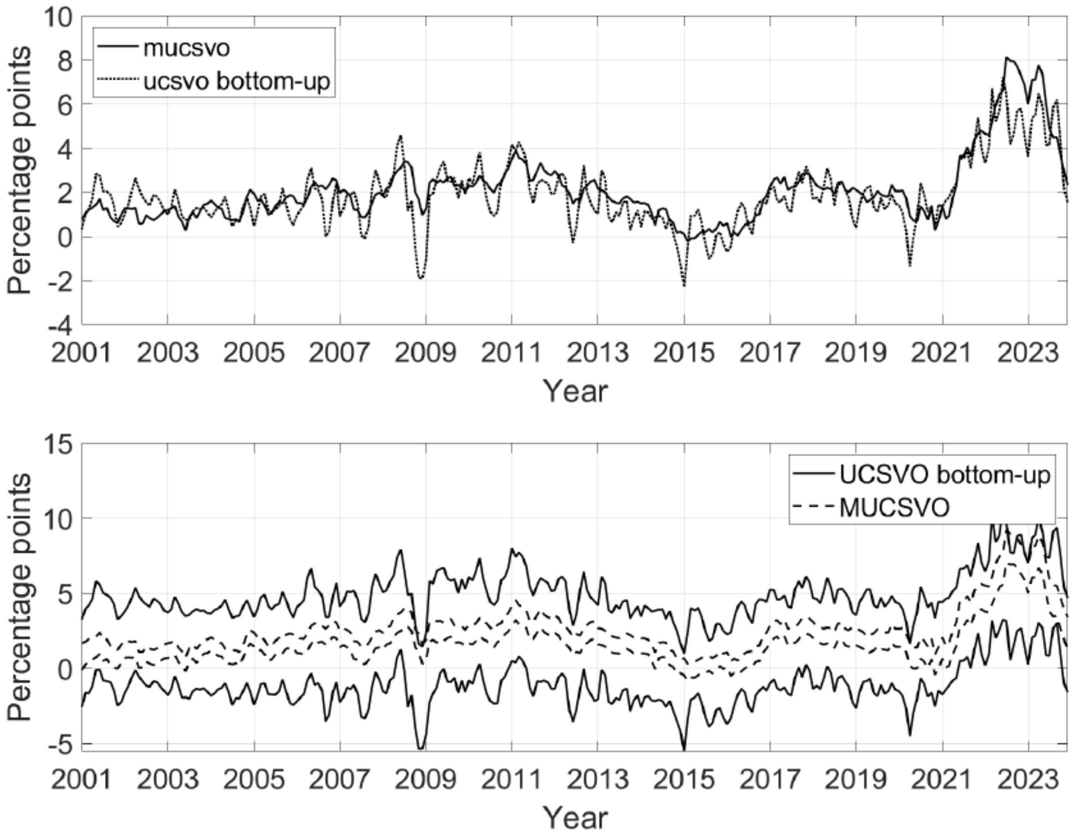
Note: The figure plots the estimates of stochastic volatilities of trend and transitory from January 2001 to December 2023 for the two components of the aggregate trend: unique and common.

Accuracy of trend estimates

To evaluate model based accuracy of the estimated trend, we compare the posterior uncertainty interval widths across the models: UCSVO model applied on headline (aggregate) inflation, UCSVO model applied to sectoral inflation, and MUCSVO. First, we compare the aggregate inflation trend and from the multivariate model (MUCSVO) alongside the bottom-up aggregated trend from UCSVO model in Figure 12. The bottom-up approach aggregates the estimated univariate trends of each sector using time-varying and sectoral weights. The upper panel shows that the trend lines from both models align closely overall, with inflation picking up in periods following 2008 financial crisis, 2012 to 2014 recovery period and around key episodes of Brexit and post pandemic inflation of 2022. Our findings show that incorporating sectoral price dynamics enhances trend inflation estimation.

Additionally, we examine error band of those trend estimates to provide a comparison of model accuracy. The bottom panel in Figure 12 plots the 68% credible intervals for aggregate trend estimates from the multivariate and the 'bottom-up' aggregated sectoral trend estimates from univariate model. The error band from the multivariate model (dashed) is 80% narrower and lies in the middle of the univariate bands (solid) but towards the end of sample, the estimated band of the multivariate model shifts upward, closer to the upper distribution of the 'bottom-up' sectoral trend. The multivariate model benefits from capturing both individual series data and their co-movements, enhancing accuracy – as depicted by the narrower band.

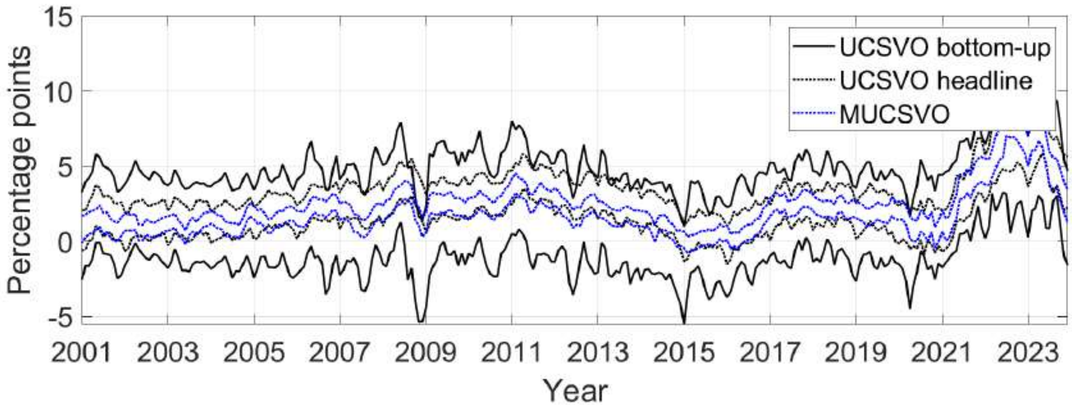
Figure 12. Aggregate Trend Inflation: Multivariate and Univariate Approach



Note: The figure plots the multivariate trend estimates from the MUCSVO model and the 'bottom-up' aggregated sectoral trend estimates from the univariate UCSVO model. The upper panel plots the estimated trend and the lower panel plots the credible interval. The sample is from January 2001 to December 2023

Furthermore, in Figure 13, we plot the credible intervals of the univariate, (dashed, black), 'bottom-up'(solid, black) and multivariate (dashed, blue) headline inflation. Comparing the error bands of the univariate models, directly estimating UK headline inflation with UCSVO model, rather than estimating each sectors and then aggregating it up using sectoral weights (i.e. 'bottom-up'), is up to 50% more accurate. This is a comparable to Stock and Watson (2016) finding based on US inflation, where the posterior intervals for multivariate model are 35% narrower than the univariate model, and for the Euro Area are 40% narrower (Stock and Watson, 2020). Across the three methodologies, we again find that the multivariate estimated widths have the narrowest credible intervals. While it is true that the multivariate model requires estimation of many more parameters, the narrowing of the bands indicate that the model's improved signal extraction justifies the additional parametrisation cost (Stock and Watson, 2016).

Figure 13. Credible Intervals for Aggregate Trend



Note: The lines represent the 68 percent credible intervals for the UCSVO bottom-up aggregated, MUCSVO, and headline inflation trend from UCSVO, providing a comparison of posterior uncertainty. The sample is from January 2001 to December 2023.

5 Insights into Model Evaluation and Forecast Performance

5.1 Beyond Unobserved Components: Incorporating Stochastic Volatilities and Outliers

One of the key advantages of the UCSVO model is in its ability to disentangle signal from noise in the inflation data. By incorporating stochastic volatility, the model adapts to changing variability in the data over time, allowing it to more effectively capture shifts in both trend and transitory components. This flexibility is particularly useful when there are sudden outliers or volatility spikes, such as during sharp economic changes and Covid-19. In contrast, a basic unobserved components (UC) model assumes constant volatility and cannot easily account for shifts in uncertainty. This makes it less responsive to fluctuations in signal strength over time, resulting in a poorer signal-to-noise separation when compared to the UCSVO model. The UCSVO model allows for better signal extraction because it adjusts dynamically to changing levels of noise and volatility, thus providing a more accurate estimate of the underlying signal from a noisy dataset. This is supported by Clark and Doh (2014) who emphasise that trend inflation models incorporating stochastic volatility perform better than those with constant volatility, particularly in capturing shifts in inflation uncertainty and providing superior signal extraction.

Comparing the signal-to-noise ratio between these models demonstrates the advantage of the UCSVO model in environments with time-varying uncertainty. To assess this, we compute the trend signal-to-noise ratio $\frac{\sigma_\tau}{\sigma_\varepsilon}$ using the estimated standard deviations of trend and transitory components (see Figure 4). This allows us to assess the relative strength from trend variations compared to transitory variations. Similarly, we compute the seasonal signal-to-noise ratio $\frac{\sigma_s}{\sigma_\varepsilon}$, allowing us to evaluate how informative is the seasonal component. As shown in Table 3 in the Appendix, for aggregate series, Goods and Services inflation benefit from time-varying volatility in the trend component, and all three series (Headline, Goods and Services) improve from time variation in the standard deviations of seasonal component. The flexibility of the UCSVO model in adjusting to periods of heightened volatility reveal that the signal-to-noise ratio remains more stable, while in a basic UC model, it tends to deteriorate during such period.

