Online Appendix

Forecasting Inflation: Phillips Curve Effects on Services Price Measures

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*Any errors are our own. The views expressed herein are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Cleveland or of the Federal Reserve System. Address: Research Department, Federal Reserve Bank of Cleveland, 1455 East 6th Street, Cleveland, OH 44114, USA. E-mail: ellis.tallman@clev.frb.org and saeed.zaman@clev.frb.org. This document is a companion to the paper that has the same title as this one.

Online Appendix

A.1. PCE 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.[1]. 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. For ease of notation, 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. Goods inflation is modeled as univariate unobserved components model with stochastic volatility.

We find that improvements in forecast accuracy for inflation in parts model are **robust** to using short-term unemployment as a measure of slack. By using short-term unemployment rate, our inflation in parts model display marginal improvements in forecast accuracy (on average about 2 percent) relative to the inflation in parts model that uses overall unemployment rate. We also find that forecast accuracy of models under consideration as benchmarks that use aggregate inflation and overall unemployment rate can be marginally improved by replacing overall unemployment rate with the short-term unemployment rate.

Table A1 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 (main text) and few other benchmarks 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 A1 displays few more statistical significant forecast improvements compared to those reported in Table 1 for OU spec. For the univariate benchmark Stock and Watson (2007), forecast accuracy improvements appear to be statistically significant in the outer year. Overall, the results are generally robust to forecast evaluation sample (pre-crisis and the full-sample).

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

Next to our benchmark models that have aggregate inflation and overall unemployment rate we replace overall unemployment with short-term unemployment rate and denote these specifications as Stella and Stock (2015) Short UR PC, Three variable BVAR Short UR, and SS-SV-BVAR Short UR respectively. So Table A1 have three additional benchmark models compared to those in Table 1. The aim of adding these additional three benchmark is for two reasons: (i) to have more fair horse-race; (ii) does replacing short-term unemployment rate with overall unemployment rate in the benchmark models improve forecast accuracy of aggregate inflation? Based on the results reported in Table A1, our inflation in parts model that uses short-term unemployment rate and services inflation outperform benchmark models that estimates relationship between aggregate inflation and short-term UR. Furthermore, benchmark models with short-term unemployment does marginally better in terms of point forecast accuracy of aggregate inflation compared to their counterparts with overall unemployment.

Tables A2 and A3 report the density forecast evaluation results for inflation in parts model with short-term unemployment rate. As can be seen, most numbers reported in Table A2 are positive suggesting that on average this model specification (i.e. STU-spec) generates the most accurate density forecasts. This finding is confirmed by the alternative density forecast metric CRPS reported in Table A3 as most numbers are negative (for CRPS lower number is preferable). It is worth noting that inflation in parts model STU spec generates on average more accurate density forecasts compared to inflation in parts OU spec.

All in all, the forecasting results confirm that our results are robust to using short-term unemployment rate as a measure of economic slack as evidenced by modest improvements in the accuracy of the aggregate inflation forecasts using a composite forecasting model of services and goods inflation that exploits the relationship between services inflation and short-term unemployment rate (Phillips curve).

Table A1: PCE Inflation Out-of-sample Forecasting Performance of Inflation in Parts Model: Short-term UR spec

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts STU spec	1.454	1.559	1.526	1.619	1.601	1.601
Relative RMSE						
Inflation in Parts STU spec	1.000	1.000	1.000	1.000	1.000	1.000
Inflation in Parts OU spec	1.006	1.010	1.013	1.018*	1.018	1.018
Stella and Stock (2015) PC	1.038	1.064**	1.079***	1.069	1.098**	1.057*
Stella and Stock (2015) Short UR PC	1.007	1.014	1.027**	1.022	1.035***	1.011**
AR4	1.059	1.183**	1.161**	1.188**	1.257***	1.255**
AR1 gap	1.028	1.052	1.033	0.995	1.031	1.044
RW (Atkeson and Ohanian)	1.105**	1.068	1.070**	1.078	1.085	1.065*
Stock and Watson (2007)	1.007	1.017	1.020*	1.002	1.025***	1.013*
Three variable BVAR	1.122	1.238**	1.196**	1.169**	1.242***	1.240**
Three variable BVAR Short UR	1.111	1.226**	1.185**	1.166**	1.250***	1.249**
SS-SV-BVAR	0.978	1.090**	1.052	1.020	1.036***	0.980
SS-SV-BVAR Short UR	0.968	1.072**	1.032	1.001	1.033*	0.990

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts STU spec	0.959	1.147	1.133	1.244	1.180	1.146
Relative RMSE						
Inflation in Parts STU spec	1.000	1.000	1.000	1.000	1.000	1.000
Inflation in Parts OU spec	0.999	1.004	1.004	1.000	1.011***	1.011
Stella and Stock (2015) PC	1.057	1.044	1.079*	1.087**	1.111**	1.108**
Stella and Stock (2015) Short UR PC	1.041*	1.009	1.049	1.067***	1.057**	1.047**
AR4	1.090	1.113	1.145	1.213	1.303	1.377
AR1 gap	1.158	1.006	1.043	1.024	1.092	1.166
RW (Atkeson and Ohanian)	1.051*	0.984	1.041	1.028	1.020	1.022***
Stock and Watson (2007)	1.012	1.013	1.033	1.046***	1.049***	1.021
Three variable BVAR	1.130	1.147*	1.214*	1.256	1.333*	1.388
Three variable BVAR Short UR	1.139	1.127*	1.184*	1.246	1.328*	1.387
SS-SV-BVAR	1.003	1.013	1.018	1.020	1.042	0.989
SS-SV-BVAR Short UR	1.001	1.016	1.013	1.013	1.025***	0.974

