Federal Reserve Bank of Cleveland Working Paper Series

Post-COVID Inflation Dynamics: Higher for Longer

Randal J. Verbrugge and Saeed Zaman

Working Paper No. 23-06R

June 2023

Suggested citation: Verbrugge, Randal J. and Saeed Zaman. 2023. "Post-COVID Inflation Dynamics: Higher for Longer." Working Paper No. 23-06R. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-202306r.

Federal Reserve Bank of Cleveland Working Paper Series
ISSN: 2573-7953

Working papers of the Federal Reserve Bank of Cleveland are preliminary materials circulated to stimulate discussion and critical comment on research in progress. They may not have been subject to the formal editorial review accorded official Federal Reserve Bank of Cleveland publications.

See more working papers at: www.clevelandfed.org/research. Subscribe to email alerts to be notified when a new working paper is posted at: https://www.clevelandfed.org/subscriptions.

Post-COVID Inflation Dynamics: Higher for Longer

Randal Verbrugge
Federal Reserve Bank of Cleveland and NBER/CRIW, 1455 E. 6th St., Cleveland, OH 44114
Email: [randal.verbrugge@clev.frb.org.](mailto:randal.verbrugge@clev.frb.org)

Saeed Zaman
Federal Reserve Bank of Cleveland, 1455 E. 6th St., Cleveland, OH 44114
Email: [saeed.zaman@clev.frb.org.](mailto:saeed.zaman@clev.frb.org)

May 31, 2023
(First version: January 13, 2023)

Abstract

We implement a novel nonlinear structural model featuring an empirically-successful frequency-dependent and asymmetric Phillips curve; unemployment frequency components interact with three components of core PCE – core goods, housing, and core services ex-housing – and a variable capturing supply shocks. Forecast tests verify model's accuracy in its unemployment-inflation tradeoffs, crucial for monetary policy. Using this model, we assess the plausibility of the December 2022 Summary of Economic Projections (SEP). By 2025Q4, the SEP projects 2.1 percent inflation; however, conditional on the SEP unemployment path, we project inflation of 2.9 percent. A fairly deep recession delivers the SEP inflation path, but a simple welfare analysis rejects this outcome.

JEL codes: E31, E32, E52, C32
Keywords: nonlinear Phillips curve, frequency decomposition, supply price pressures, structural VAR, core PCE inflation components, welfare analysis

Acknowledgments: We thank Rick Ashley, Marta Banbura, David Berger, Mark Bils, Elena Bobeica, Mark Bognanni, Andrew Figura, Ed Knotek, David Lebow, James Mitchell, Norm Morin, James Morley, Michael Palumbo, Matthias Paustian, Katia Peneva, Juan Rubio-Ramirez, Jeremy Rudd, Arsenios Skaperdas, Jim Stock, Brad Strum, and our other research colleagues at the Federal Reserve Bank of Cleveland, and seminar participants at the Board of Governors and the European Central Bank, for excellent comments that helped to greatly improve this paper. Any errors are our own. The views stated herein are those of the authors and not necessarily those of the Federal Reserve Bank of Cleveland or the Board of Governors of the Federal Reserve System.

"…you can break inflation down into three sorts of buckets. The first is goods inflation, and we see now… goods inflation coming down ... Then you go to housing services …that inflation will come down sometime next year. The third piece, which is something like 55 percent of the … PCE core inflation index, is non-housing-related core services. And that's really a function of the labor market … And we do see a very, very strong labor market, one where we haven't seen much softening, where job growth is very high, where wages are very high. Vacancies are quite elevated and … there's an imbalance in the labor market between supply and demand. So that part of it, which is the biggest part, is likely to take a substantial period to get down. The other … the goods inflation has turned pretty quickly now after not turning at all for a year and a half. Now it seems to be turning. But there's an expectation … that the services inflation will not move down so quickly, so that we'll have to stay at it so that we may have to raise rates higher to get to where we want to go. And that's really why we are writing down those high rates and why we're expecting that they'll have to remain high for a time."

FOMC Chair Jerome Powell, Press Conference, Dec. 14, 2022

1. Introduction

In his December 14, 2022, press conference, Jerome Powell, chair of the Federal Open Market Committee (FOMC), used a tripartite decomposition of core PCE inflation to explain why the FOMC expects that the federal funds rate will "have to remain high for a time." This decomposition consists of core goods inflation, housing services inflation, and core services ex-housing inflation. In the December 2022 Survey of Economic Projections (SEP), the median projection for four-quarter core PCE inflation in the fourth quarter of 2025 is 2.1 percent; this same SEP has unemployment rising to peak at 4.6 percent by the end of 2023.

In this paper, we assess the plausibility of this projection, exploring the path of inflation going forward, using the aforementioned tripartite decomposition of core PCE inflation.[1] Importantly, we carefully model the relationship between unemployment and these inflation components. Recent research (Ashley and Verbrugge, 2023; Verbrugge and Zaman, 2023a) has

[1] The idea of forecasting aggregate inflation by separately modeling and forecasting its underlying disaggregated components has a long tradition; see Tallman and Zaman (2017) and references therein.

demonstrated benefits to specifying the relationship between *aggregate* inflation and the unemployment rate as frequency-dependent – that is, to using a specification which allows inflation to respond differently to business-cycle movements in the unemployment rate than it does to low-frequency movements or to transient movements.[2] This previous work has established that the response of aggregate inflation to the various frequency components of the unemployment rate gap (i.e., to the persistent, moderately persistent, and transient components) varies not only by persistence component, but also by the *sign* of these components. Specifically, the moderately persistent component of the unemployment gap plays an influential role in determining inflation dynamics, but only when the component is *positive* – which typically occurs during a recession and for a few months into the beginning of the expansion). On the other hand, the persistent component also exerts a strong influence on inflation, but only when that component is *negative* – which occurs when the persistent component is below the natural rate, i.e., when the economy is overheating.[3] A failure to recognize these features of the unemployment-inflation relationship leads to several unreliable inferences, such as that the post-1985 Phillips curve is unstable and has weakened since 2006.

In this paper, we construct a nonlinear structural vector autoregression (SVAR), specified in terms of the tripartite core PCE decomposition noted by Chair Powell; this SVAR includes a both a variable reflecting supply-shocks, to capture recent dynamics associated with supply disruptions and their relaxation, and also the frequency components of the unemployment rate. This model is well-suited for "disciplined scenario analysis," i.e., to explore counterfactual

[2] King and Watson (1994) were perhaps the first to suggest that the Phillips curve varies with frequency; see also Stock and Watson (2010, 2020). A recent analysis using wavelets is given in Aguiar-Conraria et al. (2023).
[3] See also Forbes, Gagnon and Collins (2022). There are numerous antecedents to this finding in the nonlinear Phillips curve literature, which typically finds that the Phillips curve is "convex;" these are reviewed in Ashley and Verbrugge (2023).

conditional inflation forecasts that are at the heart of policy deliberations at present. In particular, given a proposed path for the unemployment rate, the SVAR projects the corresponding inflation path. We estimate our model over the 1985-2019 period and identify it using the data-determined method of Swanson and Granger (1997), which substantially reduces the role of subjective elements. We examine the dynamic interactions between the model variables by examining the impulse response functions (IRFs) to identified shocks; the estimated responses reveal interesting nonlinearities. For instance, housing inflation responds strongly both to the "recessionary force" associated with positive fluctuation in the moderately persistent component of the unemployment gap, and to the "overheating force" associated with a negative fluctuation in the persistent unemployment gap component. Conversely, median core services ex-housing inflation responds only modestly to the aforementioned recessionary force, but responds fairly strongly to the overheating force. We also examine the model's historical forecast performance (both conditional on the evolution of the unemployment rate, and unconditional) compared to some standard benchmarks. We find competitive forecasting properties of our model, which lends credibility to our model's conditional projections that we discuss next.

When we condition our model's forecast for 2023-2025 on the December SEP's projected path for the unemployment rate (which has unemployment increasing by a total of 0.9 percentage points), we get a notably higher path for core PCE inflation than the SEP path. The SEP path has core PCE inflation moderating to 2.1 percent by the end of 2025. But according to this model, inflation is going to remain higher for longer: by the end of 2025, our model projects that it will still be at 2.85 percent, with the 70 percent confidence interval spanning 2.16 to 3.59 percent. A key to this result is the fact that inflation is more persistent than commonly believed. We conclude that it would take a fairly deep recession to reduce inflation at the SEP's projected pace.[4] We investigate the claim of former Treasury Secretary Lawrence Summers (reported in Aldrick, 2022) and the supporting assessment of Ball, Leigh, and Mishra (2022) that it will require two years of 7.5 percent unemployment – a notable jump from its current low level of 3.6 to 3.7 percent – to bring inflation down to its 2 percent target. Our point estimates suggest that one year of 6.7 percent unemployment would accomplish this task, though there is considerable uncertainty surrounding this estimate.

But would such a recession be ideal? As a first pass at addressing this question, we perform a simple reduced-form welfare analysis using a quadratic loss function that equally penalizes quarterly deviations of inflation from 2 percent (the FOMC target level of inflation), and deviations of unemployment from 4 percent (the FOMC's estimate of the longer-run level of unemployment). In addition to producing inflation forecasts corresponding to the deep recession noted above and to the December SEP, we produce inflation forecasts corresponding to a moderate recession (defined by the path of unemployment taken in the 2001 recession) and to a soft landing for unemployment (which we define as the path of unemployment reported in the June SEP).[5] The conclusions are somewhat sensitive to the relative weight of inflation versus unemployment in the loss function. For equal weights, the analysis prefers the December SEP path for unemployment. If the weight on inflation is low, it prefers the soft landing; and if the weight on inflation is quite high, it prefers the moderate recession. (Only for *very* high weight on inflation does it prefer the more severe recession.) Importantly, this baseline analysis abstracts from any danger of the de-

[4] Our conclusions are similar to those of Cecchetti et al. (2023), who state: "…our analysis casts doubt on the ability of the Fed to engineer a soft landing in which inflation returns to the 2 percent target by the end of 2025 without a mild recession." The paper computes the sacrifice ratio for 17 large disinflationary episodes in the US and three other large economies since 1950; the paper's findings are similar to those of Ball (1994) and Tetlow (2022).
[5] Figura and Waller (2022) argue that a soft landing in the labor market is a plausible scenario.

anchoring of inflation expectations that might be associated with inflation still being quite elevated three years from now.

2. Data, Methods and Model

2.1 Data

We use quarterly data spanning from 1985:Q1 through 2022:Q4, though we estimate the model using pre-COVID data.[6] Most of the series are available at a monthly frequency, and we aggregate them up to a quarterly frequency. Following much precedent in the literature, we focus attention on the post-1984 period because inflation dynamics are thought to have changed markedly beginning in the mid-1980s onward, and because this is the period associated with anchored inflation expectations.

Our model consists of six variables. Four of these are inflation variables, and each enters as a four-quarter growth rate. The first is the PPI for core intermediate goods, denoted *PPI*. This variable captures supply price pressures, in that its innovations are generally driven by supply shocks; see discussion below, and see Appendix G for more details. The next three variables are also inflation-specific, corresponding to the tripartite decomposition of Chair Powell. The first two of these are core goods and housing services; we denote inflation in these variables by π_t^{CoreG} and π_t^{Hous}, respectively.

[6] At the time of this writing, we do not have complete 2022Q4 data. We use available monthly data to construct Q4 nowcasts for all variables. Our model is estimated using 1985-2019 data.

But rather than using core services ex-housing, we instead construct, and use, *median* core services ex-housing (whose inflation is denoted $\pi_t^{MServXH}$).[7] We do this because core services ex-housing are quite sensitive to outliers, particularly in non-market services. Verbrugge (2022) demonstrates that such sensitivity renders core inflation measures less reliable as indicators of medium-term trend inflation. Accordingly, we view median core services ex-housing inflation as a more accurate estimate of the medium-term trend in core services ex-housing, helping to more reliably capture both the persistence of this series, and its sensitivity to labor market pressures.[8]

The method used to construct the (weighted) median core services ex-housing series is similar to that of Carroll and Verbrugge (2019), who use all the available 190+ disaggregated price categories of the monthly PCE to construct the (weighted) median PCE series. We use information about the price changes in the 82 disaggregated price categories of the PCE that are part of "PCE services excluding energy, food, and housing," along with their respective nominal expenditure shares at a monthly frequency. Since we estimate the model with quarterly data, we aggregate up the monthly data to a quarterly frequency.