UCSVO model is also able to disentangle the signals from the noise of the sectoral inflation. For every sector, we compute the trend and seasonal signal-to-noise ratio from the UCSVO model and compare it to that estimated with a constant volatility UC model. Of the 31 sectors, we find 29 sectors (93%) of the basket shows improved signal extraction by including stochastic volatility in the trend component, while 21 sectors (67%) benefit from time-varying volatility in the seasonal component. These improvements are broad based across goods and services sectors, suggesting that time-varying volatility is a valuable feature in improving the model's capability to extract trend and seasonal information across sectors. We next turn to a forecasting exercise using the UCSVO model, as it has been found to improve forecasting performance over a simple UC model (Chan et al., 2013).

5.2 Forecast Performance Comparison

The focus of this paper is to use UCSVO model to produce more accurate estimates of trend inflation, providing valuable insights into long-term inflation dynamics. In turn accurate trend estimate is crucial, as it supports more reliable inflation forecasts. To assess the UCSV model's forecast accuracy, we ran an out-of-sample forecasts from 2016 to 2023 and evaluated them using Root Mean Squared Error (RMSE).

The RMSE analysis in Table 1 from the UCSV model forecasts indicates several nuanced trends in forecasting accuracy across different horizons and categories. There is a clear inverse relationship between forecast horizon length and accuracy; shorter-term forecasts are more reliable, whereas accuracy diminishes as forecasts extend further out. Barkan et al. (2023) find the same inverse relation in US CPI data using a Hierarchical Recurrent Neural Networks model. This is likely to reflect increased uncertainty over longer periods, where other factors may influence the outcomes more significantly. Additionally, forecasts based on pre-Covid data exhibit lower RMSE, suggesting that more stable economic conditions before the pandemic allowed for more precise predictions. The impact of category-specific variability is also apparent: headline inflation forecasts have a middle-range RMSE compared to other categories, with the highest RMSE observed in goods and a lower RMSE in services, likely due to the volatility inherent in goods prices relative to more stable services.

Furthermore, within individual subcategories, such as household goods and packaged holidays, the forecast horizons before the pandemic show marked RMSE differences between the 3- and 6-month forecasts. This variability diminishes post-Covid, possibly reflecting how shifts in consumer behaviour and supply chain disruptions impacted prices at different points. Together, these observations provide insights into how forecast accuracy can fluctuate across time horizons, economic conditions, and sectors, highlighting areas where the model performs more reliably and where adjustments might be necessary to improve forecasting performance.[8]

Table 1. Root Mean Squared Error from UCSVO models

	Full sample			**Pre-Covid**			**Post-Covid**		
	1m	*3m*	*6m*	*1m*	*3m*	*6m*	*1m*	*3m*	*6m*
Headline	0.40	0.79	1.32	0.14	0.28	0.47	0.52	1.01	1.70
Goods	0.60	1.15	1.96	0.24	0.48	0.90	0.76	1.46	2.48
Services	0.33	0.50	0.72	0.19	0.24	0.31	0.41	0.63	0.92
Health goods	0.64	1.03	1.68	0.30	0.36	0.41	0.80	1.32	2.19
Package holidays	0.52	1.15	2.03	0.31	0.77	1.49	0.63	1.37	2.35

Note: This table computes the root mean squared errors from UCSVO model to compare the out-of-sample forecast performance of aggregates and selected sectors over 1, 3 and 6 month period. The full sample is from January 2000 to December 2023, with pre-Covid period ending in December 2019.

6 Conclusion

Since 2021, inflation in the UK has surged, sparking debate over whether this increase is temporary or persistent, and whether it is broad-based or concentrated in specific sectors. Answering these questions is crucial for policymakers, as understanding inflation dynamics can improve both forecasting and policy decisions. This paper examines monthly inflation trends for 31 sectors of the UK Consumer Price Index (CPI), as well as aggregate inflation, using the unobserved component stochastic volatility and outlier-adjusted (UCSVO) model to separate persistent from transitory inflation.

Two key findings emerge from this study. First, we find that the aggregate headline inflation rate in the UK was low and stable until 2021, but became increasingly persistent due to higher trend volatility and shocks that lasted for long periods, fuelling further inflation persistence. During this period, while goods-related trend inflation showed increased volatility and persistence, services, in contrast, remained stable with moderate persistence. Second, by incorporating sectoral dynamics into a multivariate UCSVO (MUCSVO) model, we find that recent inflation persistence was primarily due to wide macroeconomic shocks in goods-related sectors and some sector-specific shocks in the services sector. The multivariate model, by accounting for sectoral co-movements, improves the accuracy of trend inflation estimation by at least 50% when compared to posterior uncertainty intervals of headline trend from the UCSVO model.

Finally, in practice, the shift to the UCSVO model offers substantial improvements over simple unobserved components models. By incorporating stochastic volatility and automatic outlier adjustment, the model achieves a better signal-to-noise ratio for trend and seasonal components. This enhancement leads to more accurate trend estimations, which are crucial

[8] Kanngiesser and Willems (2024) analysis of the Bank of England's forecast accuracy across all horizons reveals that the Bank's CPI inflation forecasts consistently outperform simpler models, such as random walk and autoregressive models. Incorporating stochastic volatility into forecasting models is key to further enhancing the accuracy of CPI inflation forecasts by accounting for time-varying uncertainties in the inflation process. Additionally, combining shrinkage methods with disaggregated CPI series improves headline and core forecasts at the 2-6 months horizon (Joseph et al., 2024).

for improving inflation forecasting performance, as reflected in reduced RMSE. By effectively distinguishing between underlying trends and transitory fluctuations, the new model enables policymakers to make more informed decisions, thereby enhancing the efficacy of monetary policy interventions, particularly during periods of elevated inflation.

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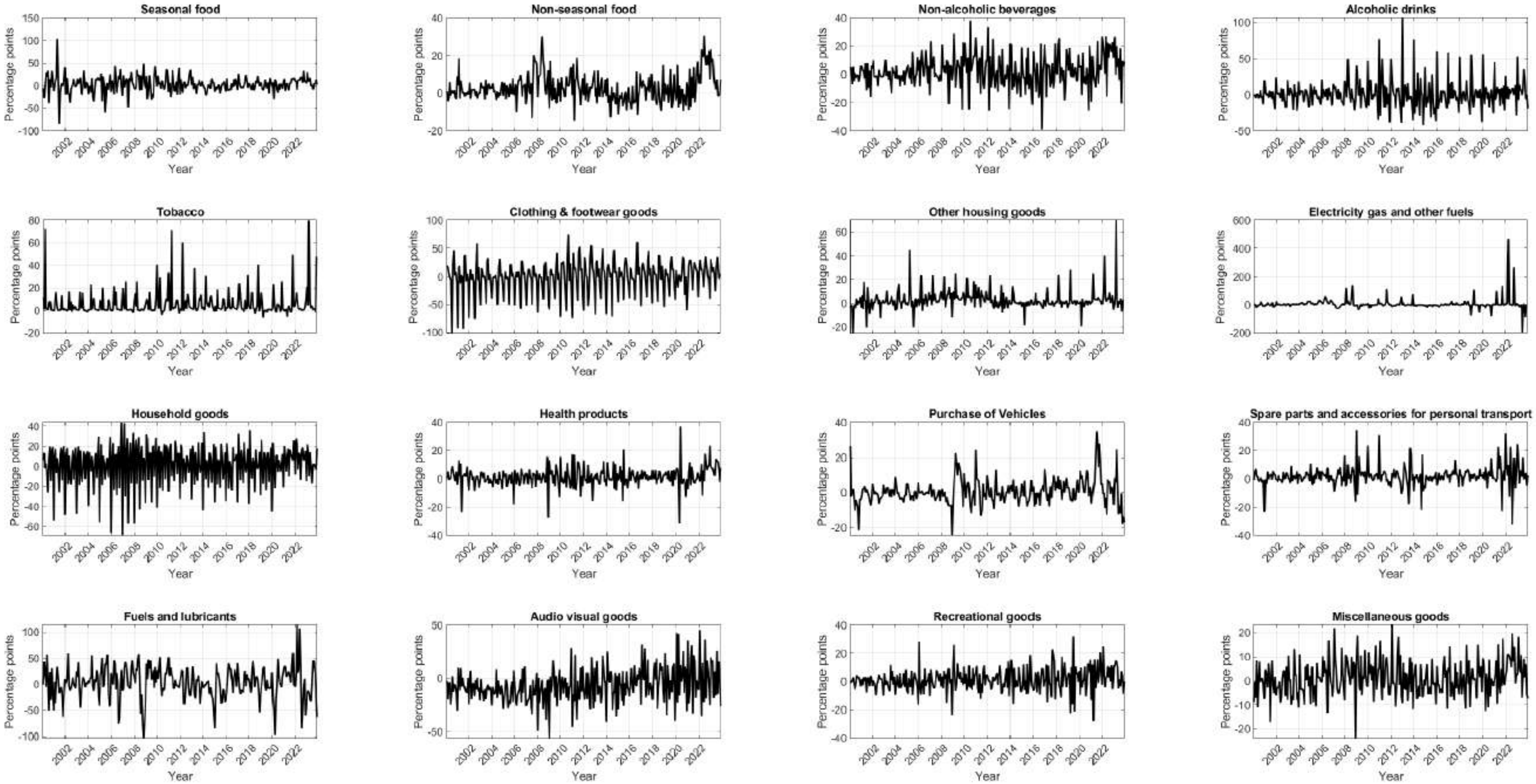
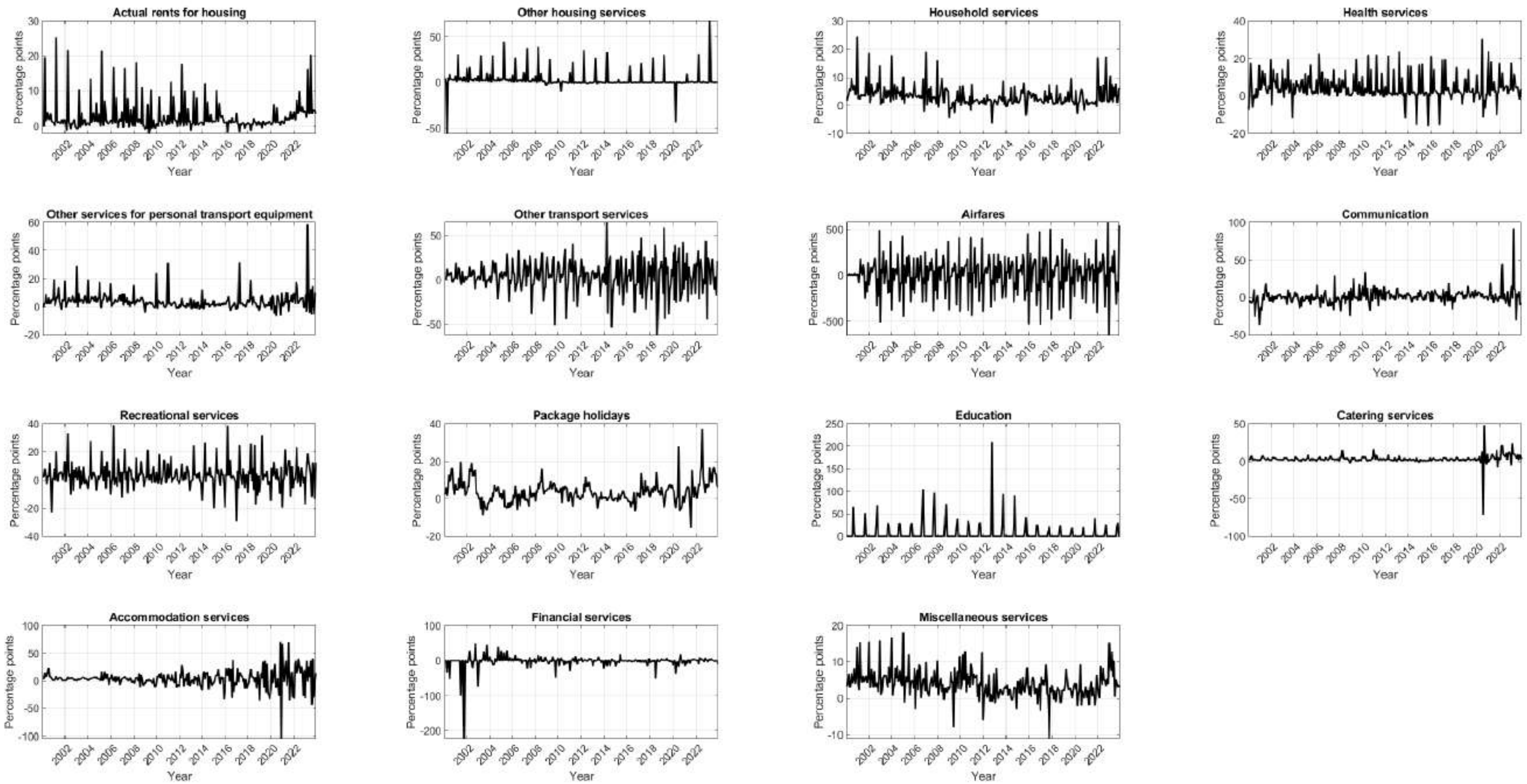
A CPI Data