Notes for Table: The first row reports the Root Mean Square Errors from the Inflation in Parts Model with Short Term Unemployment Rate (STU-spec). All other rows report the ratios of the Root Mean Square Errors of the various models relative to the Inflation in Parts STU-Spec. So a ratio of more than 1, indicates that the Inflation in Parts model with Short UR 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).

Table A2: PCE Inflation Out-of-sample Density Forecasting Performance

Relative log predictive score

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Relative Log Score: LS of Parts Model with Short UR - LS of Benchmark Model						
Inflation in Parts Short UR	0.000	0.000	0.000	0.000	0.000	0.000
Inflation in Parts Overall UR	3.653	-0.085	1.758	0.003	-0.001	-0.879
Stella and Stock (2015) PC	10.752	3.255	6.150	1.407	3.581	8.366
Stella and Stock (2015) Short UR PC	3.977	0.623	1.153	-0.270	-0.442	4.770
Stock and Watson (2007)	7.918	-0.743	1.603	-1.242	-1.090	3.584
SS-SV-BVAR	-4.227	3.108	4.381	4.189	7.812	10.955
SS-SV-BVAR Short UR	-4.993	2.531	3.496	2.797	6.349	10.320

Notes for Table: All the numbers reported in the table are sum of log score from the inflation in parts model Short UR minus the sum of log score corresponding to the benchmark listed in the row. So a **positive number** suggests that inflation in parts model is more accurate compared to the particular benchmark model. The forecast performance, i.e. sum of log score is based on recursive estimation, i.e. expanding sample.

Table A3: PCE Inflation Out-of-sample Density Forecasting Performance

Relative CRPS

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Relative CRPS: CRPS of Parts Model with Short UR - CRPS of Benchmark Model						
Inflation in Parts Short UR	0.000	0.000	0.000	0.000	0.000	0.000
Inflation in Parts Overall UR	-0.696	-1.096	-1.104	-1.569	-1.243	-1.246
Stella and Stock (2015) PC	-3.587	-4.519	-5.552	-5.392	-6.481	-5.812
Stella and Stock (2015) Short UR PC	-1.018	-1.203	-1.868	-1.913	-1.942	-1.934
Stock and Watson (2007)	0.046	-1.131	-1.369	-0.369	-1.901	-1.319
SS-SV-BVAR	0.576	-6.193	-5.122	-3.546	-5.971	-5.151
SS-SV-BVAR Short UR	1.186	-5.097	-3.765	-2.449	-5.239	-4.719

Notes for Table: All the numbers reported in the table are sum of CRPS from the inflation in parts model with Short UR minus the sum of CRPS corresponding to the benchmark listed in the row. So a **negative number** suggests that inflation in parts model is more accurate compared to the particular benchmark model. The forecast performance, i.e. sum of CRPS is based on recursive estimation, i.e. expanding sample.

A.2. Results For Consumer Price Inflation (CPI)

Figure 1: Unemployment and Estimated Trend (**CPI** Inflation)