Figure 1 plots core services ex-housing inflation alongside its median counterpart. As expected, the median series is smoother than the original series, and abstracts from the wild non-market-price-driven swings in core services ex-housing experienced as the Financial Collapse was unfolding. Over the sample period displayed, the bias, defined as the gap between their respective inflation rates, is zero. However, over specific periods, there can be notable divergence, with more

[7]Our choice of "median" variable is partly motivated by the successful track record of median CPI and median PCE variables constructed by the Federal Reserve Bank of Cleveland in tracking the trend in CPI and PCE inflation, respectively.

[8] As with core services ex-housing inflation, we find that median core services ex-housing inflation has a statistically significant Phillips curve. Its relationship to wage inflation (as measured by the Employment Cost Index (ECI) depends upon the sample period. For model parsimony, we do not include any wage variables in our model. Preliminary analysis indicates that median core services ex-housing performs well as a medium-term predictor of core services ex-housing.

recent periods appearing as a prominent example. Accordingly, in computing current forecasts of core services ex-housing inflation, we apply bias adjustment to the forecasts of the median variable.[9]

[Figure 1 about here]

2.2 Methods

2.2.1 (One-sided) frequency decomposition of unemployment rate

Following Ashley and Verbrugge (2023), the final two variables are two "components" of the unemployment rate: a persistent (or low-frequency) gap component and a moderately persistent (or medium-frequency) component.[10] The approach to filtering, which must be done in a one-sided in order to avoid inconsistent parameter estimates (see Ashley and Verbrugge, 2022a), is described in Appendix A. These components of the unemployment rate are derived from the *jobless* unemployment rate of Hall and Kudlyak (2022).[11] The jobless unemployment rate is constructed by removing the temporary layoffs from overall unemployment. We relate inflation to the jobless unemployment rate rather than the overall unemployment rate, since during the pandemic collapse, temporary unemployment experienced a 20-standard-deviation shock. Such an extreme movement severely distorts coefficient estimates and frequency partitions. We

[9] The bias-adjustment procedure is informed by estimating an AR(1) process on the historical wedge (i.e., the gap between the two series) and using the estimated processes to compute the estimates of the time-varying wedge over the forecast period. Forecasts of the median variable are then bias-adjusted using this forecast of the wedge, so as to obtain an unbiased forecast of core services ex-housing.

[10] Specifically, the unemployment rate is split into "transient," "moderately persistent," and "persistent" components. But since the transient fluctuations were found to be unimportant predictors, to keep our model parsimonious, we abstract from these fluctuations. "Moderately persistent" refers to fluctuations that take 1-4 years to complete; "persistent" fluctuations last longer than that. King and Watson (1994) were perhaps the first to suggest that the Phillips curve varies with frequency. However, to obtain valid inferences, frequency filtering must be done in a one-sided manner (see Ashley and Verbrugge 2022a and Doppelt (2021)). Hamilton (2018) recently introduced an alternative to HP filtering, but Ashley and Verbrugge (2022b) demonstrate that, for properly decomposing a time series into its lower-frequency and higher-frequency components, this procedure is inferior to the procedure used in Ashley and Verbrugge (2023) and Ashley, Tsang, and Verbrugge (2020); see Appendix A for more details. We form a low-frequency *gap* by subtracting the Zaman (2022) U_t^* estimate from the low-frequency component. Our model forecasts even slower deceleration in inflation if we instead use the CBO natural rate estimate. The U* estimates from Zaman's model are available to download from https://github.com/zamansaeed/macrostars.

[11] The data necessary to construct the jobless unemployment rate are available from the Bureau of Labor Statistics.

sidestep pandemic-related distortions by a) focusing on the relationship of inflation to the jobless unemployment rate, since the jobless unemployment rate experienced fairly typical dynamics during the COVID recession, and b) by estimating the model over the 1985-2019 period.

These two components of the jobless unemployment rate are depicted in Figure 2. Our partitioning of the jobless unemployment rate into varying persistence components is motivated by the aforementioned previous findings of persistence-dependence in the Phillips curve relationship and by an emerging literature that is re-exploring the frequency domain to obtain clues about business cycle drivers and dynamics.[12] In contrast to the previous work, which modeled the relationship between aggregate inflation (i.e., trimmed-mean PCE inflation), this paper separately models the nonlinear Phillips curve relationship for each of the inflation components using the two components of the unemployment rate. Accordingly, in our inflation equations, we admit sign asymmetry on the unemployment components. As we discuss below, each of the core PCE inflation variables is related only to the *negative* part of the persistent unemployment gap (i.e., when the persistent unemployment rate is below the natural rate of unemployment), and to the *positive* part of the moderately persistent unemployment component; these findings are generally consistent with the previous work focusing on aggregate inflation. Historically, these portions of the two components align closely with overheating and recession, respectively.[13] As we explain below, this simple partition allows us to uncover very insightful nonlinear Phillips curve relationships in all of our inflation variables.

[Figure 2 about here]

[12] See, e.g., Angeletos et al. (2020) and Beaudry et al. (2020).

[13] Notice that the positive medium-frequency component peaks shortly after the NBER recession trough. This positive component bears a striking resemblance to the (inverse of the) output gap estimated in Morley and Piger (2012). Asymmetry is an inherent feature of the business cycle.

Because we are specifying a structural model, we accordingly specify and estimate an equation for each of these unemployment components separately.

2.2.2 Identification: Swanson and Granger (1997).

Let us consider, for the moment, a linear structural vector autoregression (SVAR). Letting $M_t = \left(\pi_t^{PPI}, \pi_t^{CoreG}, \pi_t^{MServXH}, \pi_t^{Hous}, u_t^{medfreq}, u_t^{lowgap}\right)'$, and ignoring the constant for simplicity, we consider SVAR models of the following form:

$$AM_t = B(L)M_t + V_t \tag{1}$$

where A is a square matrix that denotes the "impact" matrix (indicating all contemporaneous causal influences), $B(L)$ is a matrix lag polynomial, and V_t is the vector of structural residuals, assumed to be distributed normally with a diagonal variance-covariance matrix. The corresponding reduced-form model is given by

$$M_t = A^{-1}B(L)M_t + A^{-1}V_t \equiv \Phi(L)M_t + E_t$$

where $\Phi(L)$ is a matrix lag polynomial, and E_t is the vector of reduced-form residuals.

Identification of Equation (1) based upon reduced-form parameter estimates implies obtaining estimates of A and $B(L)$, along with the diagonal variance-covariance matrix of the structural shocks. In the typical case, the data alone do not provide enough information to fully identify the system; one must impose identifying assumptions, which in this case involve restrictions on the form of the A matrix. Thus, identification amounts to determining the pattern of contemporaneous causation amongst the variables. A common approach is to assume a Cholesky ordering, whereby the vector M is rearranged and the A matrix is assumed to be lower triangular. In such cases, the assumption is that first variable is not contemporaneously caused by any of the other variables; the second variable is only contemporaneously caused by the first variable; and so on. In a system with just four variables, there are 24 different Cholesky orderings. However, Cholesky orderings represent but a small fraction of the set of possible models.

We adopt the Swanson and Granger (1997) (SG) approach to identification, described in Appendix B (along with a simple example).[14] This method is built upon the fact that most structural models, whether linear or nonlinear, imply overidentifying constraints. In particular, a given structural model implies correlation and partial correlation constraints on reduced-form regression residuals. (A partial correlation is the conditional correlation between two variables, conditioned on one or more other variables.) Under fairly weak assumptions, such overidentifying constraints may be tested using ordinary linear regressions and standard *t*-statistics. However, a rejection of a given constraint implies a rejection of *all models* that share this constraint. Thus, such tests may be used to reject entire classes of models that are inconsistent with the data. This turns out to have a lot of bite, in practice.

The method reduces the role of subjective elements typically required to identify a model (such as the imposition of a particular Cholesky ordering), because in our experience (and in the experience of Granger and Swanson), parsimonious models appear to agree with the data in most cases. (Effectively, the A matrix has many zeroes.) Accordingly, economic theory need only play a minor role in the selection of the final model. For instance, in a VAR with just four variables, there are over 100 potential models (24 of which correspond to Cholesky orderings). In the present case, as explained below, the data reject all but a handful of models.

[14] This causal discovery method builds upon work in causal modeling (e.g., Glymour and Spirtes, 1988) and is extended in Demiralp and Hoover (2003) and Demiralp, Hoover and Perez (2008); see also Moneta (2008). The method originated in Blalock (1961).

2.2.3 Nonlinear Impulse Response Functions, Forecasts, and Error Bands

In a nonlinear model, the impulse response functions (IRFs) will generally depend upon the size of the shock, its sign, and on the initial conditions. Hence, theory should dictate which of these numerous IRFs to investigate/estimate, for any given variable *X*.

The key nonlinearities in our model relate to how fluctuations in the two components of unemployment translate into forces on inflation. As discussed above, the core PCE inflation components have asymmetric relationships to both of the unemployment components: loosely speaking, the Phillips curve relationship consists of two relationships: a recession relationship, and overheating relationship. Conversely, a positive unemployment gap per se has no relationship to inflation. These facts explain why conventional Phillips curve specifications find missing disinflation and/or a weakening of the Phillips curve in the aftermath of the Great Recession – and why analysts are recently asserting that the Phillips curve has strengthened.

The asymmetries in the Phillips curve relationships suggest that the most interesting IRFs are the following. First, what happens when the medium-frequency component gets bigger, when it is already positive? (And to highlight the nonlinearity, it is interesting to contrast this IRF to its "mirror image:" what happens when the medium-frequency component falls further, either when the low-frequency component is still positive, or when it is already negative?) And second, what happens when the low-frequency gap becomes more negative, when it is already negative? (And again, to highlight the nonlinearity, it is interesting to contrast this IRF to its "mirror image," the IRF of a positive shock, occurring when the medium-frequency component is still positive.) Most of the remaining IRFs turn out to be more-or-less linear.

We describe our method for computing nonlinear IRFs (and the accompanying error bands) in Appendix H. Following Kilian and Lütkepohl (2017), we make use of the notion that an IRF is the difference between a forecast with a particular shock, and the forecast without one. In particular, given the model's nonlinear nature, we construct impulse response functions (IRFs), forecasts, and error bands via counterfactual simulations: first, for each bootstrap draw, generating a baseline simulation with shocks randomly-drawn from the model's structural residuals, and then replacing only the first-period shock (of a given variable) with the particular impulse we wish to study. To obtain accurate error band estimates, we augment the bootstrap procedure outlined in Kilian and Lütkepohl (2017) in two ways. First, we use the method of Kilian (1998) to correct for bias in estimates of parameters in the $B(L)$ matrix; Kilian (1998) and Ashley and Verbrugge (2009) have demonstrated the importance of this correction. Second, we take into account parameter estimation uncertainty via a bootstrap-upon-bootstrap method, along the lines of Potter (2000) and Pérez Forero and Vega (2016). Third, we apply a small-sample bootstrap variance correction motivated by the work of Phillips and Spencer (2011). Baseline *forecasts* and their error bands are computed similarly, although the "initial conditions" are chosen *a priori*, rather than drawn randomly. The forecast of core PCE inflation at time *t* for *h* quarters ahead is simply the composite forecast of the core goods inflation forecast, housing services inflation forecast, and the bias-adjusted median core services ex-housing inflation forecast (which, as noted above, is our proxy for the core services ex-housing forecast), combined using the share weights available as of time *t*. The weights reflect the relative shares of core goods inflation, housing services inflation, and core services ex. housing inflation in the overall core PCE inflation. Specifically, the weight for core goods inflation is computed as a nominal share of the personal consumption expenditures of core goods over the nominal PCE excluding energy and food, and similarly for the other two components.[15]

To enhance accuracy, we condition upon structural shocks that allow us to impose near-term information about core goods inflation and housing services inflation. As has been long-established in the forecasting literature, overall forecast accuracy can be enhanced by conditioning upon near-term information (see, e.g., Faust and Wright, 2013; Tallman and Zaman, 2020). We also form conditional forecasts by constructing nonlinear system forecasts that condition upon the evolution of labor market variables.

2.2.4 Approach to specification of reduced-form model.

Given our aims in the present paper, and the fact that we use quarterly rather than monthly data, we use a modification of the baseline inflation equation of Ashley/Verbrugge (2023). We are ultimately interested in reliable forecasts, so model parsimony was a chief consideration. We used step-down testing, equation by equation, removing variable lags to obtain parsimonious equations. We allowed for sign asymmetry in the two unemployment rate components, but did not impose it. In each equation, we allow up to 5 quarterly lags in the dependent variable, and up to 4 quarterly lags in each of the other variables. (Allowing for the fifth lag is quite important for accurately assessing the persistence of each series, as demonstrated in Verbrugge and Zaman, 2023a). . The equations below reflect our final preferred specifications for each equation.

[15] An "alternative" core PCE series could be constructed by directly using the unadjusted/unbiased median core services ex housing in the aggregation. In appendix E, we plot this "core PCE alternative" alongside the actual core PCE.