Figure 14. Monthly annualised inflation for 16 Goods sectors of UK CPI basket



Note: This figure plots the monthly annualised inflation rate for sectors classified as Goods in the CPI basket from January 2000 to December 2023.

Figure 15. Monthly annualised inflation for 15 Services sectors of UK CPI basket



Note: This figure plots the monthly annualised inflation rate for sectors classified as Services in the CPI basket from January 2000 to December 2023.

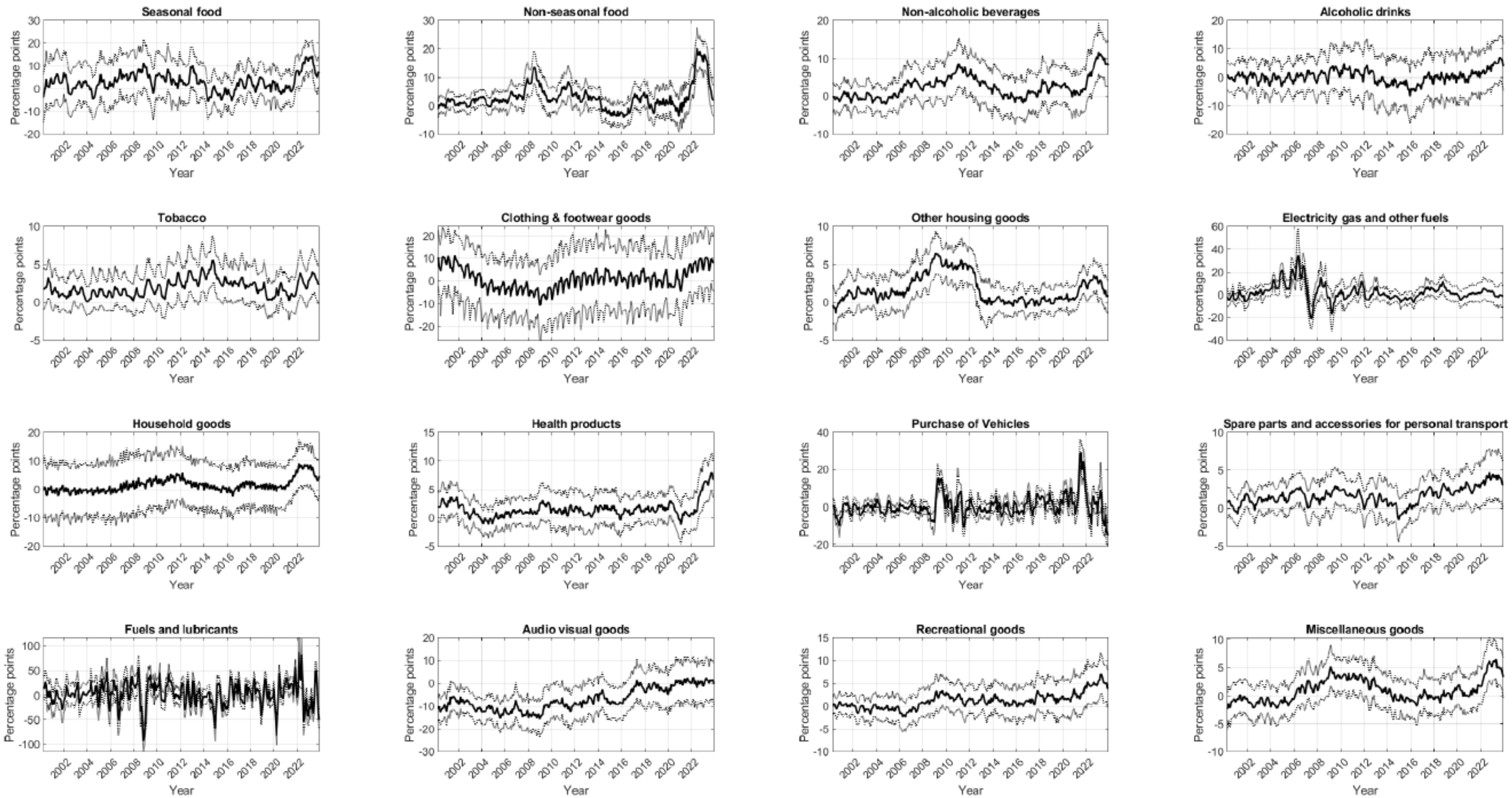
Table 2. Summary statistics for aggregate and sectoral annualised inflation for UK

Sectors	Mean	Mode	Max	Min	SD	# Obs.
Seasonal food	3.18	-84.52	103.58	-84.52	17.84	287
Non-seasonal food	2.98	-14.71	30.59	-14.71	7.43	287
Non-alcoholic beverages	2.65	-39.15	38.15	-39.15	11.45	287
Alcoholic drinks	1.44	-41.80	106.56	-41.80	19.28	287
Tobacco	5.93	-6.28	79.54	-6.28	11.46	287
Clothing & footwear	-1.31	-100.90	75.21	-100.90	29.00	287
Actual rents for housing	2.49	-2.19	25.36	-2.19	4.12	287
Other housing goods	2.60	-25.23	69.74	-25.23	8.47	287
Other housing services	2.88	0.00	67.04	-55.76	9.43	287
Electricity gas and other fuels	6.62	-195.98	466.28	-195.98	40.62	287
Household goods	1.60	-68.92	43.74	-68.92	19.97	287
Household services	3.31	-6.45	24.54	-6.45	3.65	287
Health products	1.46	-31.09	36.96	-31.09	6.94	287
Health services	4.18	-16.07	30.64	-16.07	6.59	287
Purchase of Vehicles	0.67	-24.50	34.89	-24.50	7.44	287
Spare parts	2.05	-32.30	34.42	-32.30	7.14	287
Fuels and lubricants	2.75	-103.47	113.49	-103.47	30.28	287
Other services for personal transport equipment	4.15	-6.54	58.63	-6.54	6.08	287
Other transport services	4.13	-62.27	64.35	-62.27	18.09	287
Airfares	5.60	0.00	572.27	-648.47	203.98	287
Communication	1.13	-36.53	92.63	-36.53	10.16	287
Audio visual goods	-6.57	-56.14	45.52	-56.14	16.30	287
Recreational goods	1.41	-27.75	31.95	-27.75	8.32	287
Recreational services	3.37	-28.97	39.08	-28.97	9.06	287
Package holidays	3.72	-15.34	37.18	-15.34	5.77	287
Education	6.31	0.00	210.22	0.00	20.13	287
Catering services	3.38	-71.27	48.34	-71.27	6.14	287
Accommodation services	3.84	-103.66	70.23	-103.66	16.26	287
Financial services	-1.75	0.00	48.66	-221.37	18.16	287
Miscellaneous goods	1.09	-23.69	23.16	-23.69	7.28	287
Miscellaneous services	3.89	-11.03	18.25	-11.03	3.75	287
Headline	2.55	0.00	29.36	-10.38	4.86	287
Goods	0.31	-33.38	17.85	-33.38	10.07	287
Services	3.13	-13.72	20.77	-13.72	3.39	287

Note: This table shows the summary statistics for 31 sectors and aggregates using data from January 2000 to December 2023.