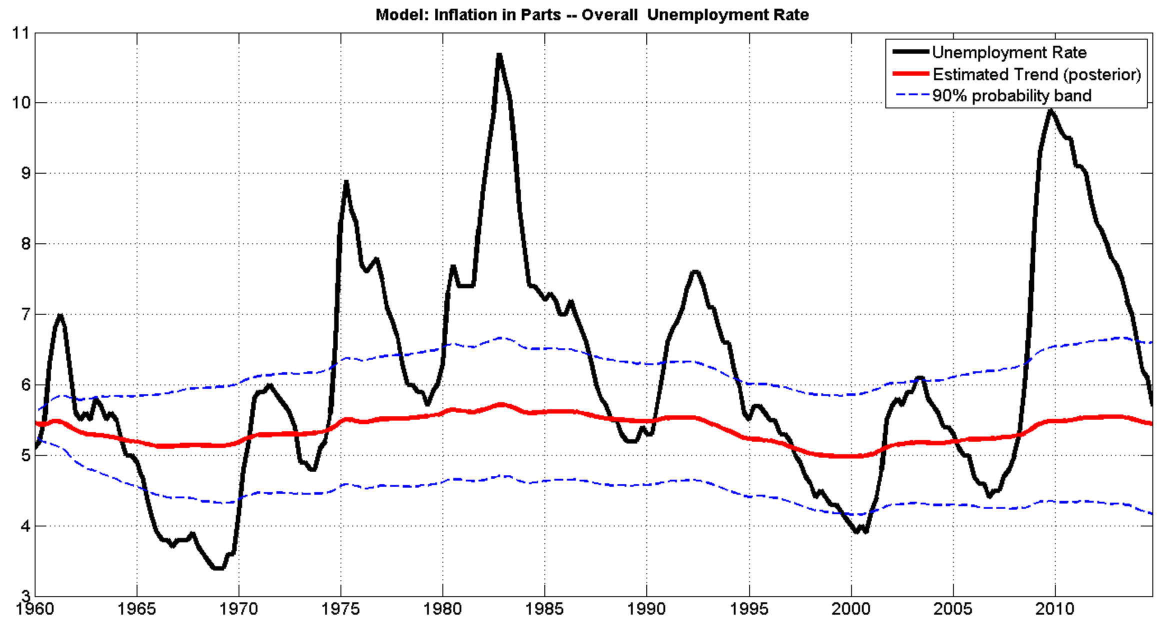
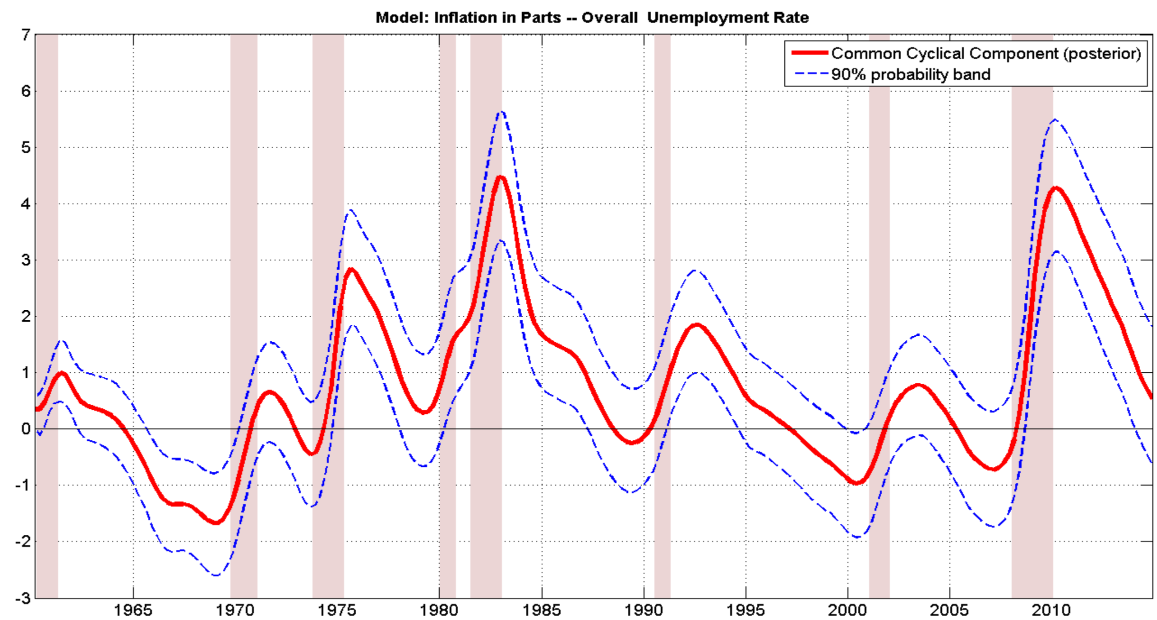


Figure 2: Cyclical UR – common cyclical component (**CPI** Inflation)



