

Better Measures of Core Inflation?*

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This version: May 2007

* I thank Laurence Ball, Ryan Brady, Edward Gamber, Louis Maccini, John Huston, Rebecca Neumann, Linghui Tang and two anonymous referees for their helpful comments and suggestions.

Abstract

Recent papers examining the measurement of core inflation, such as the weighted median, have focused on cross-section information in disaggregated inflation data. This paper improves on the literature by introducing a new measure of core inflation that exploits the time-series information in disaggregated inflation data. The new measure is based on a definition of core inflation as the best predictor of future inflation. Exploiting the time-series information in disaggregated or component inflation data produces better forecasts than exploiting cross-section information. Additionally, the new measure comes from jointly estimating the optimal weights instead of imposing weights based on the persistence of the components.

JEL: E3 – Prices, Business Fluctuations and Cycles

Keywords: Core inflation, inflation, forecasting

1. Introduction

The measures of core inflation that recent papers have examined are either popular ones such as the personal consumption expenditure deflator excluding food and energy or recently introduced measures such as the weighted median or trimmed mean of the personal consumption expenditure deflator.¹ This paper inquires whether there are better ways to use disaggregated data to capture core inflation, when core inflation is defined as the measure that forecasts future inflation best. While this is not the only possible definition of core inflation, this definition does appeal to the economic intuition about what core inflation should capture. Core inflation is often called underlying inflation indicating that core inflation is the part of inflation that persists or lasts over time.

Finding a good measure of core inflation under any definition can be difficult and it is important to consider which characteristics are critical for a measure of core inflation. There are many criteria to assess when examining possible candidates of core inflation. Rogers (1997) emphasizes that core inflation should be timely, robust and unbiased, and verifiable. The timeliness refers not only to when a measure is first available but also to the revisions that the measure may undergo as more data are added. Thus, a good measure of core inflation would not be highly revised (Rogers 1997). Wynne (1999) suggests six criteria for evaluating a measure of core inflation. The measure should be computable in real time, forward looking, have a track record, be understandable by the public, have a history that does not change and have a theoretical basis. Meeting all these different criteria at once may be very difficult. This paper ranks two criteria as the most important: the measure must be available in real time and must be understandable by the public.

Policy makers need to have a forecast of inflation that is available in real time since monetary policy affects inflation with a lag. Monetary policy makers want a core inflation measure that forecasts inflation well. Additionally, they do not control inflation perfectly and part of future inflation is determined by the public's expectations of inflation; therefore, having a measure that is understandable by the public is important. When the public knows the central bank's forecast of future inflation, the public has a clearer idea of future monetary policy and consequently, they can adjust their inflation expectations. In addition, policy makers desire to set monetary policy in response to persistent or permanent changes in prices, rather than reacting to temporary or transient changes in prices that may be reversed.

There are two main approaches to estimating core inflation. One is the statistical method, which produces measures such as the weighted median. In general, the statistical approach exploits the cross-section properties of the component level inflation data. The other method is the theoretical method. This method uses economic theory to build a model of inflation from which a measure of core inflation is extracted. Theoretical models tend to use the time-series information in inflation and other relevant economic variables.

According to Vega and Wynne (2003) the approaches differ primarily by the information sets they use. The possible information sets are cross-section information on price changes, time-series information on price changes and other information such as real economic variables. This paper combines the two approaches by using the time-series information of component level inflation data in a statistical manner.

¹ See Bryan and Cecchetti (1994), Johnson (1999), Cutler (2001), Bagliano and Morana (2003), Vega and Wynne (2003), and Smith (2004) for further details.

While others have used the time-series information in the disaggregated data to build a measure of core inflation by developing theoretical models², there have been few empirical papers that utilize the time-series data to measure core inflation. Blinder (1997) proposes a measure that takes into account the persistence of each component's inflation rate and each component's covariance with overall inflation. Cutler (2001) builds on his comments and proposes an empirical measure. She suggests a measure that uses the persistence of each component to re-weight the data and aggregates the component inflation rates to obtain forecasts of future inflation. Using the time-series properties of the components is a natural place to begin since it can account for movements in all components of inflation. Previous measures used, such as the trimmed mean, ignore many components across time by construction. Another way to use both time-series and cross-section information is to apply the exponential smoother to measures such as the trimmed mean and weighted median (Cogley, 2002). Thus, the contribution of this paper is to provide a new measure of core inflation built on the statistical properties of time-series data.

