Forecasting the Covid Surge in Inflation*

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Abstract

The persistent surge in U.S. inflation that began in 2021 caught forecasters and policymakers by surprise. The 2021 inflation shocks were viewed as transitory, not persistent, leading to large forecast errors in late 2021 and 2022. This paper asks whether time series models – using only data on current and past inflation, but incorporating stochastic volatility and exhibiting time-varying persistence – performed better. Univariate models, using real-time data, did not. Multivariate models, incorporating sectoral inflation measures, did.

Keywords: Real-time forecasting, unobserved component models, time-varying persistence
JEL: C32, C64, E37

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1 Introduction

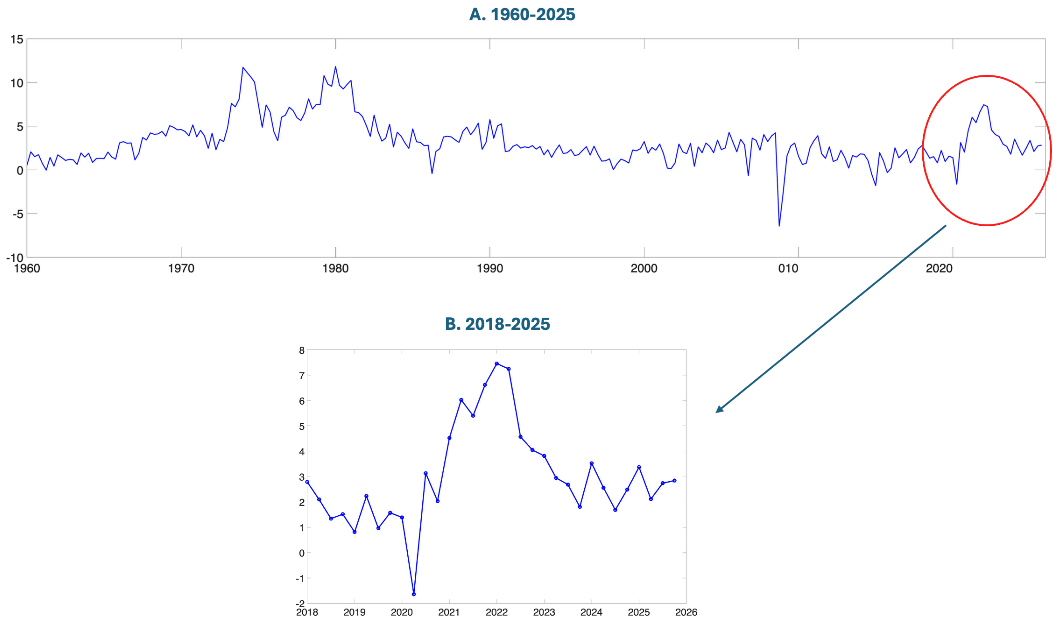
Arnold Zellner was a strong advocate for what he called the KISS principle in economic modeling – **K**eep **I**t **S**ophisticatedly **S**imple (see Zellner (1992)). Sophisticatedly simple models, he argued, were useful for both understanding and prediction; in contrast, he viewed complicated models as potential black boxes that were less useful for either task. In this paper I use simple (and perhaps sophisticated) time series models to help understand the challenges associated with predicting the surge in U.S. inflation following the Covid pandemic.

Figures 1 and 2 set the stage. Figure 1 shows U.S. inflation, as measured by the deflator for personal consumption expenditures (PCE), quarterly from 1960-2025, and where observations from 2018-25 are highlighted in a separate panel. Inflation was trending somewhat below two percent prior to the start of the Covid pandemic in 2020, increased dramatically in 2021-22, peaking at over seven percent in 2022q1, before trending down to roughly three percent in 2024-25.

Figure 2 reproduces the 2018-25 inflation data, but also includes information on inflation forecasts and the federal funds interest rate. Despite the increase in inflation during 2021, the Federal Reserve kept the federal funds rate near the zero lower bound until March 2022 and below one percent until mid-June 2022. There are two related reasons for the slow reaction of the Fed. The first was concern about the recovery of the real economy following the pandemic, and indeed, accommodative monetary and fiscal policy played an important role in the exceptional recovery of the U.S. economy following the Covid recession (see Stock and Watson (2025)). The second reason was a view that the inflation surge in 2021 was temporary, caused by short-run factors like supply chain disruptions, that would quickly be reversed. Panel B of Figure 2 shows the median forecast of Federal Reserve policymakers made in December for inflation over the subsequent year.[1] For example, in December 2019, policymakers forecast that inflation would run at 1.9 percent over 2020; the actual value was lower at 1.2 percent. At the end of 2020, policymakers predicted 2021 inflation to remain below 2 percent, when in fact it was over 5 percent. And even at the end of 2021, policymakers still forecast only moderate inflation for 2022, when the actual value was nearly 6 percent. The Fed was not alone in its sanguine view of inflation. Panel A shows the sequence of

[1] These are the median projections of PCE inflation over the following year from the Summary of Economic Projections (SEP) from each December beginning in 2019 through 2022. These projections are offered by the members of the Board of Governors and the presidents of the Federal Reserve Banks.

