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Understanding Trend Inflation Through the Lens of the Goods and Services Sectors

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Understanding Trend Inflation Through the Lens of the Goods and Services Sectors*

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1 Introduction

A key aim of monetary policy is managing the persistent (or permanent) component of inflation (see, e.g., Mishkin (2007) and Draghi (2015)), a quantity often referred to as trend inflation. Indeed, a casual reading of a monetary policy report from the Federal Reserve Board makes it clear that, in addition to headline inflation, the Federal Reserve focuses on underlying (or core) measures of inflation that exclude, for instance, food and energy prices. This strategy is predicated on the belief that fluctuations in components such as food and energy are ultimately transitory and, consequently, should be excluded from monetary policy considerations about the trend (or long-run) path of inflation.

In a prominent contribution to the inflation literature, Stock and Watson (2007) show that the fundamental change in U.S. inflation dynamics in the last three to four decades has been a considerable drop in the volatility of trend inflation. More specifically, while trend inflation was volatile during the 1970s, it has become marked stable since the mid-1980s (and especially since the 1990s). While Stock and Watson's finding is a widely accepted description of *aggregate* trend inflation dynamics, it remains an open question how much sectoral forces contribute to their narrative on the change in trend inflation volatility. At the same time, the Covid-19 pandemic has sparked interest in understanding sector-specific repercussions on inflation, especially in light of a large increase in goods inflation.

Our main contribution is to shed light on the role of the goods and services sectors as sources of aggregate trend inflation volatility for the U.S. economy. In other words, our paper aims to understand how these two sectors contribute to variation in trend inflation and, consequently, explore how a sectoral view reconciles with changes in its aggregate volatility reported in Stock and Watson (2007).[1] To do so, we build on their univariate unobserved components model with stochastic volatility (univariate UC-SV, hereafter) by developing a two-sector unobserved components model with stochastic volatility (Two-Sector UC-SV, hereafter) that features time-varying correlation between goods and services.

Our key result is the following: we find that variation in aggregate trend inflation has been entirely dominated by that in trend services inflation since the 1990s. Our key result is

[1]Throughout this paper we use the terms volatility and variation interchangeably.

a direct manifestation of several changes in inflation dynamics in both sectors, including (i) a fall in the correlation between trend goods and trend services inflation, which was moderate and positive in the 1970s, but is essentially zero today; and (ii) a change in the dynamics of goods inflation, where its variation used to be partly permanent but is now almost entirely dominated by transitory noise. We note that the above-mentioned results are robust in the context of a sample that accounts for observations up to 2021Q4, hence accounting for the inflation developments related to the Covid-19 pandemic.

Our approach is related broadly to the modeling of inflation dynamics in the literature. We briefly discuss some of these in turn. First, Stock and Watson (2007) represents the basic building block for many contributions in the trend inflation literature (see, e.g. Chan, Koop and Potter, 2013; Mertens, 2016; Stock and Watson, 2016; Chan, Clark and Koop, 2018; Hwu and Kim, 2019). At a high level, these studies all mainly aim to sharpen trend inflation estimates in terms of in-sample and out-of-sample fits relative to the original univariate UC-SV framework. In contrast, while building on the same modeling framework, our goal is not so much to improve the model fit, but instead to provide a better understanding of the sources of variation in trend inflation through the lens of the goods and services sectors.

Second, the goods and services dichotomy has been used in policy settings to frame inflation in terms of imported and domestic components. In particular, services inflation is often hypothesized to have a much tighter link to domestic economic slack, and possibly cyclically sensitive (e.g., see Tallman and Zaman, 2017; Stock and Watson, 2020; Borio et al., 2021). In contrast, goods inflation is typically discussed in terms of imported inflation (e.g., see Clark, 2004; Linder, Peach and Rich, 2013), especially when considering China's growing participation in the consumer goods market over the last 30 years. The latter spurred a strand of work exploring how and whether inflation has become increasingly globalized (see, e.g. Kamin, Marazzi and Schindler, 2006; Borio and Filardo, 2007; Bianchi and Civelli, 2015; Kamber and Wong, 2020). From this perspective, our approach of adopting the goods and services dichotomy serves as a natural broad split to understand domestic and imported inflation.[2] At the same time, the shift in consumer spending patterns that followed govern-

[2] We also relate to work which tries to understand how important relative price changes are to understanding aggregate inflation (see Reis and Watson, 2010; Ahn and Luciani, 2021).

ment policies to contain the spread of Covid-19 has placed the goods and services split at the forefront of the current debate on inflation dynamics.[3]

Third, similar to Stock and Watson (2007), we decompose inflation into a permanent and a transitory "noise" component in our Two-Sector UC-SV model. The permanent component is then labeled "trend inflation". Consequently, our approach is conceptually closer to a removal-of-noise exercise used to obtain a signal about underlying, and ultimately future, inflation. There is also corroborating evidence that our interpretation of trend inflation is consistent with that within policy circles.[4] However, we acknowledge an alternative strand of the literature that views trend inflation within the context of a time-varying inflation target (e.g. Kozicki and Tinsley, 2001; Ireland, 2007; Cogley, Primiceri and Sargent, 2010; Coibion and Gorodnichenko, 2011; Ascari and Sbordone, 2014) or optimal inflation rate (Adam and Weber, 2019). While this body of work shares the label "trend inflation", the interpretation of trend inflation differs from ours. To be clear, we view trend inflation as a measure that provides a signal of future inflation through the removal of transitory noise. Hence, no equivalence is assumed a priori between our estimates of trend inflation and the monetary authority's inflation target. We state our interpretation upfront since this distinction does not seem to have been explicitly stated elsewhere, and can be a source of confusion.

The remainder of this paper proceeds as follows: Section 2 describes the Two-Sector UC-SV model. Section 3 presents the results from our model. Section 4 extends our analysis to examine the robustness of our results. Section 5 concludes.

2 A Two-Sector UC-SV Model

We begin by describing our Two-Sector UC-SV model. We decompose goods inflation (π_t^G) and services inflation (π_t^S) into their corresponding sector-specific permanent (τ_t^G, τ_t^S) and

[3]For example, see the April 18, 2020 edition of the The Economist, *"Covid-19 could lead to the return of inflation - eventually".*

[4]For example, in the minutes of the meeting of the Federal Open Market Committee held on June 17-18, 2014, James Bullard from the St Louis Fed asks, *"If inflation comes in at 1.9 percent and we've got underlying inflation at 1.75 percent, then should I say that we've got above-normal or above-trend inflation, or am I supposed to compare it with 2 percent, which is the Committee's official target?"* To which Jeremy Rudd of the Federal Reserve Board replied, *"In our judgment, you should be comparing it with 1.75 percent. We think $1\frac{3}{4}$ percent is the underlying rate of inflation."*

transitory noise ($\zeta_t^G,\ \zeta_t^S$) components. Formally, we have:

$$\pi_t^G = \tau_t^G + \zeta_t^G, \tag{1}$$

$$\pi_t^S = \tau_t^S + \zeta_t^S. \tag{2}$$

and trends are modelled as driftless random walk processes while abstracting from autoregressive dynamics for the noise processes:[5]

$$\tau_t^G = \tau_{t-1}^G + u_t^{\tau^G}, \tag{3}$$

$$\tau_t^S = \tau_{t-1}^S + u_t^{\tau^S}. \tag{4}$$

The driftless random walk is a common modeling strategy in the trend inflation literature.[6] Consistent with the Beveridge and Nelson (1981) (BN) decomposition, which defines the trend component of time series as its long-horizon forecast based on information at time t, for each sector i, this implies

$$\tau_t^i = \lim_{h\to\infty} \mathbb{E}_t\left[\pi_{t+h}^i\right], \tag{5}$$

where one can verify that the driftless random walk assumption implies that the long-horizon forecasts of π_t^G and π_t^S are respectively τ_t^G and τ_t^S. The BN decomposition also provides a convenient link to trend inflation work that does not necessarily involve UC models, but also constructs trend inflation appealing to the BN decomposition under different modeling frameworks (e.g., Cogley, Primiceri and Sargent, 2010; Kamber and Wong, 2020).

