Forecasting Inflation: Phillips Curve Effects on Services Price Measures

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Abstract

We estimate an empirical model of inflation that exploits a Phillips Curve relationship between a measure of unemployment and a sub-aggregate measure of inflation (services). We generate an aggregate inflation forecast from forecasts of the goods sub-component separate from the services sub-component, and compare the aggregated forecast to the leading time-series univariate and standard Phillips curve forecasting models. Our results indicate notable improvements in forecasting accuracy statistics for models that exploit relationships between services inflation and the unemployment rate. In addition, models of services inflation using the short-term unemployment rate (less than 27 weeks) as the real economic indicator display additional modest forecast accuracy improvements.

Keywords: Inflation forecasting, Phillips Curve, disaggregated inflation forecasting models, trend-cycle model

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1 Introduction

Forecasting models of aggregate inflation including those that employ a Phillips Curve have been unable to outperform consistently univariate statistical models of aggregate inflation (Faust and Wright 2013).[1] Peach, Rich, and Linder (2013) suggest that the empirical estimates of a Phillips Curve may be diluted when applied to aggregate inflation because the influence of resource gap factors (such as the difference between measured unemployment and its "natural" rate) may affect the costs of services (services as non-tradable) more directly and substantially than on the costs of goods. Similarly, using data from New Zealand Hargreaves, Kite, and Hodgetts (2006) demonstrate how a Phillips Curve relationship is important for modeling inflation for non-tradable prices and therefore model tradeables and nontradeables prices separately. In each of these cases, the supporting intuition centers on how the key factors that influence tradeables (or goods) can differ materially from factors that affect prices in non-tradeables (services). Following from these ideas, we hypothesize that a resource gap measure has an important effect on services price determination, and not on goods price inflation.

In this paper, we build a composite model for inflation that consists of bi-variate state space model (unobserved components) of services inflation and the unemployment rate combined with a parsimonious univariate model for goods inflation. The services inflation model adapts the bivariate state space model as in Stella and Stock (2013) and exploits an empirical relationship between services inflation and the unemployment gap.[2] The forecasting model for aggregate inflation in this paper captures the apparent relationship in that unemployment rate deviations from trend (a latent variable estimate of the 'natural rate') appear useful for predicting services inflation.

We estimate an inflation in parts model in which we separately measure services inflation and goods inflation. Using these two inflation series separately, the model isolates a durable statistical relationship between services inflation and the unemployment rate. The bivariate state space model of services inflation exploits the empirical Phillips Curve correlation suggested in Peach, Rich, and Linder (2013). From the estimated model, we generate forecasts of services inflation and we combine it with the goods inflation forecast from an estimated trend in goods inflation (i.e. the five year moving average of the past available data) to compute a composite forecast of the aggregate inflation.[3] We then evaluate the forecasts of aggregate inflation, services inflation (from the bi-variate state space model), and goods inflation (parsimonious model).

We find that modeling inflation separately (goods as a univariate time-series model and services inflation in a state space form with unemployment) produces significant improvements in forecast accuracy for aggregate inflation relative to a standard Phillips Curve benchmark; the benchmark is a forecasting application of Stella and Stock's bivariate model for total inflation.

[1]Here we interpret the Phillips Curve as being the correlation between deviations of unemployment from its natural rate and deviations of inflation from its trend or expected rate.

[2]See Peach, Rich, and Linder (2013). They employ an empirical approach to the data that differs from our methods.

[3]Among alternative models of goods inflation, we estimated one that specifically extends the bivariate UC state space model to three variables. The resulting tri-variate unobserved components state space model consisted of: unemployment rate, services inflation, and goods inflation. In a separate specification, we model goods inflation as a trend cycle decomposition with stochastic volatility along the lines of Stock and Watson (2007). Separate models for services inflation and goods inflation produces substantially more accurate forecasts than a single model of the aggregate. These results are consistent with Peach, Rich, and Linder (2013).

We choose this particular benchmark because it modestly outperforms difficult to beat univariate approaches such as Atkeson and Ohanian (2001) and Stock and Watson (2007), though the gains are mostly limited to short-horizons.[4] We apply their specification to services inflation with the unemployment rate. Furthermore, our "inflation in parts" framework performs well in terms of forecast accuracy of aggregate inflation relative to common univariate benchmarks that are usually the most accurate in terms of root mean squared error and other point-based accuracy criteria.

Our empirical model estimates a Phillips curve relationship between services inflation and unemployment rate as evidenced by a relatively stable and negative estimate of the slope, a result consistent with Lee and Nelson (2007), Stella and Stock(2013), and King and Watson (1994).[5] Our results contrast with Atkeson and Ohanian (2001) and Stock and Watson (2007), for example, those papers document the failure of standard Phillips curve models in forecasting aggregate inflation compared to simple univariate benchmarks in the post 1990 period. Furthermore, we also show that, as advocated by Gordon 2013 and Ball and Mazumder 2014, the use of the short-term unemployment rate as proxy for economic slack in our model framework modestly improves forecasting accuracy for aggregate PCE inflation.

All results in the main text employ the Personal Consumption Expenditures price deflator as the measure for inflation. In the appendix, we also report results for Consumer Price Index (CPI) inflation, and our findings of forecasting gains extend to CPI inflation as well.

The paper is organized as follows: Section 2 describes the relevant literature, Section 3 outlines the data and empirical strategy. Section 4 discusses the estimation and forecasting results, and Section 5 concludes.

2 Review of Relevant Literature

Existing research indicates the potential for forecasting accuracy improvement from distinguishing between inflation of goods and of services in models of inflation. Peach, Rich, and Antoniades (2004) use a vector error correction model to estimate goods inflation and services inflation separately while also imposing a long-run relationship between the two measures. The paper demonstrates that the short-run to medium-run dynamics of the two inflation series depend on the deviation of the long-run equilibrium between the two inflation rates. Their empirical model consists only of the lags of good and services inflation as explanators, and therefore they do not investigate the Phillips Curve.

Clark (2004) provides a qualitative analysis of the behavior of core goods and core services inflation as measured by PCE price index. He identifies 1994 as the year in which the dynamics of the two series began to diverge.[6] Given differences in the dynamics of the two series, there maybe benefits modeling each series separately, and then combine the disaggregate forecasts as

[4]The specification in Stella and Stock (2013) exploits the Phillips curve relationship between total unemployment rate and total inflation.

[5]Each of the cited works estimates a negative correlation between aggregate inflation and unemployment rate at business cycle frequencies.

[6]Clark(2004) attributes this shift in dynamics to both the exchange rate and the increase in global competition.

an alternative to modeling the aggregate directly.

More recently, Peach, Rich, and Linder (2013) stress the importance of separately modeling goods and services inflation and show that in the case of core goods inflation, the unemployment gap does not play any material role. In contrast, the unemployment gap has significant influence on core services inflation. Peach, Rich, and Linder also suggest that long-run inflation expectations play an important role for the behavior of core services inflation but not for core goods inflation. In the case of core goods inflation they find that short-term inflation expectations (one-year out) plays a material role in explaining its time-series behavior. In their study, they emphasize that the behavior and determinants of services and goods inflation are distinct, and they limit their forecast comparison to their composite model versus the standard Phillips curve model from 2005 to 2012.

Existing research is divided on whether there are forecasting accuracy improvements from modeling aggregate inflation using sub-components of the aggregate inflation measure. In general, exising evidence suggests there may be gains from modeling disaggregates of the index using data from the United States. Bermingham and DAgostino (2011) empirically test the forecast performance of time series models with multiple-level of dis-aggregation both for US PCE inflation and Euro Area inflation. They employ Bayesian Vector Auto Regression (BVAR) and simple Auto Regressive (AR) models. Their simplest BVAR is three variable VAR that has durables goods, non-durable goods, and services. The next one is 15-variable BVAR with 15 dis-aggregated inflation variables, followed by 50, and 169 variables BVAR. In each of these models they compute the aggregate inflation from the dis-aggregates and compare it to the random walk forecast of aggregate inflation (along the lines of Atkeson and Ohanian (2001)). Similarly they also use AR models for each dis-aggregated component and then aggregate at 3-level, 15-level, 50-level, and 169-level and compare it to the same random walk forecast. They find in the USA case, dis-aggregated BVAR (especially the 15-component) generally performs well relative to random walk benchmark. Whereas, in the case of Euro Area, disaggregation through the AR models works better. In the USA case, the authors suggest that strong common co-movement among the dis-aggregated series are captured by BVARs (multivariate) (consistent with Reis and Watson (2010)). Measures for the Euro Area display less commonality among the dis-aggregated components and more individual series dynamics, which is consistent with superior performance of aggregation based on AR models.

Hubrich (2005), and Hendry and Hubrich (2006,2011) find that forecasting aggregate inflation through disaggregation does not help in forecasting Euro Area inflation but it helps for US inflation. The degree of improvement in the forecast accuracy of US inflation importantly depends on the length of the sample period and the level of the disaggregation. They use set of VARs and include disaggregates directly in the model that has aggregate inflation. Following similar approach, Luetkepohl (2010) estimates system of VARs that include both aggregate and disaggregate information for Euro Area inflation only and finds that including too many disaggregates could lead to estimation error and specification error.

Faust and Wright (2013) perform a comprehensive survey of various approaches to forecast inflation. In one exercise, they investigate whether there are gains to forecasting aggregate CPI inflation by modeling its disaggregates individually and then aggregating them. In their example, they found no material differences between the aggregate and disaggregate approaches unless parameter restrictions were imposed on the disaggregate equations.

Furthermore, country specific studies of inflation such as Duarte and Rua (2007), Bruneau et al (2007) and Moser et al (2007) use similar time series models and find that generating aggregate inflation forecasts using disaggregates helps for Portugal, France, and Austria respectively.

Stock and Watson (2015) documents evidence of estimating a superior trend inflation by using dis-aggregated 17-components of aggregate PCE inflation relative to trend estimated from the univariate model of aggregate PCE inflation. They use a multivariate extension of the univariate unobserved components stochastic volatility model of trend inflation in Stock and Watson (2007).

The evidence of forecasting improvements by modeling inflation using its components motivates our paper. We build on the results from the aforementioned studies, especially Peach, Rich and Linder (2013). In light of ample evidence documenting an important role of stochastic volatility in the inflation process and forecast accuracy (e.g. Stock and Watson 2007; Clark 2011), we allow for time variation in the variance of the innovations to various components, and that in turn implies time-varying relationship between changes in services inflation and unemployment rate.[7] We perform extensive forecast evaluation exercises, specifically comparing our model's forecast performance against a number of popular alternative models as well as across sub-samples. We use only two major components of aggregate inflation (services and goods inflation). The final product is a composite model of services inflation and goods inflation to forecast aggregate inflation.

3 Data and the Model

We employ the following quarterly data series in this research: the overall unemployment rate (16 years and over), the short-term unemployment rate (share of labor force unemployed for 26 weeks or less), two components of the Personal Consumption Expenditures deflator – the services component as well as the goods component, and these two components' relative shares of Personal Consumption Expenditures deflator. The unemployment rate(s) series are quarterly average of the monthly series available from the Bureau of Labor Statistics, and PCE inflation rate(s) including their shares are available from Bureau of Economic Analysis. The sample starts in 1960:Q1, and goes through 2014:Q4. We are interested in forecasting the quarterly annualized Personal Consumption Expenditures deflator in the aggregate, so we combine our quarterly forecasts of services and goods components using the actual weights to produce the aggregate inflation forecast. The weights represent the relative share of services and goods in the personal consumption expenditures.

Let U_t represent the unemployment rate for the aggregate data series and let U_t^N represent the natural rate of unemployment, which may vary over time. The natural rate of unemployment is a latent variable in this approach and will be estimated as part of the model estimation. We use P_t^s as the price level measure for services, P_t^g as the price level measure for goods, and P_t^T as the aggregate price level measure. For inflation as measured by these series, we represent

[7] Moreover, our framework accounts for a slowly varying local mean for services inflation, which is an important feature of accurate inflation forecasts (Faust and Wright 2013).

the rate in the services component by π_t^s and in the goods component by π_t^g.

We assume that both services inflation and unemployment rate data series can be modeled as an unobserved components, that is, the sum of a long-term trend component that is a random-walk, a stationary transitory (cyclical) component, and measurement error component. We assume a common cyclical component. The model is estimated with Bayesian Gibbs sampler.

The model specifies the latent variables (the unobserved trend and cyclical components) within a state-space form of the time series model. We outline the specification below, let:

U_t represent the aggregate unemployment rate
U_t^N represent the natural rate of unemployment
U_t^C represent the cyclical component of the unemployment rate
π_t^s represent the services inflation component
$\pi_t^{s,*}$ represent the trend services inflation
$\pi_t^{s,C}$ represent the cyclical services inflation component
π_t^g represent the goods inflation component

The variables $U_t,\ \pi_t^s,\ and\ \pi_t^g$ are observable, and the other four measures are unobservable.