Figure 1: PCE Headline Inflation, 1960-2025 and 2018-2025



Notes: Quarterly data in percentage points at annual rate.

inflation predictions from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF).[2] Throughout 2021-22, the median SPF contributor also forecast a quick reversal of the inflation surge.[3]

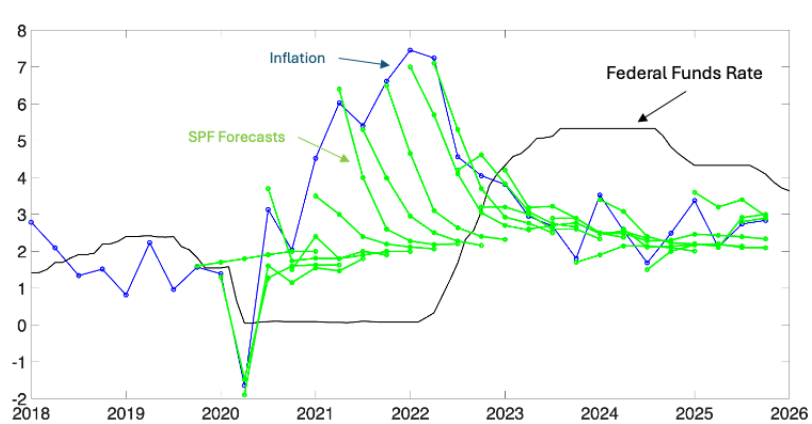
In this paper I study the forecasting performance of relatively simple time series models over this time period. Did these models also miss the persistent increase in inflation, and if so, why? I use two related models taken from Stock and Watson (2007, 2016). The first is a univariate model that extrapolates the recent behavior of inflation into the future, albeit in a way that allows the persistence in inflation to evolve through time. The second model is similar, but jointly models the evolution of the consumption sectors making up the PCE. This multivariate model captures the disparate patterns in prices for, say, motor vehicles, financial services, and housing for forecasting aggregate inflation. Both models were developed well

[2]Each SPF path shown in the figure starts with the first-release value of PCE inflation and then plots the median SPF forecast over the subsequent five quarters. See the SPF documentation at https://www.philadelphiafed.org/surveys-and-data/pce for a description of the timing of the survey and other details.

[3]See Gourio and Sarma (2025) for a more detailed comparison of SPF and Federal Reserve policymakers' forecasts over this period. Peneva, Rudd, and Villar (2025) provides an in-depth analysis of the Fed's forecasts over this period. Also see Abdelrahman, Lansing, and Oliveira (2024).

Figure 2: Inflation, Forecasts and the Federal Funds Rate

A. Inflation, SPF forecasts and the federal funds rate



B. FRB SEP 1-year-ahead forecasts and actuals

	2020	2021	2022	2023
Forecast	1.9	1.8	2.6	3.1
Actual	1.2	5.6	5.8	2.8

Notes: See footnotes 1 and 2 for a description of the forecasts.

before the pandemic, making them good representatives of time series inflation forecasting models.[4]

I reach four conclusions. First, the univariate model – armed with *ex-post* estimates of inflation persistence – correctly forecasts the inflation surge using inflation data through 2021q2. Second, the change in inflation persistence was not evident to the model in real time, so that forecasts using (quasi-) real time estimates of persistence required an extra quarter (or more) of data to recognize the inflation surge. These results rely on historically revised measures of PCE inflation. The third conclusion is that the univariate forecasts were also hindered by noisy real-time estimates of inflation. Using real-time estimates, the inflation surge was not evident until the release of data for 2021q4.[5] The fourth conclusion follows

[4]The univariate model has been used as one of the benchmark models in forecast comparison studies for inflation. For example, see Faust and Wright (2013), Mertens (2016), and Chan, Clark, and Koop (2018). The multivariate model, modified for use with monthly observations, forms the basis of the Federal Reserve Bank of New York's Multivariate Core Trend (MCT) Inflation (https://www.newyorkfed.org/research/policy/mct); see Almuzara and Sbordone (2022) for discussion.

[5]The real-time estimates are from the first release of the quarterly NIPA data. These data are typically available with a lag of one month. For example, the first release of the 2021q4 data was published at the end

from analysis of the multivariate data. Here the changes in persistence are evident earlier and data revisions are less important. Using this model, the inflation surge is evident using data through 2021q2. This highlights the usefulness of using disaggregated inflation during periods of instability.

The outline of the paper is as follows. Section 2 describes the univariate model and presents the results. Section 3 includes a parallel discussion for the multivariate model. Section 4 offers a summary and additional remarks.

2 Univariate Model and Forecasts

2.1 Model and data

The univariate model is a version of the unobserved-components (UC) local level model from Harvey (1989). In its simplest form, the model is

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

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

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

$$\eta_{\tau,t}, \eta_{\varepsilon,t} \sim i.i.d.\ \mathcal{N}(0,1). \tag{4}$$

where π_t denotes inflation, and τ_t and ε_t are unobserved components that capture persistent and transitory variation in inflation. The parameters $\sigma_{\Delta\tau}$ and σ_ε govern the importance of the two components.