[5]While modeling inflation's transitory components as noise may seem controversial, we retain this specification mainly to keep our comparison as close as possible to that of Stock and Watson (2007), thereby retaining their interpretation that the estimation of trend inflation is essentially a noise-filtering exercise, as outlined in the Introduction. In Section 4.2, we explored different specifications of the gap, and discuss why our approach is still the preferred specification. Another specification-related possibility could be to allow for correlation between the innovations driving the trends and noise (within and across sectors). We leave this for future research, but note that Uzeda (2022) examined a related issue in the context of a univariate UC-SV model finding that such type of trend-noise correlation leads to measures of trend inflation that are similar to (survey-based) short-run inflation expectations. In contrast, the usual orthogonal trend-noise assumption leads to measures of trend inflation that are more in line with (survey-based) long-run inflation expectations, hence closer to our interpretation of trend inflation in this study.

[6]See Stock and Watson (2007) and work that build directly on theirs (e.g. Mertens, 2016; Chan, Clark and Koop, 2018, etc.). Shephard (2015) generalizes the random-walk assumption to martingale UC models.

Next, to allow for changes in the (conditional) volatility and correlation of the innovations $u_t^{\tau^i}$ and ζ_t^i for $i = G,\ S$, we specify the following covariance structure:

$$\begin{bmatrix} (u_t^{\tau^G},\ u_t^{\tau^S})' \\ (\zeta_t^G,\ \zeta_t^S)' \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0_{2\times 1} \\ 0_{2\times 1} \end{bmatrix} \begin{bmatrix} \Omega_{\tau,t} & 0_{2\times 2} \\ 0_{2\times 2} & \Omega_{\zeta,t} \end{bmatrix} \right), \tag{6}$$

where a triangular (or LDL) factorization of $\Omega_{\tau,t}$ and $\Omega_{\zeta,t}$ yields:

$$\Omega_{j,t} = \begin{bmatrix} \sigma^2_{j^G,t} & \sigma_{j,t} \\ \sigma_{j,t} & \sigma^2_{j^S,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \gamma_t^j & 1 \end{bmatrix} \begin{bmatrix} \exp\left(h_t^{j^G}\right) & 0 \\ 0 & \exp\left(h_t^{j^S}\right) \end{bmatrix} \begin{bmatrix} 1 & \gamma_t^j \\ 0 & 1 \end{bmatrix} \text{ for } j \in \{\tau, \zeta\}\,. \tag{7}$$

Therefore, in addition to sector-specific trends, six new state variables $(\gamma_t^\tau, \gamma_t^\zeta,\ h_t^{\tau^G}, h_t^{\tau^S}, h_t^{\zeta^G}, h_t^{\zeta^S})$ are introduced to accommodate changes in the correlation between, and volatility of goods and services inflation.[7]

For completeness, we present the law of motion for the remaining state variables in our model:

$$\begin{aligned} h_t^{j^i} &= h_{t-1}^{j^i} + u_t^{h^{j^i}},\ \ j \in \{\tau, \zeta\}\,, i \in \{G, S\}\,, & (8) \\ \gamma_t^j &= \gamma_{t-1}^j + u_t^{\gamma^j},\ \ j \in \{\tau, \zeta\}\,, & (9) \end{aligned}$$

$$\begin{bmatrix} (u_t^{h^{\tau^G}},\ u_t^{h^{\tau^G}},\ u_t^{h^{\zeta^G}},\ u_t^{h^{\zeta^S}})' \\ (u_t^{\gamma^\tau},\ u_t^{\gamma^\zeta})' \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0_{4\times 1} \\ 0_{2\times 1} \end{bmatrix} \begin{bmatrix} \Omega_h & 0_{4\times 2} \\ 0_{2\times 4} & \Omega_\gamma \end{bmatrix} \right), \tag{10}$$

where

$$\Omega_h = \texttt{diag}\left(\sigma^2_{h^{\zeta^G}},\ \sigma^2_{h^{\zeta^G}},\ \sigma^2_{h^{\tau^G}},\ \sigma^2_{h^{\tau^G}}\right) \text{ and } \Omega_\gamma = \texttt{diag}\left(\sigma^2_{\gamma^\zeta},\ \sigma^2_{\gamma^\tau}\right). \tag{11}$$

Equations (1)-(9) describe a bivariate state space model, with the measurement and state

[7] It is easy to show that time-varying correlation estimates, ρ_t^j, can be backed out from Equation (7) by computing $\rho_t^j = \frac{\gamma_t^j \exp\left(h_t^{j^G}\right)}{\left\{\exp\left(h_t^{j^G}\right)\left[\gamma_t^{j^2}\exp\left(h_t^{j^G}\right) + \exp\left(h_t^{j^S}\right)\right]\right\}^{0.5}}$ for $j \in \{\tau, \zeta\}$.

equations given by Equations (1)-(2) and (3)-(9), respectively.[8] Aggregate trend inflation, denoted by τ_t, can be approximately calculated as a weighted average of sector-specific trends:

$$\tau_t \approx \omega_{G,t}\tau_t^G + \omega_{S,t}\tau_t^S, \tag{12}$$

where $\omega_{G,t}$ and $\omega_{S,t}$ are the expenditure weights of goods and services, respectively, and $\omega_t^G + \omega_t^S = 1$. These weights are not estimated; they denote nominal expenditure shares out of total (nominal) Personal Consumption Expenditures (PCE).[9]

We briefly comment on our approach relative to the multi-sector UC model by Stock and Watson (2016). Section A4 of the Online Appendix formally shows that Stock and Watson (2016) and our approach deliver the same canonical representation underlying the joint distribution of sector-specific trends. As we elaborate further in the Online Appendix, our approach is better suited to the two-sector case, whereas their approach is better suited for the 17-sector case. We revisit this issue in Section 4.2, where considering a finer disaggregation of inflation data like Stock and Watson (2016) generates similar results to our Two-Sector UC-SV model.

2.1 Data and Estimation

Goods and services inflation are constructed from the seasonally adjusted deflators, as they are subcomponents of the U.S. PCE. The weights are their nominal expenditure shares. All of our data are from the FRED databank.[10] We annualize the first difference of the logarithms of the deflators to obtain the goods and services inflation rates. Our sample is for the period 1959Q1 to 2021Q4, i.e., $T = 258$ observations, where the last 2 years at the end

[8] Following Stock and Watson (2007), we assume that inflation's permanent and transitory components are orthogonal, which is reflected in the block exogeneity assumption in Equation (6).

[9] We refer to (12) as an approximate relationship since there are no available weights for the subcomponents of PCE inflation. Thus, akin to Stock and Watson (2016), we rely on nominal expenditure shares to construct such weights.

[10] The FRED mnemonics for the goods and services deflators are DGDSRD3Q086SBEA and DSERRD3Q086SBEA, respectively. If we require the PCE deflator, for example when we estimate the univariate UC-SV model, we use DPCERD3Q086SBEA. The FRED mnemonics for nominal expenditures for goods and services are DGDSRC1 and PCESV, respectively. We construct the weights as the proportion of the nominal expenditure for goods or services divided by the sum of the nominal expenditure for goods and services.

of the sample coincide with the Covid-19 pandemic and the associated aftermath where the U.S. economy has experienced global supply-chain shortages as well as large unprecedented fiscal and monetary stimulus.

Our Two-Sector UC-SV model constitutes a nonlinear state space model and so, as is common in this literature, we conduct estimation using a Bayesian approach.[11] The states are estimated using precision sampling techniques as described in Chan and Jeliazkov (2009). In particular, the (log) volatility states (i.e., $h_t^{\tau^G}$, $h_t^{\tau^S}$, $h_t^{\zeta^G}$, and $h_t^{\zeta^S}$) are estimated by combining the precision sampler with the auxiliary mixture sampling method of Omori et al. (2007).

Priors

There are three blocks of model parameters in our baseline Two-Sector UC-SV model for which priors are assigned to. These blocks are the covariance matrices in Equation (11), i.e., $\Omega_h = \texttt{diag}\left(\sigma^2_{h^{\zeta^G}},\ \sigma^2_{h^{\zeta^G}},\ \sigma^2_{h^{\tau^G}},\ \sigma^2_{h^{\tau^G}}\right)$ and $\Omega_\gamma = \texttt{diag}\left(\sigma^2_{\gamma^\zeta},\ \sigma^2_{\gamma^\tau}\right)$, and the state initialization conditions collected as $\mathrm{z}_0 = \left(\tau_0^G\ \tau_0^S\ h_0^{\zeta^G}\ h_0^{\zeta^S}\ h_0^{\tau^G}\ h_0^{\tau^S}\ \gamma_0^\zeta\ \gamma_0^\tau\right)'$. We assume mutually independent priors for each parameter in these three blocks.