3.1 Modeling Services Inflation

Our setup follows closely that of Lee and Nelson (2007) and Stella and Stock (2013). We view the multivariate unobserved components model in Stella and Stock (2013) as state of the art so we use that approach as applied to modeling services inflation. Specifically, the services inflation rate is modeled as a sum of three unobserved stochastic processes: random walk trend component, a stationary cyclical component (common also to cyclical unemployment), and a serially uncorrelated measurement error component.[8] Similarly, the unemployment rate, is decomposed into the random walk trend, a stationary cyclical unemployment, and a measurement error component. The stochastic trend unemployment rate can be interpreted as the natural rate of unemployment (or alternatively as the non-accelerating inflation rate of unemployment or NAIRU), and is usually assumed to evolve independently of monetary policy actions. Other studies that have incorporated time varying random walk trends in both unemployment rate and inflation include Lee and Nelson (2007), Harvey (2011), and Stella and Stock (2013).

$$U_t = U_t^N + U_t^C + \eta_t \tag{1}$$

$$\pi_t^s = \pi_t^{s,*} + \pi_t^{s,C} + \tilde{\eta}_t \tag{2}$$

[8] The assumption that the services inflation trend follows a random walk is a reasonable one because the factors that drive it are unknown but are quite persistent, a point emphasized in Lee and Nelson (2007) for the case of aggregate inflation trend.

The trend or "permanent" components are modeled as:

$$U_t^N = U_{t-1}^N + \epsilon_t, \qquad \epsilon_t \quad i.i.d.\ \ N(0, \omega I_1) \tag{3}$$

$$\pi_t^{s,*} = \pi_{t-1}^{s,*} + \tilde{\epsilon}_t, \qquad \tilde{\epsilon}_t = \sigma_{\tilde{\epsilon},t}\xi_{\tilde{\epsilon},t} \qquad \xi_{\tilde{\epsilon},t} \quad i.i.d.\ \ N(0, I_1) \tag{4}$$

$$ln(\sigma^2_{\tilde{\epsilon},t}) = ln(\sigma^2_{\tilde{\epsilon},t-1}) + \nu_{\tilde{\epsilon},t} \qquad \nu_{\tilde{\epsilon},t} \quad i.i.d.\ \ N(0, \gamma I_1) \tag{5}$$

Our specification allows the variance of the innovations to the services inflation trend to vary over time. However, as in Stella and Stock (2013) we don't allow stochastic volatility in the innovations to trend unemployment ($\omega = 0.01$).[9]

The cyclical components are modeled as follows:

$$U_t^C = \alpha_1 U_{t-1}^C + \alpha_2 U_{t-2}^C + \zeta_t \qquad \zeta_t = \sigma_{\zeta,t}\xi_{\zeta,t} \qquad \xi_{\zeta,t} \quad i.i.d.\ \ N(0, I_1) \tag{6}$$

$$ln(\sigma^2_{\zeta,t}) = ln(\sigma^2_{\zeta,t-1}) + \nu_{\zeta,t} \qquad \nu_{\zeta,t} \quad i.i.d.\ \ N(0, \gamma I_1) \tag{7}$$

$$\pi_t^{s,C} = \lambda U_t^C \tag{8}$$

The cyclical services inflation component is a function of unemployment cycle. The parameter λ relates the unemployment gap and the services inflation gap across business cycle frequencies. The estimated parameters determine the importance of a Phillips curve relationship. Specifically, there is time-variation in the innovation variances to the various latent components of the multivariate UC model described above. This implies a corresponding time-varying bivariate vector autoregressive (VAR) in the changes in unemployment gap and services inflation gap. At each point in time, the particular values of the innovation variances characterize the implied coefficients of the bivariate VAR.[10] The model generates an implied estimate of the slope of the Phillips curve which is the sum of the coefficients on the current and lagged changes in unemployment gap of the services inflation gap equation of this implied bivariate VAR.[11]

Finally, the measurement error components are as follows[12]:

$$\eta_t \qquad i.i.d.\ \ N(0, \gamma I) \tag{9}$$

$$\tilde{\eta}_t = \sigma_{\tilde{\eta},t}\xi_{\tilde{\eta},t} \qquad \xi_{\tilde{\eta},t} \quad i.i.d.\ \ N(0, I) \tag{10}$$

$$ln(\sigma^2_{\tilde{\eta},t}) = ln(\sigma^2_{\tilde{\eta},t-1}) + \nu_{\tilde{\eta},t} \qquad \nu_{\tilde{\eta},t} \quad i.i.d.\ \ N(0, \gamma I) \tag{11}$$

[9] Our results are not sensitive to this restriction.

[10] A multivariate unobserved component (UC) model with common trend such as the one laid out above has a companion implied vector autoregressive (VAR) representation of an infinite lag length. This VAR representation results from the Kalman filter's (recursive) predictive filtering algorithm, specifically the estimated predictive filtering weights constitute the coefficients of the corresponding implied VAR model. The predictive weights computed through the Kalman filter depend on the joint autocovariances of the variables of the UC model, which in turn depend on the innovation variances. A UC model that allows for stochastic volatility in the innovation variances would lead to a time-varying joint autocovariance of the variables in the UC model, implying a time-varying predictive filtering weights (resulting in time-varying coefficients of the corresponding implied VAR).

[11] This feature of time-variation in the Phillips curve slope is an innovative characteristic of the Stella and Stock model that differentiates their application from most other specifications of Phillips curve models based on unobserved components. Koopman and Harvey (2003), and Harvey (2006) provide generic algorithms for the unobserved components class of models to derive the implied weights of the corresponding VAR model representation.

[12] The scalar parameter γ is fixed at 0.2

As discussed in Stella and Stock (2013), allowing for stochastic volatility in the measurement error of unemployment equation poses a challenging empirical problem of separately estimating the cyclical unemployment and the related measurement error. To simplify this challenge, we restrict the variance of the measurement error to be constant. Stella and Stock (2013) highlight that the forecasting performance of their model was not sensitive to whether one has constant or time-varying variance in the measurement error, but they show that time-varying variance in the measurement error introduced considerable high-frequency noise to the estimated trend unemployment.

The unobserved components models of Stella and Stock (2013) and Lee and Nelson (2007) share common features although there are three major differences between them. Firstly, Stella and Stock (2013) incorporate a measurement error component in addition to random walk trend and stationary cyclical components; secondly, they introduce stochastic volatility in all the unobserved components (total of five); and they estimate the model using Bayesian methods which together with multiple stochastic volatility processes makes it computationally quite intensive to generate recursive forecasts.[13]

The model is estimated using Bayesian Gibbs sampler, and the algorithm is described briefly below:[14]

The prior density for the parameters (α_1, α_2, and λ) is assumed to be normal conjugate with mean of zero, and variance of 100.

Steps:

1. Conditional on observed data (services inflation, and unemployment rate), parameters (α_1, α_2, and λ), and stochastic volatilities draw the unobserved state variables $U^N, \pi^{S,*}$, and U^C

2. Conditional on the unobserved state variables, and stochastic volatilities draw the parameters (α_1, α_2, and λ) from the posterior distribution. The draws of autoregressive coefficients on the lags of the unemployment cyclical component, α_1, and α_2 are subject to linear constraints so to ensure stationary cyclical component.[15]

3. Conditional on the unobserved state variables, and the parameters (α_1, α_2, and λ) we draw stochastic volatilities. This step is based on work by Kim, Shephard, and Chib (1998).

[13] Lee and Nelson (2007) estimate two specifications of the bivariate model, unrestricted, and restricted. The restricted version imposes two sets of restrictions: (1) the cyclical unemployment rate was treated as exogeneous with respect to cyclical inflation by setting the coefficients on lags of cyclical inflation to zero in the cyclical unemployment rate equation. (2) they also restrict the autoregressive coefficients of cyclical inflation in its own equation to zero on the premise that by removing the random walk inflation trend, any persistence that still remains is due to the cyclical unemployment rate, which displays considerable inertia. The restricted specification in Lee and Nelson (2007) closely resembles the specification in Stella and Stock (2013) except that the latter introduces stochastic volatility to all the latent components. Using Lee and Nelson framework, our forecasting results remain similar to the baseline results using Stella and Stock techniques, although the baseline is ordinally more accurate. That said, the estimates of the latent components are different, especially the estimate of the trend unemployment rate. The Lee and Nelson (2007) model is, as noted, simpler to implement and interested readers can contact the authors for those results.

[14] We employ the same procedures as found in Stella and Stock (2013)

[15] Specifically, they are constrained to satisfy the following conditions: $\alpha_2 <= 1 - abs(\alpha_1)$, and $\alpha_2 >= -1$, see Morley (1999).

The above steps are repeated for N+"burn in" draws.

At each forecast origin, the model is simulated with N+ "burn in" draws discarding the first "burn in" draws. For each draw, the forecasts of the services PCE inflation are generated by iterating forward the above model equations h periods forward (recursive substitution). The mean forecast of these N forecasts forms our posterior forecast of services PCE inflation.[16]

The h-step ahead forecast of services inflation for draw i, is

$$\hat{\pi}^{s}_{t+h,i} = \hat{\pi}^{s,*}_{t+h,i} + \hat{\pi}^{s,C}_{t+h,i} + \hat{\hat{\eta}}_{t+h,i} \tag{12}$$

$$where \;\; h = 1, ..., 8$$

Accordingly, the mean forecast for the PCE services inflation is:

$$\hat{\pi}^{s}_{t+h} = 1/N \sum_{i=1}^{N} \hat{\pi}^{s}_{t+h,i} \tag{13}$$

3.2 Modeling Goods Inflation

In modeling goods inflation, we adopt a parsimonious approach. That is, we assume that our best forecast for goods inflation next period is the current estimated trend of goods inflation. To estimate trend inflation, we explore various univariate specifications and choose the one that leads to the most accurate out-of-sample forecasts of goods inflation for horizons one quarter up to 12 quarters ahead over the period 1985:Q1 to 1993:Q4 (i.e. using sample that predates formal forecast evaluation sample).[17] The horse race includes various exponential smoothing specifications, moving average specifications ranging from one year to six years, HP filter, and the univariate unobserved components model with stochastic volatility (along the lines of Stock and Watson (2007)). The five-year moving average specification on average fared best, hence we choose that as our favored approach.[8] Interestingly, our method of five year moving average also performs quite well relative to other smoothing methods over the forecast evaluation sample period 1994:Q1 to 2014:Q4 (the sample period of interest)[18].

Specifically, an estimate of future goods inflation in our modeling framework is a simple arithmetic average of the available last five years of goods inflation data (i.e. moving average

[16]We simulate the model with N=10,000, and "burn in"=5,000

[17]All the models investigating goods inflation forecasts are estimated with data beginning 1959:Q1.

[8]This finding is consistent with that of Brayton, Roberts, and Williams (1999) who find that polynomial distributed lag specification of order up to 25 quarters fit much better for aggregate inflation than shorter unrestricted lags, and also with the finding of Stock and Watson (2007) who find that rational longer lag specification fits well for aggregate inflation.

[18]Alternatively, an exponential smoothing model with alpha=0.05 is a close approximation to the 5 year moving average, and could also have been used for the baseline. Since these results are quite similar to the forecasting evaluation performed over the training period 1985-1993 we do not report them but are available on request from the authors.

of last 20 quarters):[19]

$$\pi^g_{t+h} = 1/n \sum_{i=t-n}^{t} \pi^g_i \tag{14}$$

where n=20, we evaluate forecasts of goods inflation for values of n=1, 2, 3, 4, 5, 6, 8, 12, 16, 20, and 24. Using a value of n=20, leads to best forecasts of goods inflation over the pre-forecast evaluation sample (i.e. training sample), and so we stick with this value for our baseline model. Figure 9 plots the estimated trend goods inflation with the actual goods inflation. Table 4 reports the out-of-sample forecasting results comparing various smoothing methods in estimating the goods inflation trends over the training sample (1985:Q1 to 1993:Q4).

3.3 Forecasting Aggregate Inflation

The forecast of the aggregate inflation (quarterly annualized) at time t for h quarters ahead is simply the composite forecast of the services inflation forecast and the goods inflation forecast (both quarterly annualized) combined using the share weights available as of time t. The weights reflect the relative share of services inflation, and goods inflation in overall headline inflation. Specifically, the weight for services inflation is computed as nominal share of personal consumption expenditures of services over nominal PCE, similarly weight for goods inflation is computed as the nominal share of goods consumption expenditures over nominal PCE. Over our forecast evaluation sample (1994.Q1 to 2014.Q4), the shares have been fairly stable at roughly 65 percent going to services expenditure and the remaining 35 percent to goods expenditures.

$$\hat{\pi}_{t+h} = w^s_t \hat{\pi}^s_{t+h} + w^g_t \hat{\pi}^g_{t+h} \tag{15}$$

We compare the forecasting results of our framework against the following five benchmark models:

Random Walk model (Atkeson and Ohanian (2001)). According to this model, the forecasts of aggregate inflation for h-quarters into the future is simply the average of the most recent four available quarterly readings.

$$\hat{\pi}_{t+h} = 1/4 \sum_{i=t}^{t-3} \pi_i$$

[19] Multivariate modeling of all three components produced ordinary out-of-sample forecasting accuracy. A tri-variate state space model that jointly estimates the relationship between goods inflation, service inflation, and unemployment rate produced inferior forecasts for goods inflation. The model estimates since 1985 suggested weak empirical relationship between the cyclical unemployment rate and cyclical goods inflation. The estimation results of this tri-variate model specification are available on request from the authors. Movements in exchange rates and in energy prices influence goods inflation, so we also evaluate the forecasts of goods inflation from a multivariate model (BVAR) that consists of goods inflation, energy inflation, and exchange rates. With the exception of one period ahead, forecasts from this model were generally inferior to the best smoothing procedures.