An ARIMA representation of this UC model is also useful for describing persistence in π. Noting that $(1-\mathrm{L})\pi_t = \sigma_{\Delta\tau}\eta_{\tau,t} + \sigma_\varepsilon(\eta_{\varepsilon,t} - \eta_{\varepsilon,t-1})$, by Granger's lemma (see Ansley, Spivey, and Wrobleski (1977)), π_t has the ARIMA(0,1,1) representation

$$(1-\mathrm{L})\pi_t = (1-\theta\mathrm{L})a_t \tag{5}$$

where $0 \le \theta \le 1$, with $\theta = \theta(\xi)$ where $\xi = \sigma_\varepsilon/\sigma_{\Delta\tau}$ with $\theta'(\xi) > 0$, $\theta(0) = 0$ and $\lim_{\xi\to\infty}\theta(\xi) = 1$. Thus, the parameter θ serves as a measure of persistence, where lower values of θ indicate

of January, 2022.

higher levels of persistence.[6]

Inflation forecasts from the model have a simple structure. Using standard notation, let $\tau_{t|k} = \mathbb{E}\left[\tau_t | \{\pi_j\}_{j=1}^k\right]$, where $\tau_{t|t}$ denotes the filtered (i.e., one-sided) estimate of τ_t and $\tau_{t|T}$ denotes the smoothed (two-sided) estimate. In the UC model, τ follows a random walk and ε is white noise, so the forecast of π_{t+k} satisfies $\pi_{t+k|t} = \tau_{t+k|t} + \varepsilon_{t+k|t} = \tau_{t|t}$. Thus, $\tau_{t|t}$ is both the one-sided estimate of the persistent component, and the forecasted value of inflation in the future. Moreover, from the ARIMA(0,1,1) representation in (5) (ignoring complications associated with initial conditions), $\tau_{t|t} = \pi_{t+k|t} \approx (1-\theta)(1-\theta\mathrm{L})^{-1}\pi_t = (1-\theta)\sum_i \theta^i \pi_{t-i}$, so that $\tau_{t|t}$ is an exponentially weighted average of current and past values of inflation. Smaller values of θ place more weight on recent obervations; equivalently, recent inflation receives more weight when $\sigma_{\Delta\tau}$ is large relative to σ_ε.

The simple form of the model misses two important features of inflation that are evident in Figure 1. The first is that the persistence of inflation in the U.S. has changed over time. Notably, the level of inflation wandered up and then down from 1960-1985 (suggesting a large value of $\sigma_{\Delta\tau}$ and small value of θ), but was then relatively stable until the onset of the Covid pandemic (suggesting a smaller value of $\sigma_{\Delta\tau}$ and larger value of θ). (See Stock and Watson (2007) and Cogley, Primiceri, and Sargent (2010).) The second feature is the handful of sharp changes in inflation evident in the plot (e.g., the decrease in inflation at the end of 2008) that are not well described by the Gaussian shocks assumed to drive inflation in the model. To accommodate both of these features, Stock and Watson (2016) implemented a version of the model that incorporates stochastic volatility in $(\sigma_{\Delta\tau}, \sigma_\varepsilon)$ and fat-tailed innovations for ε. The resulting model replaces (2)-(3) with

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau,t}\eta_{\tau,t} \tag{6}$$

$$\varepsilon_t = \sigma_{\varepsilon,t} s_t \eta_{\varepsilon,t} \tag{7}$$

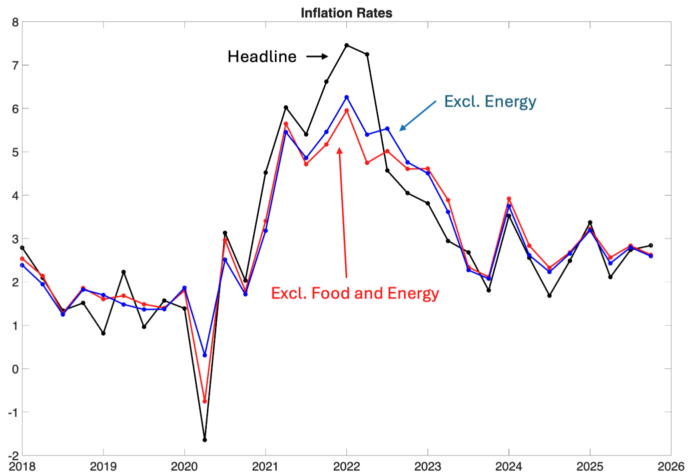
$$\Delta \ln(\sigma_{\Delta\tau,t}) = \gamma_{\Delta\tau}\nu_{\Delta\tau,t} \tag{8}$$

$$\Delta \ln(\sigma_{\varepsilon,t}) = \gamma_\varepsilon \nu_{\varepsilon,t} \tag{9}$$

$$\nu_{\Delta\tau,t}, \nu_{\varepsilon,t} \sim i.i.d.\ \mathcal{N}(0,1). \tag{10}$$

[6]The model has a long history in the analysis of inflation. For example, Nelson and Schwert (1977) used the ARIMA(0,1,1) to forecast CPI inflation and Ball and Cecchetti (1990) used the unobserved component formulation to study inflation uncertainty.

Figure 3: Headline and Core Inflation



and the variable s_t in (7) captures outliers, with $s_t = 1$ with probability p and $s_t \sim U[2, 10]$ with probability $(1 - p)$.[7] The model, while allowing for time-varying volatility and outliers, retains the key forecasting property of the simple model with $\pi_{t+k|t} = \tau_{t|t}$.

One important source of variability in inflation is energy prices, which are highly variable and largely unforecastable. In the 1970s, shocks to food prices were similarly large and unforecastable, and this led researchers and policymakers to focus on measures of "core inflation" that omitted food and energy. However, more recent research has suggested that, while energy prices remain volatile and difficult to forecast, the same is not true for food prices, suggesting a core measure that excludes energy, but retains food prices.[8] Figure 3 plots aggregate "headline" inflation and the two core measures since 2018. The major differences include the large drop in energy prices at the beginning of the pandemic and the sharp increase associated with Russia's invasion of Ukraine in the first quarter of 2022. In what follows I will focus on the core measure that excludes energy prices.