Over the last few years there has been renewed interest in using disaggregates to forecast aggregates. Hendry and Hubrich (2006) show theoretically that using disaggregated variables in an aggregate model should outperform the alternatives: first, forecasting the disaggregated variables individually then aggregating those forecasts and second, using lagged aggregate variables. They find empirically that for the Euro area and the US that using disaggregate

² This paper takes a different approach than other papers that use time series information. First, this paper uses a statistical approach to the time-series information. It does not try to provide a structural approach such as Quah and Vahey (1995). Second, this paper does not attempt to replicate the dynamic factor index (DFI) literature. Instead, it uses time-series information in the components of the PCE in a simple and understandable way to predict future inflation. Additionally, with DFI measures of core inflation there are limitations on the number of components that can be used due to complicated calculations needed to produce DFI measures. The approach in this paper is not limited in the number of components that can be used to calculate core inflation. See Bryan and Cecchetti (1993), Bryan and Pike (1991) and Le Bihan and Sedillot (2002) for more details.

information helps produce better forecasts of aggregate inflation. In addition, a paper by Hubrich (2005) finds that aggregating forecasts of disaggregated variables does not help forecast the 12-month Harmonized Index of Consumer Prices inflation rate in the Euro area. Both of these papers provide insight that exploiting the time series information in the disaggregated data may be a better way to get an optimal forecast of aggregate inflation.

This paper examines the United States since 1983. Specifically, I have disaggregated component level data from the personal consumption expenditure deflator, and I use the time-series properties of the components to find an optimal re-weighting. I compare the predictive power of these new measures to more traditional measures of core inflation. These results demonstrate that disaggregating aggregate inflation and re-weighting based on the time-series properties of the components produces better forecasts than other, more popularly recognized, measures of core inflation. In addition, I find that estimating the weights jointly and not using the persistence of the components produces better forecasts. Blinder (1997), Cutler (2001), Hubrich (2005) and Henry and Hubrich (2006) pushed the literature in the right direction by suggesting that examining the time-series properties of disaggregated data may be more productive than examining the cross-section properties. This paper extends this research.

The rest of this paper is outlined as follows. Section 2 discusses the intuition for this new measure of core inflation. Section 3 examines the data. The empirical models and results are examined in Section 4. Finally, Section 5 concludes.

2. Intuition for “New” Measure of Core Inflation

Bryan and Cecchetti’s (1994) idea of using disaggregated information on prices to obtain core inflation has sparked great interest. With the trimmed mean and weighted median, which exploit the cross-section information in the components, core inflation is constructed period-by-

period. Each component can have a different weight every period. Specifically, in the case of the weighted median a component can have a zero weight (not the median element) in period 1 and then in period 2 have a weight of one (the median element). This lack of smoothness of weights across time may disregard some information relevant to future inflation.

Blinder's (1997) and Cutler's (2001) idea of disaggregating and re-weighting the component inflation rates involves disaggregation along another dimension. Following their methodology, I use component level data and exploit the persistence (time-series) information of the components. This method produces less variation in weights on the components across time. The weighted median and trimmed mean, on the other hand, place different weights on each component every period. Some components may be more informative than others since some have more persistent shocks. Blinder states in reference to the weighted median that "you pay no attention to the *name* of each component. But I want to suggest that we should perhaps pay attention to the component's name. Why? Because I imagine that some components have more ability to forecast future 'underlying' inflation than others" (p. 159). Blinder suggests considering the time-series properties of the components.

The budget shares of the components might seem to be the first natural specification when examining the time-series properties of the components. Headline inflation uses the budget share of each component to compute aggregate inflation. Using the budget shares treats each component as if its budget share conveys all the information about how each component affects aggregate inflation. The problem under this specification is that components that tend to have temporary fluctuations (i.e. components that are subject to frequent tax changes or weather related disturbances) are not weighted less. These components should be weighted less because they will convey very little information about future movements in inflation. If the goal core

inflation is to provide a measure that is useful to the central bank for monetary policy then failing to decrease the weight on components that tend to have transitory shocks should produce poor forecasts of inflation.

Using the weighted median and trimmed mean to calculate core inflation has been researched extensively.³ The use of the time-series properties of the components to construct core inflation is less researched. This paper examines this alternative method of utilizing the time-series information of the components of the personal consumption expenditure deflator to provide a better forecast of inflation.

3. Data

The data are the components of the personal consumption expenditure deflator (PCE) from 1978 to April 2006. The 51 components⁴ used are listed in Appendix A. I forecast the 12-month ahead inflation rate⁵, which is calculated by

$$\pi_{t+12,t} = \ln\left(\frac{P_{t+12}}{P_t}\right) * 100, \quad (1)$$

where P is the personal consumption expenditure deflator. I also compute lagged inflation as the previous 12-month inflation rate of the personal consumption expenditure deflator and lagged inflation minus food and energy from the personal consumption expenditure deflator minus food and energy.