3. Results

3.1 Specification of reduced-form model

In the *PPI* equation, the inclusion of all other inflation series was rejected. However, *PPI* has a significant Phillips curve relationship. The data reject sign asymmetry in both unemployment rate components. Subsequently, both components appeared to enter as first differences. We thus entered both as first differences, and this yielded an equation that fit the data almost equally well; furthermore, u^{lowgap} was no longer statistically significant. Dropping this term yielded a more parsimonious equation with almost no decline in fit, and so was favored by the BIC.

$$\pi_t^{PPI} = \alpha^{PPI} + \sum_{j=1}^{4} \beta_j^{PPI} \pi_{t-j}^{PPI} + \delta \Delta u_{t-1}^{medfreq} + e_t^{PPI} \tag{2}$$

Labor market variables are denoted as follows: $\Delta u_t^{medfreq}$ refers to the 1-quarter change in the medium-frequency component, $u_t^{+medfreq}$ refers to the positive portion of the medium-frequency component, and $u_t^{-lowgap}$ refers to the negative portion of the low-frequency gap.

The core PCE component inflation rate equations are specified as

$$\begin{aligned}\pi_t^{CoreG} &= \alpha^{CoreG} + \phi_1^{CoreG} \pi_{t-1}^{CoreG} + \phi_2^{CoreG} \pi_{t-4}^{CoreG} + \phi_5^{CoreG} \pi_{t-5}^{CoreG} + \\ &\quad + \beta_1^{CoreG} \pi_{t-3}^{PPI} + \lambda^{CoreG} u_{t-4}^{+medfreq} + \psi I^{1995} + e_t^{CoreG}\end{aligned} \tag{3}$$

$$\begin{aligned}\pi_t^{MServXH} &= \alpha^{MServXH} + \gamma_1^{MServXH} \pi_{t-1}^{MServXH} + \gamma_2^{MServXH} \pi_{t-2}^{MServXH} + \gamma_5^{MServXH} \pi_{t-5}^{MServXH} + \\ &\quad + \lambda^{MServXH} u_{t-1}^{+medfreq} + \mu^{MServXH} u_{t-1}^{-lowgap} + e_t^{MServXH}\end{aligned} \tag{4}$$

$$\pi_t^{Hous} = \alpha^{Hous} + \sum_{j=1}^{5} \eta_j^{Hous} \pi_{t-j}^{Hous} + \lambda^{Hous} u_{t-1}^{+medfreq} + \mu^{Hous} u_{t-4}^{-lowgap} + e_t^{Hous} \tag{5}$$

where I^{1995} is a dummy variable that is 1 prior to 1995Q1. This variable allows us to capture an evident mean shift in core goods inflation in the mid-1990s; see Clark (2004). As noted above, in keeping with previous work, symmetry in the unemployment components was clearly rejected by the data in each equation. As noted above, negative realizations of $u_t^{medfreq}$, and positive realizations of u_t^{lowgap}, were found to be statistically insignificant determinants of inflation.[16] As previous work has established, movements in the variable $u_t^{+medfreq}$ apply *downward* ("recessionary") force on inflation; movements in the variable $u_t^{-lowgap}$ apply *upward* ("overheating") force on inflation.

Finally, our $u^{medfreq}$ equation was specified as

$$u_t^{medfreq} = \sum_{j=1}^{2} \lambda_j^{med} u_{t-j}^{medfreq} + \sum_{j=1}^{4} \mu_j^{med} u_{t-j}^{lowgap} + \beta^{med} \pi_{t-1}^{PPI} + e_t^{medfreq} \tag{6}$$

and our u^{lowgap} equation was specified as

$$u_t^{lowgap} = \alpha^{lowgap} + \sum_{j=1}^{2} \mu_j^{low} u_{t-j}^{lowgap} + \sum_{j=1}^{4} \lambda_j^{low} u_{t-j}^{medfreq} + \sum_{j=1}^{3} \beta_j^{low} \pi_{t-j}^{PPI} + e_t^{lowgap} \tag{7}$$

3.2 Identification of structural model

The variant of the SG approach that we use begins by estimating all pairwise correlations amongst the regression residuals. Our variant relies upon a "faithfulness" assumption (see Appendix 1), which assumes that if variable *X* causes variable *Y* contemporaneously, then the regression residuals from the *X* equation and the *Y* equation have a non-zero correlation.

We found a significant correlation between *PPI* residuals and core goods residuals, between *PPI* residuals and median core services ex-housing residuals, and between u^{lowgap} and $u^{medfreq}$ residuals; we also found a borderline-significant correlation between median core

[16] The work of Kilian and Vigfusson (2011) suggests that one must exercise care in choosing to include asymmetric terms, since one can easily estimate misleading IRFs and draw incorrect inferences. To guard against this, we checked whether our final specification should include the "full" unemployment components. But these terms entered the equation with fairly small coefficient estimates, and p-values at 0.3 and greater. Thus in the present case, the data quite clearly supports our specification, and the estimated IRFs are reliable.

services ex-housing residuals and housing residuals. All other correlations were insignificant. Thus, as explained in Appendix B, no further testing of partial correlation constraints was necessary. If variables *X* and *Y* are contemporaneously correlated, we must assign a direction of causality. On the basis of economic theory and *a priori* timing grounds, we assume that contemporaneously, *PPI* causes core goods, *PPI* causes median core services ex-housing, median core services ex-housing causes housing, and $u^{medfreq}$ causes u^{lowgap}. Our assumptions lead to the following loading matrix *A* (only nonzero entries are indicated):

$$A\mathrm{M}_t = \begin{bmatrix} 1 & & & & & \\ -a_{21} & 1 & & & & \\ -a_{31} & & 1 & & & \\ & & -a_{43} & 1 & & \\ & & & & 1 & \\ & & & & -a_{65} & 1 \end{bmatrix} \begin{bmatrix} \pi_t^{PPI} \\ \pi_t^{CoreG} \\ \pi_t^{MNHServ} \\ \pi_t^{Hous} \\ u_t^{medfreq} \\ u_t^{lowgap} \end{bmatrix}$$

Maximum likelihood estimation of *A*, based on the variance-covariance matrix from the equation residuals and the zeroes of the loading matrix *A*, verified that all nonzero entries were statistically significant.[17]

Under the assumption that the structural model is correct, then the sparsity of the *A* matrix and the assumption that structural residuals are mutually uncorrelated imply that the structural model can be estimated by simply including the relevant contemporaneous terms into the reduced-form equations (3), (4), (5), and (7) (see Kilian and Vigfusson, 2011).

Thus, the four respecified equations are

[17] There is some abuse of notation. Our full structural model has 11 equations, 5 of which are identities, as explained below. But what matters for identification is determining the contemporaneous causation structure among the variables.

$$\pi_t^{CoreG} = \alpha^{CoreG} + \phi_1^{CoreG}\pi_{t-1}^{CoreG} + \phi_2^{CoreG}\pi_{t-4}^{CoreG} + \phi_5^{CoreG}\pi_{t-5}^{CoreG} + \\ +\beta_0^{CoreG}\pi_t^{PPI} + \beta_1^{CoreG}\pi_{t-3}^{PPI} + \lambda^{CoreG}u_{t-4}^{+medfreq} + \psi I^{1995} + v_t^{CoreG} \tag{8}$$

$$\pi_t^{MServXH} = \alpha^{MServXH} + \gamma_1^{MServXH}\pi_{t-1}^{MServXH} + \gamma_2^{MServXH}\pi_{t-2}^{MServXH} + \gamma_5^{MServXH}\pi_{t-5}^{MServXH} + \\ +\beta_0^{MServXH}\pi_t^{PPI} + \lambda^{MServXH}u_{t-1}^{+medfreq} + \mu^{MServXH}u_{t-1}^{-lowgap} + v_t^{MServXH} \tag{9}$$

$$\pi_t^{Hous} = \alpha^{Hous} + \sum\nolimits_{j=1}^{5}\eta_j^{Hous}\pi_{t-j}^{Hous} + \beta_0^{Hous}\pi_t^{MServXH} + \lambda^{Hous}u_{t-1}^{+medfreq} + \mu^{Hous}u_{t-4}^{-lowgap} + v_t^{Hous} \tag{10}$$

$$u_t^{lowgap} = \alpha^{lowgap} + \sum\nolimits_{j=1}^{2}\mu_j^{low}u_{t-j}^{lowgap} + \sum\nolimits_{j=0}^{4}\lambda_j^{low}u_{t-j}^{medfreq} + \sum\nolimits_{j=1}^{4}\beta_j^{low}\pi_{t-j}^{PPI} + v_t^{lowgap} \tag{11}$$

Further, in equations (2) and (6), the reduced-form residuals *e* are relabeled as structural residuals *v*. Coefficient estimates are reported in Appendix C.

The *PPI* is highly correlated with transportation prices. Furthermore, inasmuch as unemployment captures the influence of demand on *PPI*, the structural residuals of the *PPI* equation may be interpreted as supply shocks. In Appendix G, we provide some additional evidence that suggests that *on net*, *PPI* shocks mostly reflect supply shocks, with demand shocks being much less important. However, during some periods – such as during 2020 – demand has played a notable role in driving *PPI*.

For simulating the system – necessary for estimation of forecasts and their error bands – we must augment these 4 equations with 5 additional equations: 4 equations that split each unemployment rate component projection into positive and negative parts, and a final one that defines the first difference of $u^{medfreq}$.

$$u_t^{+lowgap} \equiv \max\left(0, u_t^{lowgap}\right) \tag{12}$$

$$u_t^{-lowgap} \equiv \min\left(0, u_t^{lowgap}\right) \tag{13}$$

$$u_t^{+medfreq} \equiv \max\left(0, u_t^{medfreq}\right) \tag{14}$$

$$u_t^{-medfreq} \equiv \min\left(0, u_t^{medfreq}\right) \tag{15}$$

$$\Delta u_t^{medfreq} \equiv u_t^{medfreq} - u_{t-1}^{medfreq} \tag{16}$$

The full structural model consists of equations (2),and (6) (with residuals *v*), and equations (8) through (16).

We estimate our model using ordinary least squares, but then bias-correct these estimates using the method of Kilian (1998), as discussed in Section 2.2.3 above.

3.2 Impulse Response Functions

In a nonlinear model, the IRFs will generally depend upon the size of the shock, its sign, and on the initial conditions. Hence, theory should dictate which of these numerous IRFs to investigate/estimate, for any given variable *X*. Several types of nonlinear IRFs exist in the literature. Given that the nonlinearity in the present model relates to the different impacts of fluctuations in unemployment by frequency and sign, of most interest is a particular subset of IRFs:

- IRFs to positive shocks to the medium-frequency component, conditioned on this component starting in a positive initial condition; and the "mirror image," IRFs to negative shocks in this component, conditioned either on the low-frequency gap being initially somewhat positive (i.e., greater than 0.25 ppts), or initially negative.
- IRFs to positive shocks to the low-frequency (highly-persistent) gap component, conditioned on medium frequency component being positive; and IRFs to negative shocks to the low frequency gap component, when the it is already negative.
- IRFs to shocks to *PPI*, drawing uniformly from all initial conditions.

Our estimates indicate that many of the IRFs are essentially linear. The chief exceptions are the the IRFs of the three core PCE inflation components to shocks in the two unemployment components. In keeping with their nonlinear Phillips curve specifications, these variables display differential responses to positive versus negative shocks in $u^{medfreq}$ and u^{lowgap}.

To better display the nonlinearity, all IRFs to *negative* shocks are reflected about the *x* (time) axis. Thus for example, in Figure 4, panel (a), we depict the IRF of core goods inflation to a positive shock of size 0.20 to u^{lowgap} (in black), and we also depict the *inverse* of the IRF to a negative shock of size 0.20 to u^{lowgap} (in yellow). However, in all IRF figures, when the IRF to a positive shock is virtually indistinguishable from the inverse of the IRF to a negative shock, we depict only the IRF to a positive shock.

We first consider a positive shock to $u^{medfreq}$, depicted in Figure 3, in black. A shock to this component is amplified in the subsequent two quarters (partly via induced movements to other variables), and then declines to 0 about three years quarters later, with a subsequent bit of overshooting. Recall that a *positive* movement in this component induces a "recessionary" downward force on inflation. *PPI* falls notably in response to this increase in this component, providing some additional downward force on the other variables; later it overshoots, before slowly decelerating back to 0. As is well known, housing inflation has a strong Phillips curve relationship; this component responds quite strongly (dropping more than 0.6 ppts after two years). But both core goods inflation and median core services ex-housing drop are also responsive to recessionary pressure, each dropping by about 0.2 ppts after two years. The u^{lowgap} variable rises in response, reaching its peak 10 quarters after the shock; but (aside from feedback influences on $u^{medfreq}$), positive movements in this component do not further influence dynamics of the other variables.