More precisely, we adopt an inverse-gamma prior for each (conditional) variance term in Ω_h and Ω_γ, i.e., $\sigma^2_{h^{\ell^i}} \sim \mathcal{IG}\left(\nu_{h^{\ell^i}},\ S_{h^{\ell^i}}\right)$ and $\sigma^2_{\gamma^\ell} \sim \mathcal{IG}\left(\nu_{\gamma^\ell},\ S_{\gamma^\ell}\right)$, for $\ell = \zeta$ and τ and $i = G$ and S, where we set $\nu_{h^{\ell^i}} = \nu_{\gamma^\ell} = \frac{T}{10}$ and $S_{h^{\ell^i}} = S_{\gamma^\ell} = 0.2^2(\nu_{h^{\ell^i}} - 1)$. The last expression implies $\mathbb{E}\sigma^2_{h^{\ell^i}} = \mathbb{E}\sigma^2_{\gamma^\ell} = 0.2^2$. In other words, we assume that the conditional variance for the states that govern second moments in our model are, on average, equivalent *a priori*. Our prior beliefs are, however, diffuse, as reflected in the calibration of the shape hyperparameters $\nu_{h^{\ell^i}} = \nu_{\gamma^\ell} = \frac{T}{10}$.[12] Lastly, we assume a diffuse Gaussian prior for the initial conditions, i.e., $\mathrm{z}_0 \sim \mathcal{N}\left(\widehat{\mathrm{z}_0}, \boldsymbol{\Sigma}_{\mathrm{z}_0}\right)$, where $\widehat{\mathrm{z}_0} = \left(\pi_1^G,\ \pi_1^S,\ 0, \cdots, 0\right)'$ and $\boldsymbol{\Sigma}_{\mathrm{z}_0} = 100 \times I_8$, such that I_q denotes a $q \times q$ identity matrix and $q = 8$ (i.e., the number of state initialization conditions).

We note that our priors are standard relative to the extant trend inflation literature and the particular choice of hyperparameter calibration described above is guided by empirical

[11] A detailed description of the posterior sampling algorithm can be found in Section A1 of the Online Appendix. Briefly, we develop a Markov Chain Monte Carlo (MCMC) algorithm, whereby we retain 150,000 draws from the 175,000 runs of our MCMC sampler. The first 25000 burn-in draws are discarded.

[12] See, e.g., Kroese and Chan (2014), chapter 11 for details on the parametrization of the inverse gamma distribution which we adopt.

research on U.S. inflation that relies on a similar modeling framework (e.g., Stock and Watson, 2007; Mertens, 2016; Stock and Watson, 2016; Chan, Clark and Koop, 2018). We also conduct a number of prior sensitivity checks to assess the robustness of our results, which we discuss in Section 4.1. In particular, we allow for alternative prior calibrations and also change the class of prior distribution.

3 Empirical Results

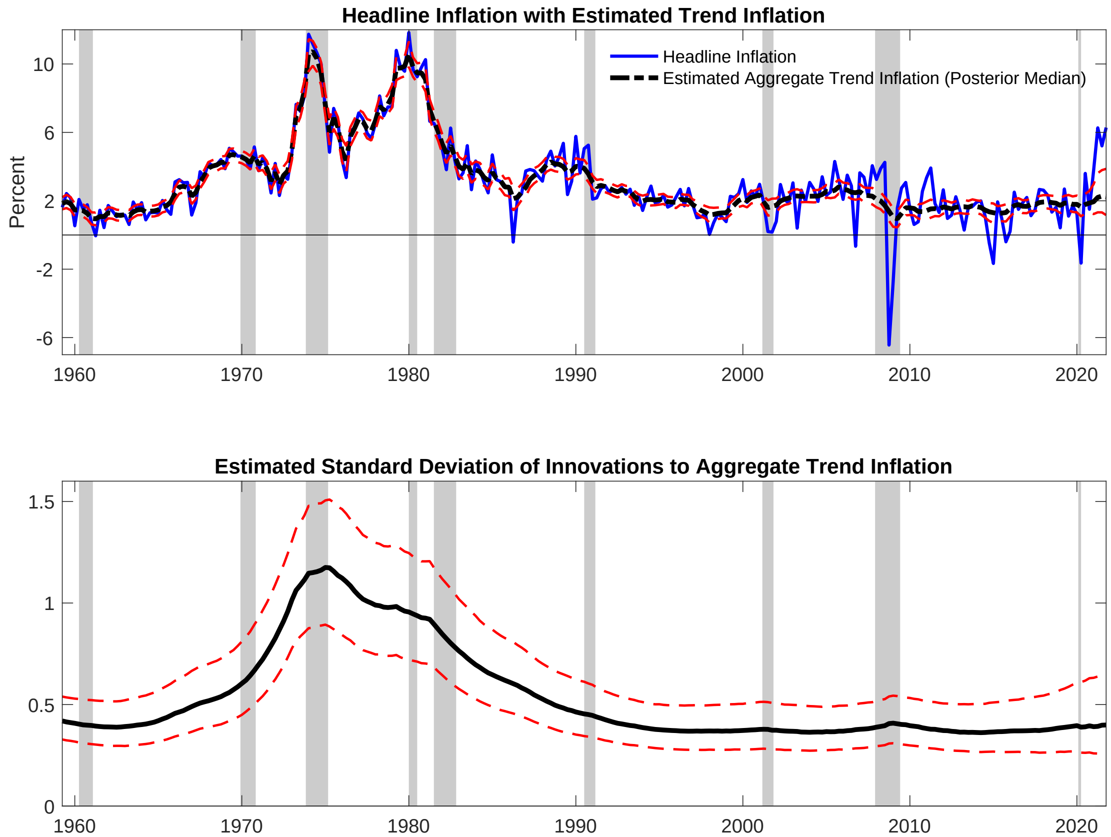
We first briefly present and discuss some basic estimation results from our model before moving on to our key finding about the sources of variation in aggregate trend inflation.

3.1 Some Basic Results

We first present the implications of our model to aggregate trend inflation. The top panel of Figure 1 plots the (smoothed) estimates of aggregate trend inflation from the Two-Sector UC-SV model, together with PCE inflation. We report the posterior median as well as the 67% credible sets of our trend estimate. Overall, our trend inflation estimate broadly mimics the history of postwar U.S. inflation. In particular, trend inflation peaked during the Great Inflation in the 1970s, and began to disinflate in the early to mid-1980s. We also observe that, while episodes of large swings in quarter-on-quarter headline inflation occurred historically, trend inflation has remained low and stable since the 1990s.

Towards the end of our sample, our point estimates suggest that trend inflation has been rising, albeit modestly, since the beginning of the Covid-19 pandemic and sits slightly above two percent. We do however document a widening of the posterior credible sets towards the end of the sample. Since the sudden shift in inflation dynamics occurs at the end of the sample, it is less certain whether such a shift implies the early stages of a permanent change in inflation or a more transitory phenomenon, and is accordingly reflected in a greater degree of estimation uncertainty towards the end of the sample. Therefore, while the point estimate of our model suggests that the increase in inflation associated with the Covid-19 pandemic is largely transitory noise, the model also accordingly attaches a greater degree of uncertainty on interpreting such an increase as a permanent shift in inflation or transitory noise.

Figure 1: Estimated Level and Volatility of Aggregate Trend Inflation



Notes: The top panel plots annualized quarter-on-quarter PCE inflation together with our posterior median estimate of aggregate trend inflation with the associated 67% credible interval. The bottom panel depicts the estimated posterior median standard deviation of innovations to aggregate trend inflation with associated 67% credible interval. All inflation rates are annualized. The shaded areas denote NBER recession dates.