The model is estimated, and forecasts are constructed, using Bayes methods with a likelihood based on the approximation in Omori, Chib, Shephard, and Nakajima (2007). Priors

[7] There are alternative and more flexible ways to allow for outliers in ε. See, for example, Carriero, Clark, Marcellino, and Mertens (2024), Antolín-Díaz, Drechsel, and Petrella (2024), and Müller and Watson (2026). For inflation over the sample period under study here, the formulation in (7) is adequate, and retains the off-the-shelf Stock and Watson (2016) model.

[8] See Gordon (1975) and Eckstein (1981) for early analysis of core inflation, Stock and Watson (2016), Almuzara and Sbordone (2025), and Wright (2026) for more recent analyses.

for the various parameters and methods for computing draws from the posterior, etc., are taken from Stock and Watson (2016).

2.2 Forecasting results

In the UC model, the persistent component of inflation follows a random walk and the transitory component is white noise, so that $\tau_{t|t}$ is a forecast of future inflation across all horizons. This is a useful simplification for forecasts over relatively short horizons, say 1-8 quarters ahead, but is unlikely to be useful for longer-run forecasts. That said, it usefully focuses attention on the scalar variable $\tau_{t|t}$, and this section reports how $\tau_{t|t}$ evolved during the 2021-2022 inflation surge. I consider two key questions: first, how quickly did the model adapt to the increased persistence in the inflation data (that is, when did it recognize the increased variance of $\Delta\tau$), and second, did noisy real-time inflation data confound the forecasts?

With this in mind, I have constructed three versions of $\tau_{t|t}$. The first uses the fully revised inflation data with parameters ($\sigma_\varepsilon, \sigma_{\Delta\tau}$, and θ) estimated over the full sample period. The resulting estimate, denoted $\tau_{t|t}^{\text{FS-parms}}$, shows best-case forecasts from the UC model as it incorporates *ex-post* information on parameter values and data revisions. The second estimate, denoted $\tau_{t|t}^{\text{revised}}$, continues to use the *ex-post* revised data, but relies on recursive estimates of the model parameters; that is, the parameters are estimated using the (revised) data through time t. This estimate shows how quickly the model could have learned about the changes in inflation persistence, absent data revisions. The third estimate, $\tau_{t|t}^{\text{realtime}}$, uses real-time data and parameter estimates, and thus shows how the UC model's forecasts actually evolved over the sample period.[9]

Figures 4-6 and Table 1 summarize the results. Figure 4 shows the revised and real-time inflation data, Figure 5 shows the evolution of the model parameters and Figure 6 shows the resulting values of $\tau_{t|t}$. Table 1 summarizes values of the variables over 2020q1-2022q4.[10]

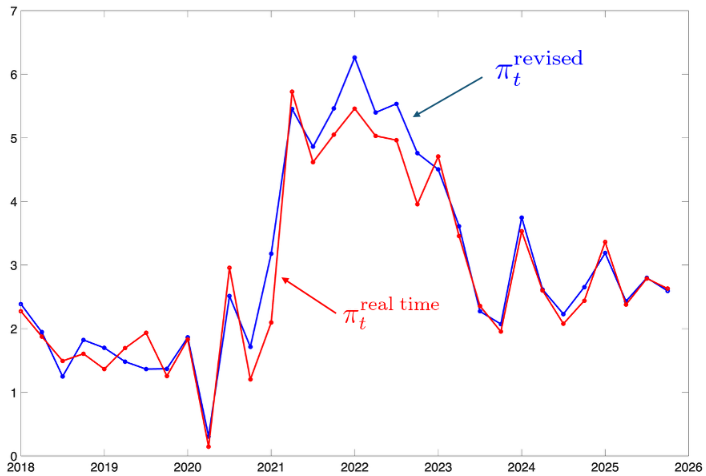
I highlight three results.

First, there was a marked increase in $\sigma_{\Delta\tau}$, although the exact timing is unclear. The one-

[9]The real-time data in Figure 4 is taken from the ALFRED database maintained by the Federal Reserve Bank of St. Louis. The revised data were downloaded from FRED on 4/7/2026.