We next consider the impact of a *negative* shock to $u^{medfreq}$, also depicted in Figure 3, in yellow and green, in panels (a) – (c). (Recall that these IRFs are reflected about the x axis, to highlight the nonlinearity. The other IRFs are essentially linear, and thus we only depict the IRFs to a positive shock.) While this movement directly influences *PPI* (causing it to rise), it does not directly influence the other inflation variables. However, the fall in $u^{medfreq}$ induces a fall in u^{lowgap}, and *this* induced movement then provides "overheating" (upward) force on inflation. But if the low frequency gap component is initially positive (yellow IRFs), then its influence is muted, and delayed, relative to the case when the low frequency gap component is initially negative (green IRFs). In the latter case, median core services ex-housing rises by over 0.4 ppts after three years, while housing inflation rises by almost a full ppts after three years. (Core goods rises by about 0.15 ppts at about the 2½ year mark.)

[Figure 3 about here]

We next consider shocks to u^{lowgap}, depicted in Figure 4. The subsequent dynamics closely parallel those discussed above. A shock to this component is amplified, quite notably, in the subsequent six or seven quarters (partly via induced movements to other variables), and then slowly declines, reflecting its low-frequency (persistent) nature. We first consider a *positive* shock (of size 0.2) in u^{lowgap}. Positive movements in u^{lowgap} do not directly influence the other inflation variables. However, the rise in u^{lowgap} induces a rise in $u^{medfreq}$, and *this* induced movement then provides recessionary (downward) force on inflation (though the recessionary force is smaller, since this component returns to zero more rapidly). The subsequent dynamics are similar to those experienced after a positive shock to $u^{medfreq}$ As in that case, *PPI* falls notably in response to this increase in this component, providing additional force on the other variables; later it overshoots, before slowly decelerating back to 0. Housing inflation also responds quite strongly (dropping 0.4 ppts by quarter 7). Core goods inflation responds less (dropping by about 0.15 ppts after two years); median core services ex-housing inflation drops about 0.1 ppts.

We next consider the impact of a *negative* shock to u^{lowgap}, which induces overheating force. Induced reductions in $u^{medfreq}$ cause *PPI* to rise (*PPI* does not respond directly to u^{lowgap}).

Core goods inflation rises by about 0.1 ppts. Median core services ex-housing inflation responds strongly to this overheating force; it rises to peak at nearly +0.3 ppts, about 3 years later. Housing also responds strongly to this force, rising to a peak response of +0.4 ppts, about 2½ years later.

[Figure 4 about here]

In Figure 5, we consider positive and negative shocks of size 2.0 to *PPI*. As is now evident, a key to understanding the subsequent dynamics is to determine how such a shock influences the unemployment components. Interestingly, in this case, the IRFs are nearly linear: the impact of *PPI* on core goods is dominated by the direct impact. The induced upward movements in $u^{medfreq}$ on the other two components of inflation (from a positive *PPI* shock) turns out to be nearly identical to the impact of induced downward movements on u^{lowgap} (from a negative *PPI* shock); and uncertainty is quite large, so most of these changes are not statistically significant.

[Figure 5 about here]

Finally, in Figure 6, we display the median IRFs of the three core PCE inflation components to their own shocks (of size 0.1). (We don't display IRFs of other variables to these shocks since inflation in these components does not feed back into other variables to any appreciable extent.) This figure demonstrates the differential persistence levels and dynamics exhibited by these three components. Goods inflation accelerates a bit for a year, then decelerates rapidly, followed by a "rebound" that brings it back to 0.4 ppts, three years after the shock. Housing inflation accelerates for a year. After that, it falls fairly rapidly. By quarter 7, about half of the shock has dissipated; but then housing inflation remains roughly at that level for the next two years, before slowly decelerating. Finally, median core services ex housing is the most persistent. After quarter 2, it decelerates over the next three quarters to reach 0.06 ppts. But then its downward progress stalls out. Its half-life is about 18 quarters.[18]

[Figure 6 about here]

3.3 Forecasts

3.3.1 Forecasting Performance

We now compare the point forecast accuracy of our VAR model with those of standard univariate benchmark models. We perform a pseudo recursive out-of-sample forecast comparison spanning the period 2007Q1 through 2019Q3. The forecasts are evaluated using an expanding window of data. Specifically, the first recursive run uses data from 1985Q1 through 2006Q4 for estimation, and generates forecasts up to eight quarters out, corresponding to 2007Q1 through 2008Q4. The second run uses data from 1985Q1 through 2007Q1 for estimation, and produces forecasts for periods 2007Q2 through 2009Q1, and so on. The last recursive run uses data for estimation spanning 1985Q1 through 2018Q3, but for this last run, only forecasts up to four quarters out (with four-quarter ahead corresponding to 2019Q3) are evaluated. We focus on the evaluation sample period 2007 to 2019 for several reasons. First, this period is associated with numerous inflation puzzles, such as missing disinflation, and the Phillips curve is widely thought to have weakened over this period. Our goal is to be able to provide accurate forecasts conditioned on the path of unemployment, and this is a period with a full business cycle – and in particular, a very large

[18] For this variable, the sum of the autoregressive coefficients is 0.98.

recession, a long recovery, and also a period of overheating. Success in forecasting inflation over this period provides strong support to our claim that we have accurately captured the unemployment-inflation relationship. Second, since we are using a nonlinear model, we start in 2007 because wish to have a sufficiently long estimation period so that coefficient estimates have approximately converged. Third, we end our evaluation in 2019 because we do not wish our results to be driven by the atypical dynamics associated with the COVID pandemic.[19]

Table 1 reports the results of the point forecast evaluation comparing forecasts of the unemployment rate and core PCE inflation from our model (denoted "VZ VAR") to "hard-to-beat" benchmarks.[20] The panel (a) reports results for core PCE inflation, and panel (b) for the unemployment rate. In each panel, the numbers reported in the first row are the mean squared errors from the respective benchmark univariate models: a Random Walk (RW) model, in the case of core inflation, and an autoregressive model with four lags (AR4), in the case of the unemployment rate. The remaining rows below the first row are ratios that report relative MSEs, i.e., relative to MSEs from the univariate benchmarks. Hence, a ratio more than 1 indicates that the univariate benchmark is more accurate on average than the model being compared. Since we are working with four-quarter growth rates, the inflation forecast from the RW model is the latest value of the four-quarter core PCE inflation. We report results for two forecast horizons, four and eight quarters ahead.

As is evident looking at the relative MSEs, our VAR model forecasts for both the unemployment rate and core PCE inflation are competitive to the univariate benchmarks. In fact, eight quarters out, our VAR model forecasts are notably more accurate (and statistically

[19] The forecasts from our model are competitive with most alternatives post-2019; given the unusual shocks over this period, few models performed well. An exception is Verbrugge and Zaman (2023a).
[20] For unemployment, there is no standard alternative benchmark, so we also report the forecast accuracy of an AR(1) model.

significant) for core PCE inflation, partly driven by large gains in a handful of periods, mainly when the economy is in a recession.[21] As expected, the short-term forecasts of core inflation from our VAR model when we condition on the evolution of the unemployment rate are more accurate than the unconditional forecasts (four quarters ahead, relative MSE of 0.84 vs. 0.96); but are comparable eight quarters ahead. The unemployment results also indicate that AR4 model produces somewhat more accurate forecasts than the AR1 model, though the gains are not statistically significant.

As a second exercise, we compute a historical 10-year forecast from our model, starting in 2007, and compare this to the forecast from a counterpart bivariate VAR model specification that relies upon a conventionally-specified linear Phillips curve.[22] These forecasts are recursive, in that the forecast does not rely upon any inflation data from 2007Q1 onwards, but are conditional, in that they rely upon the evolution of the unemployment rate over the forecast period. To conserve space, we report this exercise in Appendix D. The inflation forecast from the conventional model is notably inferior to that from our nonlinear VAR model. Overall, our forecasting results lend credibility to our nonlinear VAR model forecasts.

[Table 1 about here]

3.3.2 Looking Ahead: Conditional Forecasts for 2023-2025

In this subsection, we provide a number of forecasts for inflation, all of which conditional on various assumed paths for the unemployment rate. This exercise allows us to assess whether the

---

[21] Our findings – forecast improvements are mainly episodic – are in line with the literature (e.g., Stock and Watson 2010 and Ashley and Verbrugge 2023), and not surprising, since our unemployment terms only influence forecasts during two portions of the business cycle.

[22] For this type of comparison, the UCSV model and the RW model would perform poorly.

inflation projection in the December SEP is consistent with the unemployment projection, and to determine the inflation implications of alternative unemployment projections. These results provide policymakers with the information necessary to understand the tradeoffs they face going forward.

As has been long-established in the inflation forecasting literature, overall forecast accuracy can be enhanced by conditioning upon near-term information (see, e.g., Faust and Wright, 2013).[23] The variables where such information is most useful for our purposes are core goods inflation (where monthly inflation has decelerated sharply) and housing inflation (where models relying on short-term information, discussed below, suggest that we will have at least one more quarter of inflation growth).

We incorporate the recent deceleration in core goods inflation by conditioning a path for quarterly core goods inflation over the next four quarters that leaves it at 0.7 ppt in 2023Q4.[24] If anything, doing so imposes a strong downward bias on our forecasts, since the model by itself (i.e., unconditionally) predicts a slower deceleration in core goods inflation.

We incorporate short-term information in housing services by use of a short-term housing services forecasting model, informed by Adams et al. (2022). This paper uses confidential CPI rent microdata to demonstrate that new-tenant rents lead official CPI rents (the ultimate source of the housing services inflation information in the core PCE) by about 4 quarters, and that the CoreLogic Single-Family Rent Index (SFRI) has historically tracked a CPI-microdata-based new-tenant rent

[23] More recently, it has been established that forecast accuracy, particularly over the medium-term, can be enhanced by conditioning on longer-term information (see, e.g., Tallman and Zaman, 2020). In the present context, we do this by ensuring that our bias-corrected and bootstrapped median conditional forecasts converge to their in-sample means via (minor) adjustments to the estimated constants in our structural equations.

[24] Following the nowcasting inflation work of Knotek and Zaman (2017), who found superior accuracy of core PCE nowcasts and short-term forecasts using simple models including AR processes, we construct the short-term forecast path for monthly core goods inflation using a simple AR(2) model estimated over our sample.

index fairly well. We use a simple model for monthly housing services inflation[25] using lags of both housing services inflation and SFRI rent inflation to produce a forecast for housing services inflation for January, February, and March of 2023. This yields a 2023Q1 estimate of 8.0 percent (quarterly annualized or 8.0 percent 4Q-trailing basis), which we use as a starting condition for housing services inflation.

We first present the model projection for core PCE inflation through 2025, along with 70 percent confidence intervals, and the SEP projection in Figure 7. To reiterate, our model projections are conditional on the December SEP path for unemployment. (For interpretive ease, we have interpolated between the SEP projected values for core PCE inflation, which are provided only for 2023Q4, 2024Q4, and 2025Q4.)

[Figure 7 about here]

Both inflation projections begin at 4.5 percent, and both decelerate briskly for the next three quarters. In our model, inflation initially decelerates briskly because the 2023 increase in the unemployment rate that is a feature of the SEP projection is rapid enough that it induces a notable uptick in $u^{medfreq}$, which in turn puts downward pressure on all of the inflation variables. But $u^{medfreq}$ returns to zero fairly rapidly, thereby removing this downward pressure. Thereafter, the persistence of inflation reflected in our model estimates becomes evident, and progress toward the 2 percent target slows through mid-2024, and slows further after that. Conversely, the SEP projection continues on a very strongly decelerating path in 2024, so that by the end of 2024, this moves the SEP projection outside of the confidence interval. It remains outside of the confidence interval

[25] We thank Mark Bognanni and Katia Peneva for advice in constructing this model.

throughout all of 2025. Hence, from late 2024 onward, the SEP projection is assessed as too optimistic relative to our model's assessment. Conditional on the SEP unemployment projection, our model forecast is at 2.85 percent by the end of 2025; it does not reach 2.1 percent inflation until several years later.

Figure 8 presents our model projections for our three components: core goods inflation, core services ex-housing inflation, and housing inflation, conditional on their respective short-term conditions (as discussed above) and the SEP path for unemployment over the 2023-2025 period. We condition on 4Q core goods inflation decelerating to 0.6 percent by the end of 2023, then the model implies that 4Q core goods inflation rebounds somewhat before falling gradually to 0.2 ppts by the end of 2025.. Core services ex-housing inflation is projected to steadily decelerate from 4.4 percent to 3. percent by the end of 2025. Housing services inflation is projected to decline at a steady rate through mid 2024, but then its downward progress stalls out, likely reflecting the sluggish dynamics of rent (see Adams et al., 2023 and Gallin and Verbrugge, 2019). During 2025, it settles in at a 5.3 percent pace. Outside of the forecast horizon, all variables continue to decelerate.