The bottom panel of Figure 1 presents our estimate of the time-varying volatility of trend inflation. We plot the estimated (conditional) standard deviation of the innovations to aggregate trend inflation, together with their associated 67% posterior credible interval.[13] We find that there has been a large fall in the variance of the permanent component of aggregate inflation since the late 1970s. In particular, trend inflation volatility exhibits a hump shape that captures its rise and subsequent fall between 1970 and 1980, a feature

[13]We use Equation (13) to calculate the standard deviation of aggregate trend inflation. Also note that because trend inflation is a random walk, its (asymptotic) unconditional variance is not defined. Thus, throughout this paper when we mention variance of trend inflation we are in fact referring to its conditional variance.

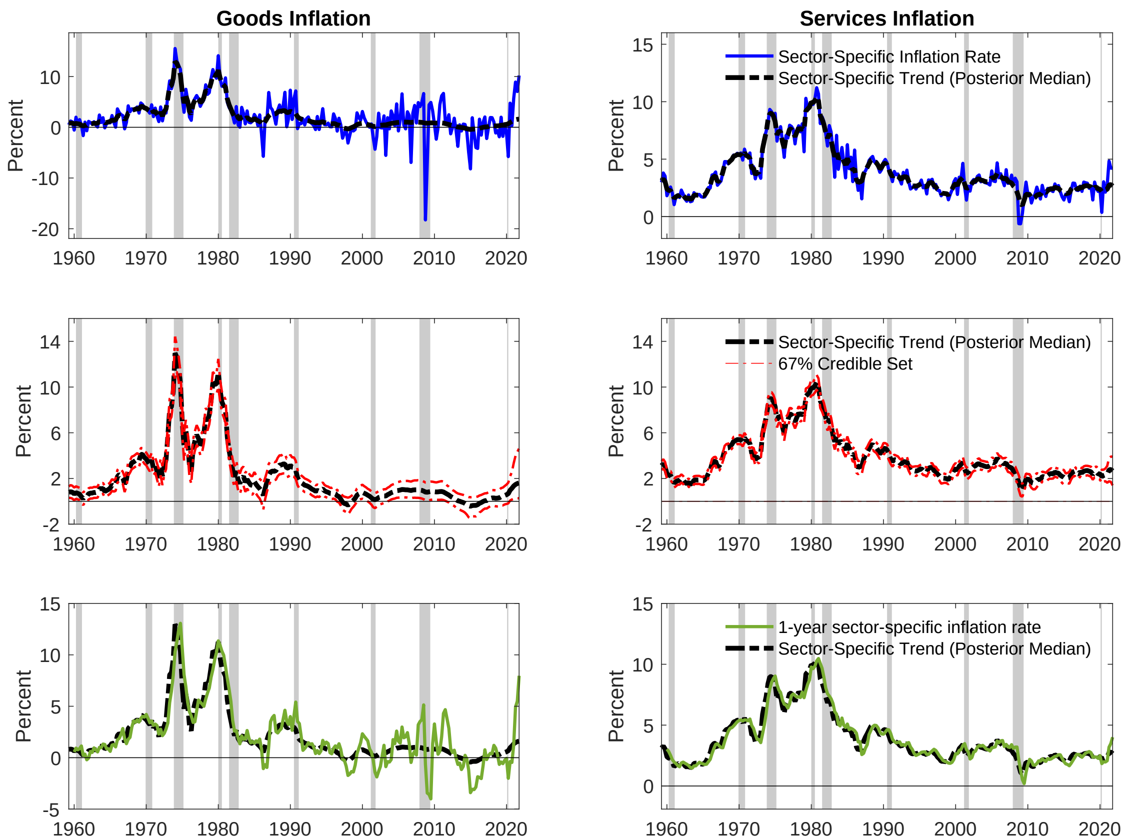
shown by Stock and Watson (2007), and also by other authors (e.g. Cecchetti et al., 2007; Eo, 2016).

A key facet of external validation of our modeling approach is whether our model can reproduce the basic empirical facts documented by Stock and Watson (2007) for aggregate trend inflation. In Section A3 of the Online Appendix, we make explicit comparisons of the results between our two-sector model and Stock and Watson's univariate UC-SV model, including an out-of-sample forecasting exercise. In short, the level and volatility estimates of U.S. trend inflation implied by our two-sector model are very much in line with those presented by Stock and Watson (2007). Our approach also produces very similar (and in some instances even slightly superior) forecasting performance relative to that of the univariate UC-SV model.

Turning to our sector-specific results, the top two panels of Figure 2 present the posterior median estimates of our sector-specific trends together with the annualized quarter-on-quarter inflation in the goods and service sector. Notably, estimates of sector-specific trend inflation are quite different when comparing their dynamics during the 1970s and early 1980s against the period from the mid-1980s onwards. In particular, during the 1970s both trend services and trend goods inflation are roughly equivalent to actual goods and services inflation, respectively. In contrast, the second half of our sample witnesses marked differences in the dynamics of sector-specific trend inflation. More precisely, since the 1990s, while goods inflation has fluctuated at a relatively higher frequency, its sector-specific trend has moved very little. On the other hand, trend services inflation has continued to track services inflation more closely. We also observe that, akin to the aggregate case, sector-specific trends have been rising modestly since the onset of the Covid-19 pandemic.

The two middle panels in Figure 2 report the sector-specific trends together with the associated 67% credible sets. The latter suggest that our sector-specific trends are fairly precise, although we note (again) that the posterior bands become relatively wider towards the end of the sample. On a related theme, the noisier nature of goods inflation, especially since the 1990s, suggests that trend detection may be intrinsically harder in the goods sector, which may manifest in wider posterior credible bands for trend estimates of goods inflation relative to its services counterpart. Indeed, we find that the average width of the 95%, 67%

Figure 2: Sectoral Trend



Notes: The solid line in the top panels are sector-specific annualized quarter-on-quarter inflation rates and the dotted lines represent our posterior median estimate of the sector-specific trend with its associated 67% credible set. The bottom panels present our posterior median estimate of the sector-specific trend with its associated 67% credible set relative to 1-year inflation in the respective sector. All inflation rates are annualized. The shaded areas denote NBER recession dates.

and 50% (or interquartile range) posterior credible sets associated with each sectoral trend over the whole sample is approximately 20% wider for trend goods inflation (relative to services). We therefore conclude that trend detection is indeed more challenging for goods relative to services inflation, but not by a substantially large margin.

Finally, while we adopt a UC model to estimate sector-specific trends, one may wonder if simpler smoothing approaches would lead to similar results. One such approach, commonly used by practitioners, is to simply look at the 1-year sectoral inflation rates, or $100 \times \left[p_t^i - p_{t-4}^i\right]$, where p_t^i represents the log of the price index in sector i. The bottom panels in Figure 2 report these series against our sector-specific trends. Notably, while reasonably similar for services inflation, the 1-year measure for goods inflation is markedly different from our UC estimates in the later part of the sample. In particular, 1-year goods inflation fluctuates significantly more than its UC (trend) counterpart, highlighting a potential drawback of using 1-year measures to infer longer price trends. The 1-year metrics are (by construction) more likely to produce measures with sharp and short-lived reversals, especially if the underlying series is extremely volatile, which may seem counterintuitive when thinking long-run (or trend) dynamics. This issue is evidenced, e.g., by the large (but quickly reversed) drop in goods inflation during the 2008/09 financial crisis. To be clear, we do not advocate that 1-year measures are uninformative to understand inflation dynamics more broadly. Instead, we simply see the task of identifying the high- and low-frequency components of inflation as one that warrants formalizing a signal extraction approach, which a UC model does, albeit not solely.