Univariate AR4 model. An (unrestricted) autoregressive model of aggregate inflation with four lags. The forecasts of aggregate inflation for h-quarters into the future are computed iteratively.

We estimate the model using OLS, and then compute the one step ahead forecast for aggregate inflation as:

$$\hat{\pi}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1\pi_t + \hat{\beta}_2\pi_{t-1} + \hat{\beta}_3\pi_{t-2} + \hat{\beta}_4\pi_{t-3}$$

Similarly, the remainder of the forecasts for h-1 horizons are generated by recursive substitution as follows:

$$\hat{\pi}_{t+h} = \hat{\beta}_0 + \hat{\beta}_1\hat{\pi}_{t+h-1} + \hat{\beta}_2\hat{\pi}_{t+h-2} + \hat{\beta}_3\hat{\pi}_{t+h-3} + \hat{\beta}_4\hat{\pi}_{t+h-4}$$

Univariate AR1 inflation in gap model. This model is similar to that used in Faust and Wright (2013). They show that this simple model was the most accurate, only judgment forecasts (e.g. Survey of Professional Forecasts) were able to outperform it. Specifically inflation is modeled in a gap form[20],

$$\pi_t^{gap} = \beta_0 + \beta_1\pi_{t-1}^{gap} + \epsilon_t, \quad \epsilon_t \ i.i.d \ \ N(0,1)$$

where $\pi_t^{gap} = \pi_t - \pi_t^{LR}$ (π_t^{LR} refers to the long-run inflation expectations as measured by the Blue Chip consensus inflation expectation five-to-ten years ahead that are available in real-time).

The forecasts of inflation gap for h-quarters into the future are computed iteratively. Then the last available value of the trend (as of time t) is added to the forecast of the gap to compute the implied forecast of the aggregate inflation.

Stock and Watson (2007) univariate unobserved component model with stochastic volatility (UC-SV) model. This univariate UC-SV model has been among the most accurate models over the forecasting period of our focus. The model forecasts for aggregate inflation for h-quarters into the future are simply the model's current estimated trend inflation rate. Specifically it decomposes aggregate inflation into a stochastic trend component and a transitory component, assuming time varying variances of the respective shocks to these two components. The specification (consisting of four equations for estimation and one equation for forecasting) is as follows (retaining the notation in Stock and Watson (2007)):

$$\pi_t = \tau_t + \eta_t, \qquad where \ \ \eta_t = \sigma_{\eta,t}\zeta_{n,t} \qquad \zeta_{n,t} \ \ is \ \ i.i.d. \ \ N(0, I_1)$$

$$\tau_t = \tau_{t-1} + \varepsilon_t, \qquad where \ \ \varepsilon_t = \sigma_{\varepsilon,t}\zeta_{\varepsilon,t} \qquad \zeta_{\varepsilon,t} \ \ is \ \ i.i.d. \ \ N(0, I_1)$$

$$ln(\sigma^2_{\eta,t}) = ln(\sigma^2_{\eta,t-1}) + \nu_{\eta,t}, \qquad where \ \ \nu_{\eta,t} \ \ is \ \ i.i.d. \ \ N(0, \gamma I_1)$$

[20] We modify the Faust and Wright (2013) 'fixed-ρ' specification by adding the intercept term, and estimated coefficients.

$$ln(\sigma^2_{\varepsilon,t}) = ln(\sigma^2_{\varepsilon,t-1}) + \nu_{\varepsilon,t}, \qquad where\ \ \nu_{\varepsilon,t}\ \ is\ i.i.d.\ N(0, \gamma I_1)$$

γ is a scalar parameter that helps characterize the smoothness of the stochastic volatility process, and so it can either be estimated or fixed. We follow Stock and Watson (2007) and fix it at 0.2.

Forecast of the future aggregate inflation is the current estimated trend inflation (i.e. filtered estimate of τ_t)

$$\hat{\pi}_{t+h} = \hat{\tau}_t$$

Stella and Stock (2013) Phillips Curve (PC). As discussed earlier, our services inflation Phillips curve specification closely follows Stella and Stock (2013). They jointly model aggregate inflation and overall unemployment and find empirical support of the existence of the Phillips curve. We use their model to produce forecasts of aggregate inflation.

Three variable BVAR. Given quarterly data on services inflation, goods inflation, and unemployment rate, one could simply estimate a Bayesian Vector Auto-Regression of these three variables. The quarterly forecasts of the services and goods inflation from the BVAR can be combined using the expenditure weights to form a composite forecast of aggregate inflation. We estimate a small BVAR in growth rates (four lags) estimated with the Minnesota and Sum of coefficient (SOC) priors as one of the benchmark models. We set to one the values of the both the hyper parameters that control for the tightness for Minnesota and SOC priors. Results in which values for the hyper parameters at each forecast origin are determined by maximizing the marginal likelihood leads to substantially less accurate forecasts of inflation medium to long-run.

Let us denote vector $Y_t = [\pi^g_t, \pi^s_t, UR_t]$, then the forecasts are computed as follows

$$\begin{aligned}
\hat{Y}_{t+h} &= B_0 + B_1\hat{Y}_{t+h-1} + B_2\hat{Y}_{t+h-2} + B_3\hat{Y}_{t+h-3} + B_4\hat{Y}_{t+h-4} \\
\hat{\pi}_{t+h} &= w^s_t\hat{\pi}^s_{t+h} + w^g_t\hat{\pi}^g_{t+h}
\end{aligned}$$

3.4 Services Inflation and Short-Term Unemployment Rate

Gordon (2013) and Ball and Mazumder (2014) provide evidence that inflation behavior of the past few years fits much better using short-term unemployment rate as the proxy for real activity in the Phillips curve. The short-term unemployment rate, measured as the share of labor force unemployed for 26 weeks or less, is likely the more relevant measure of wage and price slack because it is claimed that the long-term unemployed exert negligible downward pressure on wages and inflation. Empirical evidence in Clark (2014) finds little support for using short-term unemployment rate versus overall unemployment rate in his empirical framework; the model in his paper can explain equally well the recent inflation behavior without using the short-term unemployment rate. Proponents of using short-term unemployment rate in the Phillips curve claim to solve the missing disinflation puzzle (fall in inflation predicted by conventional models that did not materialize) in the aftermath of the crisis. Clark (2014), however, explains the missing disinflation by treating trend inflation as long-run forecast from the Survey of Professional Forecasts (SPF) instead of the random-walk trend that is a common feature of the conventional models.[21]. He argues that it is the treatment of inflation trend that matters not the choice of the overall unemployment rate or the short-term rate.

Given the mixed evidence, we investigate whether there are gains in the forecast accuracy of the aggregate inflation if we use short-term unemployment versus the overall unemployment rate in the specification of the services inflation forecasting model. We denote our inflation in parts specification that uses short-term unemployment rate as STU spec, and the one that uses overall unemployment rate as OU spec.

4 Results

4.1 In Sample Results

Figures 1 and 2 plot the posterior estimate of the natural rate of unemployment along with the 90 percent probability band from the inflation in parts OU spec (upper panel) and STU spec (lower panel) models respectively. The estimated trend unemployment (i.e. model's implied natural rate) averages around 5.5 percent, and the point estimate does not move above 6 or below 5 through the entire estimation and forecast sample. The model attributes most of the time variation in the overall unemployment rate to the cyclical component. The degree of uncertainty around the posterior estimate of the natural rate is quite wide as the 90 percent probability band on average ranges from -1 to +1 percentage points. On the other hand, estimated trend unemployment for the short-term unemployment rate (spec 2), exhibit somewhat more movements. Over our sample, it has ranged between 4 and 5 percent, it inched few tenths higher at depths of the financial crisis, since then has gradually fallen, and currently is about couple tenths lower than 4 percent (lowest reading since 1960). Again, the uncertainty around this estimate is quite wide.

Figure 3 plots the posterior estimate of the trend in services inflation (including the uncertainty around it) alongside the actual services inflation for OU spec. The trend estimate for services inflation generally moves in tandem with actual services inflation up until about 1990. Since then, trend inflation has ranged between 2 and 4 percent and movements in actual services inflation are largely attributed to cyclical factors. Over the last three years, estimated trend services inflation has been declining and was 2.1 percent at the end of 2014. [22]

Figure 4 plots the estimated trend in services inflation alongside the actual services inflation for STU spec. Among the differences between the two specifications, the gap between the trend and actual services inflation over the past few years (i.e. post-crisis period) is substantially narrower (close to zero in the past two years or so) in the case of STU spec. The short-term unemployment rate has been falling sharply in the past few years in turn helping to moderate the gap between the estimated trend and actual services inflation (i.e. cyclical component) and

[21] SPF is available from the Federal Reserve Bank of Philadelphia

[22] The overall unemployment rate declined slowly so that the gap between the estimated trend and actual services inflation has been elevated. In the past few quarters the gap has diminished driven mainly by sharp fall in the overall unemployment rate. Overall, the contours of the trend services inflation estimated by the model are quite similar to the estimated trend in aggregate inflation estimated in various other studies such as Cogley and Sargent (2002), Ireland (2007), Lee and Nelson (2007), Cogley and Sbordone (2008), and Kim, Manopimoke, and Nelson (2014).

the trend that has been quite stable around 2.2 percent (since the end of the Great Recession). In the last two quarters (i.e. 2014:Q3, and 2014:Q4), the estimated trend has slightly inched lower to 2.0 percent.

Figure 5 plots the posterior estimate of the (common) cyclical component of the unemployment rate along with the recession bars (as dated by the National Bureau of Economic Research dating committee). The visual inspection of the figure suggests movements in the cyclical component unemployment rate are in line with the business cycle. That is, cyclical unemployment increases during recessions, and similarly the cyclical component of unemployment falls with an expanding economy. Figure 6 plots the estimated cyclical short-term unemployment rate component; as in the previous figure, the cyclical component short-term unemployment accords with the Business cycle.

Figure 7 plots the time-varying posterior estimate of the slope of the Phillips curve displaying a negative (inverse) relationship between services inflation gap and the unemployment rate gap. In our sample, the posterior estimate varies very little between -0.17 and -0.2 percent with 90 percent band ranging between -0.1 and -0.35 percent. Figure 8 plots the equivalent estimates from STU spec in which the posterior estimate of the slope varies between -0.2 and -0.35 percent with the 90 percent band ranging from -0.1 to -0.58 percent. The estimated slope steepened in the 1970-80s, flattened in the 90s, steepened from the late 1990s until the onset of the Great Recession, and then flattening out sharply from that point. The estimates exploit a Phillips curve relationship that varies over the business cycle and there is considerable uncertainty around it.

4.2 Pseudo Out-of-Sample Forecasting Results

In this section, we compare the point forecast evaluation statistics of our inflation in parts framework with the models described above. Relative root mean square error (RMSE) is the accuracy metric for comparing point forecast accuracy for horizons from 1 to 12 quarters ahead, all of which are included in Tables 1 and 2. The target variable is the quarterly annualized PCE inflation rate. Given limited availability of real time data for services and goods PCE inflation separately, we resort to pseudo out of sample forecast evaluation. Hence, we use the data vintage as of first quarter of 2015. To gauge whether the forecast gains are statistically significant we report the significance statistics from the Diebold-Mariano test (with the Newey-West correction) for equal forecast accuracy between the inflation in parts model and the alternative benchmark models.

We evaluate forecast accuracy using an expanding window of data. That is, we increase the estimation sample by one quarterly observation for each forecast. Specifically, the initial estimation sample runs from 1960:Q1 to 1993:Q4 (generating forecasts from 1994:Q1 to 1996:Q4). We then estimate the model using data from 1960:Q1 to 1994:Q1 (forecasts from 1994:Q2 to 1997:Q1), .., and the final sample runs from 1960:Q1 to 2014:Q3. Accordingly, the forecast evaluation sample spans 1994:Q1 to 2014:Q4, giving us about 84 one-step ahead forecast errors, 83 two-step ahead errors, 82 three-step ahead errors and so on. We denote this as the full-sample, but also report results of the forecast sample that end in 2007:Q3 (denote it as 'pre-crisis' sample), meaning that we use no data beyond 2007:Q3 to evaluate the forecasts. The limited sample results provide a check on the robustness of our results and help evaluate the impact of the financial crisis on the forecast accuracy of inflation from these models.

Table 1 reports forecast evaluation results for the OU spec. The first panel of the table reports results for the full sample (1994:Q1 - 2014:Q4) and the second panel for the pre-crisis sample (i.e. 1994:Q1 to 2007:Q3). The first row reports the root mean square errors (RMSE) of the inflation in parts model. The remaining rows report relative root mean square error (relative RMSE) in which each row reports the ratio of RMSE of benchmark model listed in that row (numerator) relative to inflation in parts model (OU spec, denominator). So a ratio (relative RMSE) of greater than one indicates that inflation in parts model is on average more accurate in forecasting aggregate inflation than the corresponding benchmark alternative.

On average over the full forecast evaluation sample, the inflation forecasts from the inflation in parts model that exploits the Phillips curve relationship between services inflation and unemployment rate are at least as accurate than any of the alternative benchmark models. The statistically significant forecasting improvement occurs mainly from the 4 quarter or longer forecast horizon.