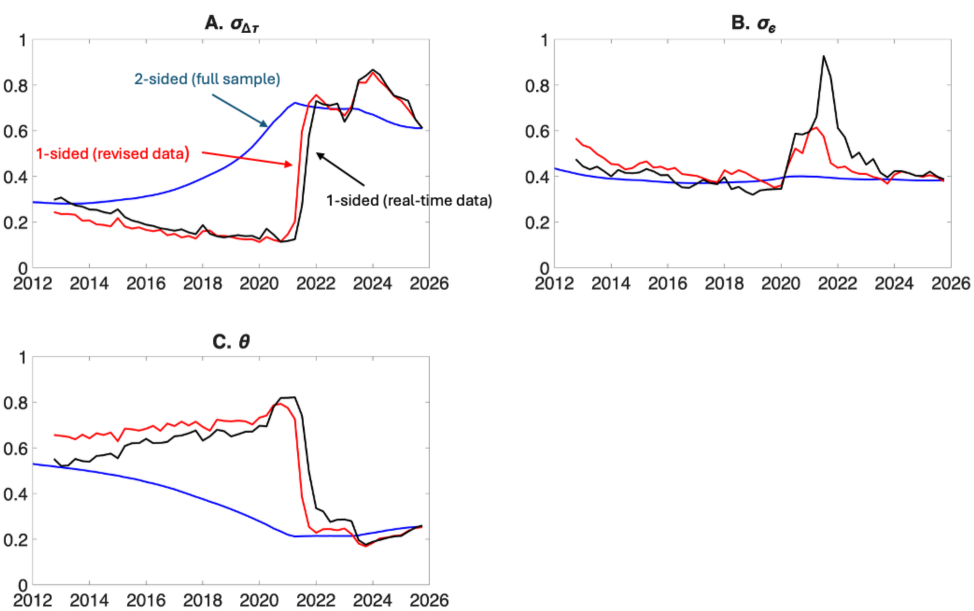
[10]The parameter and $\tau_{t|t}$ values in the figures and table are the posterior means from Bayes estimation of the UC model. The value of θ_t is a local-version of the MA parameter. It is computed from the UC parameters $(\sigma_{\Delta\tau,t}, \sigma_{\varepsilon,t})$ using the local moment equality $\theta_t/(1+\theta_t^2) = \sigma_{\varepsilon,t}^2/(\sigma_{\Delta\tau,t}^2 + 2\sigma_{\varepsilon,t}^2)$. Recursive estimates of the model were computed beginning in 2012q4 through 2025q4.

Figure 4: Revised and Real Time Inflation



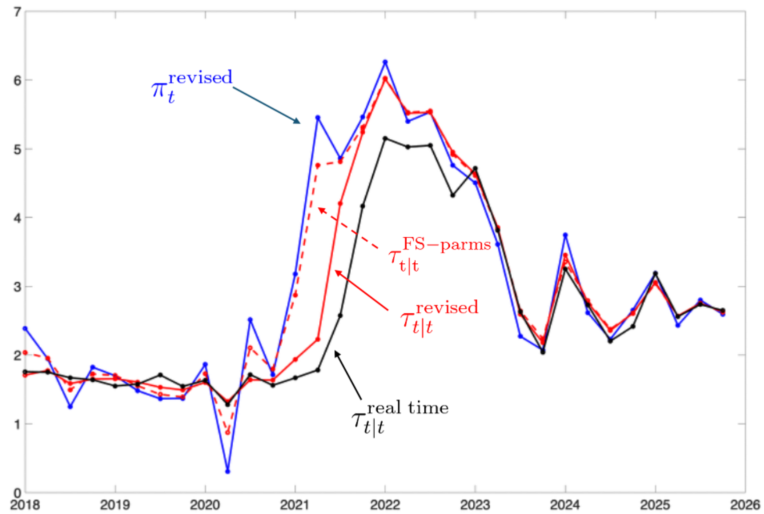
Notes: The real-time estimates are from the first release of the quarterly NIPA data.

Figure 5: Univariate Model Parameter Values



Notes: The figures show the sample paths for $(\sigma_{\Delta\tau,t}, \sigma_{\varepsilon,t}, \theta_t)$ estimated using (a) the full-sample (1960-2025q4), labeled "2-sided (full sample)," (b) revised data through time t, labeled "1-sided (revised data)," and (c) real-time data through time t, labeled "1-sided (real-time data)."

Figure 6: Estimates of τ



Notes: Values shown are the filtered estimates of τ using the data and parameters described in the text.

Table 1: Summary of Univariate Results

	2020q4	2021q1	2021q2	2021q3	2021q4	2022q1	2022q2	2022q3	2022q4
π_t^{revised}	1.7	3.2	5.5	4.9	5.5	6.3	5.4	5.5	4.8
π_t^{realtime}	1.2	2.1	5.7	4.6	5.0	5.5	5.0	5.0	4.0
	Estimates of τ_t								
$\tau_{t\|t}^{\text{FS-Parms}}$	1.8	2.9	4.8	4.8	5.3	6.0	5.5	5.5	4.9
$\tau_{t\|t}^{\text{revised}}$	1.6	1.9	2.2	4.2	5.2	6.0	5.5	5.5	4.9
$\tau_{t\|t}^{\text{realtime}}$	1.6	1.7	1.8	2.6	4.2	5.2	5.0	5.0	4.3
	Estimates of θ_t								
$\theta_t^{\text{FS-Parms}}$	0.23	0.22	0.21	0.21	0.21	0.21	0.21	0.21	0.21
$\theta_t^{\text{revised}}$	0.79	0.78	0.73	0.38	0.25	0.23	0.24	0.24	0.24
$\theta_t^{\text{realtime}}$	0.82	0.82	0.82	0.74	0.49	0.34	0.32	0.28	0.29

sided estimates of $\sigma_{\Delta\tau,t}$ based on the revised data show a large jump in 2021q3; the real-time estimates jump one quarter later in 2021q4. In contrast, the full-sample estimates smoothly increase beginning well before the pandemic; undoubtedly this is associated with the model's Gaussian random walk model for $\ln(\sigma_{\Delta\tau})$, which penalizes large jumps in the process. Thus, the smooth increase in the two-sided estimates of $\sigma_{\Delta\tau}$ is more a feature of the model than of the data.[11]