3.2 Sources of Variation in Aggregate Trend Inflation

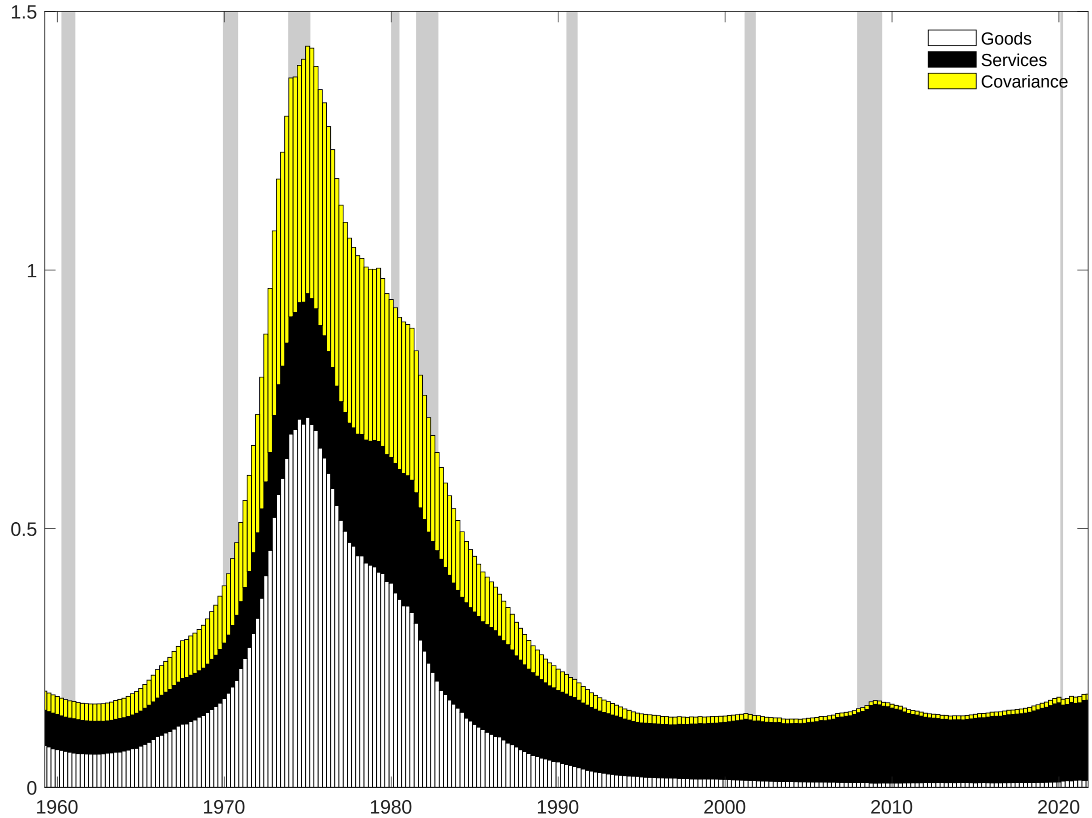
We now turn to understanding the sources of variation in aggregate trend inflation. By expanding on Equation (12), the variance aggregate trend inflation, *conditional* on information up to t-1, from the Two-Sector UC-SV model can be written as:

$$var(\tau_{t|t-1}) \approx \omega_{G,t}^2 var(u_t^{\tau^G}) + \omega_{S,t}^2 var(u_t^{\tau^S}) + 2\omega_{G,t}\omega_{S,t} Cov(u_t^{\tau^G}, u_t^{\tau^S}). \tag{13}$$

Equation (13) shows that the Two-Sector UC-SV model naturally implies a simple decomposition where the conditional variance of aggregate trend inflation can be approximately decomposed into three components: the variances of the innovations to the goods and services sectors, and a covariance term that accounts for the correlation between the two sectors.

Figure 3 presents the decomposition of the estimated variance of aggregate trend inflation into the three components implied by Equation (13), which we denote as *Goods*, *Services*, and *Covariance*. The overall volatility has a hump shape pattern where the hump represents the high variance for aggregate trend inflation during the Great Inflation and the subsequent disinflation, as also documented in the bottom panels of Figure 1. It is clear that all three

Figure 3: Decomposition of Volatility of Aggregate Trend Inflation



Notes: Trend inflation is in units of annualized quarter-on-quarter inflation. Goods, services, and covariance refer to the decomposition components of aggregate trend inflation, as presented in Equation (13). The shaded areas denote NBER recession dates.

components have contributed to the total variance of aggregate trend inflation before the 1990s, which is especially more pronounced during the Great Inflation in the 1970s. However, since the 1990s, the goods and covariance components no longer contribute to the variation in aggregate trend inflation. In other words, over the past three decades the volatility of aggregate trend inflation has been driven (almost) exclusively by the services sector. Figure 3 also provides insights why our estimates of trend inflation has only risen modestly during the Covid-19 pandemic. Because a large proportion of the increase in inflation during the Covid-19 pandemic has been associated with the disruption of global supply-chains, which largely manifests itself in increases in the price of goods, our model thus interprets this increase as being largely characterized by transitory noise.

The decomposition in Figure 3 thus leads to the key result and conclusion of our paper:

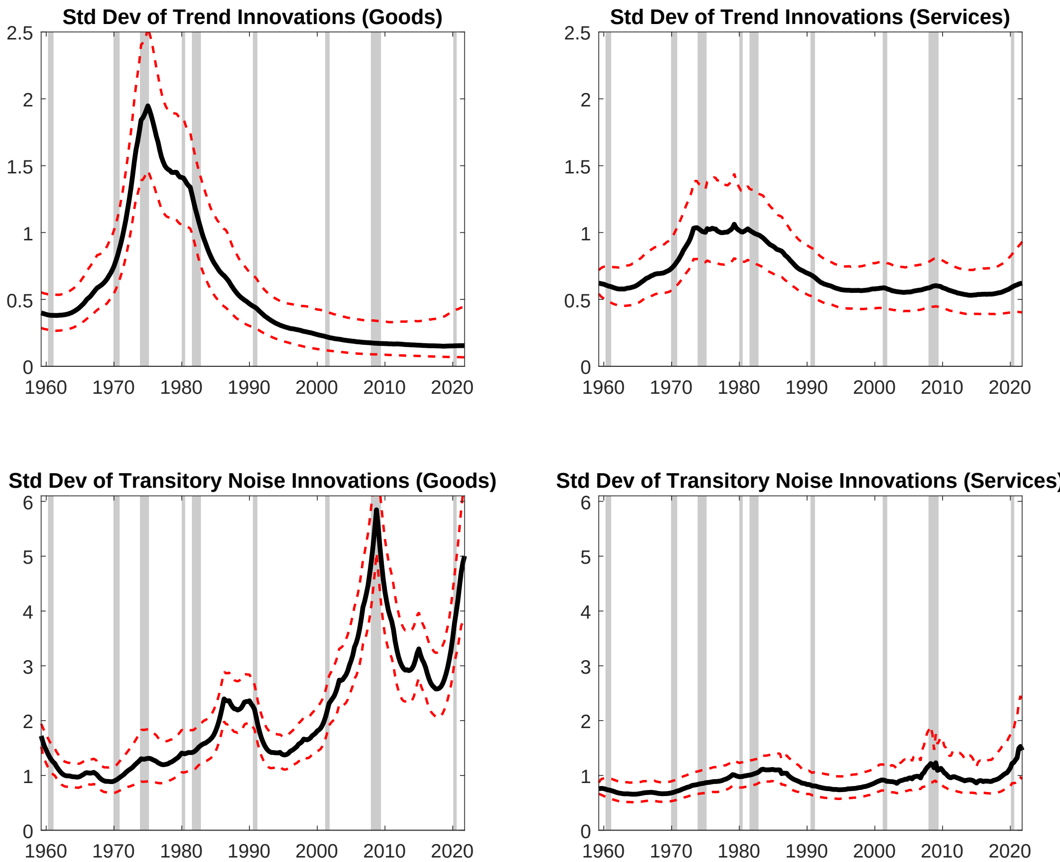
the variation in aggregate trend inflation used to be driven by inflation in both the goods and services sectors, but since the 1990s such overall variation is almost entirely driven by inflation in the services sector. We note that our key result may be more general than just the U.S., as we show in Section A6 of the Online Appendix that the same patterns emerge for both Australia and Canada, two small open economies. Because the decomposition in Figure 3 is mechanically driven by the volatility of sector-specific trends and the correlation of trend innovations between both sectors, we discuss each these points in turn to shed more light on the drivers of our key result.

Changing Volatility of Sector-Specific Trend Inflation

The top two panels of Figure 4 present the estimated time-varying standard deviation of the innovations to trend goods and services inflation (i.e., $std(u_t^{\tau^G})$ and $std(u_t^{\tau^S})$). Similar to aggregate volatility, as presented in the bottom panel of Figure 1, both sectors display a hump-shaped pattern. While the volatilities of both trend services and trend goods inflation display a hump-shaped pattern, the pattern is much sharper and pronounced in the goods sector. More specifically, our posterior estimates for $std(u_t^{\tau^G})$ are about twice those of $std(u_t^{\tau^S})$ at the height of the Great Inflation. Towards the end of the sample, the standard deviation of trend goods inflation is close to zero, and only about one-fifth of the standard deviation of trend services inflation. Notably, our finding that the standard deviation of the innovations of trend goods inflation is close to zero more recently is why the decomposition in Figure 3 finds little role for trend goods inflation and is also consistent with the near-constant dynamics for trend goods inflation over the past 20 years, as shown in Figure 2.