Among the specific alternative benchmarks, the inflation in parts forecasts are about 6 to 10 percent more accurate (and in some cases statistically significantly more accurate) than the forecasts generated from the model that exploits the Phillips curve relationship between aggregate inflation and unemployment (Stella and Stock 2013). The inflation in parts model retains an accuracy improvement over the pre-crisis sample. Forecasts from the inflation in parts model are on average 15 to 25 percent more accurate than forecasts from the univariate autoregressive process of aggregate inflation (AR4) over the full sample. Again the forecast improvements are statistically significant. The forecasting gains extend to the pre-crisis sample, and are statistically significant in medium and long-term only with about 20 to 30 percent more accurate in relative sense.

The inflation forecasts from AR1 gap model over the full-sample are on average less accurate anywhere from 1 to 10 percent (and 0 to 19 percent over the pre-crisis sample) compared to inflation in parts model but are statistically not significant. It is worth noting that once inflation is modeled in gap form (i.e. deviation from its long-run trend) inflation forecasts in the medium to longer horizons are substantially more accurate compared to say AR4 model in which inflation is modeled without accounting for its underlying slowly varying long-run trend (results consistent with Faust and Wright 2013, and Zaman 2013).

Over the full-sample the inflation in parts model outperforms the univariate benchmarks: Atkeson and Ohanian (2001) (RW) and Stock and Watson (2007). We see forecasting accuracy improvements relative to Atkeson and Ohanian (2001) that are statistically significant in the majority of the horizons. The Stock and Watson (2007) forecasts are statistically not significantly different from those of the inflation in parts model. Over the pre-crisis forecast evaluation sample, the inflation in parts model displays RMSE statistics that are statistically significantly lower than both Atkeson and Ohanian (2001) and Stock and Watson (2007) starting at 5 quarter forecast horizon and beyond.

The inflation in parts model outperforms the three variable BVAR both in full-sample and pre-crisis sample. The RMSE over the full sample are on average 20 percent smaller and statistically significant; and in the pre-crisis sample the relative forecast error reduction ranges from 10 percent in the short-term horizon to 30 percent or more in the later horizon, and are mostly statistically significant.

Table 2 reports the forecast evaluation results for the Inflation in parts model (STU spec) and compares them with the same benchmark models used in Table 1 for both full sample and pre-crisis sample. We find evidence in support of using short-term unemployment rate in the services inflation model. The improvements on average are modest; the RMSE for STU spec are slightly better than OU spec. However, Table 2 displays several more statistical significant forecast improvements compared to those reported in Table 1 for OU spec. For the univariate benchmarks of Atkeson and Ohanian (2001) and Stock and Watson (2007), forecast accuracy improvements appear to be statistically significant in general. Overall, the results are robust to forecast evaluation sample (pre-crisis and the full-sample).

We employ the Stella and Stock (2013) model using short-term unemployment rate to estimate the relationship between short-term unemployment rate and aggregate inflation (denote this SS (2013) Short-UR). The exercise helps uncover whether the relationship between aggregate inflation and the chosen unemployment rate measure differs from the relationship between services inflation and the chosen unemployment measure. The last row of both panels in Table 2 shows the relative performance of this specification to inflation in parts STU spec. As can be observed, STU spec outperforms SS (2013) Short-UR and the relative gains are very much in line with the gains STU spec achieved over the Stella and Stock (2013) that uses overall unemployment. In the pre-crisis period there does not appear to be much benefit in using short-term unemployment with aggregate inflation but post-crisis period the relative RMSE in full-sample is somewhat smaller for the short-UR specification. The inflation in parts model outperformed the Stella and Stock (Short UR) by smaller margin than the original Stella and Stock (2013), suggesting that in a model with aggregate inflation the use of overall or short-term unemployment does not matter for out-of-sample forecasting in the pre-crisis period. Second, the use of short-term unemployment rate with services inflation is helpful because the out-of-sample forecasts of aggregate inflation from the model that uses services inflation and short-term unemployment rate are statistically more accurate over both the pre-crisis and post-crisis samples.

It is worth mentioning, that across the board root mean square errors for the aggregate inflation over the pre-crisis sample are notably smaller compared to the evaluation sample that includes the Great Recession period. The RMSEs over the pre-crisis forecast evaluation sample are on average five tenths lower (equivalently 40 to 50 percent lower).

We compare the accuracy of services inflation forecasts from the OU spec versus STU spec to gauge the relative predictive value of short-term versus overall unemployment rate in the specification. Table 3 reports the root mean square errors (RMSE) for services inflation for OU and STU specs respectively. STU spec forecasts are more accurate than those of OU spec and the degree of improvement somewhat varies depending on the forecast horizon. For example, over the full forecast evaluation sample, one step ahead, STU spec RMSE for services inflation is 0.489 versus 0.500 from OU spec, an improvement of about 3 percent, and 9 quarters out the RMSE is 0.941 versus 0.989, a modest 5 percent improvement. The forecast improvements are generally greater over the pre-crisis evaluation sample with services inflation forecasts from STU spec 10,11, and 12 steps ahead about 7 to 9 percent more accurate compared to those from OU spec.

All in all, the forecasting results provide modest evidence of statistically significant improvements in the accuracy of the aggregate inflation forecasts using a composite forecasting model of services and goods inflation that exploits the short-run relationship between services inflation and short-term unemployment rate (Phillips curve).

5 Conclusions

In this paper, we model aggregate inflation by estimating sub-components of inflation (services and goods separately). We employ the unobserved components model with stochastic volatility as in Stella and Stock (2013) to exploit the correlation between unemployment and services inflation as emphasized in Peach, Rich and Linder (2013) and use a simple moving average for the goods component of inflation. We estimate the models from 1960:Q1 to 1993:Q4, forecast from 1 to 12 quarters ahead and iterate this process in an increasing data window until the end of 2014. The combination of forecasts from the subcomponents produces aggregate inflation forecast that displays smaller RMSE than a set of the leading inflation forecasting (benchmark) models. We note that the contribution to forecast accuracy arising from the empirical Phillips Curve relationship is notable, and we also find that there are further gains in forecast accuracy over this period when using the short-term unemployment rate in the model for services inflation.

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6 Tables and Figures

Figure 1: Decomposition of Total Unemployment Rate (Inflation in Parts OU-Spec)

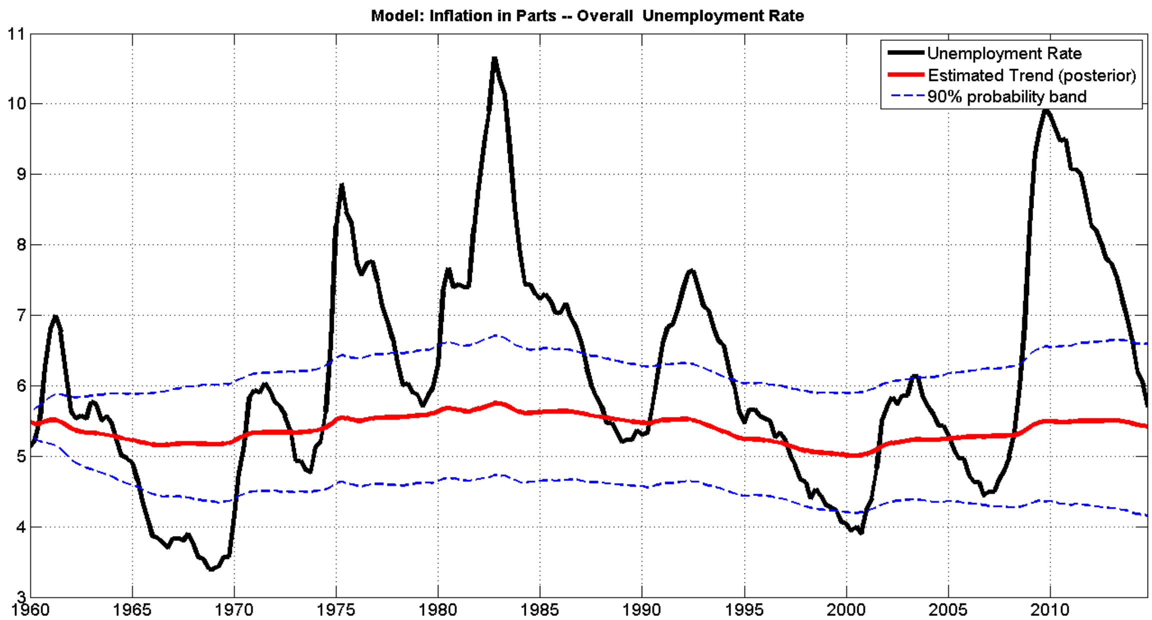
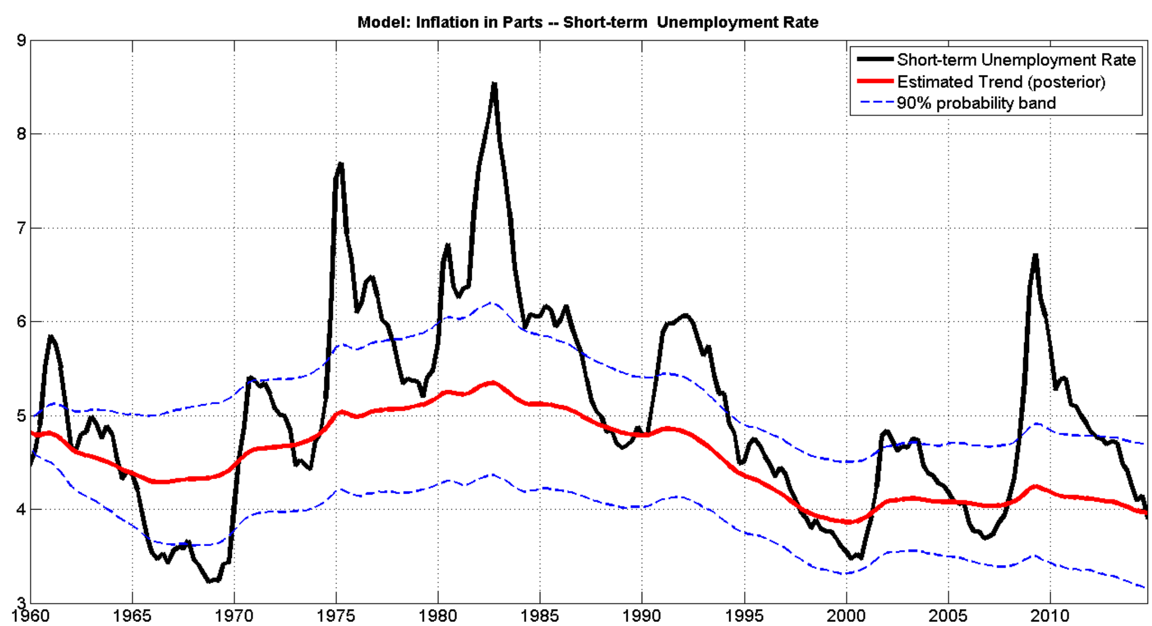


Figure 2: Decomposition of Short-Term Unemployment Rate (Inflation in Parts STU-Spec)



Notes: The estimates above are smoothed, reflecting information based on full-sample from 1960:Q1 through 2014:Q4.

Figure 3: Decomposition of Services Inflation (Inflation in Parts OU-Spec)