I find the previous 12-month inflation rates for the components from the monthly price indexes by

³ See Byran and Cecchetti (1994), Alvarez and de los Llano (1999), Apel and Jansson (1999), Cockerell (1999), Johnson (1999), LeBihan and Sedillot (2003), and Smith (2004).

⁴ The list of components is borrowed from Clark's (2003) Appendix Table 2.

⁵ Smith (2004) finds that there is very little difference in the ranking of core inflation measures in forecasts at the 12, 18 or 24 month time horizon.

$$\pi_{t,t-12}^j = \ln\left(\frac{P_t^j}{P_{t-12}^j}\right) * 100, \quad (2)$$

where j denotes the component and P is the price index for component j .

I also compute the weighted median and trimmed mean from these components. The weighted median is

$$\bar{\pi}_\alpha = \frac{1}{N-2m} \sum_{i=m}^{N-m} w^i \pi_{t-k,t}^i$$

$$\pi_{t-k,t}^i = \ln\left(\frac{P_t^i}{P_{t-k}^i}\right), m = N\alpha$$

where m is the largest integer less than or equal to $N\alpha$,

w^i is the relative importance weight and i indicates the component.

$k = 12$;

$\alpha = .50$ for the weighted median;

$N =$ number of components $= 51$.

The trimmed mean is

$$\bar{\pi}_{\alpha,\beta} = \frac{1}{1-\alpha-\beta} \sum_{i=\hat{i}_i(\alpha)}^{\hat{i}_i(1-\beta)} w_{t-k}^i \pi_{t-k,t}^i$$

$$\pi_{t-k,t}^i = \left(\frac{P_t^i}{P_{t-k}^i}\right) - 1, \quad \alpha = .194, \beta = .254$$

4. Empirical Models and Results

I examine several models that re-weight the component inflation rates using the time-series information of the components, and I compare these models to standard measures. The new measure proposed is a weighted average of the lagged inflation components. Core inflation is

$$\pi_{ts}^c = \beta_1 \pi_{t-1}^1 + \beta_2 \pi_{t-1}^2 + \dots + \beta_t \pi_{t-1}^t + \varepsilon_t, \quad (3)$$

where π_{ts}^c is core inflation based on time-series information. Lagged inflation is a special case where β_j is equal to the budget shares.

The next question that arises is how to determine the weights using the time-series information. I use two methods to calculate the weights. In the first method I estimate the weights that provide the best fit from a time-series regression, and in the second method I impose the weights. When imposing the weights I follow a methodology similar to Cutler and estimate the weights based on the persistence of each component and then impose the weights to forecast headline inflation. I return to Cutler's specification later.

The first model regresses aggregate inflation on the component inflation rates in the following regression:

$$\pi_{t+12,t} = \alpha + \beta_1 \pi_{t,t-12}^1 + \beta_2 \pi_{t,t-12}^2 + \dots + \beta_{51} \pi_{t,t-12}^{51} + \varepsilon_t, \quad (4)$$

where $\pi_{t+12,t}$ is the 12-month ahead inflation rate and $\pi_{t,t-12}^j$ is the previous 12 month component inflation rate. This is the regression based (components) model. I estimate this equation using Ordinary Least Squares (OLS) and use Newey-West corrected standard errors due to the overlapping nature of the data.

I compare these regression results to forecasts made with more standard measures. The first uses lagged inflation as the forecaster.

$$\pi_{t+12,t} = \alpha + \beta \pi_{t,t-12} + \varepsilon_t, \quad (5)$$

The second uses either the lagged weighted median, lagged trimmed mean or lagged PCEX as the forecaster.

$$\pi_{t+12,t} = \alpha + \beta x_{t,t-12} + \varepsilon_t, \quad (6)$$

where x is the weighted median, trimmed mean or the minus food and energy.

Table 1 reports the results. The sum of squared residuals (SSR) is 19.63 for the regression based (components) model. The regression based model, which uses the time-series information and estimates the weights, performs better than any of the lagged inflation measures. The SSR are 139.68 and 134.77 for lagged inflation and the weighted median, respectively. For lagged inflation the coefficients are the budget shares⁶. I test if the coefficients from the regression based model are equivalent to the budget shares. Both sets of weights are presented in Table 2. I normalize the regression based coefficients so that they sum to one and are more easily comparable to the budget shares. I reject that the two sets of coefficients are equal. The $\chi^2(51)$ statistic is 2267.52 with a p-value of 0.00. From these results it appears that disaggregating along time improves forecasting future inflation over disaggregating along the cross section, which is the methodology used to construct the weighted median. Also the budget shares of the components do not appear to be the optimal weighting for predicting inflation.