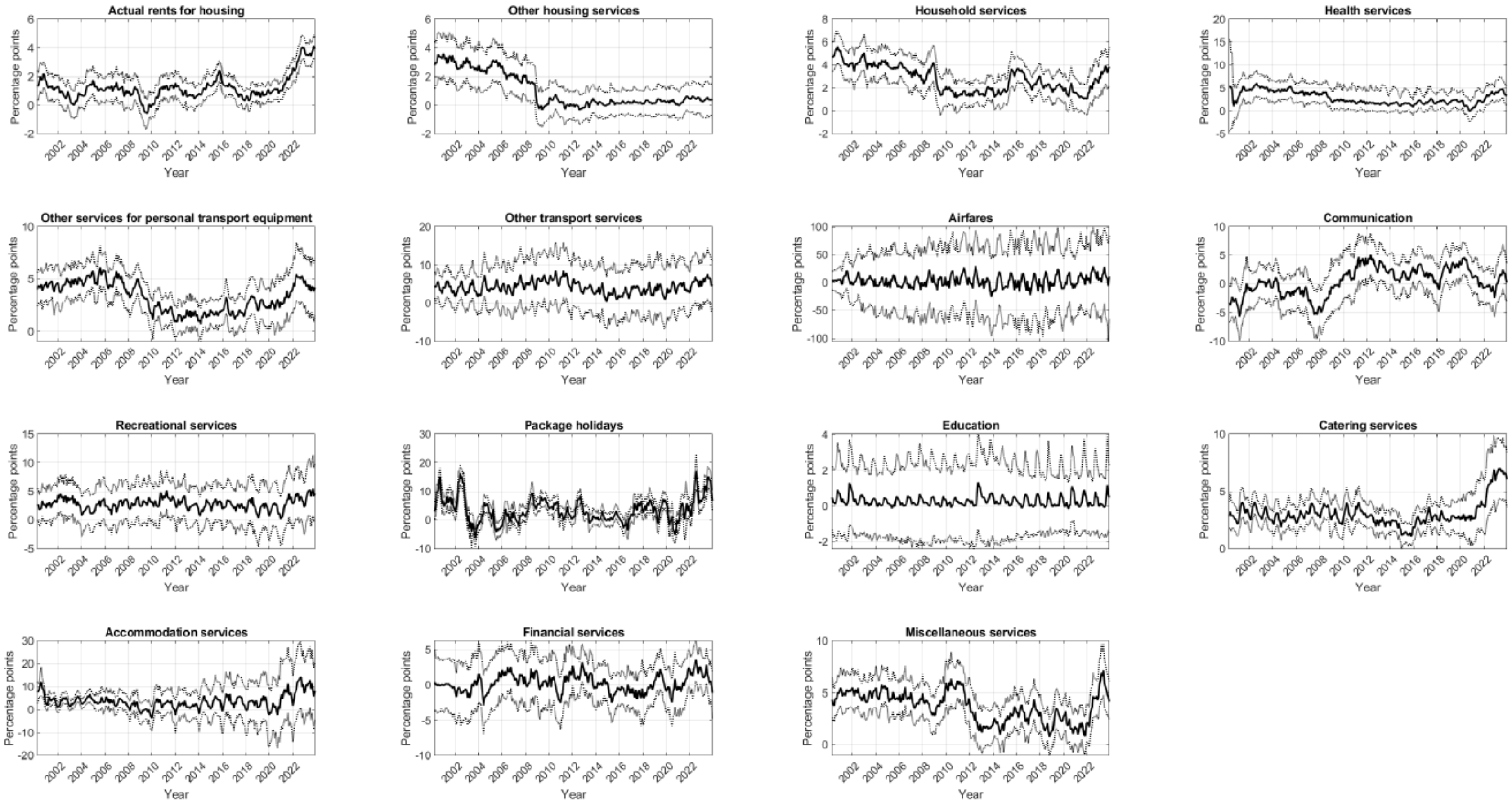
B Results

Figure 16. Estimated Trend Component from UCSVO model - Goods Sectors



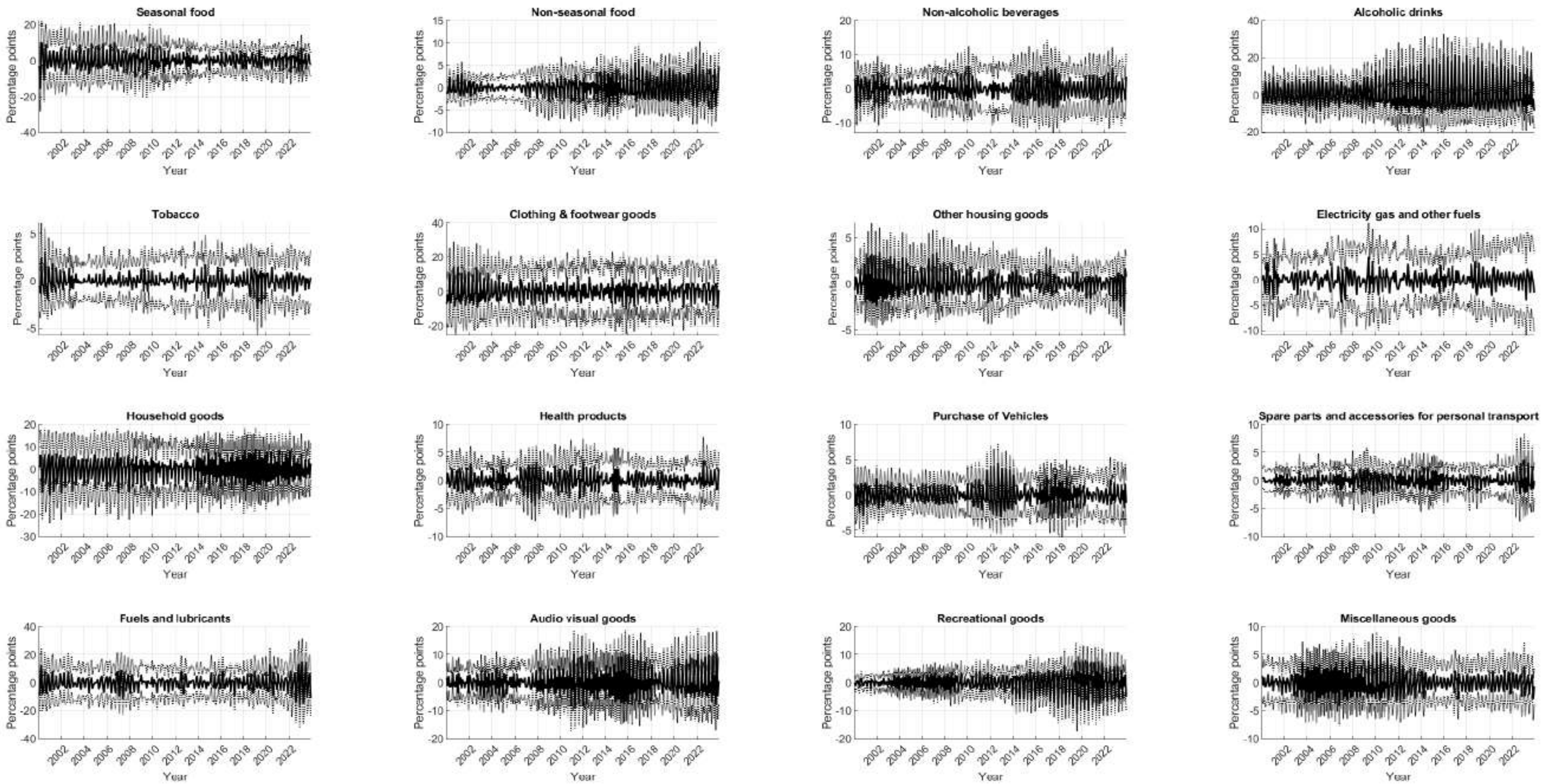
Note: The figure plots estimated trends from UCSVO model for Goods sectors of CPI using data from January 2000 to December 2023.