For completeness, the two bottom panels in Figure 4 present the estimated time-varying standard deviation of the sector-specific transitory noise components (i.e., $std(u_t^{\zeta^G})$ and $std(u_t^{\zeta^S})$). We do not observe any discernible pattern with the volatility of the transitory noise component of services inflation, although we note it rises modestly towards the end of the sample. In contrast, the same component for goods inflation has become increasingly volatile over time with two noticeable peaks at the end of the sample corresponding to the Great Recession and the Covid-19 pandemic.

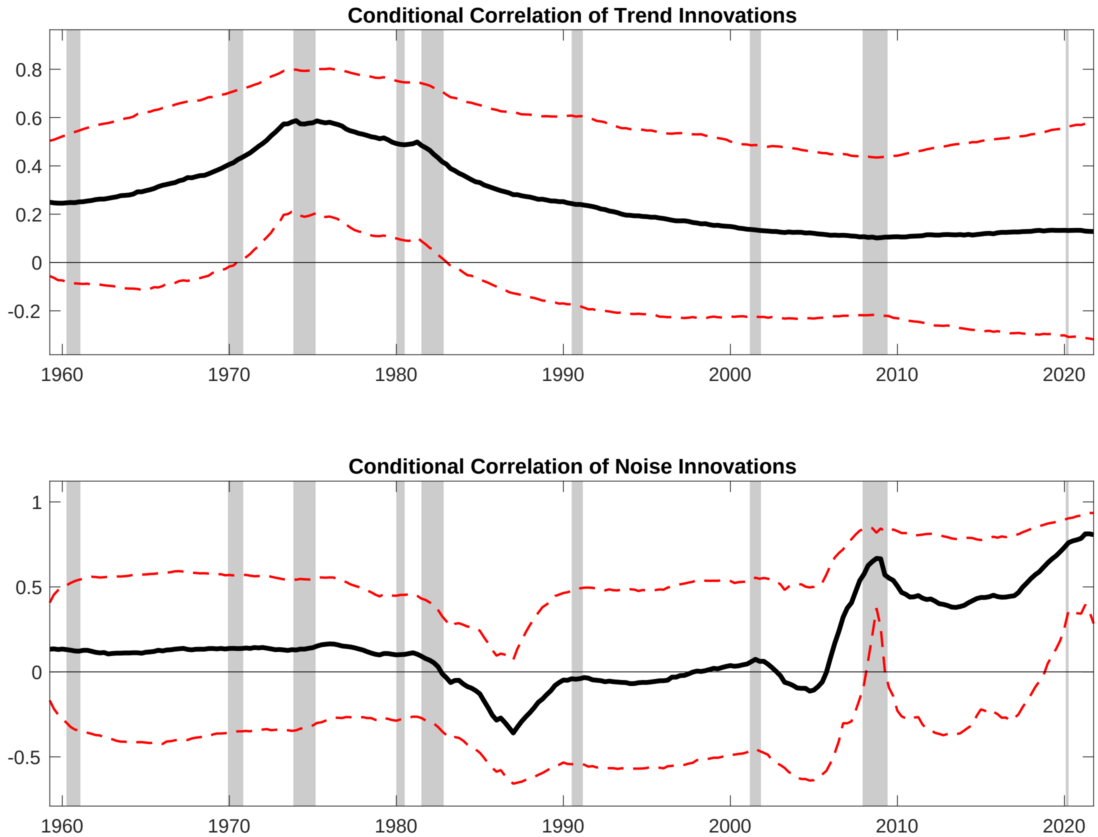
Figure 4: Estimated Conditional Standard Deviation of Innovations



Notes: All (posterior median) estimates are plotted with their associated 67% posterior credible intervals. The shaded areas denote NBER recession dates.

Overall, the results in Figure 4 indicate that, while goods inflation has always been relatively volatile, what has changed in fact is the *composition* of its overall volatility. In other words, unlike the 1970s, where the overall volatility of goods inflation exhibited a substantial permanent component, since the 1990s changes in the volatility of goods inflation have been driven almost exclusively by its transitory noise component.[14]

Figure 5: Time-Varying Correlation between Innovations to Goods and Services Inflation



Notes: All (posterior median) estimates are plotted with their associated 67% posterior credible intervals. The shaded areas denote NBER recession dates.

Changing Correlation of Trend Innovations

The top panel of Figure 5 presents the estimated time-varying correlation between the trend innovations. Our estimates indicate that the correlation was modest before the 1970s, but steadily rose during the Great Inflation. Thereafter, with the 1980s disinflation, the correlation in both sectors fell steadily. We find this correlation is essentially close to zero in the last two decades or so. Because trend services and trend goods inflation are essentially uncorrelated in the last two decades or so, this has meant that the covariance term no longer contributes to aggregate trend inflation volatility, as shown in Figure 3. We also note that

[14] In Section A5 of the Online Appendix, we show that much of this (transitory component-related) result can be attributed to volatile components such as food and energy prices.

the bounds of our credible interval suggests that the correlation between the trend innovations appears to be imprecisely estimated. Even so, our model supports, with a high degree of probability, that this correlation is not only moderate to high, but probably was not zero during the Great Inflation of the 1970s.

The bottom panel of Figure 5 reports the time-varying correlation of the innovations to the transitory noise components. Our results suggest that comovement between transitory noise in these two sectors has been fairly muted until the 2008/09 financial crisis. Since then, the comovement between the transitory noise components has remained elevated and peaking during the Covid-19 pandemic. This indicates that, unlike the Great Inflation of the 1970s, the comovement between goods and services inflation during the last two recessions seem to be characterized by transitory noise.

Finally, given that we find a correlation between the innovations to trend goods and services which was only present during the oil crisis of the 1970s, one may postulate a role for volatile components such as energy prices in understanding these correlation patterns.[15] Nonetheless, we are able to rule out energy prices as we re-estimated our model using core measures of goods and services inflation, i.e., excluding food and energy prices. Such an exercise led to similar patterns to all the results we report in this paper.[16]

The role of sector-specific weights

One may posit that the increasing importance of the services sector as a driver of aggregate trend inflation volatility may simply reflect the continual rise in the expenditure share of services (e.g., see Cœuré, 2019). Indeed, while a roughly 50-50 expenditure split between goods and services was observed around 1970, by the end of the sample the share corresponding to the services sector accounted for nearly 70%. We thus conduct a counterfactual experiment which recomputes the decomposition in Equation (13) for 2019Q4 (the last quarter before the Covid-19 pandemic) by fixing the sectoral weights at their 1975Q1 values. We select 1975Q1 because it coincides with the largest estimate of the volatility for aggregate trend inflation

[15]Energy price shocks present themselves as a candidate explanation for our results considering broader evidence which indicates a reduction in the pass-through from energy prices to core inflation since the 1980s (e.g., see Hooker, 2002; Clark and Terry, 2010).

[16]All the ex-food and energy results, as well as details on how we reconstruct the ex-food and energy indices, are reported in Section A5 of the Online Appendix.