[Figure 8 about here]

But what sort of unemployment path would be consistent with the SEP's inflation projection? And, for example, what would be the inflation implications associated with the June SEP unemployment projection? To answer such questions, we next provide a number of additional inflation projections, conditional on three alternative unemployment rate scenarios: a soft landing scenario, a moderate recession scenario, and a severe recession scenario. The soft landing scenario, which conditions on the projected unemployment path from the June SEP, has unemployment peaking at 4.1 percent by the end of 2024.[26] The moderate recession scenario conditions on a path for unemployment from 2023Q1 onward that mimics the 2001 recession. For this path, unemployment tops out at 5.0 percent in 2025Q3. Finally, the severe recession scenario (inspired by the Summers/Ball/Leigh/Mishra assertions) conditions on a path for unemployment that peaks at 6.9 percent in 2025Q3.[27] Unemployment rates in all scenarios, with the exception of the severe recession, are assumed, after 2025Q4, to descend linearly to hit 4 percent by the end of 2029 or earlier. All of these scenario paths are plotted below in Figure 9. In our specification, because inflationary pressure ceases once the low-frequency gap becomes positive, and disinflationary pressure ceases once the medium frequency unemployment rate becomes negative, the exact path of unemployment taken after 2024 in its descent toward 4 percent is essentially immaterial for inflation. However, these paths will impact the simple welfare analysis conducted below. The implied forecasts for core PCE inflation are shown in Figure 10.

[Figures 9 and 10 about here]

Our model sees rapid deceleration of inflation over 2023, for all of these scenarios, driven by rapid deceleration in core goods prices and by initial movement of the inflation variables back towards their long-run trends. Recessionary downward force, i.e., the deceleration pressure associated with the positive portion of the medium-frequency component of unemployment, notably amplifies this descent for all scenarios except the soft landing. The Phillips curve is alive

[26] The SEP projection reports the forecast of the overall unemployment rate. To back out the implied projection of the underlying jobless unemployment rate, we take the temporary-layoff rate reported by the BLS for the month of December 2022 and assume that it will persist into the future.

[27] For disinflation, what matters in a recession is not the peak unemployment rate, but rather the amount of (positive) area under the medium frequency unemployment rate path. The ratio of the area under the medium frequency component relative to the trough-to-peak change in the unemployment rate varies from 1.1 to 2 over recessions from 1970-2019. For our more severe recession scenario, we scale up the movements in the low-frequency gap in the early 2000s recession by 2.7, and (to be conservative) the movement in the medium-frequency component by 0.7 of that, since the early 2000s ratio was on the high side, at 1.6. This brings the more severe recession's ratio to 0.95, below the median of 1.2 over the post-1970 average.

and well (and stable), a fact that is quite important for policymakers. This disinflationary pressure eases in early 2024 for the December SEP path and the moderate recession path, but continues through 2025 in the severe recession scenario. And once the deceleration pressures ease, progress toward 2 percent slows markedly. Inflation is more persistent than is commonly believed.

Regarding that persistence, allowing for (though not imposing) the fifth lag in each of the three core PCE component inflation variables is quite important. An autoregressive process with a weight of (say) 0.8 on the first lag, 0.1 on the fifth lag, and 0 on all other lags, is more persistent than an autoregressive process with a weight on 0.9 on the first lag and 0 on all other lags (see appendix of Verbrugge and Zaman, 2023a). The model forecasts imply that it takes a very long time for inflation to return to trend. This lengthy return to the inflation target is consistent with the inflation experience over the 2012-2019 period, when trend inflation moved a mere 0.5 percentage point. We further note that our core PCE projections are very similar to those of the model in Verbrugge and Zaman (2023a), which is built upon trimmed-mean PCE inflation, and also to those from the headline PCE forecasts of the model in Verbrugge and Zaman (2023b).

3.3 A Simple Welfare Analysis

Despite its higher inflation path, is a soft landing preferable? We conduct a simple welfare analysis, using a standard (though ad hoc) quadratic loss function. In some contexts, such loss functions are a second-order Taylor series approximation to the expected utility of the economy's representative household (Woodford, 2002), specified as

$$L\{u_t, \pi_t\}_{t=t_1}^{t_2} = \sum_{s=0}^{t_2-t_1} \left[(1-w)\left(u_{t_1+s} - u_t^*\right)^2 + w\left(\pi_{t_1+s} - \pi^*\right)^2 \right]$$

Guided by the December SEP and the FOMC's inflation target, we set $u_t^* = 4.0$ and $\pi^* = 2.0$.

We examine losses from $t_1 =$ 2023Q1 to $t_2 =$ 2029Q4. We compare the soft landing, moderate recession, severe recession, and December SEP scenarios. We report the losses in Table 1, for $w = \{0.1, 0.19, 0.25, 0.5, 0.75, 0.81, 0.9\}$.

[Table 2 about here]

In Table 2 the minimum-loss scenario for each value of *w* appears in red font. The preferred outcome depends on the value of *w*. For a low weight on inflation (0-0.18), the soft landing is preferred. For values of *w* between 0.19 and 0.80, the SEP path results in the smallest welfare loss. For values of *w* between 0.81 and about 0.89, the moderate recession results in smallest welfare loss. Finally, for very high values of *w*, the more severe recession is preferred.

It is important to keep in mind that this welfare analysis abstracts from any danger of the de-anchoring of inflation expectations that might be associated with core PCE inflation still being near 3 percent, three years from now.

4. Conclusion

This paper implements a nonlinear structural VAR model to jointly estimate the dynamics of inflation, as measured by three components of core PCE inflation, a variable that is a good signal of supply-chain pressures, and two components of the jobless unemployment rate: a persistent component and moderately persistent component.

The model is estimated with post-1985 quarterly data and identification of structural shocks is achieved using the data-determined method of Swanson and Granger (1997), which substantially reduces the role of subjectivity.

Looking ahead, our model projects that inflation only very gradually falls back to 2 percent. Progress toward target is very much influenced by the path that unemployment will take over the next several years. Conditional on the December SEP median unemployment rate projections, inflation is projected to still be 2.8 percent by the end of 2025, far above the SEP's median projection of 2.1 percent. A moderate recession (roughly equal to the recession of 2001) would put inflation at 2.5 percent by the end of 2025; conversely, a soft landing (which we define as the path of unemployment in the June SEP projection) would put inflation a touch above 3 percent by the end of 2025. What kind of recession would it take to hit the SEP projection for inflation, according to the model developed in this paper? We investigate the claim of former Treasury Secretary Lawrence Summers (reported in Aldrick, 2022) and the supporting assessment of Ball, Leigh, and Mishra (2022) that it will take two years of 7.5 percent unemployment from its current low level to bring inflation down to its 2 percent target. In keeping with the firm and stable Phillips curve relationship we uncover, our model implies that that one year of 5.9 percent unemployment would accomplish this task – although there is considerable uncertainty around this estimate.

A simple welfare analysis based on a standard quadratic loss function favors, for equal weights on inflation and unemployment, the December SEP unemployment rate path. However, this welfare analysis abstracts from any danger of the de-anchoring of inflation expectations that would be associated with core PCE inflation still being 2.8 percent three years from now.

Ashley and Verbrugge (2023) summarize a large number of extant theoretical works whose predictions are consistent with their (and our) empirical results regarding the nonlinearity of the Phillips curve. We hope that the present paper provides further impetus for the development of structural models that are consistent with, and provide a theoretical explanation for, our findings.

References

Adams, Brian, Lara P. Loewenstein, Hugh Montag, and Randal J. Verbrugge. Forthcoming. "Disentangling Rent Index Differences: Data, Methods, and Scope." *American Economic Review: Insights*.

Aguiar-Conraria, Luís, Manuel M.F. Martins, and Maria Joana Soares. 2023. "The Phillips Curve at 65: Time for Time and Frequency." *Journal of Economic Dynamics and Control* 151 (June): 104620. https://doi.org/10.1016/j.jedc.2023.104620.

Aldrick, Philip. 2022. "Larry Summers Says US Needs 5% Jobless Rate for Five Years to Ease Inflation." *Bloomberg.Com*, June 20, 2022. https://www.bloomberg.com/news/articles/2022-06-20/summers-says-us-needs-5-jobless-rate-for-five-years-to-ease-cpi.

Angeletos, George-Marios, Fabrice Collard, and Harris Dellas. 2020. "Business-Cycle Anatomy." *American Economic Review* 110 (10): 3030–70. https://doi.org/10.1257/aer.20181174.

Ashley, Richard A., Kwok Ping Tsang, and Randal J. Verbrugge. 2020. "A New Look at Historical Monetary Policy (and the Great Inflation) through the Lens of a Persistence-Dependent Policy Rule." *Oxford Economic Papers* 72 (3): 672–91. https://doi.org/10.1093/oep/gpaa006.

Ashley, Richard A., and Randal J. Verbrugge. 2008. "Frequency Dependence in Regression Model Coefficients: An Alternative Approach for Modeling Nonlinear Dynamic Relationships in Time Series." *Econometric Reviews* 28 (1–3): 4–20. https://doi.org/10.1080/07474930802387753.

Ashley, Richard A., and Randal J. Verbrugge. 2009. "To Difference or Not to Difference: A Monte Carlo Investigation of Inference in Vector Autoregression Models." *International Journal of Data Analysis Techniques and Strategies* 1 (3): 242. https://doi.org/10.1504/IJDATS.2009.024295.

Ashley, Richard A., and Randal J. Verbrugge. 2022a. "Death to Regression Modeling on Bandpass-Filtered Data: New Results on the General Undesirability of Filtering Dynamic Regressions, with a Proposed Solution." Manuscript, Virginia Tech.

Ashley, Richard A., and Randal J. Verbrugge. 2022b. "Time Series Filtering for Studying Frequency Dependence: What Works, What Doesn't." Manuscript, Federal Reserve Bank of Cleveland.

Ashley, Richard A., and Randal J. Verbrugge. 2023. "The Intermittent Phillips Curve: Finding a Stable (But Persistence-Dependent) Phillips Curve Model Specification." Working paper 19-09R2. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-201909r2.

Ball, Laurence M. 1994. "What Determines the Sacrifice Ratio?" In *Monetary Policy*, edited by N. Gregory Mankiw, 155–93. The University of Chicago Press. https://www.nber.org/books-and-chapters/monetary-policy/what-determines-sacrifice-ratio.

Ball, Laurence M., Daniel Leigh, and Prachi Mishra. 2022. "Understanding US Inflation during the COVID Era." In *BPEA Conference Drafts, September 8-9, 2022*. https://www.brookings.edu/bpea-articles/understanding-u-s-inflation-during-the-covid-era/.

Beaudry, Paul, Dana Galizia, and Franck Portier. 2020. "Putting the Cycle Back into Business Cycle Analysis." *American Economic Review* 110 (1): 1–47. https://doi.org/10.1257/aer.20190789.

Blalock Jr, Hubert M. 1961. *Causal Inferences in Nonexperimental Research*. Chapel Hill: University of North Carolina Press.

Carroll, Daniel R., and Randal J. Verbrugge. 2019. "Behavior of a New Median PCE Measure: A Tale of Tails." *Economic Commentary*, no. 2019–10 (July). https://doi.org/10.26509/frbc-ec-201910.

Cecchetti, Stephen G., Michael E. Feroli, Peter Hooper, Frederic S. Mishkin, and Kermit L. Schoenholtz. 2023. "Managing Disinflations." Chicago Booth. http://www.chicagobooth.edu/research/igm/USMPF/USMPF%20Paper.

Christiano, Lawrence J., and Terry J. Fitzgerald. 2003. "The Band Pass Filter." *International Economic Review* 44 (2): 435–65. https://doi.org/10.1111/1468-2354.t01-1-00076.

Clark, Todd E. 2004. "An Evaluation of the Decline in Goods Inflation." *Economic Review* 89 (Q II): 19–51. https://ideas.repec.org//a/fip/fedker/y2004iqiip19-51nv.89no.2.html.

Clark, Todd E., and Sharon Kozicki. 2005. "Estimating Equilibrium Real Interest Rates in Real Time." *The North American Journal of Economics and Finance* 16 (3): 395–413. https://doi.org/10.1016/j.najef.2005.04.002.

Clark, Todd E., and Saeed Zaman. 2013. "Forecasting Implications of the Recent Decline in Inflation." *Economic Commentary*, no. 2013–15 (November). https://doi.org/10.26509/frbc-ec-201315.