Figure 17. Estimated Trend Component from UCSVO model - Services Sectors



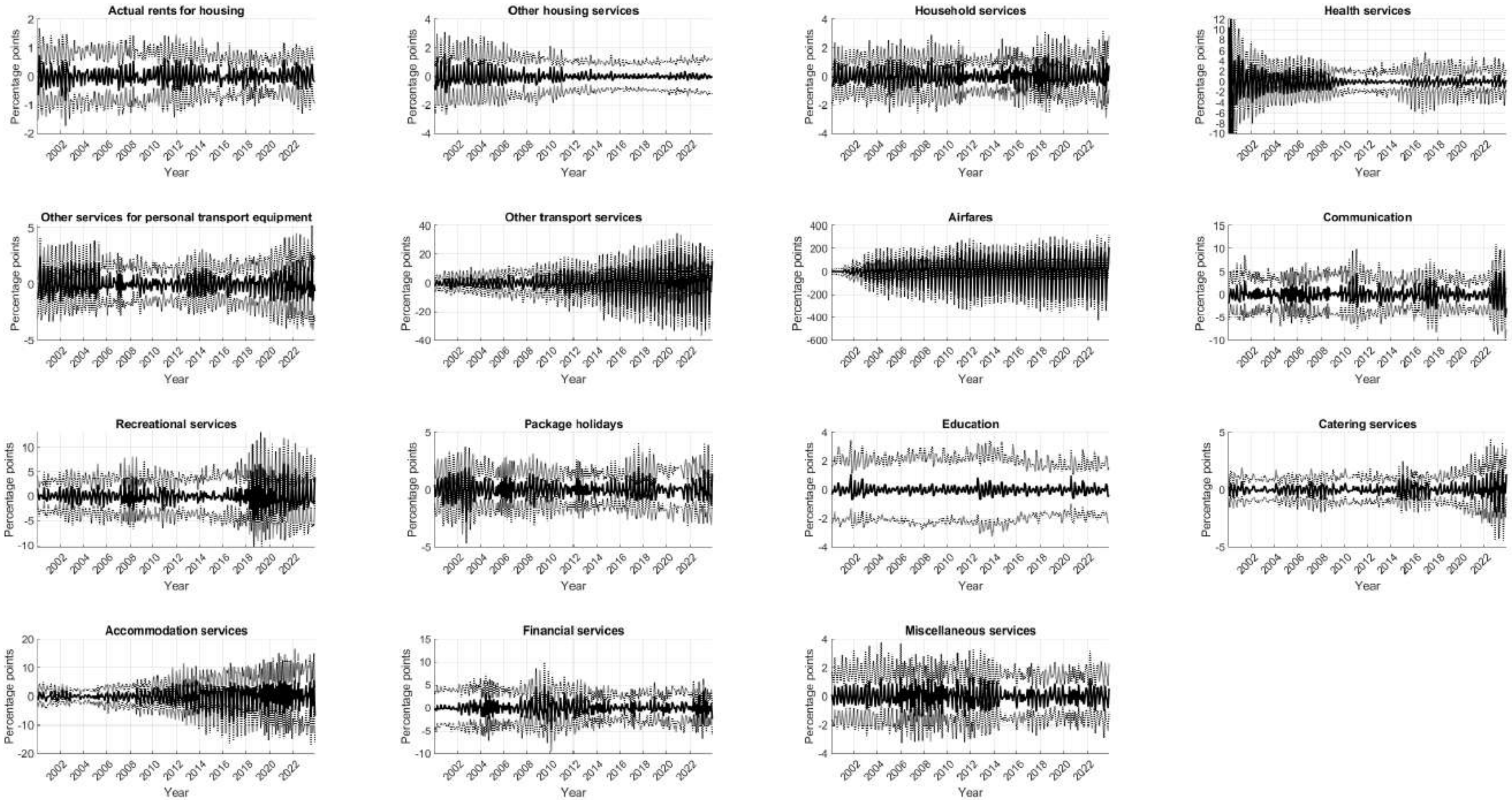
Note: The figure plots estimated trends from UCSVO model for Services sectors of CPI using data from January 2000 to December 2023.

Figure 18. Estimated Seasonal Component from UCSVO model - Goods Sectors



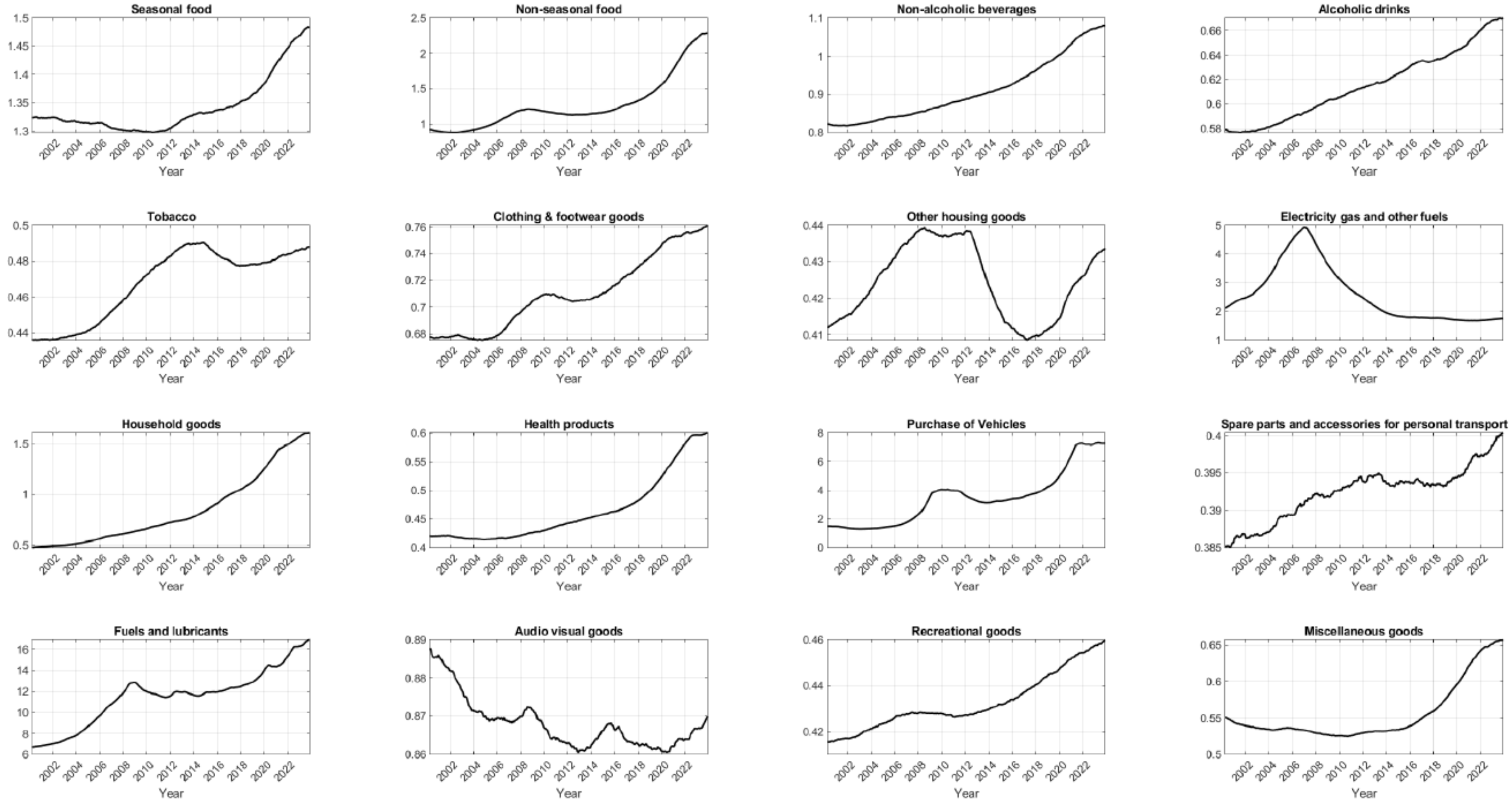
Note: The figure plots estimated seasonal from UCSVO model for Goods sectors of CPI using data from January 2000 to December 2023.