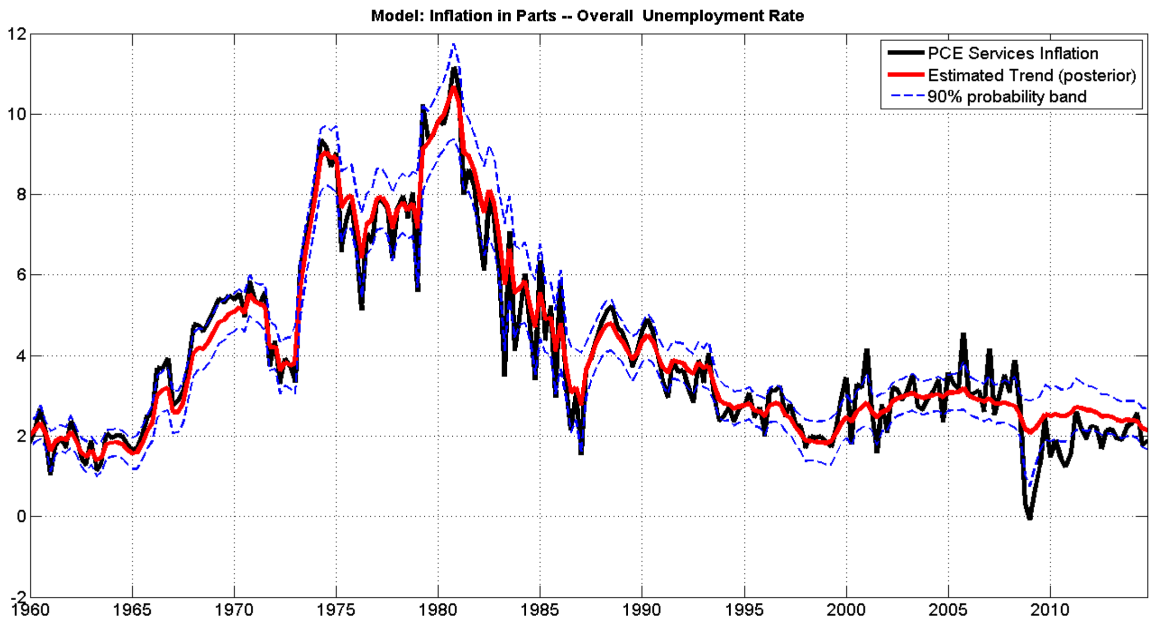
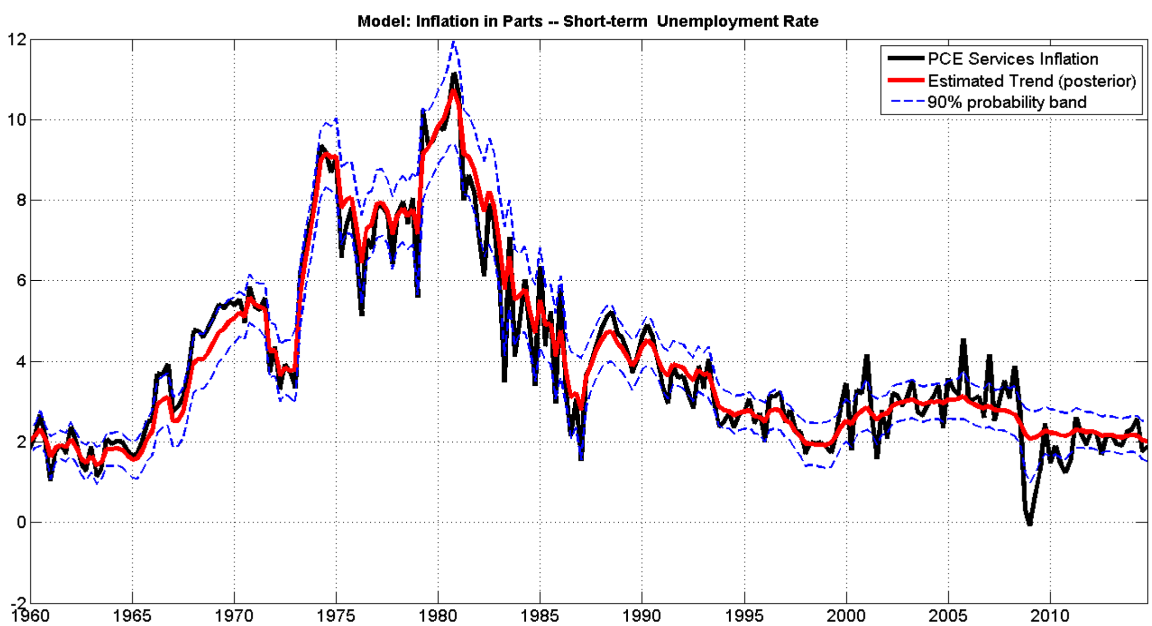


Figure 4: Decomposition of Services Inflation (Inflation in Parts STU-Spec)



Notes: The estimates above are smoothed, reflecting information based on full-sample from 1960:Q1 through 2014:Q4.

Figure 5: Cyclical UR – common cyclical component (Inflation in Parts OU-Spec)

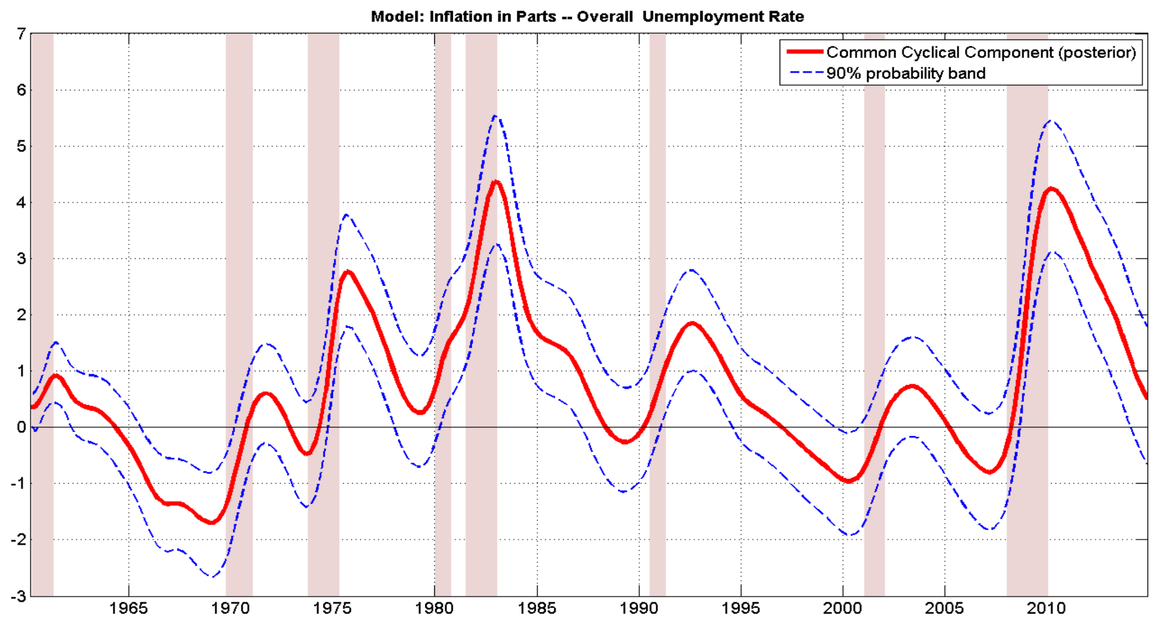
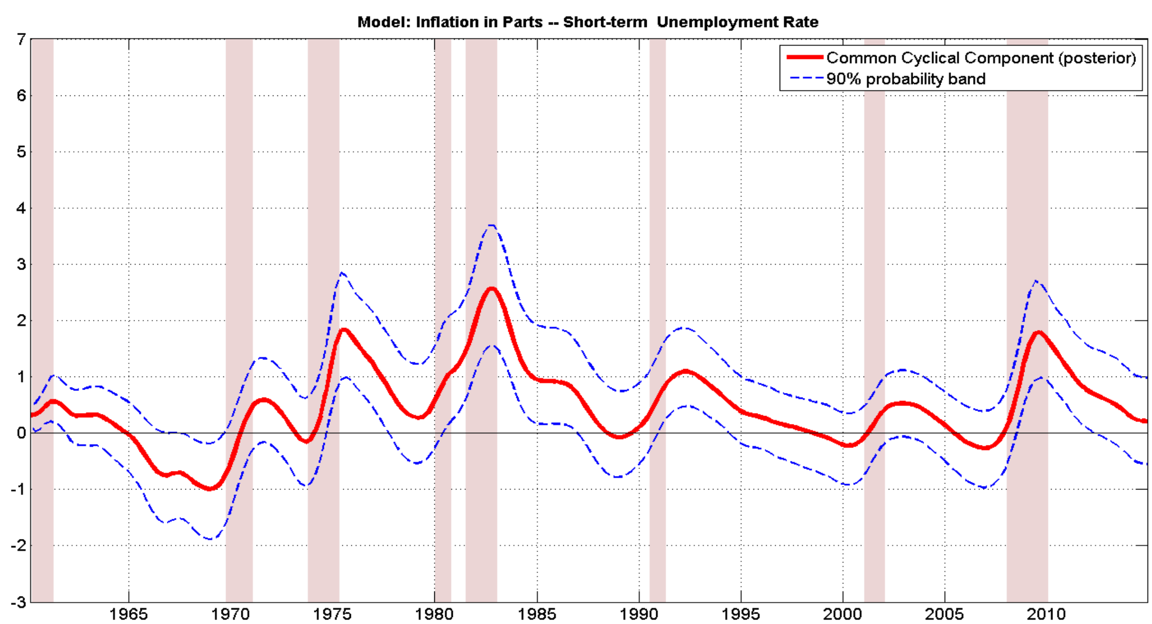


Figure 6: Cyclical Short UR – common cyclical component (Inflation in Parts STU-Spec)



Notes: The estimates above are smoothed, reflecting information based on full-sample from 1960:Q1 through 2014:Q4.

Figure 7: Time-varying estimate of implied slope of Phillips curve: Inflation in Parts OU-Spec

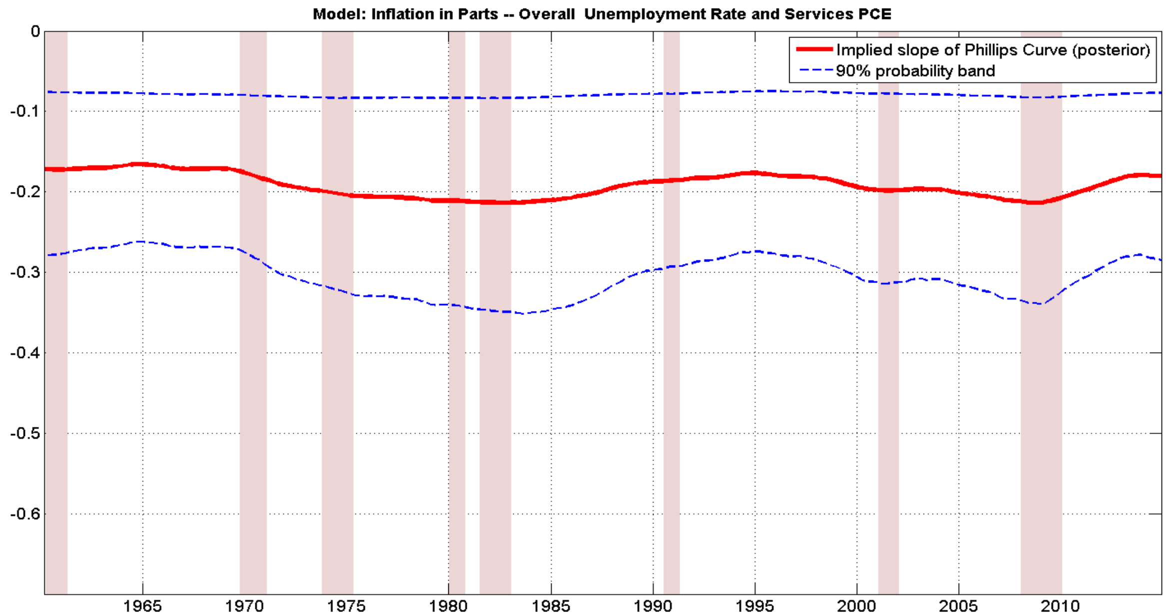
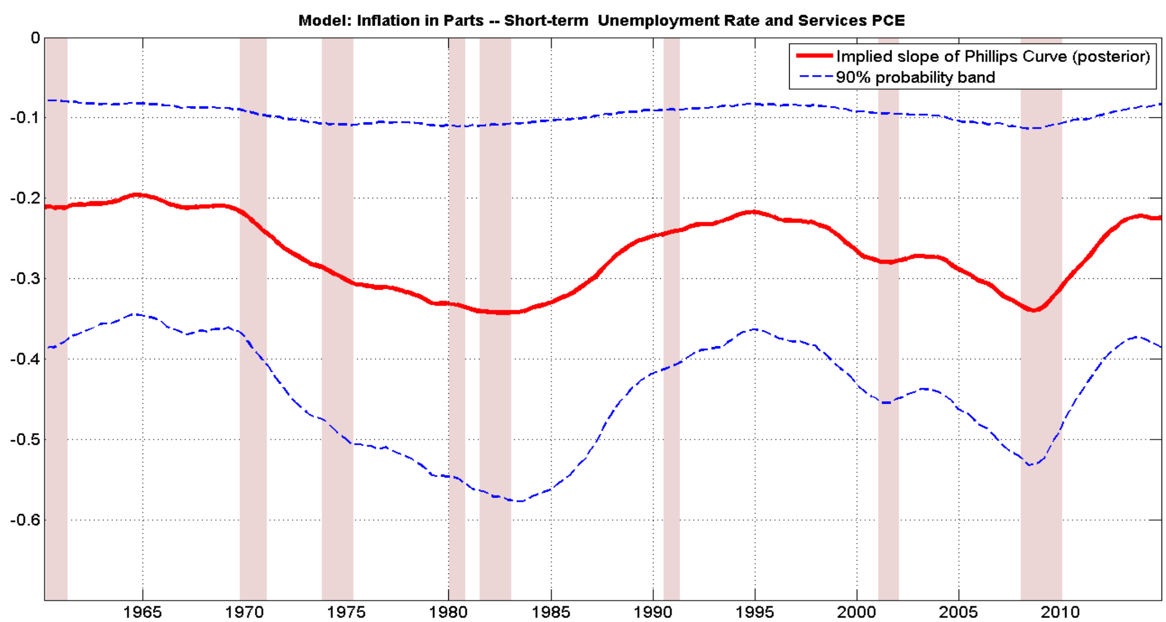


Figure 8: Time-varying estimate of implied slope of Phillips curve: Inflation in Parts STU-Spec



Notes: The estimates above are smoothed, reflecting information based on full-sample from 1960:Q1 through 2014:Q4.