Table 1: Sources of variation in aggregate trend inflation: comparison using actual and counterfactual expenditure shares

	Aggregate volatility	Contributions		
		Goods (%)	Services (%)	Covariance (%)
1975Q1 (Actual weights)	1.680	0.904 (53.83%)	0.276 (16.44%)	0.500 (29.73%)
2019Q4 (Actual weights)	0.156	0.002 (1.25%)	0.152 (97.43%)	0.003 (1.32%)
2019Q4 (1975Q1 weights)	0.095	0.005 (4.83%)	0.088 (92.64%)	0.002 (2.53%)
2021Q4 (Actual weights)	0.164	0.003 (2.10%)	0.158 (96.56%)	0.002 (1.34%)
2021Q4 (1975Q1 weights)	0.111	0.006 (5.87%)	0.102 (91.95%)	0.002 (2.19%)

Weights		
	Goods	Services
1975Q1	47.5%	52.5%
2019Q4	31.0%	69.0%
2021Q4	34.6%	65.4%

Notes: The results for *Actual weights* are based on the expenditure shares at their 1975Q1, 2019Q4 and 2021Q4 values. The results for counterfactual decompositions are based on expenditure shares kept fixed at their 1975Q1 values. The decomposition components of goods sector, services sector, and covariance reported in the table correspond respectively to $\omega^2_{G,t} var(\Delta\tau_t^{\tau^G})$, $\omega^2_{S,t} var(\Delta\tau_t^{\tau^S})$, and $2\omega_{G,t}\omega_{S,t} cov(\Delta\tau_t^{\tau^G}, \Delta\tau_t^{\tau^S})$ in Equation (13).

in our sample. The intuition is that if our results are a mere manifestation of a change in weights, then observing 1970s weights over the end of the sample should overturn our key result. We report results for this exercise in Table 1 as well as the respective expenditure weights. Based on our estimated sample, we find that the volatility of aggregate trend inflation dramatically decreases from 1.68 in 1975Q1 to 0.156 in 2019Q4. Our counterfactual exercise suggests that even with 1970s weights, the volatility of aggregate trend inflation would be 0.095, comparable to 0.156 obtained using the current weights. More importantly, our counterfactual also shows that variation in the services sector would still account for over 90% of overall volatility in aggregate trend inflation had the sectoral weights remained at their 1970s levels. Next, because the Covid-19 pandemic was associated with a shift into the consumption of goods and non-consumption of certain services such as air travel or hospitality due to lockdowns, one may be concerned that the expenditure weights might have been badly mismeasured during such a period. Repeating the exercise for 2021Q4, which is the last data point of our sample and coincides with the ongoing aftermath of the pandemic, we find a similar result to the counterfactual for 2019Q4. Notably, adopting 1970s expenditure weights would constitute a large overestimation of the role of goods consumption. We therefore conclude that the change in expenditure weights since the 1970s, notwithstanding possible measurement errors, does not alter our main insights from Figure 3. Consequently, we rule out the change in the expenditure weights as a reason behind the services sector becoming the main driver of the overall variation in trend inflation since the 1990s.[17]

4 Robustness

In this section, we consider a number of robustness checks. In particular, we: (i) explore the degree of prior sensitivity; and (ii) consider alternative modeling approaches. To summarize, our key results carry over to all the above-mentioned checks. In what follows, we report a few selected results and refer to additional analysis in the Online Appendix.

4.1 Prior Sensitivity

We conduct a number of prior sensitivity checks to ensure our main findings are not a manifestation of the particular choice of priors discussed in Section 2.1. In this regard, a key check is to verify the sensitivity of the variation in sector-specific trends to priors that are conducive to more flexible dynamics in the log-volatility states, i.e. h^{ℓ^i} for $\ell = \zeta$ and τ and $i = G$ and S. Therefore, we considered different prior calibrations for $\sigma^2_{h^{\ell i}}$ in Equation (11), where we set $\sigma^2_{h^{\ell i}} \sim \mathcal{IG}\left(\nu_{h^{\ell i}},\ S_{h^{\ell i}}\right)$, such that $S_{h^{\ell i}} = \kappa 0.2^2(\nu_{h^{\ell i}} - 1)$ and $\mathbb{E}\sigma^2_{h^{\ell i}} = (\kappa 0.2)^2$ for $\kappa \in \{2,\ 3,\ 4,\ 5\}$ and $\ell = \zeta$ and τ and $i = G$ and S. That is, we allow the scale hyperparameter of the inverse gamma distribution associated with the innovations driving all log-volatilities in our model to be up to five times greater relative to our baseline setting.

In addition to changing prior calibration, we also re-estimated our model applying a different class of priors. Specifically, akin to Stock and Watson (2016), instead of an inverse

[17]Note that our statement on the role of expenditure weights and their implications to our key result, are only with regards to the *variance* and not the *level* of trend inflation. Level-related implications from changes in the weights are beyond the scope of this study.

gamma prior, we adopt an uniform prior and set $\sigma^2_{h^{\ell i}} \sim U(0,\ 1)$ for $\ell = \zeta$ and τ and $i = G$ and S.[18] Overall, our main findings are robust to all these different prior settings and related results can be found in Section A2 of the Online Appendix.

4.2 Alternative Specifications

We consider two alternative specifications for robustness. First, we introduce persistence into the specification of the inflation-gap component by modeling it as an autoregressive process. Second, we follow Stock and Watson (2016) and adopt factor-based methods to model comovements across inflation subcomponents.

Allowing for Persistence in the Inflation Gap

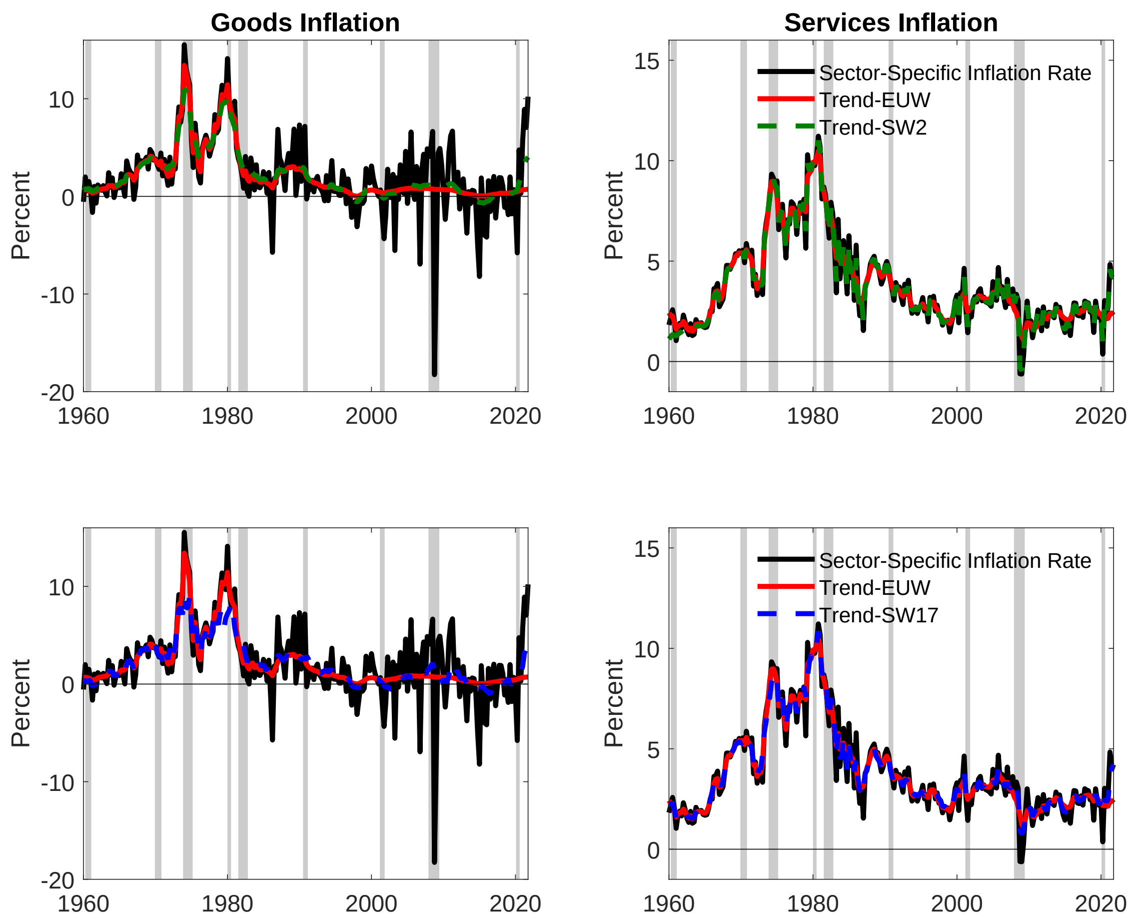
Our baseline model treats the transitory component of inflation as high-frequency noise. While consistent with the broader literature, such a specification precludes the possibility that transitory sector-specific inflation may exhibit serially correlated-type dynamics. This may in turn potentially exacerbate the amount of low frequency movement in inflation that is attributed to the sector-specific trends. To allow for the possibility for persistent dynamics in the transitory component, guided by Chan, Koop and Potter (2013) and Chan, Koop and Potter (2016), we consider two alternative specifications which models the sector-specific transitory component as a stationary inflation gap, c^i_t, that evolve as an AR(1) and as a time-varying parameter (TVP) AR(1) process, i.e.:

- *Two-Sector UC-SV-AR :* $$\begin{cases} c^i_t = \phi^i c_{t-1} + \zeta^i_t, \quad \text{for } i = G \text{ and } S, \end{cases}$$
- *Two-Sector UC-SV-TVP-AR :* $$\begin{cases} c^i_t = \phi^i_t c_{t-1} + \zeta^i_t, \\ \phi^i_t = \phi^i_{t-1} + u^{\phi^i}_t, \quad u^{\phi^i}_t \overset{i.i.d.}{\sim} \mathcal{N}\left(0,\ \sigma^2_{\phi^i}\right) \text{ for } i = G \text{ and } S. \end{cases}$$

We report the results of these specification in A2 of the Online Appendix, but make two points. First, allowing for a persistent inflation gap does not meaningfully alter our main

[18] A formal argument in favor of adopting an uniform prior, instead of an inverse gamma, for variance parameters can be found in Gelman (2006).

Figure 6: Sector-Specific Trends from Different Models



Notes: Trend-SW2 and Trend-SW17 denote the sector-specific trends obtained from the factor-based approach in Stock and Watson (2016) when applied to a 2- and 17-sector split of inflation data, respectively. Trend-EUW, denotes the sector-specific trends obtained from our baseline UC model discussed in Section 2. The shaded areas denote NBER recession dates.

findings. Second, these competing models above did not outperform our baseline ('noisy-gap') specification in a model comparison exercise.

Factor Methods and Further Disaggregation

As commented briefly in Section 2 when introducing the Two-Sector UC-SV (and discussed in greater detail in Section A4 of the Online Appendix), our modeling approach is a suitable one in a two-sector setting. Nevertheless, one could opt for a dynamic factor approach like Del Negro and Otrok (2008), which has been applied by Stock and Watson (2016) in the context of modeling sectoral inflation data. Therefore, we also estimated measures of trend inflation for the goods and services sectors using the dynamic factor model with time-varying loadings and stochastic volatility adopted by Stock and Watson (2016). Specifically, we fit their model to a dataset based on our 2- and the Stock and Watson (2016) 17-component split of inflation data.

Figure 6 shows the series for trend inflation corresponding to goods and services that were obtained from our baseline model and from the factor-based approach by Stock and Watson (2016). In both the 2- and 17-sector cases, our (UC-based) and their (factor-based) frameworks generate reasonably similar measures of sector-specific trends. We note, however, that the factor approach by Stock and Watson (2016) suggests a more noticeable rise in sector-specific trends during the Covid-19 period when compared against estimates from our model.[19] At the time of writing this paper, we can only speculate whether the ongoing inflationary pressures associated with the Covid-19 pandemic will unfold as a more permanent or transitory phenomenon. That being said, our end-of-sample estimates for aggregate trend inflation reported in Figure 1 are in line with economic projections from the Federal Reserve and survey-based measures of inflation expectations from the Survey of Professional Forecasters.[20]

Table 2 reports the contribution from the goods and services sectors to the overall volatility of trend inflation. Again, the results are based on our Two-Sector UC-SV model and the factor-based framework of Stock and Watson (2016) applied to a 2- and 17-sector split of inflation. For convenience, we report estimates for the same dates used in the counterfactual exercise in Section 3.2, namely 1975Q1 (i.e., peak volatility), 2019Q4 (last pre-Covid 19 observation) and 2021Q4 (last observation in our sample). While we note some quantitative differences, the framework by Stock and Watson (2016) further supports our main finding on services inflation being the main driver of trend inflation variation in recent years.[21] In

[19] Such discrepancies are likely associated with the end-of-sample problem, somewhat common in signal extraction applications, whereby different strategies for trend extraction can be more (or less) sensitive to abrupt time series changes at the end of a sample.

[20] For instance, projections from the Federal Open Market Committee (FOMC) released on December 2021 point to a reversal of PCE inflation to 2.6% by the end of 2022 (for details, see https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20211215.pdf). We also show in Section A3 of the Online Appendix that our end-of-sample estimates for aggregate trend inflation are in line with survey-based projections for inflation at various horizons.

[21] In part, quantitative discrepancies may reflect the different formulas used to compute the decomposition of volatility in our UC model and in the factor model by Stock and Watson (2016). We stress that such

Table 2: Decomposition of volatility of aggregate trend inflation: results from different models (in %)

Model	Goods	Services	Covariance
	1975Q1		
Model	Goods	Services	Covariance
Two-Sector UC-SV	53.83	16.44	29.73
SW-2	71.29	24.61	4.10
SW-17	81.29	18.51	0.20
	2019Q4		
Model	Goods	Services	Covariance
Two-Sector UC-SV	1.25	97.43	1.32
SW-2	24.08	70.24	5.69
SW-17	25.30	73.61	1.10
	2021Q4		
Model	Goods	Services	Covariance
Two-Sector UC-SV	2.10	96.56	1.34
SW-2	30.99	64.24	4.76
SW-17	38.58	60.59	0.82

Notes: SW-2 and SW-17 denote the volatility decomposition results obtained from the factor-based approach in Stock and Watson (2016) when applied to a 2- and 17-sector split of inflation data, respectively. These results were computed using Equation A51 in Section A4 of the Online Appendix. Two-Sector UC-SV, denotes the volatility decomposition results obtained from our baseline UC model discussed in Section 2. These results were computed using Equation (13).

addition, like our model, the framework by Stock and Watson (2016) reinforces the idea that goods inflation used to exert a stronger influence on trend inflation volatility in the 1970s. To sum up, the results in Figure 6 and Table 2 suggest that our key empirical finding on the importance of services inflation is neither specific to a particular class of model nor contingent on the level of data disaggregation.

5 Conclusion

We develop an empirical two-sector model of trend inflation to understand the role of the goods and services sectors in explaining the dynamics of trend inflation. Our main finding is that variation in aggregate trend inflation is now predominantly driven by that in services inflation. This is a more recent occurrence, as before the 1990s both the goods and services

different formulas follow directly from the different parametrization of trend inflation in each inferential framework. For brevity, we leave details on how to compute the decomposition of volatility based on the framework by Stock and Watson (2016) to Section A4 in the Online Appendix.

sectors contributed to the variation in aggregate trend inflation with goods inflation being the main driver during the 1970s. A key change driving our main result is that, while overall goods inflation has remained volatile, the variance of trend goods inflation has fallen so sharply that we estimated trend goods inflation featuring little to no volatility since around the 1990s. Also, the disappearance of comovement between trend goods and trend services inflation contributed to the reduction of variation in aggregate trend inflation. Notably, our results are also robust to the inclusion of the Covid-19 pandemic, albeit with a greater degree of uncertainty given the Covid-19 pandemic occurs at the end of our sample.

While the main focus of this paper is to document new stylized facts about changes in trend inflation volatility in the goods and services sectors and how these changes relate at an aggregate level, the interpretation and policy implications of our results remain more suggestive. First, because variation in goods inflation appears to be mostly transitory since the 1990s and potentially represents foreign inflation (see, e.g., Kamber and Wong, 2020; Luciani, 2020), it raises the issue of whether monetary policy should actively offset swings in goods, or more broadly, foreign inflation. This is especially so given there are indications that goods and services inflation may respond very differently to monetary policy (see Cœuré, 2019; Borio et al., 2021) and also to the general state of the business cycle (Stock and Watson, 2020). Second, Cecchetti et al. (2007), through the use of more indirect evidence, argue that the conduct of monetary policy can explain the large fall in the volatility in aggregate trend inflation. While we can rule out energy inflation as a driver of variation in trend inflation dynamics, it remains open whether one can potentially draw a more direct link to the conduct of monetary policy in understanding our key result. Third, our results may provide a starting point for thinking about cross-country and the global determinants of inflation. As we report in the Online Appendix, similar patterns also hold for Australia and Canada, two small open economies, suggesting that our results may reflect a broader phenomenon beyond just the U.S. economy. We leave these avenues for future research.

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