Second, forecasts using a small value of θ were significantly more accurate than those with a large value of θ during 2021. The increase in $\sigma_{\Delta\tau}$ led to a marked decrease in the moving average parameter θ: the recursive estimates suggest that $\theta_t \approx 0.8$ in 2020, but θ_t then falls sharply to around 0.2 in late 2021. The formula from the simple model $\tau_{t|t} \approx (1-\theta)\sum_i \theta^i \pi_{t-i}$ suggests that the inflation forecasts at the beginning of the pandemic put substantial weight on lagged inflation, while the forecasts in late 2021 were nearly random-walk forecasts. The forecasts using the full-sample estimated parameters placed little weight on lagged inflation throughout the pandemic, but again, this is undoubtedly a reflection of the Gaussian stochastic volatility model used to describe the evolution of $\sigma_{\Delta\tau,t}$ and $\sigma_{\varepsilon,t}$.[12]

Third, the real-time data affected the forecasts in two ways: noisy real-time data increased the estimated value of σ_ε, which delayed the decrease in θ and helped confound persistent versus transitory inflation shocks; and the real-time inflation data underestimated inflation by an average of approximately 50 basis points from the second half of 2021 through 2022, holding down the forecasts of inflation even after it was recognized as persistent.[13] This is yet another example of the challenges faced by forecasters and policymakers using real-time data (cf. Croushore (2011)).

In summary, the primary challenge for the model (and forecasters in general) was determining whether the Covid inflation shocks were persistent or transitory. The "forecasts" using the full-sample parameter estimates, $\tau_{t|t}^{\text{FS-parms}}$, provide a diagnostic counterfactual: conditional on knowing that the variance of the persistent component had risen, the univariate model would have placed much greater weight on recent inflation during 2021. The real-time

[11] That said, Lansing (2022), writing in March 2022, documents the increase in persistence in inflation and notes that this increase may have started before the Covid pandemic.

[12] In a related calculation, Stevanović (2026) shows that forecasts of inflation constructed from ARMA(1,1) models with parameters estimated during the 1970s performed relatively well during 2021. During the 1970s, trend inflation was volatile, $\sigma_{\Delta\tau}$ was large and the resulting value of θ was small.

[13] The data revisions in late 2020 are largely associated with motor vehicles, while those later in the sample are largely associated with financial services and insurance.

difficulty was learning that the variance shift had occured. The real-time estimates from the UC model required data through 2021q4 to recognize this. This resulted from two main factors, a delayed recognition of the increased volatility in the persistent component of inflation, exacerbated by real-time inflation data that were subsequently revised.

3 Multivariate Model

The multivariate model is a sectoral version of the univariate model. It uses data on the 17 sectors that make up aggregate personal consumption expenditures; there are 7 goods sectors, 8 service sectors, and 2 energy sectors. The sectors are listed in Table 2.

Table 2: 17-Sector Decomposition of PCE

Durable goods		Services		Energy Sectors
1. Motor vehicles and parts		8. Housing (Ex-energy)		16. Gasoline & other energy gds
2. Furn, and dur hous. equip.		9. Health care		17. Housing (gas & elec. util)
3. Rec. goods and vehicles		10. Transportation services		
4. Other durable goods		11. Recreation services		
Nondurable goods		12. Food serv. and accom.		
5. Food and beverages		13. Fin. services and insurance		
6. Clothing and footwear		14. Other services		
7. Other nondurable goods		15. Final cons exp of nonprofits		

In the multivariate model, each sector follows a random-walk + white-noise unobserved component model as in the univariate model, but these components are further decomposed into parts that are common across the sectors and parts that are unique to each sector. This produces a dynamic factor model in which inflation in the ith sector is given by

$$\pi_{i,t} = \alpha_{i,\tau,t}\tau_{c,t} + \alpha_{i,\varepsilon,t}\varepsilon_{c,t} + \tau_{i,t} + \varepsilon_{i,t} \tag{11}$$

where $\tau_{c,t}$ denotes the common τ-component, $\tau_{i,t}$ is the sector-specific component, and $\alpha_{i,\tau,t}$ is a factor loading that measures the sensitivity of sector i to $\tau_{c,t}$. The $\varepsilon_{c,t}$ and $\varepsilon_{i,t}$ components are defined analogously. As in the univariate model, the τ-components follow random walks with stochastic volatility as in (6) and (8) and the ε-components follow white noise processes with stochastic volatilities and with mixed normal innovations as in (7) and (9). All components are mutually independent. The factor loadings $(\alpha_{i,\tau,t}, \alpha_{i,\varepsilon,t})$ are allowed to evolve through time as independent random walks.

Aggregate inflation is given by

$$\pi_t = \sum_{i=1}^{17} w_{i,t}\pi_{i,t} \tag{12}$$

where $w_{i,t}$ is the nominal expenditure share for sector i. Using the simplification $w_{i,t+k} \approx w_{i,t}$, forecasts of inflation are then given by

$$\pi_{t+k|t} = \sum_{i=1}^{17} w_{i,t}\pi_{i,t+k|t} = \sum_{i=1}^{17} w_{i,t}\mathbb{E}\left(\alpha_{i,\tau,t}\tau_{c,t} + \tau_{i,t}|\{\pi_{j,l}\}_{j=1,l=1}^{17,t}\right).$$

(See Stock and Watson (2016) for details.) With the focus on forecasting aggregate inflation excluding energy, the expenditure weights are for non-energy PCE, so that $w_{i,t} = 0$ for the two energy sectors in Table 2. That said, data for the energy sectors are used in the estimation of the model and the common components. I estimate the model and construct forecasts using the Bayes methods described in Stock and Watson (2016).