Figure 19. Estimated Seasonal Component from UCSVO model - Services Sectors



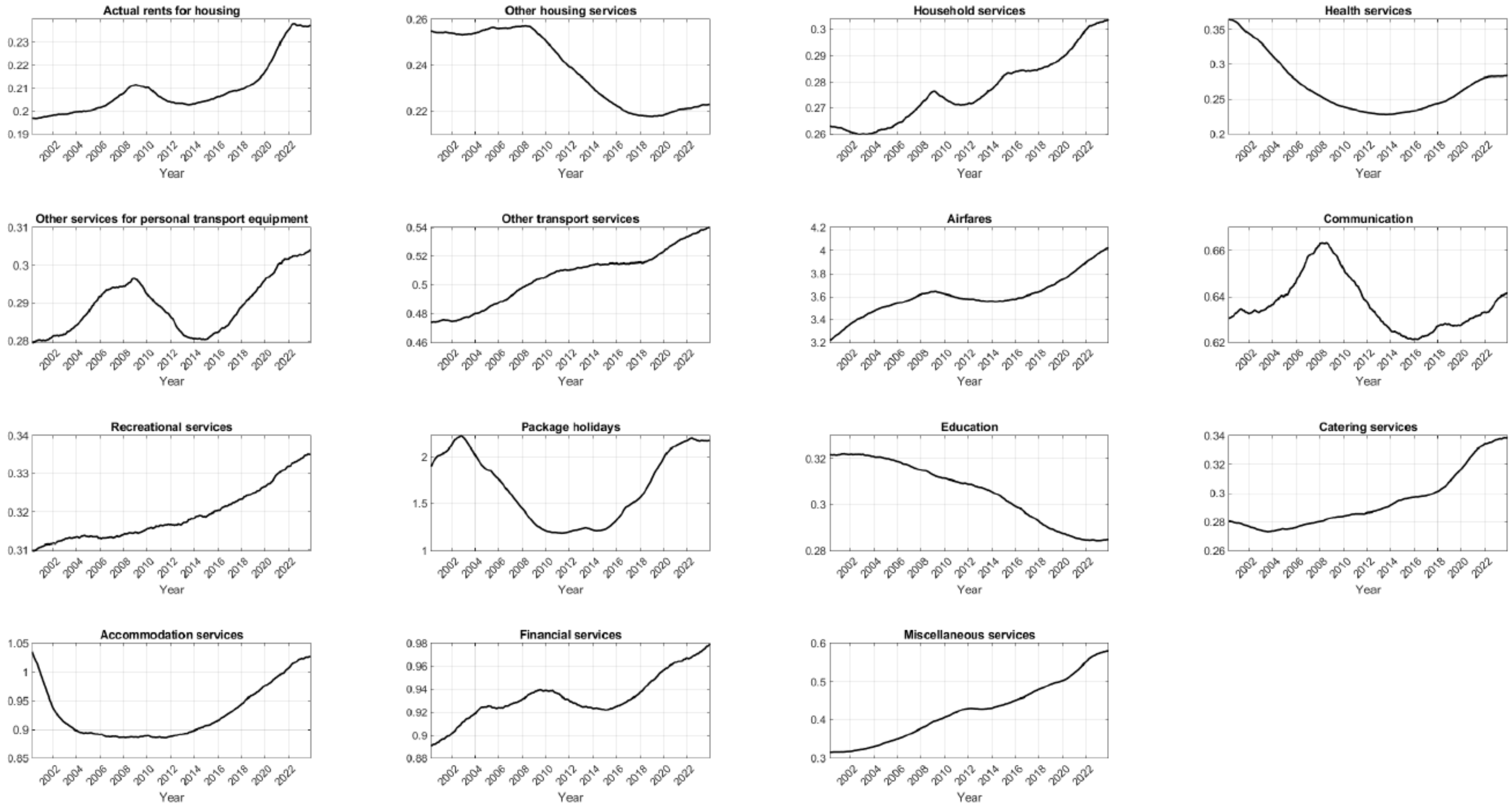
Note: The figure plots estimated seasonal from UCSVO model for Services sectors of CPI using data from January 2000 to December 2023.

Figure 20. Sectoral Trend Stochastic Volatilities for Goods from UCSVO model



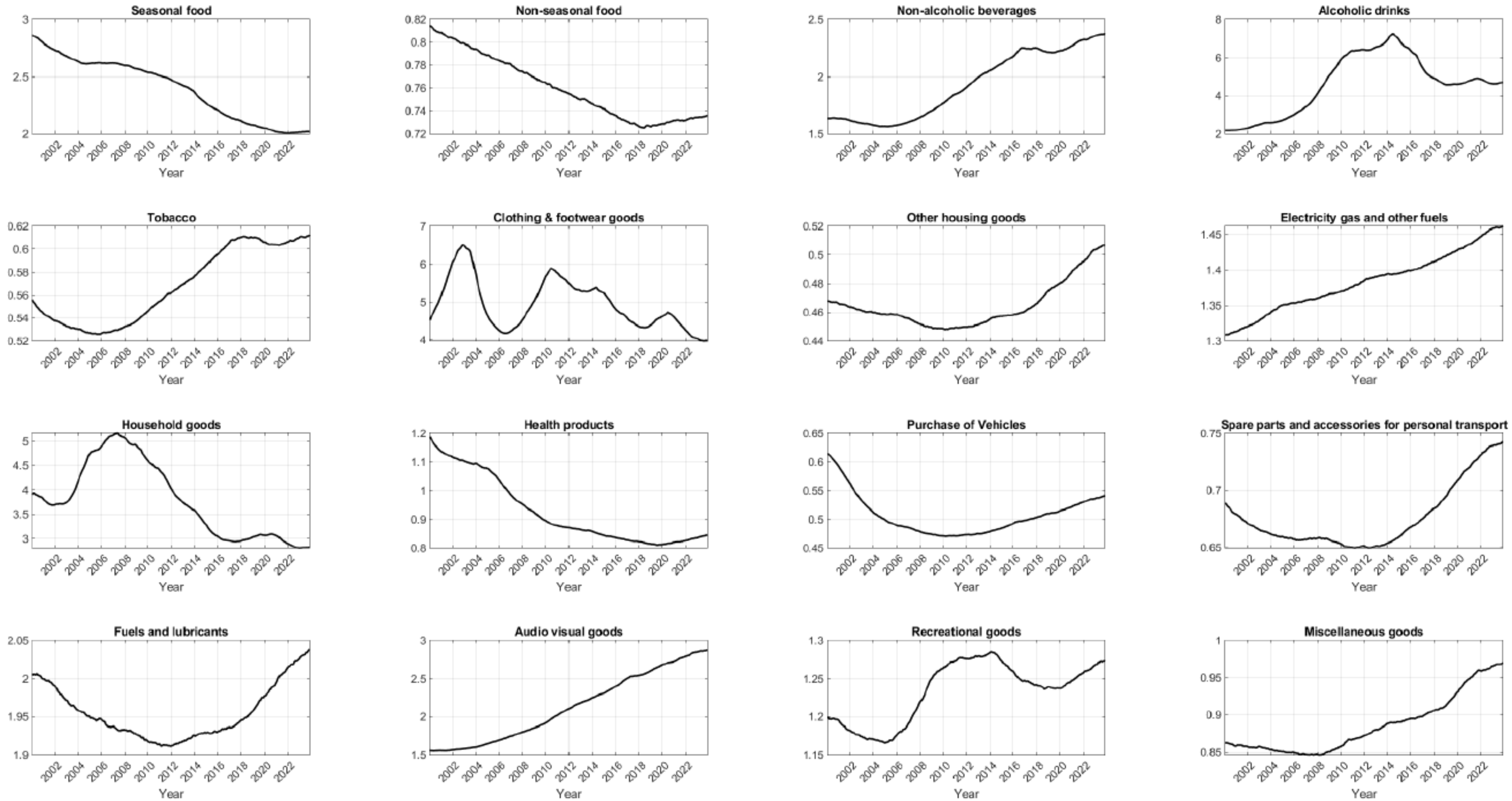
Note: The figure plots estimated stochastic volatilties from UCSVO model for Goods sectors of CPI using data from January 2000 to December 2023.

Figure 21. Sectoral Trend Stochastic Volatilities for Services from UCSVO model



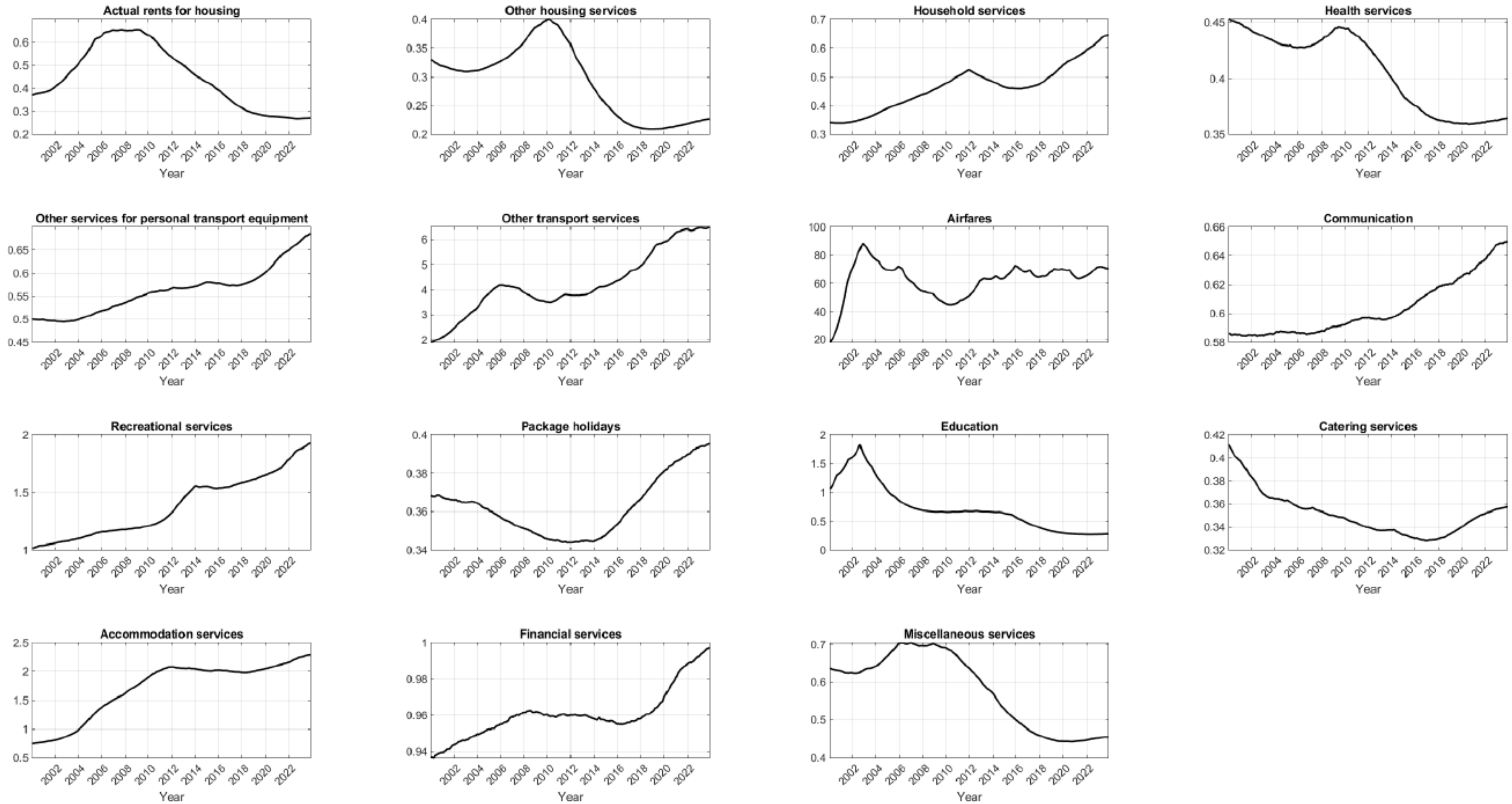
Note: The figure plots estimated stochastic volatilities from UCSVO model for Services sectors of CPI using data from January 2000 to December 2023.