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

Figure 3: CPI Services Inflation and the Estimated Trend

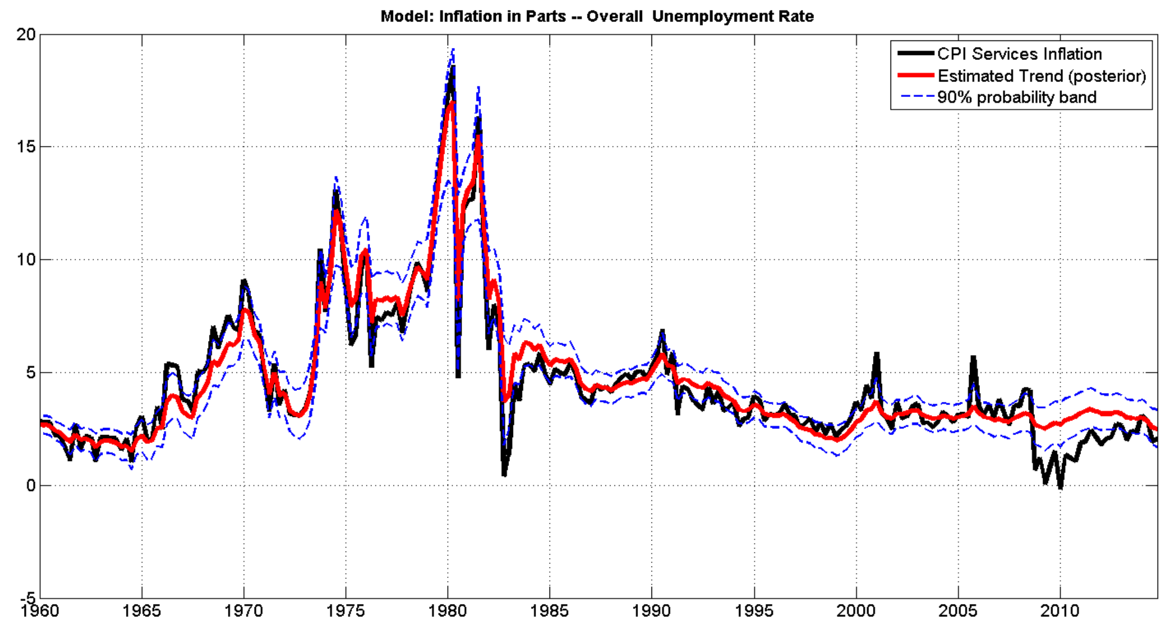
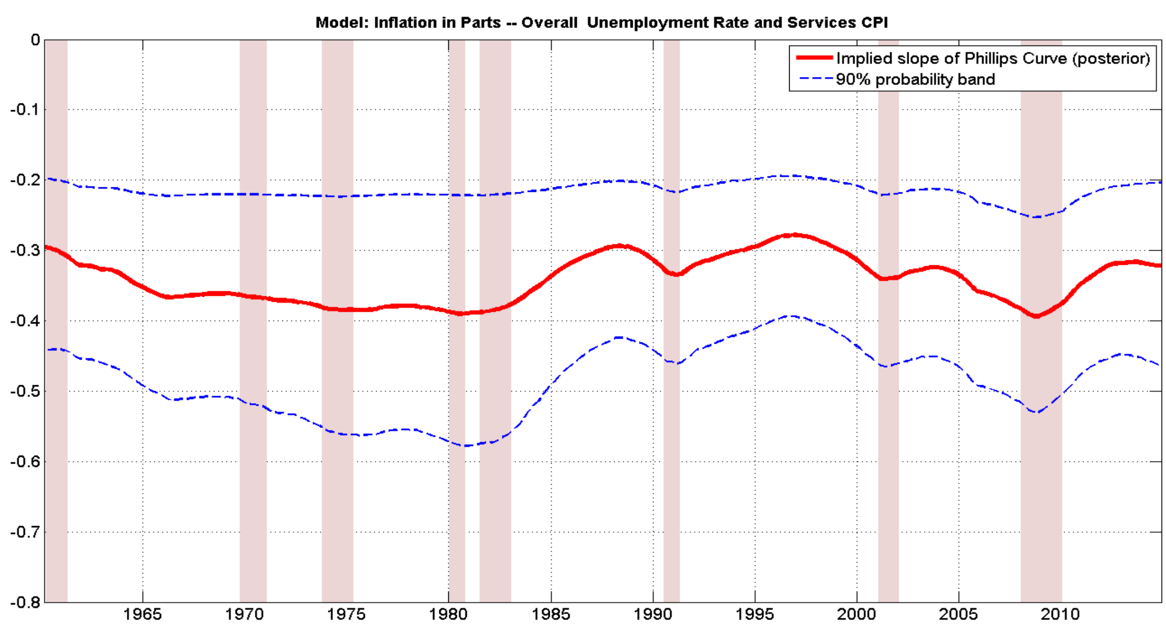


Figure 4: Time-varying estimate of Phillips curve slope: **CPI** Inflation Model



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

Table A4: **CPI** Inflation Out-of-sample Forecasting Performance of Inflation in Parts Model

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts	2.102	2.184	2.144	2.265	2.211	2.277
Relative RMSE						
Inflation in Parts	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2015) PC	1.029**	1.033*	1.047***	1.036	1.042***	1.013
AR4	1.092	1.141*	1.108	1.123**	1.174***	1.148***
AR1 gap	1.043	1.008	1.000	0.961	0.999	0.984
RW (Atkeson and Ohanian)	1.090*	1.051	1.051*	1.067	1.080	1.032
Stock and Watson (2007)	1.005	1.000	1.007	0.982	1.001	0.985
Three variable BVAR	1.192	1.273**	1.241**	1.181*	1.229*	1.175*
SS-SV-BVAR	0.969	1.003	0.995	0.981	1.022	0.957

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts	1.359	1.547	1.521	1.618	1.537	1.541
Relative RMSE						
Inflation in Parts	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2015) PC	1.038*	1.007	1.050	1.066**	1.044**	1.060***
AR4	1.103	1.083	1.092	1.154	1.214**	1.254
AR1 gap	1.165*	0.938	0.983	0.948	0.997	1.024
RW (Atkeson and Ohanian)	1.028	0.963	1.023	1.044***	1.033**	1.008
Stock and Watson (2007)	1.015	0.991	1.021	1.022	1.002	1.009**
Three variable BVAR	1.131	1.199**	1.212*	1.185*	1.174	1.179
SS-SV-BVAR	0.974	0.948	0.990	1.004	1.049	1.027*

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). 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 A5: **CPI** Inflation Out-of-sample Forecasting Performance of Inflation in Parts Model
Forecasting Average Inflation