As in the univariate model, the random-walk + white noise components imply that the forecast $\pi_{t+k|t}$ does not depend on the horizon k, and for notational consistency with the univariate model I will denote $\pi_{t+k|t}$ by the scalar $\tau_{t|t}$, where in the multivariate model this incorporates the common and sector-specific τ-components, together with the factor loadings $\alpha_{i,c,t}$ and expenditure weights $w_{i,t}$.

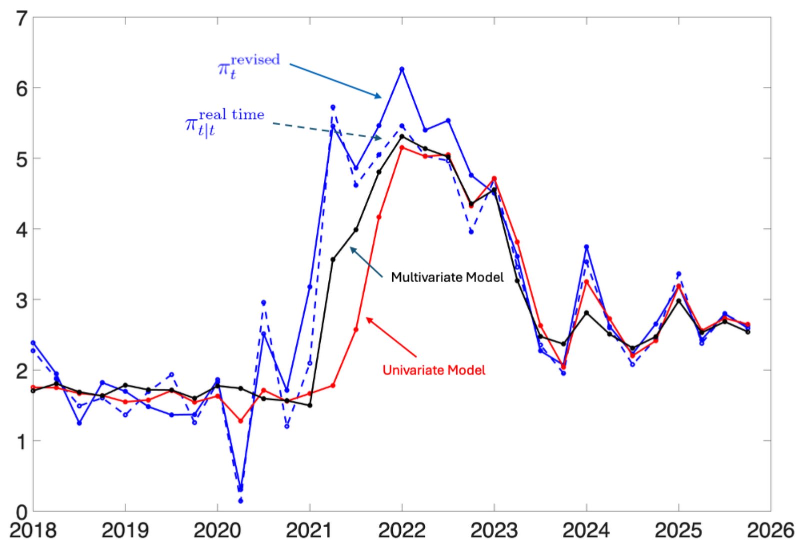
Also, as in the univariate model, I compute three versions of $\tau_{t|t}$: $\tau_{t|t}^{\text{FS-parms}}$ uses the fully revised sectoral inflation data and full-sample estimates of all of the model parameters $\left(\sigma_{\Delta\tau_c,t}, \sigma_{\varepsilon_c,t}, \{\sigma_{\Delta\tau_i,t}, \sigma_{\varepsilon_i,t}, \alpha_{i,\tau,t}, \alpha_{i,\varepsilon,t}\}_{i=1}^{17}\right)_{t=1}^{T}$; $\tau_{t|t}^{\text{revised}}$ uses the revised data and 1-sided recursively computed estimates of the parameters, and $\tau_{t|t}^{\text{realtime}}$ uses the real-time data and parameter values. Table 3 shows the value of these forecasts over 2020q4-2022q4. The key takeaway from the calculations is that the multivariate model was much quicker to recognize the inflation surge. Figure 7 compares the real-time multivariate and univariate forecasts. The inflation surge is evident using the multivariate model after 2021q2, two quarters earlier than it is evident using the univariate model.

A key reason for the multivariate model's rapid recognition of the inflation surge was

Table 3: Multivariate Forecasts of Inflation

	2020q4	2021q1	2021q2	2021q3	2021q4	2022q1	2022q2	2022q3	2022q4
	2-sided estimate of τ_t								
$\tau_{t\|T}$	2.2	2.8	4.2	4.6	5.3	5.5	5.6	5.7	4.9
	1-sided estimate of τ_t								
$\tau_{t\|t}^{\text{FS-parms}}$	1.9	2.4	4.1	4.5	5.3	5.7	5.7	5.8	4.9
$\tau_{t\|t}^{\text{revised}}$	2.0	2.0	3.2	4.6	5.5	5.9	5.5	6.0	4.9
$\tau_{t\|t}^{\text{realtime}}$	1.6	1.5	3.6	4.0	4.8	5.3	5.1	5.0	4.4

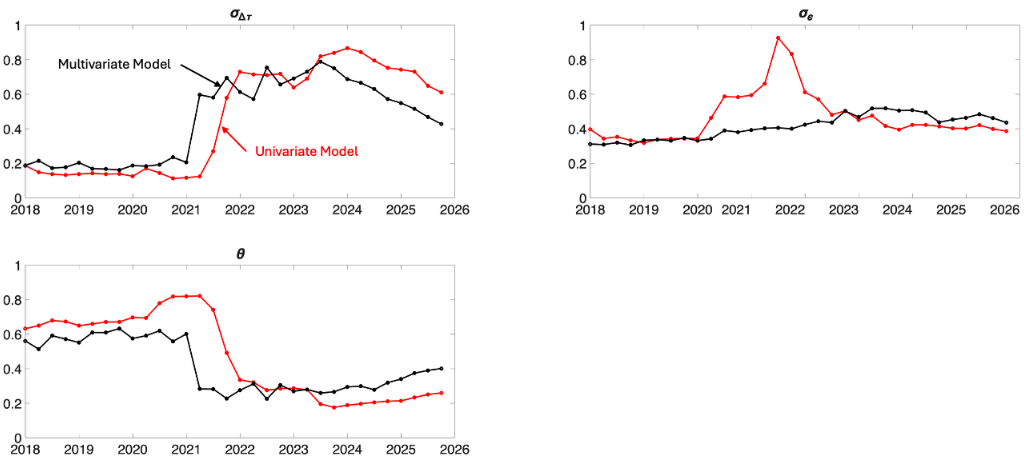
Figure 7: Real-Time Inflation Forecasts, Univariate and Multivariate UC Models