Figure 22. Sectoral Seasonal Stochastic Volatilities for Goods from UCSVO model



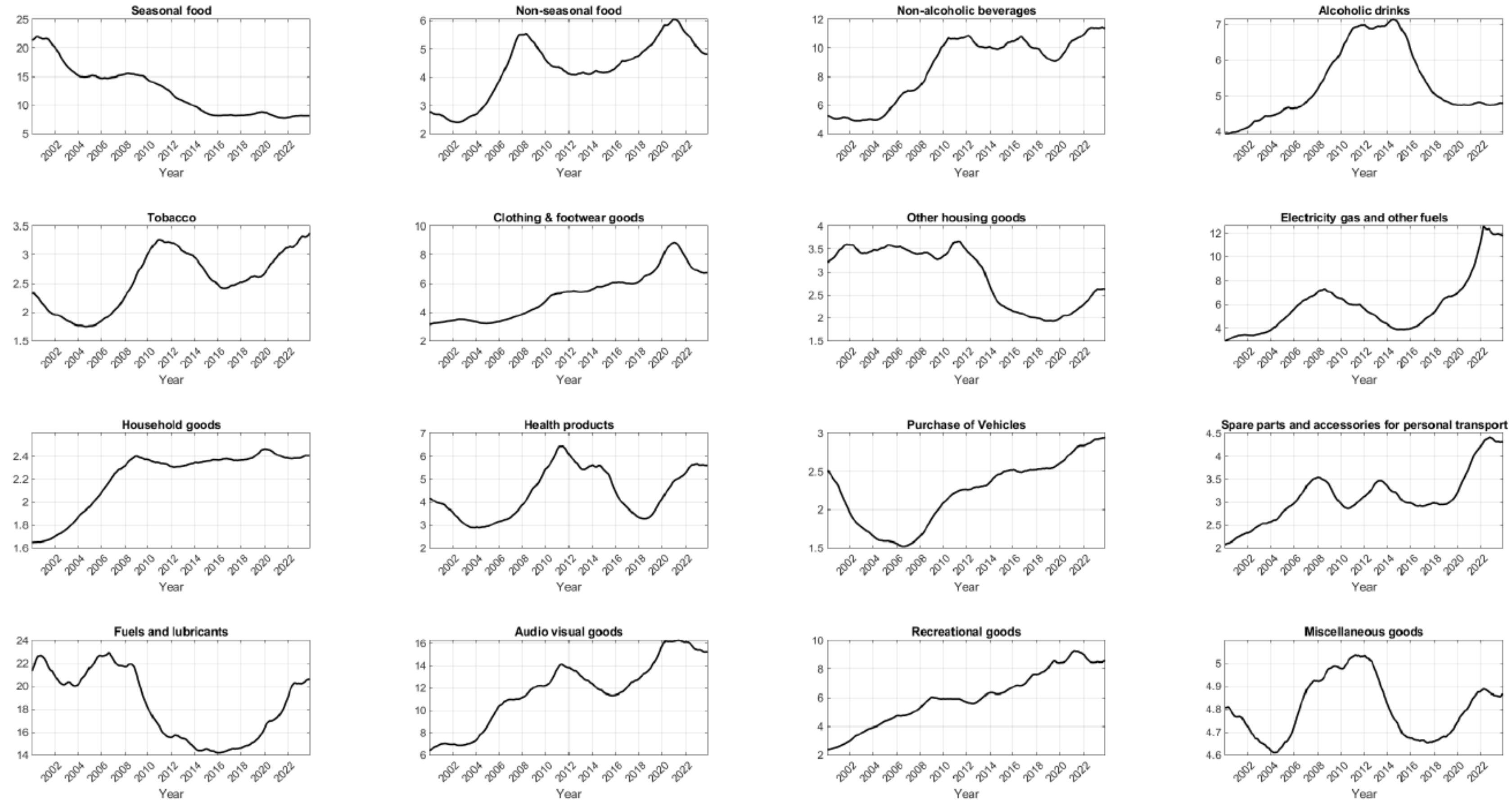
Note: The figure plots estimated seasonal stochastic volatilities from UCSVO model for Goods sectors of CPI using data from January 2000 to December 2023.

Figure 23. Sectoral Seasonal Stochastic Volatilities for Services from UCSVO model



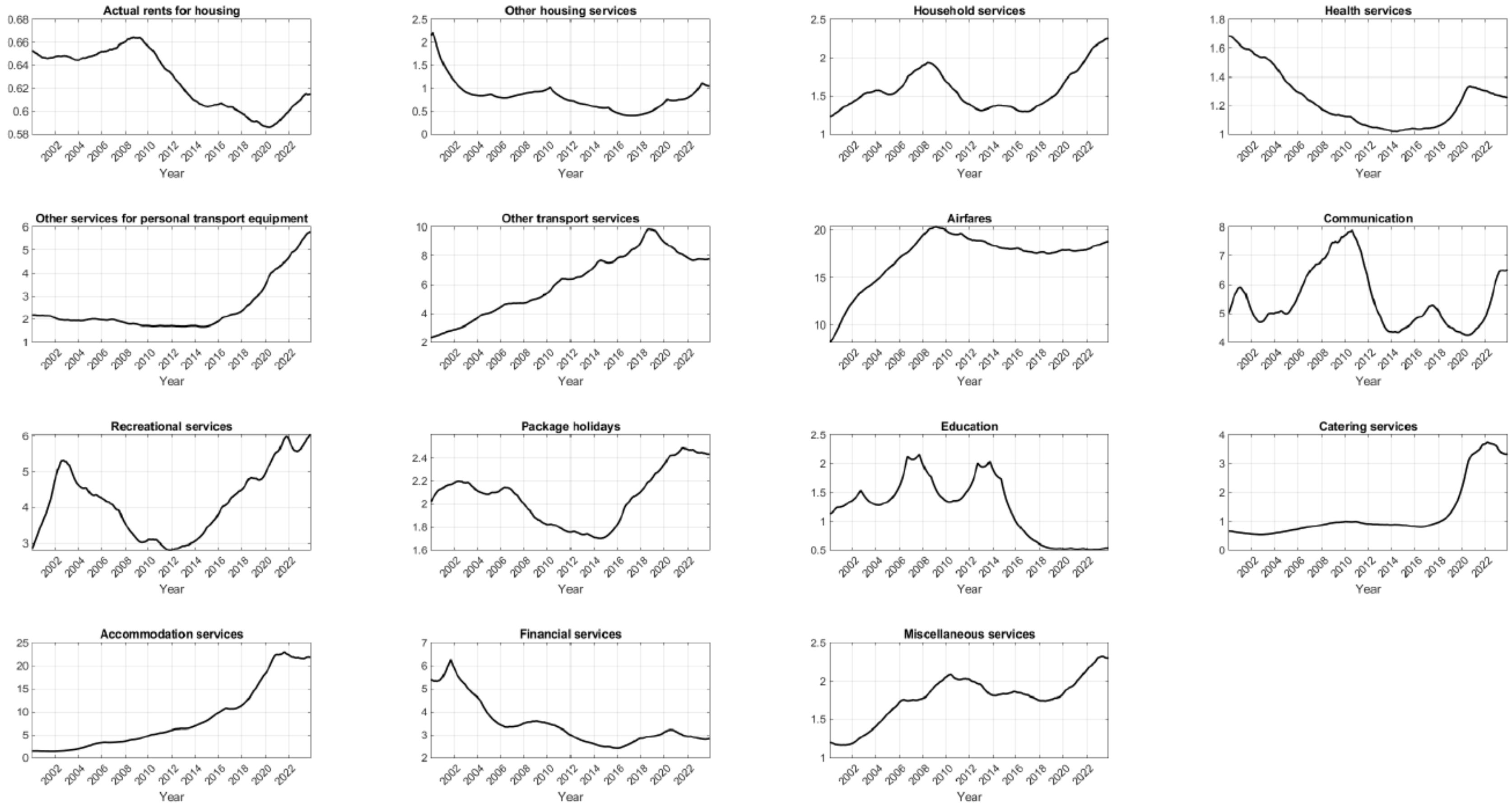
Note: The figure plots estimated seasonal stochastic volatilities from UCSVO model for Services sectors of CPI using data from January 2000 to December 2023.