Dagum, Estela Bee. 1987. "Current Issues in Seasonal Adjustment." *Survey Methodology* 13 (1): 63–74. https://www150.statcan.gc.ca/n1/en/catalogue/12-001-X198700114509.

Demiralp, Selva, and Kevin D. Hoover. 2003. "Searching for the Causal Structure of a Vector Autoregression." *Oxford Bulletin of Economics and Statistics* 65 (s1): 745–67. https://doi.org/10.1046/j.0305-9049.2003.00087.x.

Demiralp, Selva, Kevin D. Hoover, and Stephen J. Perez. 2008. "A Bootstrap Method for Identifying and Evaluating a Structural Vector Autoregression." *Oxford Bulletin of Economics and Statistics* 70 (4): 509–33. https://doi.org/10.1111/j.1468-0084.2007.00496.x.

Doppelt, Ross. 2021. "Should Macroeconomists Use Seasonally Adjusted Time Series? Structural Identification and Bayesian Estimation in Seasonal Vector Autoregressions." Manuscript, Michigan State University. https://www2.gwu.edu/~forcpgm/Doppelt_Seasonality_2021.pdf.

Faust, Jon, and Jonathan H. Wright. 2013. "Chapter 1 - Forecasting Inflation." In *Handbook of Economic Forecasting*, edited by G. Elliott and A. Timmermann, 2, Part A:2–56. Elsevier. https://doi.org/10.1016/B978-0-444-53683-9.00001-3.

Figura, Andrew, and Christopher J. Waller. 2022. "What Does the Beveridge Curve Tell Us about the Likelihood of a Soft Landing?" FEDS Notes. Board of Governors of the Federal Reserve System. https://doi.org/10.17016/2380-7172.3190.

Forbes, Kristin J., Joseph E. Gagnon, and Christopher G. Collins. 2022. "Low Inflation Bends the Phillips Curve around the World." *Economia* 45 (89): 52–72. https://doi.org/10.18800/economia.202201.003.

Gallin, Joshua, and Randal J. Verbrugge. 2019. "A Theory of Sticky Rents: Search and Bargaining with Incomplete Information." *Journal of Economic Theory* 183 (September): 478–519. https://doi.org/10.1016/j.jet.2019.06.003.

Glymour, Clark, and Peter Spirtes. 1988. "Latent Variables, Causal Models and Overidentifying Constraints." *Journal of Econometrics* 39 (1): 175–98. https://doi.org/10.1016/0304-4076(88)90044-9.

Granger, Clive W. J. 1969. "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods." *Econometrica* 37 (3): 424–38. https://doi.org/10.2307/1912791.

Hall, Robert E., and Marianna Kudlyak. 2022. "The Unemployed with Jobs and without Jobs." *Labour Economics* 79 (December): 102244. https://doi.org/10.1016/j.labeco.2022.102244.

Hamilton, James D. 2018. "Why You Should Never Use the Hodrick-Prescott Filter." *The Review of Economics and Statistics* 100 (5): 831–43. https://doi.org/10.1162/rest_a_00706.

Iacobucci, Alessandra, and Alain Noullez. 2005. "A Frequency Selective Filter for Short-Length Time Series." *Computational Economics* 25 (1): 75–102. https://doi.org/10.1007/s10614-005-6276-7.

Kaiser, Regina, and Agustín Maravall. 1999. "Estimation of the Business Cycle: A Modified Hodrick-Prescott Filter." *Spanish Economic Review* 1 (2): 175–206. https://doi.org/10.1007/s101080050008.

Kilian, Lutz. 1998. "Small-Sample Confidence Intervals for Impulse Response Functions." *The Review of Economics and Statistics* 80 (2): 218–30. https://doi.org/10.1162/003465398557465.

Kilian, Lutz, and Helmut Lütkepohl. 2017. *Structural Vector Autoregressive Analysis:* 1st ed. Themes in Modern Econometrics. Cambridge, United Kingdom ; New York, NY, USA: Cambridge University Press. https://doi.org/10.1017/9781108164818.

Kilian, Lutz, and Robert J. Vigfusson. 2011. "Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases? Are Responses of the U.S. Economy Asymmetric?" *Quantitative Economics* 2 (3): 419–53. https://doi.org/10.3982/QE99.

King, Robert G., and Mark W. Watson. 1994. "The Post-War US Phillips Curve: A Revisionist Econometric History." *Carnegie-Rochester Conference Series on Public Policy* 41 (December): 157–219. https://doi.org/10.1016/0167-2231(94)00018-2.

Knotek II, Edward S., and Saeed Zaman. 2017. "Nowcasting U.S. Headline and Core Inflation." *Journal of Money, Credit and Banking* 49 (5): 931–68. https://doi.org/10.1111/jmcb.12401.

Meyer, Brent H., Brian Prescott, and Xuguang Simon Sheng. 2022. "The Impact of the COVID-19 Pandemic on Business Expectations." *International Journal of Forecasting* 38 (2): 529–44. https://doi.org/10.1016/j.ijforecast.2021.02.009.

Mise, Emi, Tae-Hwan Kim, and Paul Newbold. 2005. "On Suboptimality of the Hodrick–Prescott Filter at Time Series Endpoints." *Journal of Macroeconomics* 27 (1): 53–67. https://doi.org/10.1016/j.jmacro.2003.09.003.

Moneta, Alessio. 2008. "Graphical Causal Models and VARs: An Empirical Assessment of the Real Business Cycles Hypothesis." *Empirical Economics* 35 (2): 275–300. https://doi.org/10.1007/s00181-007-0159-9.

Morley, James, and Jeremy Piger. 2012. "The Asymmetric Business Cycle." *Review of Economics and Statistics* 94 (1): 208–21. https://doi.org/10.1162/REST_a_00169.

Pérez Forero, Fernando J., and Marco Vega. 2016. "Asymmetric Exchange Rate Pass-through: Evidence from Nonlinear SVARs." Working paper 63. Peruvian Economic Association. https://perueconomics.org/wp-content/uploads/2014/01/WP-63.pdf.

Phillips, Kerk L., and David E. Spencer. 2011. "Bootstrapping Structural VARs: Avoiding a Potential Bias in Confidence Intervals for Impulse Response Functions." *Journal of Macroeconomics* 33 (4): 582–94. https://doi.org/10.1016/j.jmacro.2011.02.007.

Potter, Simon M. 2000. "Nonlinear Impulse Response Functions." *Journal of Economic Dynamics and Control* 24 (10): 1425–46. https://doi.org/10.1016/S0165-1889(99)00013-5.

Stock, James H., and Mark W. Watson. 1999. "Forecasting Inflation." *Journal of Monetary Economics* 44 (2): 293–335. https://doi.org/10.1016/S0304-3932(99)00027-6.

Stock, James H., and Mark W. Watson. 2010. "Modeling Inflation After the Crisis." Working paper 16488. National Bureau of Economic Research. https://doi.org/10.3386/w16488.

Stock, James H., and Mark W. Watson. 2020. "Slack and Cyclically Sensitive Inflation." *Journal of Money, Credit and Banking* 52 (S2): 393–428. https://doi.org/10.1111/jmcb.12757.

Swanson, Norman R., and Clive W. J. Granger. 1997. "Impulse Response Functions Based on a Causal Approach to Residual Orthogonalization in Vector Autoregressions." *Journal of the American Statistical Association* 92 (437): 357–67. https://doi.org/10.1080/01621459.1997.10473634.

Tallman, Ellis W., and Saeed Zaman. 2017. "Forecasting Inflation: Phillips Curve Effects on Services Price Measures." *International Journal of Forecasting* 33 (2): 442–57. https://doi.org/10.1016/j.ijforecast.2016.10.004.

Tallman, Ellis W., and Saeed Zaman. 2020. "Combining Survey Long-Run Forecasts and Nowcasts with BVAR Forecasts Using Relative Entropy." *International Journal of Forecasting* 36 (2): 373–98. https://doi.org/10.1016/j.ijforecast.2019.04.024.

Tetlow, Robert J. 2022. "How Large Is the Output Cost of Disinflation?" Finance and Economics Discussion Series 2022–078. Board of Governors of the Federal Reserve System. https://doi.org/10.17016/FEDS.2022.079.

Verbrugge, Randal. 2022. "Is It Time to Reassess the Focal Role of Core PCE Inflation in Assessing the Trend in PCE Inflation?" *Economia* 45 (89): 73–101. https://doi.org/10.18800/economia.202201.004.

Verbrugge, Randal J., and Saeed Zaman. Forthcoming. "Improving Inflation Forecasts Using Robust Measures." *International Journal of Forecasting*. https://doi.org/10.26509/frbc-wp-202223r.

Verbrugge, Randal J., and Saeed Zaman. Forthcoming. "The Hard Road to a Soft Landing: Evidence from a (Modestly) Nonlinear Structural Model." *Energy Economics*.

Woodford, Michael. 2002. "Inflation Stabilization and Welfare." *The B.E. Journal of Macroeconomics* 2 (1): 1–53.

Zaman, Saeed. 2022. "A Unified Framework to Estimate Macroeconomic Stars." Working paper 21-23R. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-202123r.

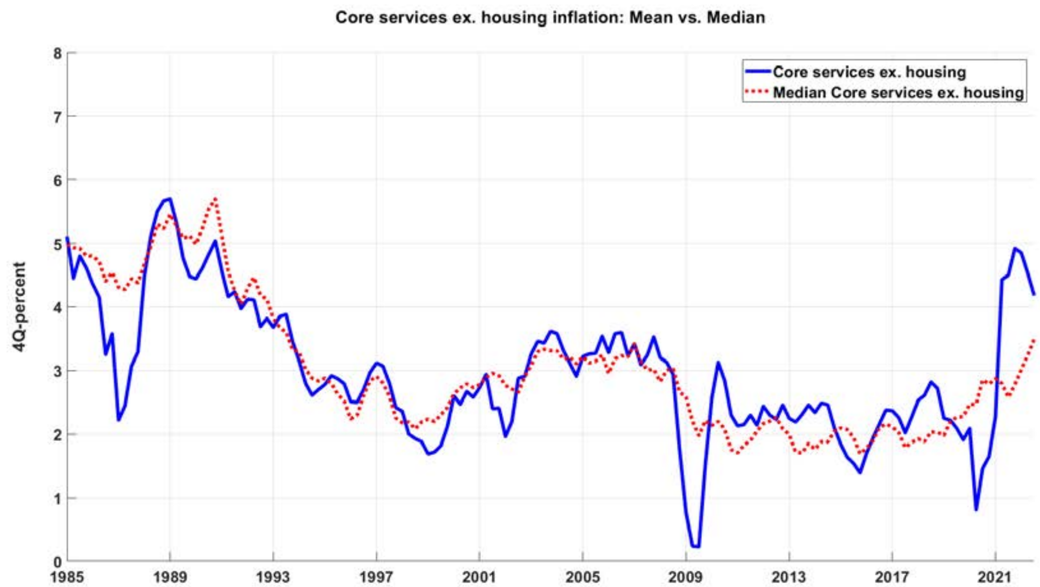


Figure 1: Core services ex. housing inflation indicators.

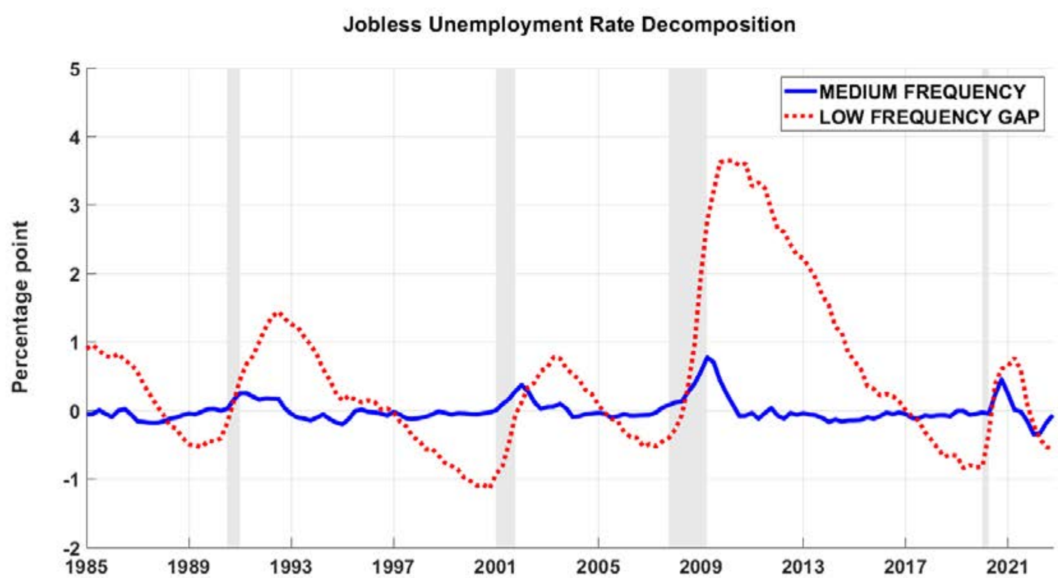


Figure 2: Two most persistent components of the jobless unemployment rate.