Figure 9: Goods PCE Inflation and the Estimated Trend

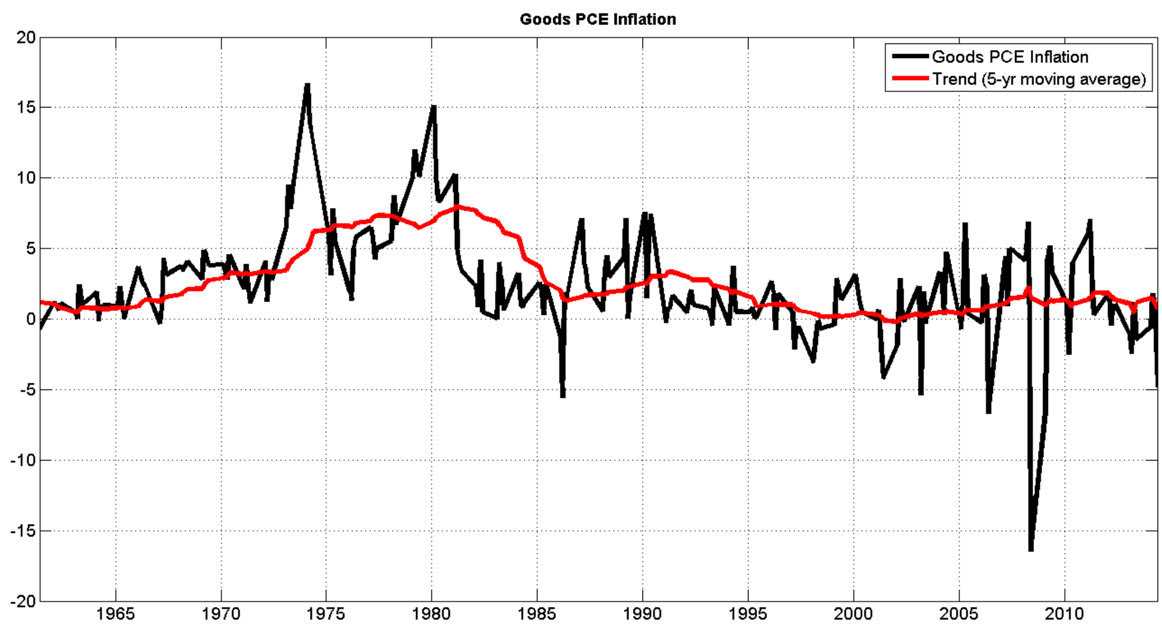


Table 1: PCE Inflation Pseudo out-of-sample Forecasting Performance of Inflation in Parts Model (OU-Spec)

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)												
Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Inflation in Parts OU-Spec Relative RMSE	1.450	1.526	1.533	1.522	1.489	1.536	1.594	1.586	1.576	1.558	1.565	1.582
Inflation in Parts OU-Spec	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.041	1.062*	1.052	1.081***	1.096***	1.085**	1.088**	1.091*	1.096**	1.111***	1.084***	1.071***
AR4	1.066	1.216*	1.221	1.225**	1.203**	1.180**	1.211**	1.235***	1.280***	1.316***	1.298***	1.298***
AR1 gap	1.028	1.097	1.041	1.074**	1.054	1.016	1.007	1.011	1.027	1.053	1.058	1.049
RW (Atkeson and Ohanian)	1.117*	1.110*	1.077	1.098*	1.101***	1.095*	1.112	1.105	1.102	1.118*	1.082***	1.081**
Stock and Watson (2007)	1.013	1.020	1.012	1.042*	1.044*	1.021	1.015	1.026	1.034	1.052	1.030*	1.021
Three variable BVAR	1.123	1.265	1.294	1.284**	1.242**	1.202**	1.203**	1.223***	1.271***	1.306***	1.286***	1.288***

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)												
Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Inflation in Parts OU-Spec Relative RMSE	0.965	1.004	1.069	1.087	1.042	1.090	1.110	1.115	1.113	1.112	1.159	1.119
Inflation in Parts OU-Spec	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.048	1.064	1.029	1.095	1.167***	1.115	1.126	1.216**	1.177	1.176**	1.148***	1.131***
AR4	1.107	1.104	1.083	1.206**	1.281*	1.245	1.293	1.399**	1.405**	1.437**	1.443*	1.472*
AR1 gap	1.162	1.109	0.983	1.066	1.138	1.088	1.090	1.143	1.141	1.157	1.154	1.192
RW (Atkeson and Ohanian)	1.071	1.079	1.033	1.057	1.152**	1.117***	1.128**	1.168***	1.120*	1.102**	1.027**	1.067
Stock and Watson (2007)	1.006	1.026	0.991	1.067*	1.121***	1.072*	1.088*	1.162***	1.118*	1.106**	1.076***	1.041
Three variable BVAR	1.144	1.110	1.153	1.240**	1.356**	1.283**	1.378*	1.446***	1.428***	1.467**	1.449*	1.483*

Notes for Table: The first row reports the Root Mean Square Errors from the Inflation in Parts Model. All other rows report the ratios of the Root Mean Square Errors of the various models relative to the Inflation in Parts OU-Spec (i.e. UC model that uses total UR). So a ratio of more than 1, indicates that the Inflation in Parts model does better than the particular model. The forecast performance is based on recursive estimation, i.e. expanding sample. The table reports statistical significance based on Diebold-Mariano test (*10 percent, **5 percent, and ***1 percent significance levels respectively). Stock-Watson (2007) refers to univariate UC-SV model. Atkeson and Ohanian (2001) quarterly random walk model forecasts in our exercise are the quarterly average of the lagged four quarter available PCE inflation annualized rates. Three variable BVAR consists of unemployment rate, services inflation, and goods inflation, and is equipped with the Minnesota and Sum of Coefficient priors. The hyper values of the prior are set to one. The composite forecast of aggregate inflation is computed at recursive forecast evaluation round by combining the goods and services inflation forecasts using the actual weights as of the forecast origin date.

Table 2: PCE Inflation Pseudo out-of-sample Forecasting Performance of Inflation in Parts Model (STU-Spec)

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)												
Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Inflation in Parts STU-Spec	1.443	1.513	1.520	1.506	1.471	1.510	1.564	1.557	1.547	1.529	1.536	1.558
Relative RMSE												
Inflation in Parts STU-Spec	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.046	1.071*	1.061	1.093***	1.110***	1.104**	1.109**	1.111*	1.115**	1.131***	1.104**	1.088**
AR4	1.071	1.226*	1.231	1.238**	1.218**	1.200**	1.234***	1.258***	1.304***	1.340***	1.323***	1.318***
AR1 gap	1.033	1.107*	1.049	1.086**	1.067*	1.034	1.026	1.030	1.046	1.073	1.078	1.066
RW (Atkeson and Ohanian)	1.122*	1.120*	1.086	1.110*	1.115***	1.115*	1.133	1.126	1.122	1.139**	1.103***	1.098***
Stock and Watson (2007)	1.017	1.029	1.020	1.054**	1.057***	1.039	1.035	1.045*	1.053*	1.071***	1.049***	1.037***
Three variable BVAR	1.129	1.277	1.305*	1.298**	1.258***	1.224**	1.226***	1.246***	1.294***	1.331***	1.311***	1.308***
SS (2013) Short UR	1.015	1.035	1.022	1.050**	1.057***	1.048*	1.058**	1.050	1.057	1.075***	1.047***	1.036***

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)												
Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Inflation in Parts STU-Spec	0.967	1.004	1.068	1.081	1.040	1.085	1.101	1.108	1.102	1.101	1.138	1.101
Relative RMSE												
Inflation in Parts STU-Spec	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.046	1.064	1.030	1.101	1.170**	1.121	1.135	1.223**	1.190	1.188*	1.169***	1.149***
AR4	1.104	1.103	1.084	1.213**	1.284*	1.251	1.304*	1.408**	1.420***	1.451**	1.469**	1.497*
AR1 gap	1.160	1.108	0.984	1.071	1.140	1.093	1.099	1.149	1.154	1.169	1.175	1.212
RW (Atkeson and Ohanian)	1.068	1.079	1.034	1.062	1.154**	1.123**	1.138**	1.175***	1.132*	1.112**	1.046**	1.084
Stock and Watson (2007)	1.004	1.026	0.992	1.073	1.123***	1.077	1.097*	1.169***	1.130*	1.117**	1.095***	1.058**
Three variable BVAR	1.141	1.110	1.154	1.246***	1.359***	1.289***	1.329**	1.455***	1.444***	1.482***	1.474*	1.507*
SS (2013) Short UR	1.031	1.044	1.004	1.075	1.140***	1.087	1.103	1.187**	1.145	1.136*	1.109***	1.083***

Notes for Table: The first row reports the Root Mean Square Errors from the Inflation in Parts Model. All other rows report the ratios of the Root Mean Square Errors of the various models relative to the Inflation in Parts STU-Spec (i.e. UC model that uses short-term UR). So a ratio of more than 1, indicates that the Inflation in Parts STU-Spec model does better than the particular model. The forecast performance is based on recursive estimation, i.e. expanding sample. The table reports statistical significance based on Diebold-Mariano test (*10 percent, **5 percent, and ***1 percent significance levels respectively). Stock-Watson (2007) refers to univariate UC-SV model. Atkeson and Ohanian (2001) quarterly random walk model forecasts in our exercise are the quarterly average of the lagged four quarter available PCE inflation annualized rates. Three variable BVAR consists of unemployment rate, services inflation, and goods inflation, and is equipped with the Minnesota and Sum of Coefficient priors. The hyper values of the prior are set to one. The composite forecast of aggregate inflation is computed at recursive forecast evaluation round by combining the goods and services inflation forecasts using the actual weights as of the forecast origin date.

Table 3: Services PCE Inflation Pseudo out-of-sample Forecasting Performance Inflation in Parts Model OU-Spec versus STU-Spec

Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)												
Inflation in Parts OU-Spec	0.500	0.634	0.728	0.744	0.736	0.852	0.897	0.935	0.989	0.978	1.046	1.128
Inflation in Parts STU-Spec	**0.489**	**0.608**	**0.705**	**0.717**	**0.713**	**0.819**	**0.870**	**0.899**	**0.941**	**0.942**	**1.006**	**1.099**
Pre-Crisis (Recursive evaluation: 1994.Q1-2007.Q3)												
Inflation in Parts OU-Spec	0.407	0.430	0.494	0.496	0.492	0.648	0.641	0.623	0.624	0.596	0.675	0.713
Inflation in Parts STU-Spec	**0.398**	**0.416**	**0.482**	**0.478**	**0.475**	**0.619**	**0.623**	**0.597**	**0.577**	**0.564**	**0.622**	**0.662**

Notes for Table: The table reports the Root Mean Square Errors from the Inflation in Parts Model OU-Spec (the model that uses total unemployment Rate), and Inflation in Parts Model STU-Spec (the model that uses short-term unemployment rate). Bold entries refer to the smaller Root Mean Square Error at a given horizon of two models being compared.

Table 4: Which smoothing method for Goods Inflation? Using Forecasting Performance over **1985:Q1 to 1993:Q4**

Smoothing method	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12	
	Root Mean Square Error (RMSE)												Average RMSE
UC-SV	2.947	3.240	3.230	3.697	3.429	2.950	2.990	3.356	3.501	3.693	3.847	3.672	3.379
AR4	2.814	3.078	3.184	3.454	3.156	2.853	2.527	2.708	2.809	2.890	2.966	2.908	2.946
Last value	3.071	3.753	3.429	4.212	3.767	3.518	3.325	3.727	3.997	4.109	4.449	4.229	3.799
MA: 2q	2.912	3.137	3.410	3.717	3.235	2.947	3.025	3.307	3.586	3.787	3.848	3.634	3.379
MA: 3q	2.836	3.143	3.252	3.238	2.948	2.882	2.896	3.235	3.546	3.559	3.474	3.175	3.182
MA: 4q (AO)	2.903	3.083	3.021	3.019	2.922	2.924	2.939	3.288	3.506	3.340	3.215	3.163	3.110
MA: 5q	2.866	2.649	2.844	2.952	2.907	2.950	3.001	3.220	3.291	3.128	3.166	3.124	3.008
MA: 6q	2.673	2.774	2.805	2.923	2.934	3.047	2.969	3.109	3.133	3.090	3.117	3.115	2.974
MA: 8q	2.641	2.758	2.849	3.039	3.075	3.051	2.852	3.003	3.124	3.080	3.196	3.157	2.985
MA: 12q	2.783	2.852	2.889	2.993	3.030	3.072	2.951	3.060	3.100	2.969	2.954	2.893	2.962
MA: 16q	2.764	2.888	3.011	3.084	3.129	3.119	2.817	2.868	2.866	2.814	2.807	2.749	2.910
MA: 20q	2.904	3.024	3.114	3.149	3.210	3.171	2.695	2.690	2.652	2.606	2.598	2.620	**2.870**
MA: 24q	3.084	3.216	3.283	3.277	3.329	3.182	2.563	2.570	2.509	2.530	2.571	2.580	2.891
ExpSmooth(alpha 0.05)	3.166	3.209	3.211	3.184	3.190	3.057	2.547	2.549	2.541	2.562	2.607	2.624	2.871
ExpSmooth(alpha 0.15)	2.923	3.013	3.034	3.101	3.039	2.958	2.720	2.821	2.901	2.856	2.867	2.808	2.920
ExpSmooth(alpha 0.25)	2.941	3.063	3.079	3.202	3.054	2.944	2.829	3.005	3.144	3.126	3.150	3.054	3.049
ExpSmooth(alpha 0.5)	3.079	3.283	3.283	3.570	3.253	2.936	2.890	3.176	3.377	3.466	3.554	3.379	3.270
Hpfilter	3.142	3.248	3.287	3.422	3.358	3.385	3.418	3.567	3.711	3.634	3.640	3.576	3.449
BVAR (energy,exc rate, goods)	3.219	3.634	3.450	3.223	2.735	2.839	2.908	3.294	3.478	3.298	2.978	2.890	3.162

Notes for Table: The table reports the Root Mean Square Errors of goods PCE inflation (quarterly annualized) from the various smoothing methods/models. The last column reports the average of the columns (h=1 to h=12), and is the metric used to select the smoothing method that will be used to forecast goods inflation over the forecasting period of interest (which is 1994:Q1 to 2014:Q4). The estimation sample begins 1959:Q1.