The regression based (components) model estimates the coefficients to find the best fit over time but there is another method to determine the weights that also uses the time-series information of the components. In this method the coefficients are imposed after estimating the weights separately. Each weight is estimated by a procedure similar to those suggested by Cutler and is not estimated jointly to find the optimal weighting.

Cutler uses a stationary model (an AR(1)) to model the persistence of each component's inflation rate.⁷ This persistence coefficient then becomes the weight for that component. To obtain forecasts she aggregates the component inflation rates by these estimated persistence weights. She allows the persistence weights to vary annually.

⁶ I use the budget shares from June 1995 since this is approximately the half-way point of the sample period.

⁷ Cutler's data are for the United Kingdom and she uses eighty-one components at a monthly frequency.

For the United States, I use monthly data for 51 components. To find the persistence weight for each component I estimate an AR(1). The following regression is estimated by OLS for each component.⁸

$$\pi_t^j = \alpha + \beta_j \pi_{t-1}^j + \varepsilon_t, \quad (7)$$

where β_j is the estimated coefficient. If β_j is positive then there is persistence in the component and the persistence coefficient is equal to β_j and if β_j is negative then the persistence coefficient is equal to zero because there is no persistence in that component. The weights are normalized to sum to one. The persistence weights do not vary monthly but annually. After obtaining the persistence weights I transform the data to obtain the persistence-weighted forecast of aggregate inflation. The first model to use persistence weights is named persistence weighted (vary by year).

The next model uses a combination of persistence weights and the budget shares. The weight on each component equals the persistence weight multiplied by the budget share for each component. This specification prevents a component that is highly persistent but is relatively unimportant from dominating the forecast. This measure may be more useful than the other persistence-weighted measure because it takes account of both factors: the persistence of an individual component over time and the importance of an individual component in aggregate inflation.

Both of these persistence-weighted models perform poorly. Lagged inflation performs as well or better than either of these models. Specifically, the SSR are 139.69 and 156.32 for the time-varying persistence-weighted model, and the persistence-weighted model that includes the

⁸ For the first five years of the sample I use data from 1978-1982 to find the 1983 persistence weights. After 1983 the persistence weights vary by year.

budget shares, respectively. The coefficient estimates of the time-varying persistence weights⁹ are presented in Table 2. For this model I check if the coefficient estimates are equivalent to those obtained from the regression based model. I reject the null that the coefficients from the persistence-weighted models are equal to those from the regression based model.

Another model combines the idea of persistence weights and the regression based model. In this model (regression based – pw components) I first calculate the persistence weights as described above (equation 7) and then I calculate the persistence weighted component inflation rates. With these inflation rates, I then run a regression based model similar to the one in equation 4. The SSR is slightly smaller, 19.52 for the regression based model with the persistence-weighted component inflation rates. There does not seem to be much gain from persistence weighting first and then using a regression to find the optimal weights.

In addition, to allowing the component inflation rates to follow an AR process, it might be more realistic if they followed an ARMA model. I find the best-fitting ARMA model for each component (testing up to 12 AR elements and 12 MA elements). I then predict each component's inflation rate using the ARMA model. To get the forecast of aggregate inflation I use the budget shares to combine the forecasted component inflation rates. This ARMA (components) model performs worse than the lagged inflation and lagged weighted median.

The final model tested uses both time-series and cross-section information. This “supermeasure” combines the idea of persistence weighting and the weighted median. I first compute the annual persistence weights as I did for the persistence weighted model. Then, for each month I find the median by using the persistence weights instead of the budget shares to rank the component inflation rates. This “supermeasure” named median persistence weighted

⁹ I use the persistence weights from June 1995.

performs slightly better than the persistence-weighted measures but not nearly as well as the regression based model. The SSR is 126.48.¹⁰

In Figure 1, I present the actual, forecast and residuals from four of the models (regression based, lagged inflation, lagged weighted median, and persistence weighted). From these graphs, the superiority of the regression based model can be seen. The residuals are much smaller than from any of the other models. This is also indicated by the much lower SSR of the regression based model over the other models.