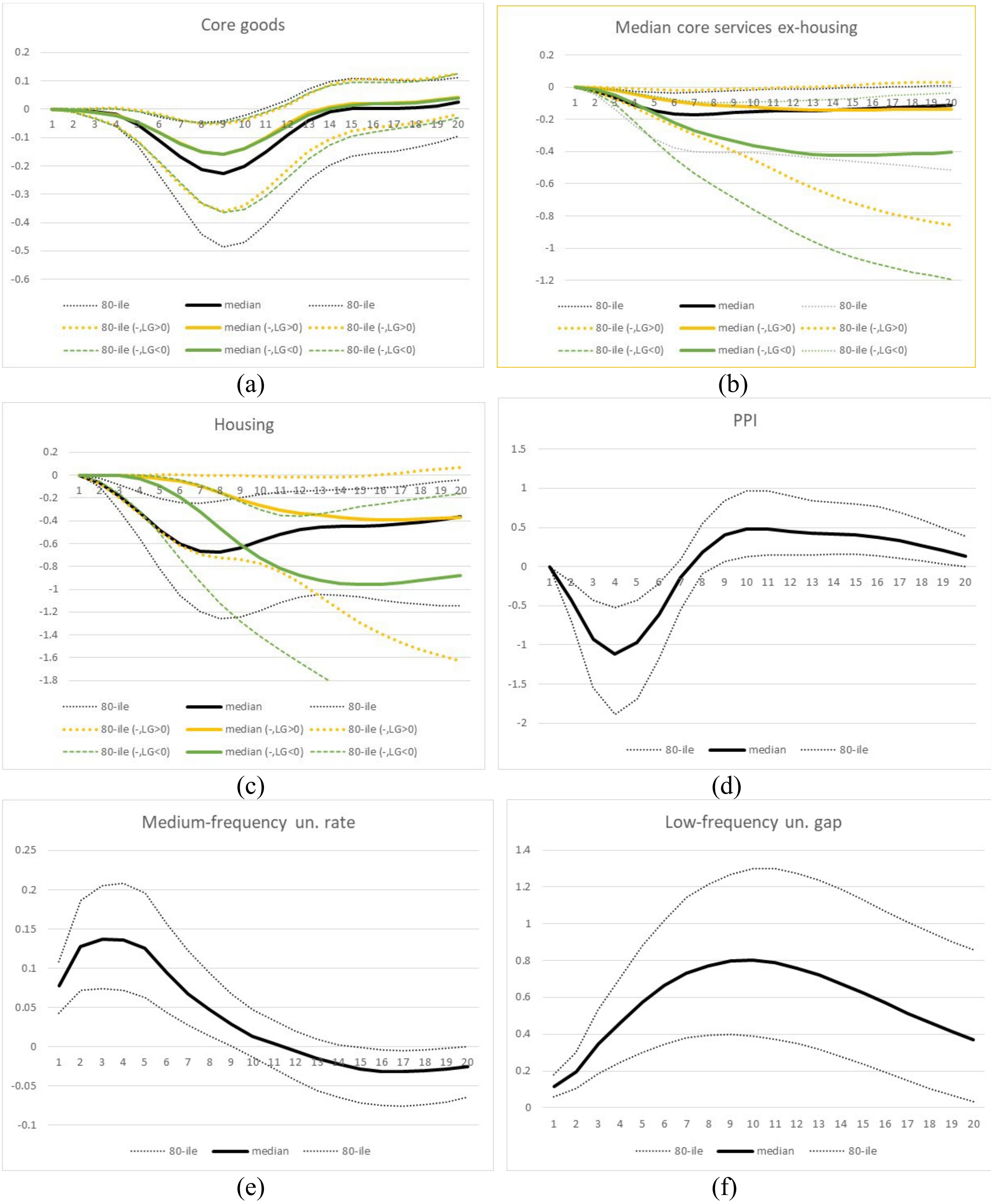


Figure 3: 20-quarter IRFs of each variable to a +/-0.075 shock to medium-frequency unemployment rate. Initial conditions for + shocks: medium-frequency component positive; for – shocks, low-frequency gap either positive (LG > 0, yellow) or negative (LG < 0, green). Responses to negative shocks are reflected about the x axis. IRF nonlinearity is negligible except for component inflation variables, so only the IRF to a + shock is displayed for unemployment components and PPI-IG.

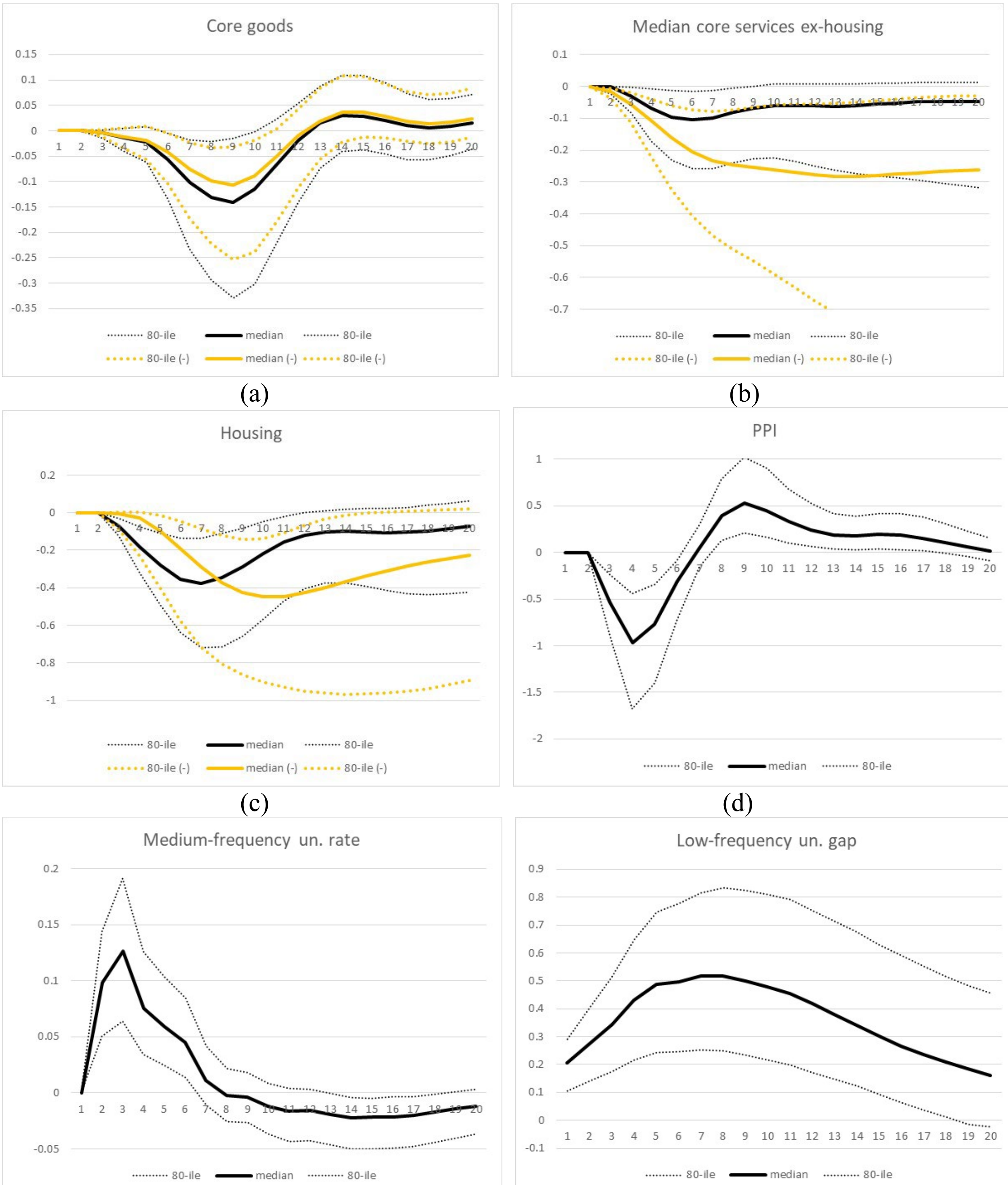
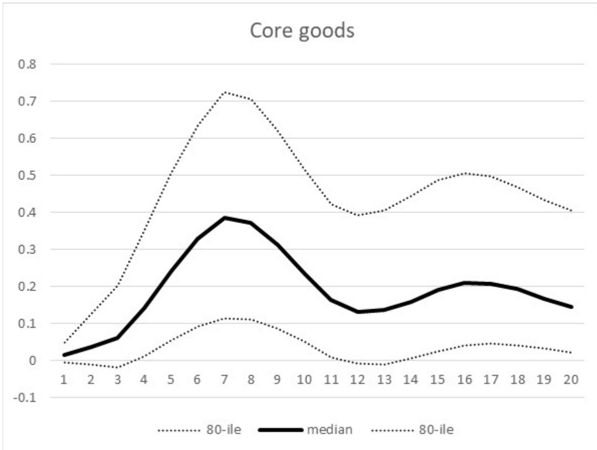
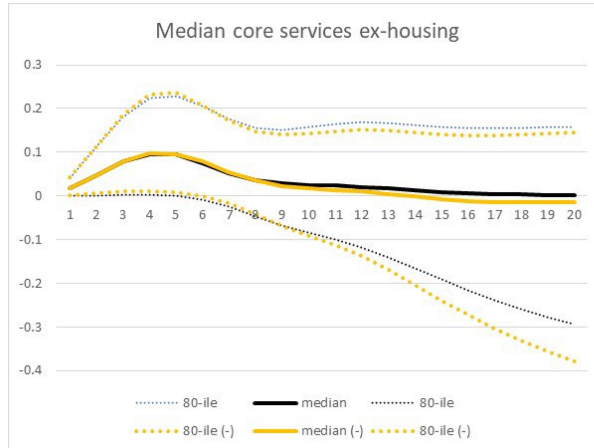


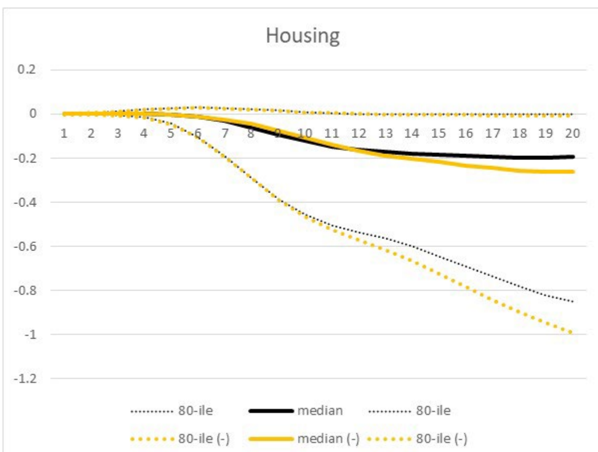
Figure 4: 20-quarter IRFs to +/- shock of size 0.20 to u^{lowgap}. Responses to negative shocks (yellow) are reflected about the x axis. IRF nonlinearity is negligible except for component inflation variables, so only the IRF to a + shock is displayed for those variables.