Online Appendix

A1. Results Using Consumer Price Inflation (CPI)

Figure 10: Decomposition of Total Unemployment Rate (**CPI** Inflation in Parts OU-Spec)

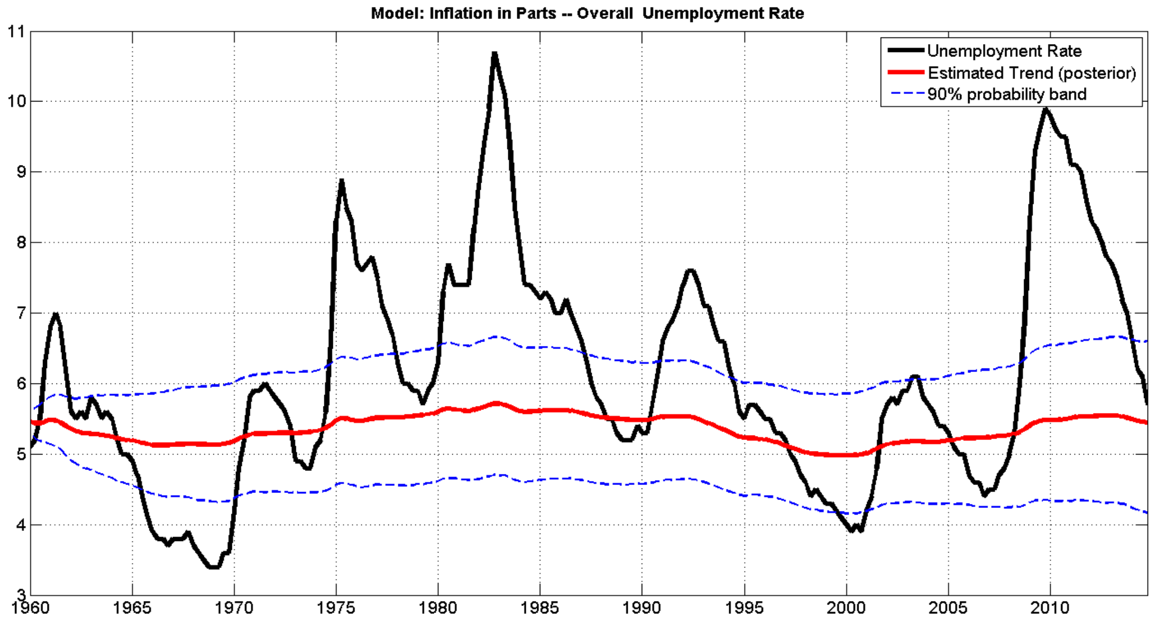
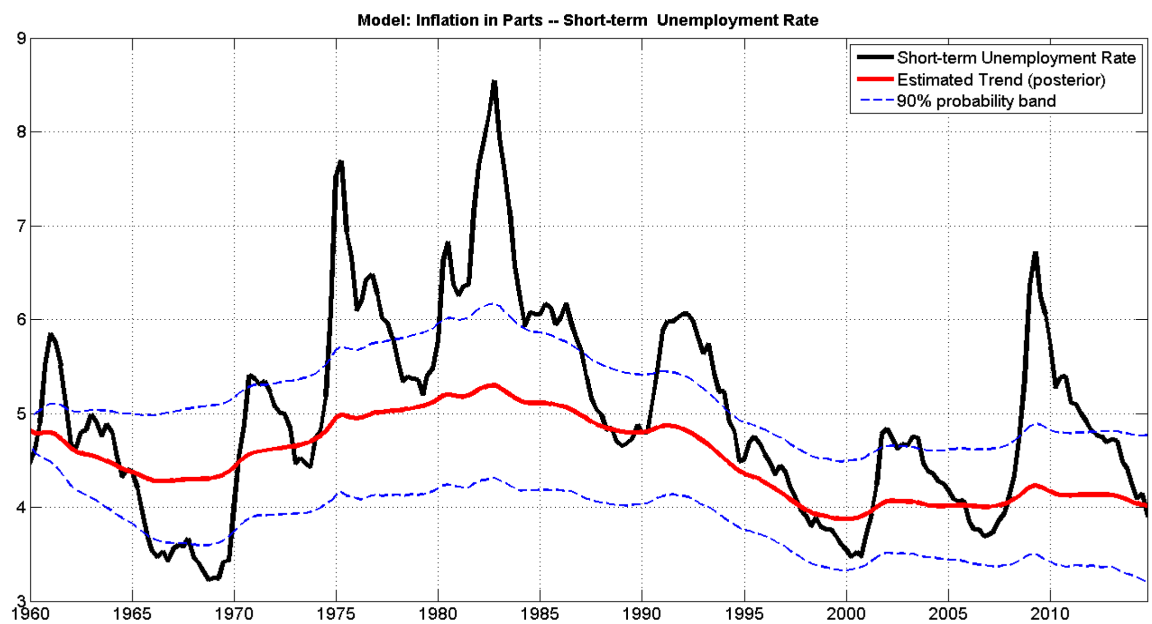


Figure 11: Decomposition of Short-Term Unemployment Rate (**CPI** Inflation in Parts STU-Spec)



Notes: The estimates above are smoothed, reflecting information based on full-sample from 1960:Q1 through 2014:Q4.

Figure 12: Decomposition of Services Inflation (**CPI** Inflation in Parts OU-Spec)

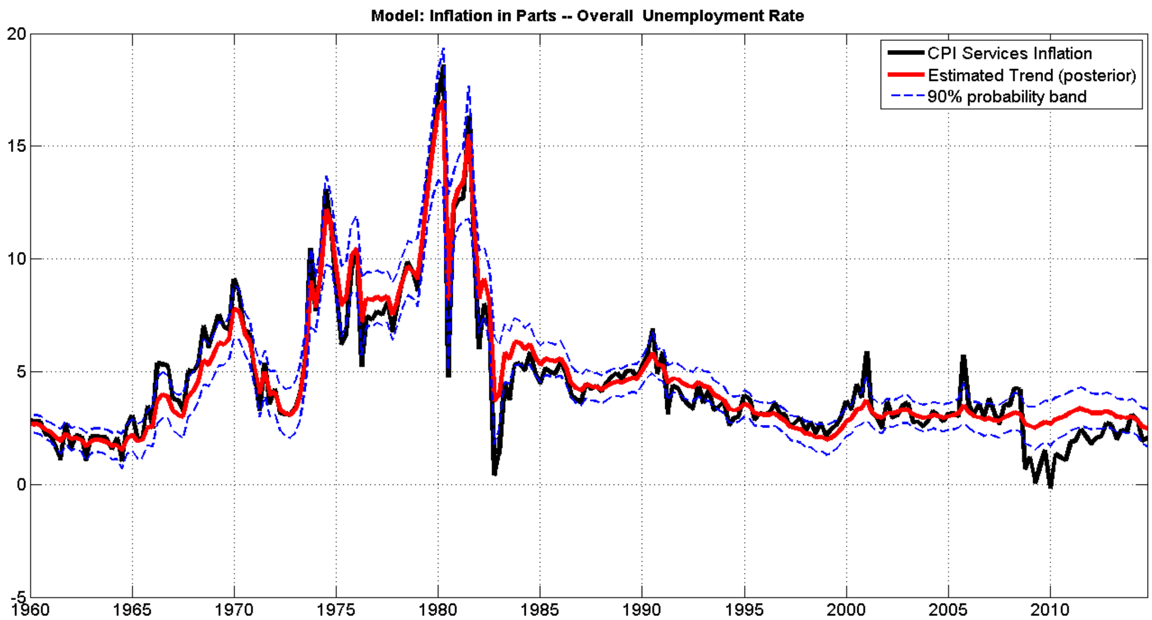
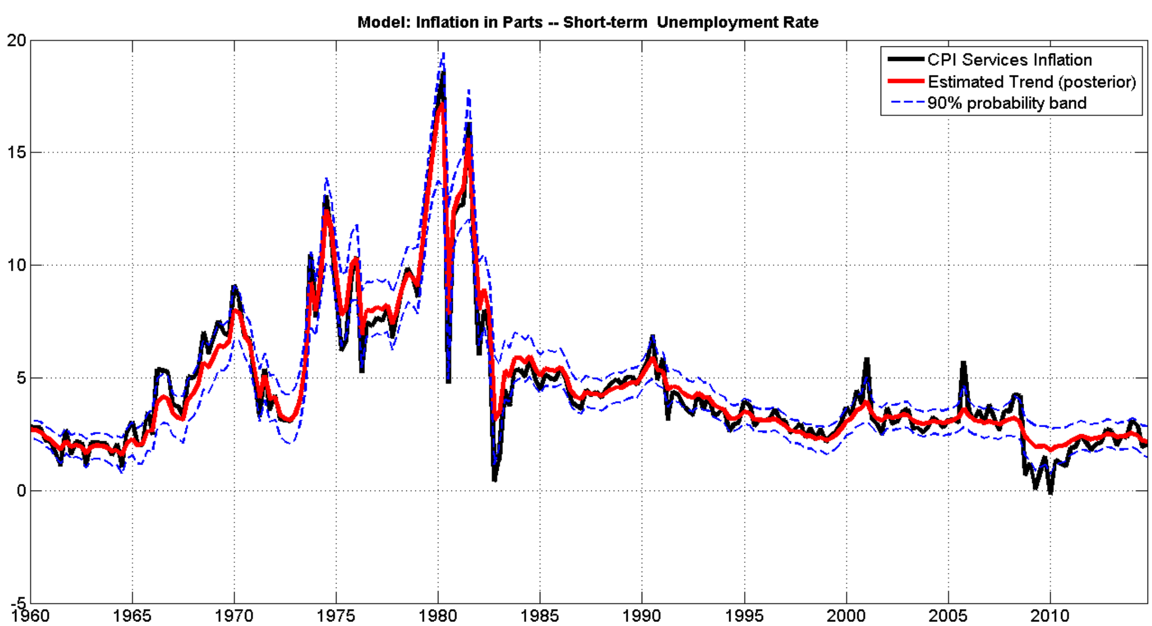


Figure 13: Decomposition of Services Inflation (**CPI** Inflation in Parts STU-Spec)



Notes: The estimates above are smoothed, reflecting information based on full-sample from 1960:Q1 through 2014:Q4.

Figure 14: Cyclical UR – common cyclical component (**CPI** Inflation in Parts OU-Spec)