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts	2.102	1.350	1.230	1.110	1.044	0.978
Relative RMSE						
Inflation in Parts	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2015) PC	1.029**	1.074*	1.097*	1.126*	1.137*	1.137**
AR4	1.092	1.311	1.348	1.403*	1.473**	1.535**
AR1 gap	1.043	1.077	1.050	0.952	0.939	0.921
RW (Atkeson and Ohanian)	1.090*	1.173	1.199	1.268	1.315	1.346
Stock and Watson (2007)	1.005	0.995	1.001	0.985	0.997	1.008
Three variable BVAR	1.192	1.588	1.658*	1.679**	1.733**	1.779*
SS-SV-BVAR	0.969	1.016	1.008	0.968	0.986	0.975

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). 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 A6: **CPI** Inflation Out-of-sample Density Forecasting Performance
Relative log predictive score

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Relative Log Score: LS of Parts Model - LS of Benchmark Model						
Inflation in Parts	0.000	0.000	0.000	0.000	0.000	0.000
Stella and Stock (2015) PC	2.752	0.083	3.768	3.315	4.301	4.048
Stock and Watson (2007)	1.046	-2.015	-1.897	0.015	4.646	2.095
SS-SV-BVAR	-11.629	-4.038	-1.780	3.227	8.934	12.720

Notes for Table: All the numbers reported in the table are sum of log score from the inflation in parts model minus the sum of log score corresponding to the benchmark listed in the row. So a **positive number** suggests that inflation in parts model is more accurate compared to the particular benchmark model. The forecast performance, i.e. sum of log score is based on recursive estimation, i.e. expanding sample.

Table A7: **CPI** Inflation Out-of-sample Density Forecasting Performance
Relative CRPS

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Relative CRPS: CRPS of Parts Model - CRPS of Benchmark Model						
Inflation in Parts	0.000	0.000	0.000	0.000	0.000	0.000
Stella and Stock (2015) PC	-2.793	-3.222	-3.923	-4.434	-4.907	-3.932
Stock and Watson (2007)	1.122	0.969	0.629	1.794	-0.616	0.589
SS-SV-BVAR	3.007	-0.130	-0.411	1.726	-5.126	-4.107

Notes for Table: All the numbers reported in the table are sum of CRPS from the inflation in parts model minus the sum of CRPS corresponding to the benchmark listed in the row. So a **negative number** suggests that inflation in parts model is more accurate compared to the particular benchmark model. The forecast performance, i.e. sum of CRPS is based on recursive estimation, i.e. expanding sample.

A.3. Results For Core Consumer Price Inflation (CPI excluding food and energy)

Table A8: **Core CPI** Inflation Out-of-sample Forecasting Performance of Inflation in Parts Model

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts Relative RMSE	0.495	0.658	0.661	0.805	0.866	0.851
Inflation in Parts	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2015) PC	1.005	1.003	0.991	0.972**	0.988	0.965
AR4	1.232**	1.840***	2.035***	2.237***	2.354***	2.593***
AR1 gap	1.124*	1.411**	1.457***	1.388***	1.366**	1.443***
RW (Atkeson and Ohanian)	1.115**	1.056	1.060	0.996	0.950	0.942**
Stock and Watson (2007)	1.037	1.066	1.036	0.951	0.958	0.949
Three variable BVAR	1.686***	1.478***	1.467**	1.715*	1.881*	2.069**
SS-SV-BVAR	1.152	1.063	0.884	0.898	0.996	1.018

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts Relative RMSE	0.440	0.616	0.619	0.708	0.777	0.786
Inflation in Parts	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2015) PC	0.974	1.002	0.996	0.978**	0.994	0.983
AR4	1.302***	2.038***	2.306***	2.713***	2.817***	3.023***
AR1 gap	1.130*	1.384**	1.471**	1.520*	1.470	1.502*
RW (Atkeson and Ohanian)	1.083*	0.993	1.000	1.008	0.981	0.942
Stock and Watson (2007)	1.000	1.026	1.024	0.987	0.992	0.979
Three variable BVAR	1.496***	1.417**	1.406	1.589	1.719	1.933
SS-SV-BVAR	0.983	0.950	0.893	0.874	1.013	1.055

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). 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 core inflation is computed at recursive forecast evaluation round by combining the core goods and core services inflation forecasts using the actual weights as of the forecast origin date.

Table A9: **Core CPI** Inflation Out-of-sample Forecasting Performance of Inflation in Parts Model

Forecasting Average Inflation						
Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts	0.495	0.436	0.437	0.485	0.517	0.516
Relative RMSE						
Inflation in Parts	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2015) PC	1.005	1.011	1.003	0.973***	0.973***	0.976***
AR4	1.232**	1.872***	2.059***	2.376***	2.529***	2.786***
AR1 gap	1.173*	1.521**	1.598**	1.643***	1.639***	1.705***
RW (Atkeson and Ohanian)	1.115**	1.170	1.164	1.107	1.072	1.070
Stock and Watson (2007)	1.037	1.105	1.101	1.033	1.013	1.026
Three variable BVAR	1.759***	1.858***	1.834***	1.793**	1.870*	2.000*
SS-SV-BVAR	1.152	1.242	1.157	1.007	1.026	1.077

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). 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 core inflation is computed at recursive forecast evaluation round by combining the core goods and core services inflation forecasts using the actual weights as of the forecast origin date.