The in-sample results lend credence to the idea that using the time-series information provided in component level data is beneficial. The regression based model where the coefficients are jointly estimated outperforms standard measures such as lagged inflation and the weighted median; however, persistence weighted measures similar to those proposed by Blinder and Cutler do not fare as well and the use of information about the persistence of the components may not be helpful in forecasting.

To check the robustness of the in-sample results discussed earlier, I perform out-of-sample forecasts at two time horizons (12 months and 24 months). I compute the 1-month ahead forecasts using Recursive Least Squares (RLS). The rankings of models are very similar to the in-sample results. The root mean squared error (RMSE) of the regression based model is .38 and .30 at the 12-month and 24-month horizons, respectively.¹¹ At the 12-month time horizon the RMSE is 45% better than the RMSE of the forecast made with median persistence weighted measure, the next best measure. Finally, I test using the Diebold-Mariano test if the difference in

¹⁰ I also test if combining lagged inflation with another inflation measure improves prediction. The results, which are available from the author upon request, indicate that combining two inflation measures did not improve forecasts as Smith (2004) indicates.

¹¹ There are 270 observations in the 12-month ahead forecasts and 258 observations in the 24-month ahead forecasts.

the RMSE of each model is significantly different from the regression based model. I reject the null hypothesis for all models except the regression based model that uses persistence weights at both the 12-month and 24-month forecast horizon. This confirms that the regression based model is substantially better than other models at forecasting future inflation.

In Figure 2, the forecast errors from three models (lagged inflation, lagged weighted median, and persistence weighted) are compared with the forecast errors from the regression based model at the 12-month time horizon. In these graphs, the forecast errors of the regression based model are smaller than the other forecast errors confirming the superiority of the regression based model for forecasting.

The out-of-sample forecasts support the earlier conclusion that using a measure that exploits time-series information can provide better forecasts than using cross-section information alone. However, focusing on persistence does not seem to be the best way to exploit time-series information at least not in the current monetary policy regime of the United States.

5. Conclusion

This paper examines whether disaggregating along the time-series dimension can lead to a better forecast of inflation. I find that exploiting the time-series information in disaggregated or component inflation data produces better forecasts than exploiting cross-section information in component inflation data. In addition, this paper explores several different models that utilize the time-series properties of the component inflation rates. One set of models estimates the weights and the other imposes the weights on the various components of inflation. The models based on the persistence of the components do not fare well. They are outperformed by measures of core inflation, which are computed by jointly estimating the weights on the components.

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Appendix A: List of Components

New autos	Other recreation
Net purchases of used autos	Personal care
Other motor vehicles	Personal business
Tires, tubes, accessories, and other parts	Education and research
Furniture, including mattresses and bedsprings	Religious and welfare activities
Kitchen and other household appliances	
China, glassware, tableware, and utensils	
Video and audio goods, including musical instruments	
Other durable house furnishings	
Ophthalmic products and orthopedic appliances	
Wheel goods, sports and photographic equipment, boats	
Jewelry and watches	
Books and maps	
Food purchased for off-premise consumption	
Alcoholic beverages purchased for off-premise consumption	
Purchased meals and beverages	
Alcohol in purchased meals	
Food furnished to employees	
Shoes	
Women's and children's clothing and accessories except shoes	
Men's and boys' clothing and accessories except shoes	
Gasoline, fuel oil, and other energy goods	
Tobacco products	
Toilet articles and preparations	
Semi-durable house furnishings	
Cleaning and polishing preparations, and miscellaneous	
Drug preparations and sundries	
Nondurable toys and sport supplies	
Stationery and writing supplies	
Magazines, newspapers, and sheet music	
Flowers, seeds, and potted plants	
Owner-occupied non-farm dwellings--space rent	
Tenant-occupied non-farm dwellings--rent	
Rental value of farm dwellings	
Other housing	
Electricity and gas	
Other household operation	
User-operated transportation	
Purchased local transportation	
Purchased intercity transportation	
Physicians	
Dentists	
Other professional services	
Hospitals and nursing homes	
Health insurance	
Admissions to specified spectator amusements	

TABLE 1: Comparison of in-sample models

Model	Stationary specification		
	SSR	AIC	SIC
Lagged PCE inflation	139.68	2.20	2.23
Lagged PCEX inflation	160.26	2.34	2.37
Lagged PCEMED inflation	134.77	2.17	2.19
Lagged PCETM inflation	143.93	2.23	2.26
Regression based (components)	19.63	0.61	1.31
Regression based (pw components)	19.52	0.61	1.30
Persistence weighted(vary by year)	139.69	2.20	2.23
Median persistence weighted	126.48	2.10	2.13
Persistence weighted*budget shares	156.32	2.31	2.34
ARMA (components)	161.61	2.35	2.37