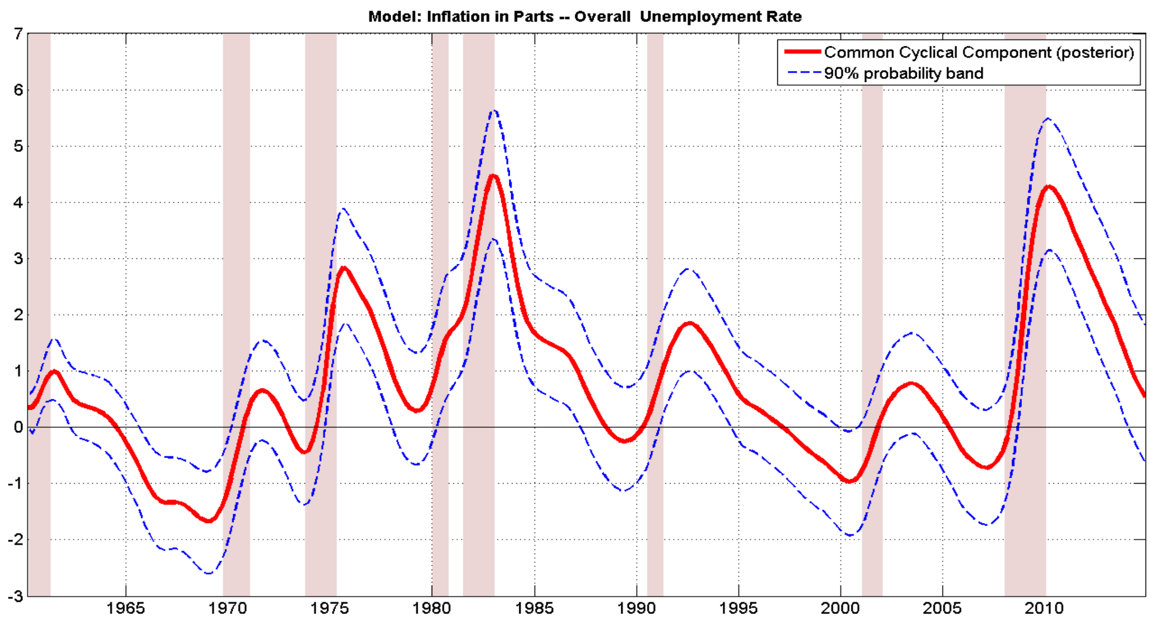
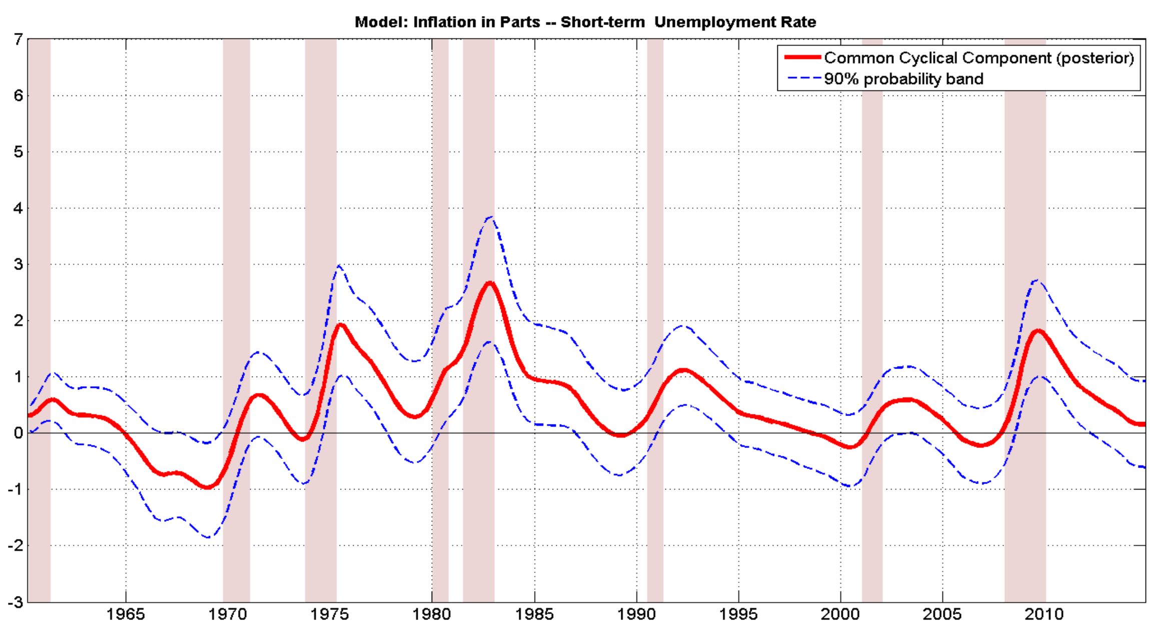


Figure 15: Cyclical Short UR – common cyclical component (**CPI** Inflation in Parts STU-Spec)



Notes: The estimates above are smoothed, reflecting information based on full-sample from 1960:Q1 through 2014:Q4.

Figure 16: Time-varying estimate of Phillips curve slope: **CPI** Inflation in Parts OU-Spec

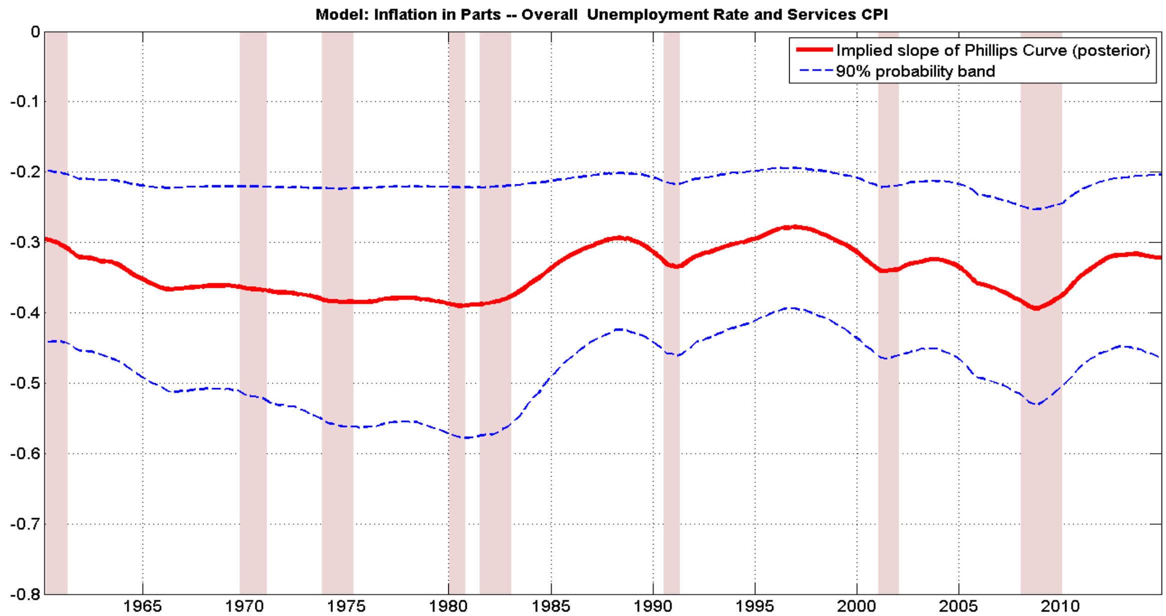
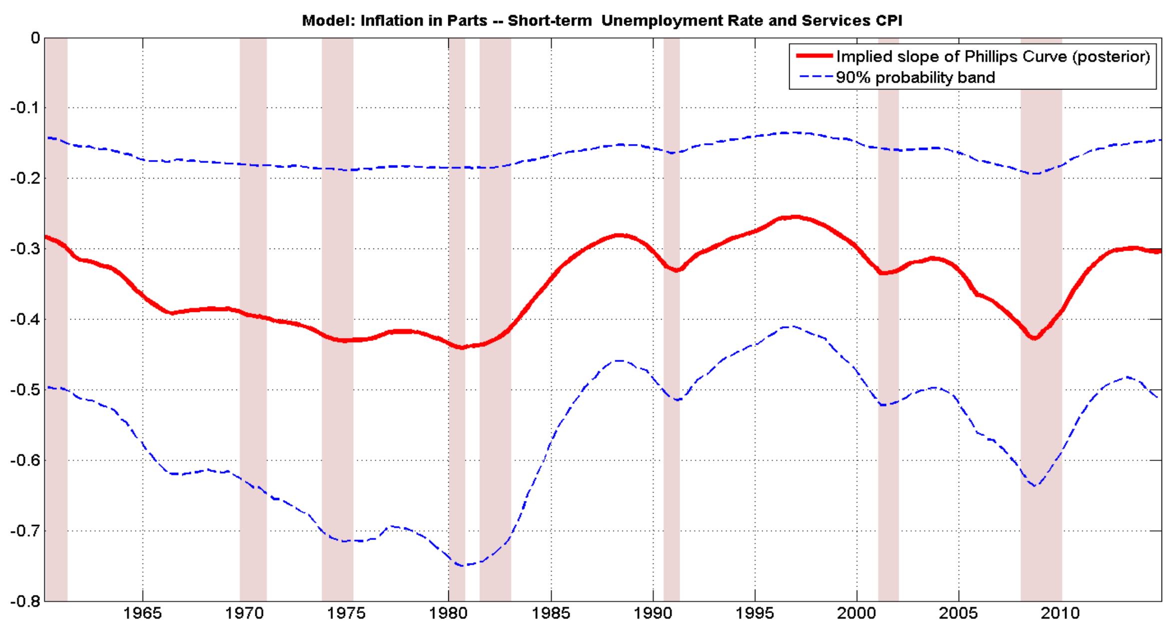


Figure 17: Time-varying estimate Phillips curve slope: **CPI** Inflation in Parts STU-Spec



Notes: The estimates above are smoothed, reflecting information based on full-sample from 1960:Q1 through 2014:Q4.

Table 5: CPI Inflation Pseudo out-of-sample Forecasting Performance of Inflation in Parts Model (OU-Spec)

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)												
Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
CPI Inflation in Parts OU-Spec	2.086	2.160	2.141	2.122	2.083	2.134	2.208	2.184	2.179	2.129	2.152	2.213
Relative RMSE												
CPI Inflation in Parts OU-Spec	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.037	1.042	1.031	1.055**	1.069***	1.063**	1.056*	1.071	1.078**	1.080***	1.057***	1.039
AR4	1.095	1.189	1.204	1.173**	1.141*	1.131*	1.156**	1.170**	1.209***	1.221***	1.212***	1.184***
RW (Atkeson and Ohanian)	1.102*	1.093*	1.066	1.081	1.083***	1.098*	1.105	1.106	1.099	1.117**	1.075***	1.060**
Stock and Watson (2007)	1.014	1.010	1.002	1.030	1.035	1.009	0.997	1.020	1.034	1.039	1.028*	1.012

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)												
Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
CPI Inflation in Parts OU-Spec	1.343	1.372	1.426	1.459	1.409	1.406	1.453	1.448	1.479	1.452	1.481	1.463
Relative RMSE												
CPI Inflation in Parts OU-Spec	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.051	1.048	0.998	1.061	1.119***	1.076	1.073*	1.175***	1.149**	1.102*	1.121***	1.112***
AR4	1.128	1.062	1.056	1.169*	1.203	1.185*	1.211*	1.315**	1.308***	1.306***	1.359***	1.344**
RW (Atkeson and Ohanian)	1.065	1.095	1.037	1.043	1.115**	1.139***	1.125***	1.192***	1.134***	1.116**	1.061***	1.085
Stock and Watson (2007)	1.033	1.030	0.969	1.049	1.099**	1.044	1.047	1.144***	1.105***	1.051	1.081***	1.063

Notes for Table: The first row reports the Root Mean Square Errors from the Inflation in Parts Model. All other rows report the ratios of the Root Mean Square Errors of the various models relative to the Inflation in Parts OU-Spec (i.e. UC model that uses total UR). So a ratio of more than 1, indicates that the Inflation in Parts model does better than the particular model. The forecast performance is based on recursive estimation, i.e. expanding sample. The table reports statistical significance based on Diebold-Mariano test (*10 percent, **5 percent, and ***1 percent significance levels respectively). Stock-Watson (2007) refers to univariate UC-SV model. Atkeson and Ohanian (2001) quarterly random walk model forecasts in our exercise are the quarterly average of the lagged four quarter available CPI inflation annualized rates. The composite forecast of aggregate inflation is computed at recursive forecast evaluation round by combining the goods and services inflation forecasts using the actual weights as of the forecast origin date.

Table 6: CPI Inflation Pseudo out-of-sample Forecasting Performance of Inflation in Parts Model (STU-Spec)

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)												
Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
CPI Inflation in Parts STU-Spec	2.078	2.147	2.129	2.114	2.066	2.106	2.177	2.148	2.149	2.101	2.123	2.185
Relative RMSE												
CPI Inflation in Parts STU	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.041	1.048	1.037	1.059***	1.078***	1.077***	1.071*	1.089*	1.094**	1.094***	1.072***	1.052**
AR4	1.099	1.196*	1.211	1.178**	1.151*	1.145**	1.172*	1.190**	1.226***	1.237***	1.229***	1.199***
RW (Atkeson and Ohanian)	1.106*	1.099*	1.072	1.086	1.092***	1.112*	1.120	1.124	1.115	1.132**	1.090***	1.073*
Stock and Watson (2007)	1.018	1.016	1.007	1.034	1.043*	1.022	1.012	1.037**	1.049**	1.052***	1.042***	1.025

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)												
Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
CPI Inflation in Parts STU-Spec	1.346	1.372	1.423	1.460	1.409	1.405	1.454	1.446	1.478	1.442	1.473	1.453
Relative RMSE												
CPI Inflation in Parts STU	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.049	1.047	1.000	1.060	1.119***	1.076	1.071	1.176***	1.150**	1.109*	1.127***	1.120***
AR4	1.126	1.061	1.058	1.168**	1.203	1.186*	1.210*	1.317**	1.309***	1.315***	1.367***	1.353***
RW (Atkeson and Ohanian)	1.062	1.095	1.040	1.042	1.116**	1.139***	1.123***	1.193***	1.135***	1.124**	1.067***	1.092
Stock and Watson (2007)	1.031	1.029	0.971	1.048	1.100***	1.044	1.046	1.145***	1.106***	1.058	1.087***	1.070*

Notes for Table: The first row reports the Root Mean Square Errors from the Inflation in Parts Model. All other rows report the ratios of the Root Mean Square Errors of the various models relative to the Inflation in Parts STU-Spec (i.e. UC model that uses short-term UR). So a ratio of more than 1, indicates that the Inflation in Parts STU-spec does better than the particular model. The forecast performance is based on recursive estimation, i.e. expanding sample. The table reports statistical significance based on Diebold-Mariano test (*10 percent, **5 percent, and ***1 percent significance levels respectively). Stock-Watson (2007) refers to univariate UC-SV model. Atkeson and Ohanian (2001) quarterly random walk model forecasts in our exercise are the quarterly average of the lagged four quarter available CPI inflation annualized rates. The composite forecast of aggregate inflation is computed at recursive forecast evaluation round by combining the goods and services inflation forecasts using the actual weights as of the forecast origin date.