Table A10: **Core CPI** Inflation Out-of-sample Density Forecasting Performance
Relative log predictive score

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Relative Log Score: LS of Parts Model - LS of Benchmark Model						
Inflation in Parts	0.000	0.000	0.000	0.000	0.000	0.000
Stella and Stock (2015) PC	-0.454	2.612	2.925	-0.012	-0.262	-0.018
Stock and Watson (2007)	1.149	5.354	5.044	0.161	-0.734	-0.764
SS-SV-BVAR	4.712	7.728	7.684	10.683	17.096	22.923

Notes for Table: All the numbers reported in the table are sum of log score from the inflation in parts model minus the sum of log score corresponding to the benchmark listed in the row. So a **positive number** suggests that inflation in parts model is more accurate compared to the particular benchmark model. The forecast performance, i.e. sum of log score is based on recursive estimation, i.e. expanding sample.

Table A11: **Core CPI** Inflation Out-of-sample Density Forecasting Performance
Relative CRPS

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Relative CRPS: CRPS of Parts Model - CRPS of Benchmark Model						
Inflation in Parts	0.000	0.000	0.000	0.000	0.000	0.000
Stella and Stock (2015) PC	-0.159	-0.229	-0.034	1.128	1.070	1.185
Stock and Watson (2007)	-0.503	-1.407	-0.810	2.051	2.190	1.904
SS-SV-BVAR	-2.122	-1.121	0.936	0.898	-2.365	-4.405

Notes for Table: All the numbers reported in the table are sum of CRPS from the inflation in parts model minus the sum of CRPS corresponding to the benchmark listed in the row. So a **negative number** suggests that inflation in parts model is more accurate compared to the particular benchmark model. The forecast performance, i.e. sum of CRPS is based on recursive estimation, i.e. expanding sample.

A.4. Using 5-year average model for Goods Inflation

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 of last 20 quarters):

$$\pi^{g}_{t+h} = 1/n \sum_{i=t-n}^{t} \pi^{g}_{i}$$

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 competitive forecasts of goods inflation over the pre-forecast evaluation sample (i.e. training sample), and so we stick with this approach for our baseline model. Figure 5 below plots the estimated trend goods inflation with the actual goods inflation. Table A12 below 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). Exponential smoothing with alpha=0.05 or alpha=0.15 are on average slightly more accurate. The forecasting performance over the formal evaluation sample is quite similar with 5-year average doing slightly better.

Table A12: Which smoothing method for PCE Goods Inflation? Forecasting Performance over **1985:Q1 to 1993:Q4**

Smoothing method	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q	
	Root Mean Square Error (RMSE)						Average RMSE (h=1 to h=12)
UC-SV	2.946	3.653	3.391	3.337	3.653	3.628	3.344
AR4	2.770	3.383	3.097	2.641	2.821	2.840	2.884
Last quarterly value	3.185	4.098	3.874	3.627	3.971	4.134	3.700
Average of last two quarters (2q)	2.956	3.606	3.178	3.222	3.688	3.469	3.299
Average of last three quarters (3q)	2.746	3.178	2.892	3.146	3.469	3.090	3.106
Average of last four quarters (4q)	2.846	2.964	2.863	3.195	3.248	3.091	3.032
Average of last five quarters (5q)	2.810	2.892	2.851	3.120	3.038	3.036	2.954
Average of last six quarters (6q)	2.670	2.865	2.874	3.017	3.003	3.026	2.903
Average of last eight quarters (8q)	2.588	2.976	3.014	2.913	2.990	3.065	2.910
Average of last twelve quarters (12q)	2.728	2.931	2.965	2.965	2.878	2.801	2.885
Average of last 4 years (16q)	2.707	3.018	3.061	2.774	2.724	2.657	2.832
Average of last 5 years (20q)	2.840	3.078	3.137	2.599	2.516	2.526	2.789
Average of last 6 years (24q)	3.005	3.195	3.246	2.476	2.434	2.479	2.802
Exponential with alpha=0.05	2.883	3.023	3.054	2.451	2.462	2.520	2.723
Exponential with alpha=0.15	2.623	2.910	2.890	2.733	2.769	2.721	2.769
Exponential with alpha=0.25	2.623	2.981	2.885	2.915	3.035	2.965	2.886
Exponential with alpha=0.5	2.743	3.308	3.056	3.087	3.371	3.291	3.095
Hpfilter	2.794	3.185	3.168	3.454	3.522	3.464	3.262
BVAR	3.124	3.124	2.622	3.123	3.140	2.765	3.032
Average-All	2.631	2.965	2.847	2.776	2.869	2.813	2.800
Average-two (UC-SV and 20q)	2.696	3.205	3.084	2.775	2.919	2.891	2.882

Notes for Table: The table reports the Root Mean Square Errors of goods PCE inflation (quarterly annualized: 400*log(P_t^g/P_{t-1}^g)) from the various smoothing methods/models. The last column reports the average of the RMSE from h=1 to h=12. All models are estimated with sample beginning 1960:Q1.