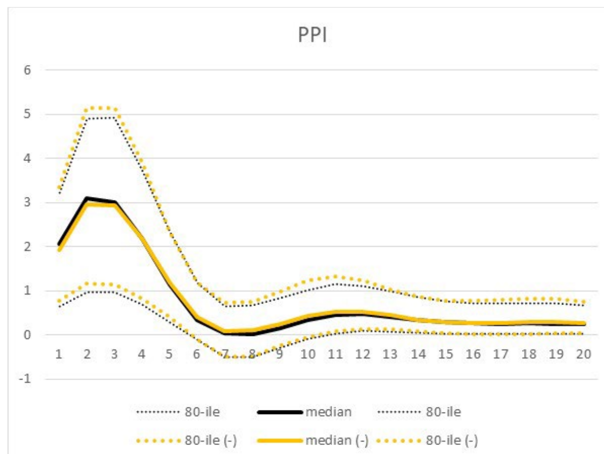
(a)



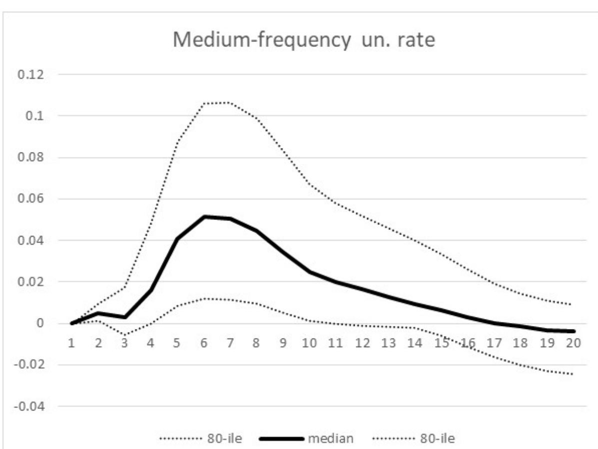
(b)



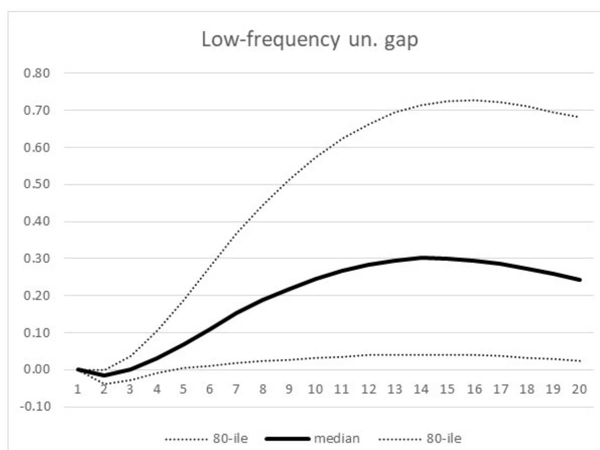
(c)



(d)



(e)



(f)

Figure 5: 20-quarter IRFs to a +/- shock of 2.0 to *PPI*. Responses to negative shocks (yellow) are reflected about the x axis. Nonlinearity is generally negligible.

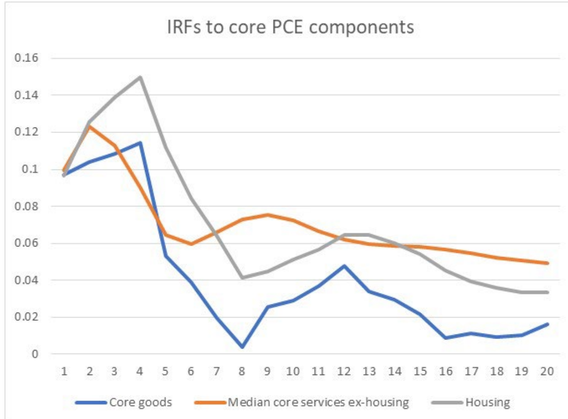


Figure 6: IRFs to core PCE components.

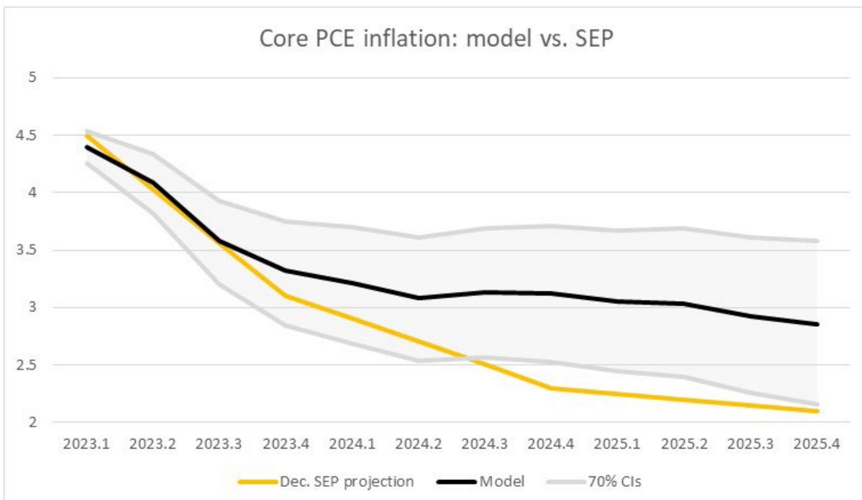
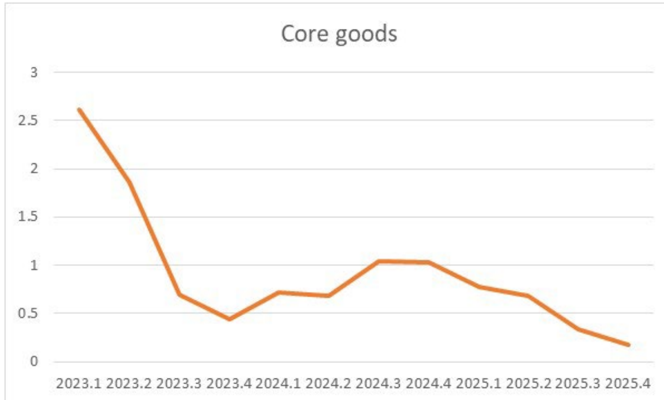
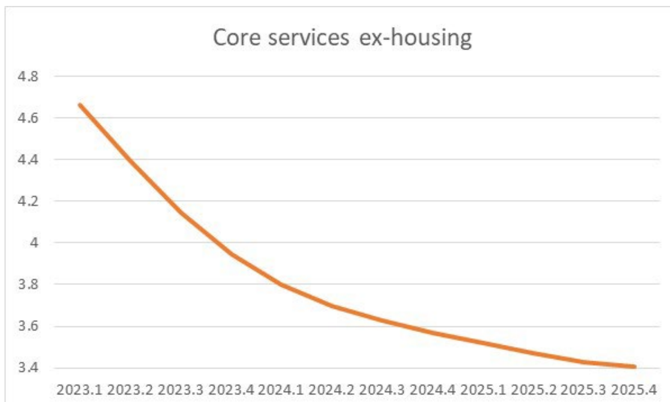


Figure 7: Projection of core PCE inflation, conditional on the December SEP projected path of unemployment.



(a)



(b)

(c)

Figure 8: Projections of the components of core PCE inflation, conditional on the December December SEP projected path of unemployment. The core services ex-housing projection is the gap-adjusted projection of median core services ex-housing.

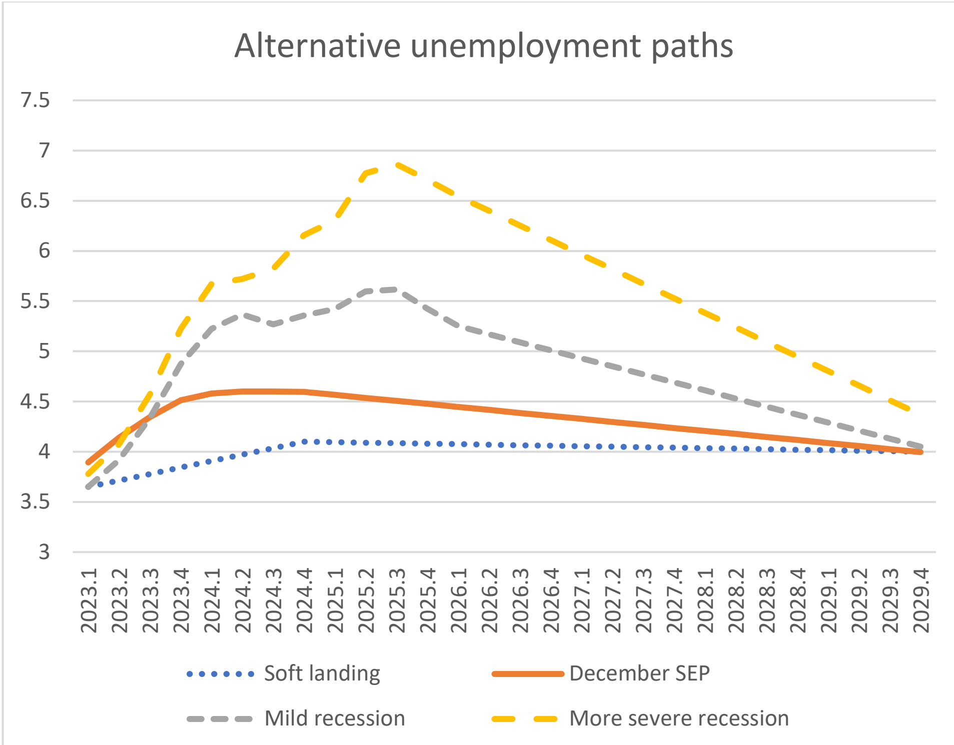


Figure 9: Alternative projections of the unemployment rate.

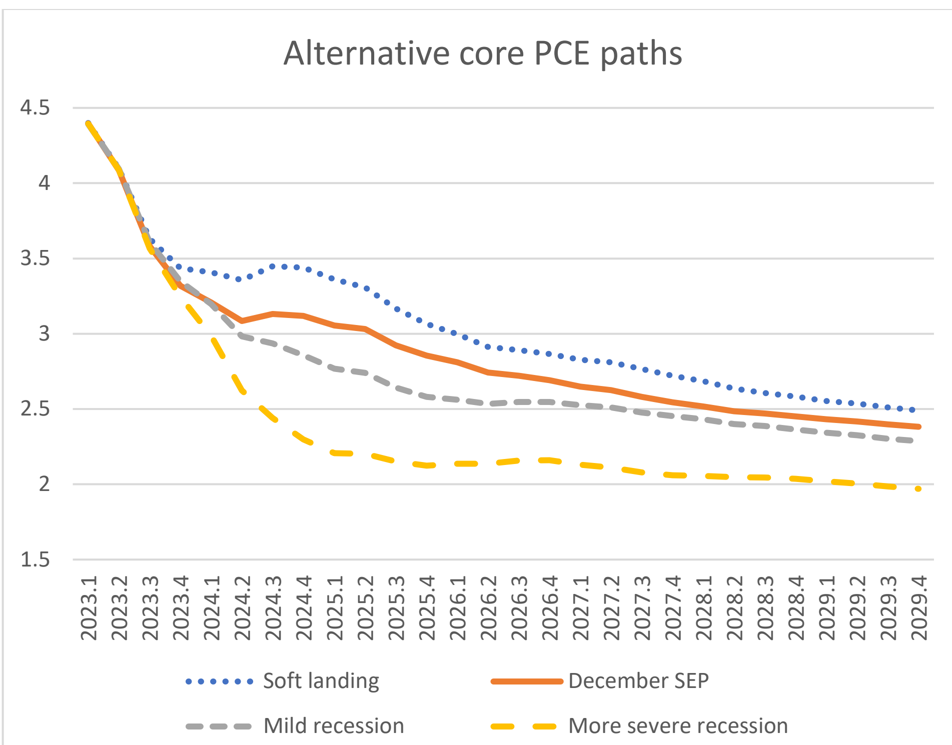


Figure 10: Model-implied alternative projections of core PCE inflation, conditional on the corresponding unemployment rate path.

Table 1: Point Forecast Accuracy Comparison

Mean Squared Error (MSE): Sample 2007-2019Q3		
(a) Core PCE Inflation (4Q-trailing rate, %)		
Models	Horizon	
	One-year out (h=4Q)	Two-years out (h=8Q)
MSE of Random Walk (RW)	0.23	0.39
Relative MSE, relative to RW		
VZ VAR (conditional on UR)	0.84	0.68**
VZ VAR (unconditional)	0.96	0.60**
UCSV (Stock and Watson)	1.17	0.92
(b) Unemployment rate (%)		
MSE of AR4 model	1.14	4.20
Relative MSE, relative to AR4		
VZ VAR (unconditional)	0.94	0.94
AR1 model	1.52*	1.32

Notes: The numbers reported in the first row of each panel are the mean squared error (MSE) from the benchmark model, RW in the case of core inflation, and AR4 in the case of the unemployment rate. The rows below the first row are ratios that report relative MSEs (relative to the benchmark model). Thus, a ratio of more than one indicates that the benchmark model is more accurate on average than the model being compared. The forecast evaluation is based on an expanding window of estimation spanning the period 2007Q1 through 2019Q3. The estimation start period is 1985Q1. A * indicates statistical significance up to 10% level, and a * indicates statistical significance at the 5% level,based on Diebold-Mariano-West test.

Table 2: Welfare losses

w	*Soft landing*	*December SEP*	*Mild recession*	*More severe recession*
0.10	7.35	8.05	25.74	78.32
0.19	10.36	10.09	25.53	72.09
0.25	12.36	11.46	25.39	67.93
0.50	20.71	17.14	24.79	50.62
0.75	29.06	22.82	24.20	33.31
0.81	31.07	24.18	24.06	29.16
0.90	34.07	26.23	23.84	22.93

Notes: These are losses from a quadratic loss function that penalizes squared deviations of inflation rate from 2 percent (multiplied by *w*), and squared deviations of the unemployment rate from 4 percent (multiplied by (1-*w*)). For each value of *w*, the minimum loss is depicted in red font.