Figure 24. Sectoral Transitory Stochastic Volatilities for Goods from UCSVO model



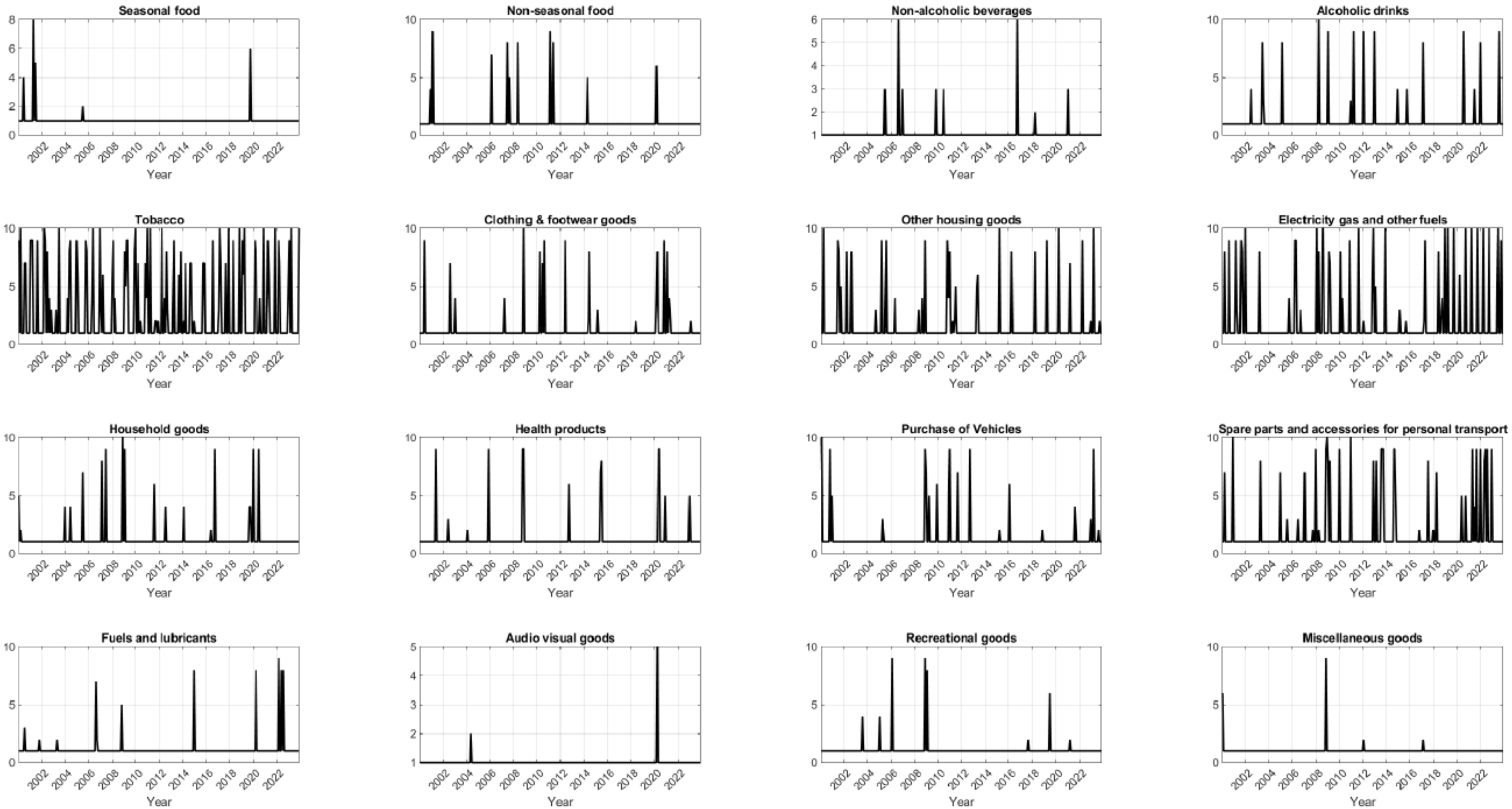
Note: The figure plots estimated transitory stochastic volatilities from UCSVO model for Goods sectors of CPI using data from January 2000 to December 2023.

Figure 25. Sectoral Transitory Stochastic Volatilities for Services from UCSVO model



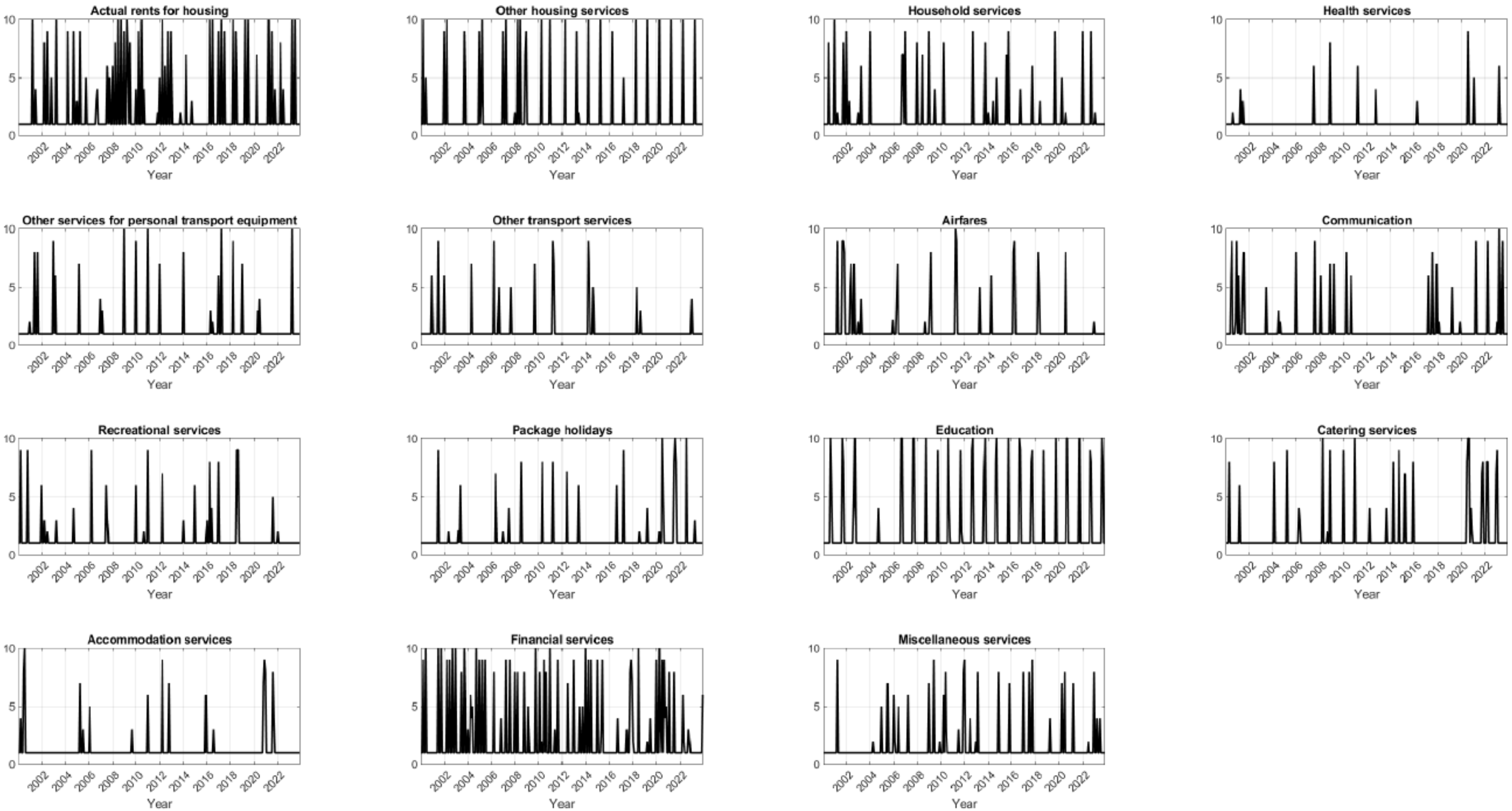
Note: The figure plots estimated transitory stochastic volatilities from UCSVO model for Services sectors of CPI using data from January 2000 to December 2023.

Figure 26. Sectoral Outliers for Goods from UCSVO model



Note: The figure plots estimated outliers from UCSVO model for Goods sectors of CPI using data from January 2000 to December 2023.

Figure 27. Sectoral Outliers for Services from UCSVO model



Note: The figure plots estimated outliers from UCSVO model for Services sectors of CPI using data from January 2000 to December 2023.

Table 3. Trend and Seasonal signal-to-Noise ratio of $\frac{UCSVO}{UC}$

Sector name	Trend	Seasonal
Seasonal food	1.43	1.31
Non-seasonal food	1.01	1.46
Non-alcoholic beverages	1.30	1.01
Alcoholic drinks	1.75	2.05
Tobacco	2.30	1.62
Clothing & footwear goods	1.69	2.03
Actual rents for housing	1.75	1.38
Other housing goods	1.32	0.50
Other housing services	0.81	0.36
Electricity gas and other fuels	1.59	0.66
Household goods	2.34	2.43
Household services	1.77	1.71
Health products	1.31	0.96
Health services	2.61	1.12
Purchase of Vehicles	1.73	1.50
Spare parts and accessories for personal transport	2.06	1.60
Fuels and lubricants	2.97	1.30
Other services for personal transport equipment	1.27	0.55
Other transport services	1.64	1.38
Airfares	2.13	1.77
Communication	1.36	0.33
Audio visual goods	1.19	0.96
Recreational goods	1.49	1.64
Recreational services	1.41	1.33
Package holidays	1.69	1.84
Education	0.37	0.54
Catering services	1.69	0.45
Accommodation services	3.21	0.46
Financial services	1.72	1.35
Miscellaneous goods	1.14	1.00
Headline	0.80	1.41
Goods	1.51	2.40
Services	1.11	1.20

Note: For 31 sectors and aggregates (column 1), the table shows the signal-to-noise ratio for Trend (column 2), calculated using stochastic volatility from the trend and transitory components, and for Seasonal (column 3), calculated using stochastic volatility from the seasonal and transitory components using data from January 2000 to December 2023.