Figure 5: Goods PCE Inflation and the Estimated Trend

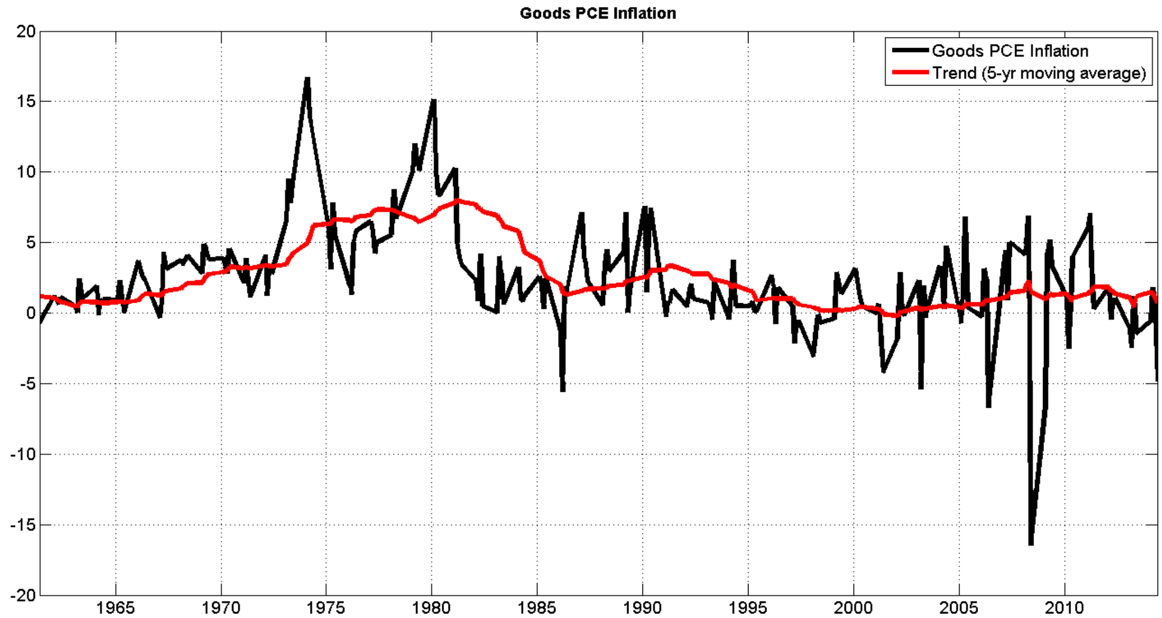


Table A13: PCE Inflation Pseudo out-of-sample Forecasting Performance of Inflation in Parts Model (Overall Unemployment-OU) And Goods Inflation Model: 5-year average

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts OU-Spec Relative RMSE	1.450	1.522	1.489	1.586	1.558	1.582
Inflation in Parts OU-Spec	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.041	1.081***	1.096***	1.091*	1.111***	1.071***
AR4	1.066	1.225**	1.203**	1.235***	1.316***	1.298***
AR1 gap	1.028	1.074**	1.054	1.011	1.053	1.049
RW (Atkeson and Ohanian)	1.117*	1.098*	1.101***	1.105	1.118*	1.081**
Stock and Watson (2007)	1.013	1.042*	1.044*	1.026	1.052	1.021
Three variable BVAR	1.123	1.284**	1.242**	1.223***	1.306***	1.288***

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts OU-Spec Relative RMSE	0.965	1.087	1.042	1.115	1.112	1.119
Inflation in Parts OU-Spec	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.048	1.095	1.167***	1.216**	1.176**	1.131***
AR4	1.107	1.206**	1.281*	1.399**	1.437**	1.472*
AR1 gap	1.162	1.066	1.138	1.143	1.157	1.192
RW (Atkeson and Ohanian)	1.071	1.057	1.152**	1.168***	1.102**	1.067
Stock and Watson (2007)	1.006	1.067*	1.121***	1.162***	1.106**	1.041
Three variable BVAR	1.144	1.240**	1.356**	1.446***	1.467**	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 A14: PCE Inflation Pseudo out-of-sample Forecasting Performance of Inflation in Parts Model (Short-term Unemployment-STU) And Goods Inflation Model: 5-year average

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts STU-Spec Relative RMSE	1.443	1.506	1.471	1.557	1.529	1.558
Inflation in Parts STU-Spec	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.046	1.093***	1.110***	1.111*	1.131***	1.088**
AR4	1.071	1.238**	1.218**	1.258***	1.340***	1.318***
AR1 gap	1.033	1.086**	1.067*	1.030	1.073	1.066
RW (Atkeson and Ohanian)	1.122*	1.110*	1.115***	1.126	1.139**	1.098***
Stock and Watson (2007)	1.017	1.054**	1.057***	1.045*	1.071***	1.037***
Three variable BVAR	1.129	1.298**	1.258***	1.246***	1.331***	1.308***
SS (2013) Short UR	1.015	1.050**	1.057***	1.050	1.075***	1.036***