its recognition of the changing persistence in the inflation process. In the univariate model, this was captured by the relative standard deviation $\sigma_\varepsilon/\sigma_{\Delta\tau}$ or its transformation θ, the MA parameter in the ARIMA(0,1,1) representation. The multivariate model is more complicated, with common and sector-specific values of $\sigma_{\Delta\tau}$ and σ_ε, together with the (potentially time varying) factor loadings and expenditure weights. However, taken together the parameters in the multivariate model can be combined to (approximately) produce analogues of the univariate parameters. In particular, from (12)

$$\pi_t = \left(\sum_i w_{i,t}(\alpha_{i,\tau,t}\tau_{c,t} + \tau_{i,t})\right) + \left(\sum_i w_{i,t}(\alpha_{i,\varepsilon,t}\varepsilon_{c,t} + \varepsilon_{i,t})\right)$$

Figure 8: Real-Time Estimates of Persistence Parameters, Univariate and Multivariate UC Models



suggesting the following multivariate analogues of the univariate parameters $\sigma_{\Delta\tau}$ and σ_{ε}:

$$\sigma_{\Delta\tau,t}^{\text{Multivariate}} = \left(\sigma_{\Delta\tau_c,t}^2 \left(\sum_i w_{i,t} \alpha_{i,\tau,t} \right)^2 + \sum_i w_{i,t}^2 \sigma_{\Delta\tau_i,t}^2 \right)^{1/2}$$

and

$$\sigma_{\varepsilon,t}^{\text{Multivariate}} = \left(\sigma_{\varepsilon_c,t}^2 \left(\sum_i w_{i,t} \alpha_{i,\varepsilon,t} \right)^2 + \sum_i w_{i,t}^2 \sigma_{\varepsilon_i,t}^2 \right)^{1/2} .$$

A multivariate analogue of θ_t can then be formed from these parameters.

Figure 8 compares the real-time estimates of ($\sigma_{\Delta\tau}, \sigma_{\varepsilon}$ and θ) from the univariate and multivariate models. The multivariate estimates improve upon the univariate in two ways. First, the multivariate estimate of $\sigma_{\Delta\tau}$ increases two quarters before its univariate counterpart, and second, the multivariate model does not show the increase in σ_{ε} over 2020-22 present in the univariate model. Taken together, these produce a fall in θ three quarters sooner in the multivariate model than in the univariate model.

Why did the multivariate model recognize the shift in persistence so much faster than the univariate model? An important factor is that the multivariate model, by using disparate series with heterogeneous parameters produces a more accurate estimate of the persistent component of inflation. And a more accurate estimate of the component makes it easier to estimate changes in its variance. The data revisions in the second half of 2020 provide a case in point. These revisions were largely caused by revisions in the prices of motor vehicles and parts (inflation in this sector was revised down from 18.5% in 2020q3 to 7.4%, but up from 1.5% in 2020q4 to 9.5%). These large changes were unprecedented, and the multivariate model labeled them as outliers, greatly reducing their impact on the estimate of trend inflation. In contrast, the aggregate variability associated with these price swings was not nearly as dramatic, and the univariate model absorbed this variability into the estimates of $\sigma_{\varepsilon,t}$.

4 Concluding Remarks

Forecasters and policymakers struggled to understand inflation during 2021. Headline inflation, measured in real time, increased from 1.5 percent in 2020q4 to 6.3 percent one year later, in 2021q4. Energy prices were partly to blame, but even after stripping them out, inflation increased from 1.2 percent to 5 percent. Was this a transitory increase in prices associated with supply chain bottlenecks as the economy recovered from Covid, or did it represent a troubling, persistent shift in inflation? Policymakers and forecasters were unsure, but "Team Transitory" held sway throughout 2021. Forecasting inflation using economic fundamentals is difficult even in the best of times, but it was made much harder by the unprecedented shocks associated with the Covid pandemic. Arguably, the economics profession still has not reached a consensus on the relative importance of the various factors that caused the Covid inflation surge.[14]

This paper asked easier questions: did (sophisticatedly-) simple time series models predict the inflation surge? And, how quickly did these models recognize that the increases in inflation during 2021 reflected a persistent rather than transitory shifts in inflation?

As it turns out, the univariate time series model examined here behaved much like other forecasters during 2021. It adapted to the increase in inflation persistence, but not until early 2022 following the release of data for 2021q4. The multivariate model performed better, recognizing the increased persistence in inflation two quarters sooner, following the release of

[14] The literature on this question is large. For a sampling of the different perspectives see Ball, Leigh, and Mishra (2022), Benigno and Eggertsson (2023), Bernanke and Blanchard (2025), Gagliardone and Gertler (2026), Giannone and Primiceri (2024), Guerrieri, Marcussen, Reichlin, and Tenreyro (2023), Hajdini, Shapiro, Smith, and Villar (2025) Ruge-Murcia and Wolman (2026), and Shapiro (2022).

the 2021q2 data.

Of course, these time series models say nothing about the underlying causes of the inflation surge. That said, the results suggest that the multivariate model provides a valuable real-time tool for tracking trend inflation. This highlights the importance of trend inflation measures such as the New York Fed's Multivariate Core Trend Inflation (MCT), which uses the same 17 sectors analyzed here, but does so at a monthly frequency. A broader lesson — drawn here from a single episode, but plausibly more general — is that disaggregated price information can materially improve real-time assessments of trend inflation during periods of instability.

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