TABLE 2: Comparison of coefficient estimates of models

	Budget shares (1995:06)	Regression based (1995:06)	Persistence weighted (1995:06)
New autos	0.018	0.027	0.020
Net purchases of used autos	0.011	0.043	0.020
Other motor vehicles	0.020	-0.172	0.020
Tires, tubes, accessories, and other parts	0.008	0.019	0.020
Furniture, including mattresses and bedsprings	0.010	-0.012	0.019
Kitchen and other household appliances	0.006	-0.123	0.020
China, glassware, tableware, and utensils	0.005	0.066	0.019
Video and audio goods, including musical instruments	0.037	0.029	0.020
Other durable house furnishings	0.011	0.064	0.020
Ophthalmic products and orthopedic appliances	0.003	-0.134	0.020
Wheel goods, sports and photographic equipment, boats	0.009	-0.049	0.020
Jewelry and watches	0.010	-0.026	0.019
Books and maps	0.005	-0.149	0.018
Food purchased for off-premise consumption	0.079	-0.117	0.020
Alcoholic beverages purchased for off-premise consumption	0.011	0.006	0.020
Purchased meals and beverages	0.052	0.319	0.020
Alcohol in purchased meals	0.006	-0.022	0.020
Food furnished to employees	0.002	0.452	0.020
Shoes	0.009	-0.075	0.020
Women's and children's clothing and accessories except shoes	0.031	-0.009	0.017
Men's and boys' clothing and accessories except shoes	0.016	0.033	0.019
Gasoline, fuel oil, and other energy goods	0.023	-0.021	0.020
Tobacco products	0.006	-0.007	0.020
Toilet articles and preparations	0.009	-0.072	0.020
Semi-durable house furnishings	0.007	0.033	0.018
Cleaning and polishing preparations, and miscellaneous	0.009	0.026	0.020
Drug preparations and sundries	0.017	0.094	0.020
Nondurable toys and sport supplies	0.011	-0.004	0.020
Stationery and writing supplies	0.003	0.005	0.019
Magazines, newspapers, and sheet music	0.005	0.399	0.019
Flowers, seeds, and potted plants	0.003	-0.003	0.018
Owner-occupied non-farm dwellings--space rent	0.098	-0.119	0.020
Tenant-occupied non-farm dwellings--rent	0.035	0.431	0.020
Rental value of farm dwellings	0.002	0.106	0.020

Other housing	0.007	0.007	0.020
Electricity and gas	0.025	-0.068	0.020
Other household operation	0.036	-0.259	0.020
User-operated transportation	0.031	-0.003	0.017
Purchased local transportation	0.002	0.051	0.020
Purchased intercity transportation	0.007	-0.008	0.019
Physicians	0.037	0.247	0.020
Dentists	0.008	-0.008	0.020
Other professional services	0.024	-0.043	0.020
Hospitals and nursing homes	0.071	0.009	0.020
Health insurance	0.011	0.030	0.020
Admissions to specified spectator amusements	0.004	0.032	0.018
Other recreation	0.031	-0.416	0.020
Personal care	0.012	0.031	0.020
Personal business	0.067	-0.056	0.020
Education and research	0.020	0.006	0.020
Religious and welfare activities	0.022	0.410	0.020

TABLE 3: Out-of-sample forecasts

Model	RMSE	Ratio	
<u>Forecast 12-month ahead</u>			
Lagged PCE inflation	0.72	1.88	*
Lagged PCEX inflation	0.78	2.03	*
Lagged PCEMED inflation	0.71	1.85	*
Lagged PCETM inflation	0.73	1.91	*
Regression based (components)	0.38		
Regression based (pw components)	0.38	1.00	
Persistence weighted(vary by year)	0.72	1.88	*
Median persistence weighted	0.69	1.80	*
Persistence weighted*budget shares	0.76	1.99	*
<u>Forecast 24-month ahead</u>			
Lagged PCE inflation	0.73	2.41	*
Lagged PCEX inflation	0.73	2.42	*
Lagged PCEMED inflation	0.69	2.28	*
Lagged PCETM inflation	0.72	2.37	*
Regression based (components)	0.30		
Regression based (pw components)	0.30	1.00	
Persistence weighted(vary by year)	0.74	2.46	*
Median persistence weighted	0.69	2.29	*
Persistence weighted*budget shares	0.76	2.52	*