Pre-Crisis Sample (Recursive evaluation: 1994.Q1-2007.Q3)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts STU-Spec Relative RMSE	0.967	1.081	1.040	1.108	1.101	1.101
Inflation in Parts STU-Spec	1.000	1.000	1.000	1.000	1.000	1.000
Stella and Stock (2013) PC	1.046	1.101	1.170**	1.223**	1.188*	1.149***
AR4	1.104	1.213**	1.284*	1.408**	1.451**	1.497*
AR1 gap	1.160	1.071	1.140	1.149	1.169	1.212
RW (Atkeson and Ohanian)	1.068	1.062	1.154**	1.175***	1.112**	1.084
Stock and Watson (2007)	1.004	1.073	1.123***	1.169***	1.117**	1.058**
Three variable BVAR	1.141	1.246***	1.359***	1.455***	1.482***	1.507*
SS (2013) Short UR	1.031	1.075	1.140***	1.187**	1.136*	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.

A.5. Sensitivity to the value of parameter Gamma

The parameter gamma governs the smoothness of stochastic volatility process (i.e. standard deviation of the innovations to the random walk log variance process). The lower the value, smoother the estimated volatility process and conversely higher value leads to more volatile estimate of the volatility process. In our paper to facilitate comparison with Stella and Stock (2015) and Stock and Watson (2007) we fix this parameter to 0.2 (equivalently variance=0.04) as this was the value they used. Furthermore, Clark and Doh (2014) mention that their estimated value was in line with 0.2 and not surprisingly they obtained very similar results by fixing the gamma at 0.2. With our goal of forecasting we opt for estimation of fewer parameters and hence we do not estimate it for the results provided in the main text. That said, we think that fixing it to a specific value for all the processes (three in the services inflation model and one in goods inflation model) is overly restrictive and so a test of sensitivity of our results to different settings of the values for gamma is warranted and so below we provide comparison table of point and density forecasts for three settings of the parameter gamma comparing it with the baseline.

Those three settings are: gamma of 0.4 (double of what is defined for the baseline) for all stochastic volatility processes in services inflation model and goods inflation model (denote it 04-04); gamma of 0.4 for all stochastic volatility processes in services inflation, and gamma of 0.2 for goods inflation model (denote it by 04-02); gamma of 0.6 for processes in the services inflation model and gamma of 0.3 for goods inflation model (denote it 06-03). We arbitrary choose three different set of values of parameter keeping in mind that they be reasonable.

The results of sensitivity analysis provide some confidence in the point forecast accuracy since the root mean squared errors from these three different exercises are very similar to those from the baseline as judged by relative RMSEs very close to 1.0. For density forecast accuracy the differences in log-score and CRPS compared to the baseline are generally small for the first half of the forecast horizon but for the second half (i.e. h=8 and beyond) there are some noticeable differences especially if we focus on the log score metric, not so much based on CRPS. Our extreme setting of gamma=0.6 does negatively impact the density forecast accuracy for the outer year (i.e. h=10, 11, and 12 quarters) relative to the baseline.

Table A15: Sensitivity of the Point Forecast Accuracy to γ parameter

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
Model	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts Baseline	1.443	1.506	1.471	1.557	1.529	1.558
Relative RMSE						
Inflation in Parts Baseline: 02-02	1.000	1.000	1.000	1.000	1.000	1.000
Inflation in Parts Specification: 04-04	0.994	1.006	1.008	0.984	1.007	0.997
Inflation in Parts Specification: 04-02	1.004	1.010	1.008	0.988	1.010	0.997
Inflation in Parts Specification: 06-03	1.005	1.009	1.006	0.995	1.011	0.990

(sum of) Log Predictive Score

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts Baseline: 02-02	-144.07	-152.72	-149.18	-147.56	-148.29	-139.41
Inflation in Parts Specification: 04-04	-142.65	-152.72	-152.17	-157.60	-161.44	-160.51
Inflation in Parts Specification: 04-02	-142.35	-151.71	-148.49	-149.39	-151.26	-145.56
Inflation in Parts Specification: 06-03	-141.85	-152.54	-154.24	-161.88	-165.77	-170.70

(sum of) Continuous Ranked Probability Score (CRPS)

Full Sample (Recursive evaluation: 1994.Q1-2014.Q4)						
	h=1Q	h=4Q	h=5Q	h=8Q	h=10Q	h=12Q
Inflation in Parts Baseline: 02-02	57.25	64.62	62.82	67.44	63.53	60.36
Inflation in Parts Specification: 04-04	57.04	64.97	63.75	68.56	66.54	64.11
Inflation in Parts Specification: 04-02	56.95	64.23	62.83	67.45	64.19	61.26
Inflation in Parts Specification: 06-03	56.82	64.52	63.33	68.20	66.39	64.41

Notes for Table: Log predictive score refers to the sum of log likelihood, and CRPS refers to the sum of CRPS, both of these sums are computed based on recursive forecast evaluation sample from 1994.Q1 to 2014.Q4.