* indicates that RMSE of the model is significantly different than the RMSE of the Regression based model according to the Diebold-Mariano test statistic

Figure 1A: In-Sample Residuals from Regression Based Model

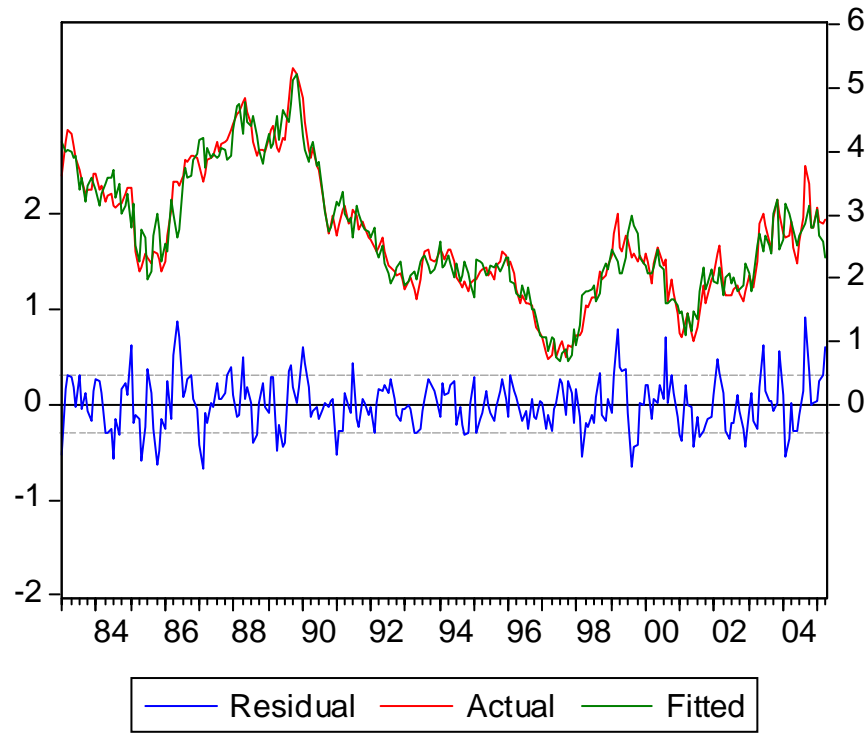


Figure 1B: In-Sample Residuals from Lagged Inflation Model

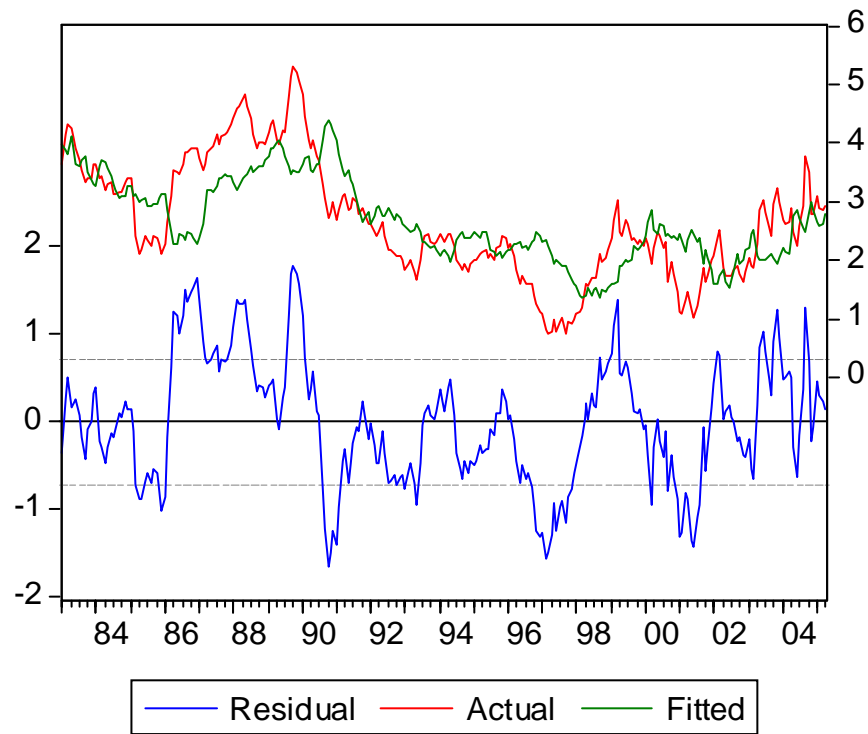


Figure 1C: In-Sample Residuals from Lagged Weighted Median Model

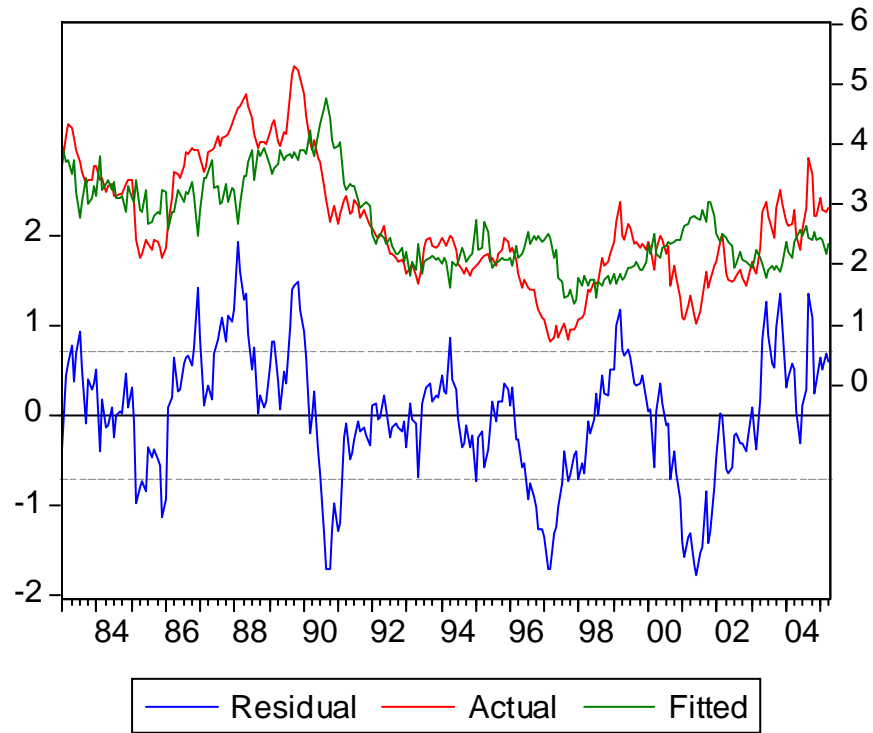


Figure 1D: In-Sample Residuals from Persistence Weighted Model

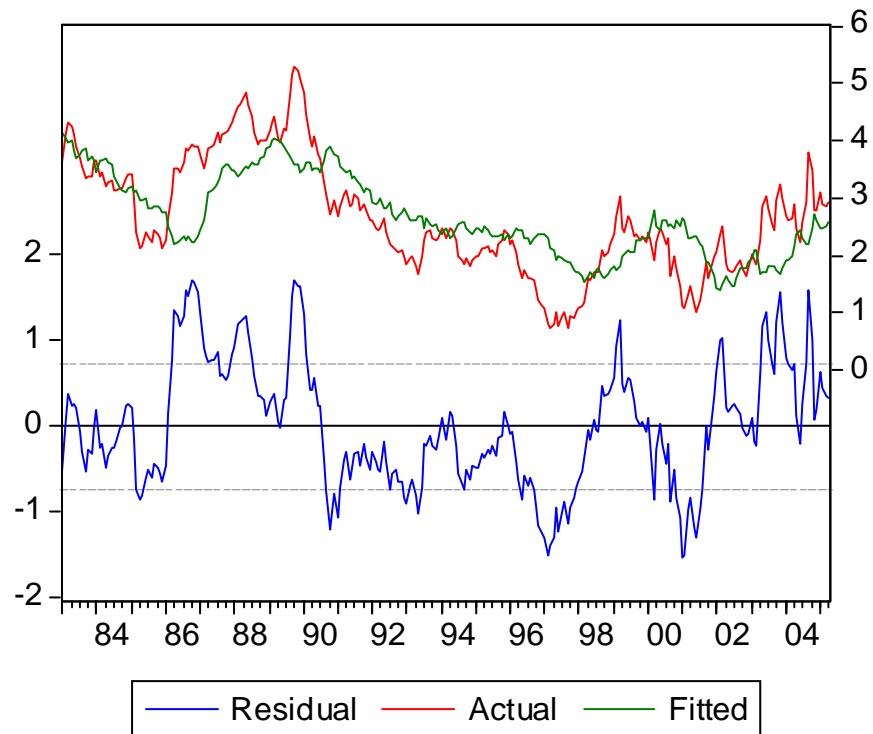


Figure 2: Out-of-Sample Residual Comparison (12-month ahead forecast)

