A Local Examination for Persistence in Exclusions-from-Core Measures of Inflation Using Real-Time Data

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January 2009

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by

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February 2009

Abstract

Using parametric and nonparametric methods, inflation persistence is examined through the relationship between exclusions-from-core inflation and total inflation for two sample periods and in five in-sample forecast horizons ranging from one quarter to three years over fifty vintages of real-time data in two measures of inflation: personal consumption expenditure and the consumer price index. Unbiasedness is examined at the aggregate and local levels. A local nonparametric hypothesis test for unbiasedness is developed and proposed for testing the local conditional nonparametric regression estimates, which can be vastly different from the aggregated nonparametric model. This paper finds that the nonparametric model outperforms the parametric model for both data samples and for all five in-sample forecast horizons.

KEY WORDS: Real-Time Data, Local Estimation, Nonparametrics, Inflation Persistence, Monetary Policy

JEL Classification Codes: E40, E52, C14

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1. Introduction

In terms of understanding the general trend of inflation and forecasting, data revisions of inflation measures also have the possibility of having a short-run effect just as changes in the relative price level and exogenous supply shocks to a given market, which can effect the formation of inflation expectations in the short-run and long-run (Gagnon 2008). Hypothetically, if inflation measures are typically underestimated and if a pattern can be determined, then the Federal Reserve can incorporate this information into their inflation forecast, which will in turn have the possibility of affecting the general public's view of expected inflation, an integral part of short-term inflation (Silver 1997). The general public's expectation of future inflation is of extreme importance to monetary policy since it helps to determine future interest rates aside from having an affect on the effectiveness of monetary policy as the rush in the early part of 2008 demonstrated when investors, who were, at first, merely concerned about potential higher future inflation rates, invested in commodities such as oil and gold. This speculation drove up prices, especially in oil futures, which had a negative and very expensive ripple effect throughout the entire economy. If the general public believes that core inflation is not a true measure of the price changes they see on a daily basis, then they will disregard the core inflation measure, which could adversely affect people's expectations about inflation thereby affecting the transparency required for the transmission of monetary policy (Johnson 1999).

The definition of core inflation varies by country with the U.S. definition of core inflation generally being total inflation minus the volatile components of food and energy, which is specifically examined in this paper. Generally, core inflation is thought of as a long-run concept, but core inflation can have implications in the short- and medium-run especially in regards to policy matters. The primary intent of core inflation is to capture the underlying trend of total inflation by not reflecting the changes in relative prices or temporary supply shocks that should be eliminated fairly rapidly. The implication of this primary intent is that core inflation should then have some predictive capability in regards to total future inflation at some forecast horizon that could include the relative short- and medium-run (Clark 2001). In addition, core inflation is used as a way of dispensing information to the general public regarding the trend of total inflation as well as matters relating to information about monetary policy decisions (Johnson 1999, Clark 2001).

The purpose of this paper is to investigate whether core inflation is able to predict the overall trend of total inflation, and if so, how fast, does this occur which is accomplished through the use of the exclusions-from-core measures of inflation. If the exclusions-from-core measures of inflation do have an impact on the in-sample forecast of inflation, then core inflation is not capturing the underlying trend of total inflation, which means that price stability, one of the mandates of monetary policy, is not achieved. In this paper, inflation persistence is examined through the use of exclusions-from-core measures of inflation over a five-period in-sample forecast horizon of one, two, four, eight, and twelve quarts using real-time data, which includes examining the effect of data revisions for fifty vintages of real-time data in two sample periods. Two types of core and total inflation measures, personal consumption expenditures (PCE) and the Consumer Price Index (CPI), are used to examine the effect that the exclusions-from-core has on total inflation.

The performance of PCE and CPI as an inflation measure is compared to see if the inflation measure has an effect on the measure of inflation persistence. Regarding PCE, the Federal Reserve currently uses the PCE to forecast core and total inflation since the PCE does not have as large of an upward bias as CPI due to the substitution effect. The PCE covers the whole consumption side of the economy as opposed to only the goods and services purchased by the typical urban consumer, which the CPI covers. The PCE is also subject to revision when additional source data becomes available, which enables a better break down between a change in real consumption and a change in consumer prices (Croushore 2007). Alternatively, as stated by Rich and Steindel (2005), since the price of capital goods purchased by firms is difficult to measure as are goods purchased by the government such as education, a consumer-based price index such as the CPI may be a better measure of inflation because items such as the costs of capital goods are ultimately passed onto the consumer, meaning that the production costs are passed along to the consumer as is government purchases through the form of taxation, which decreases consumers' purchasing ability. In addition, the CPI is also an inflation measure that is more familiar to the general public. Since it is not revised, the CPI might *appear* to be more reliable to the general public and thereby, better able to capture the general trend of inflation (Lafléche and Armour 2006). Hence, as one can see, a case for using either PCE or the CPI as a measure of inflation can easily be made.

Although this paper concerns the U.S. PCE and the U.S. CPI, much of the existing literature in this area has been done in regards to the Canadian CPI. Lafléche and Armour (2006), upon whose work this paper is heavily based, are unable to reject the null of unbiasedness in regards to the CPI core measure of inflation at the twelve-month in-sample horizon. Johnson (1999) also examines the relationship between core and total inflation using a weighted form of CPI for an in-sample forecast horizon of six, twelve, and eighteen months. At the six-month in-sample forecast horizon, Johnson (1999) finds unbiasedness, meaning that the core weighted CPI is able to capture the general trend of inflation, but rejects the null of unbiasedness at the twelve- and eighteen-month in-sample forecast horizons due to overestimation since the relationship between the excluded-from-core measure of weighted CPI and the *h*-period ahead difference in total inflation is greater than unity as indicated by the estimated slope coefficient, where *h* denotes any given length of an in-sample forecast horizon.

In addition, Cogley (2002) finds that an exponentially smoothed measure of inflation to outperform various measures of CPI and finds unbiasedness at the eight- to ten-quarter in-sample forecast horizons. Analogous to Cogley (2002), Rich and Steindel (2005) examine the in- and out-of-sample forecasts of PCE, CPI, and Cogley's (2002) exponential smoothed measure of inflation. Rich and Steindel (2005) fail to reject the null of unbiasedness at the 10% significance level at the twelve-quarter in-sample forecast horizon for PCE when a longer sample period that begins in 1959 is used, yet they reject the null of unbiasedness for the twelve-quarter in-sample forecast horizon when the data sample begins in 1978 for both PCE and CPI, and hence obtain contrary findings when the sample period is partitioned. The reason for rejecting the null of unbiasedness for the second sample as stated by Rich and Steindel (2005) is due to the inflexibility of the parametric methodology, which is relaxed in this paper through the use of nonparametrics.

For this paper, in order to examine whether core inflation is an unbiased estimator of general inflation, the regression model of Lafléche and Armour (2006), which is based upon Cogley (2002), uses a recursive parametric and nonparametric framework that is implemented using real-time data with the quarterly vintages of the real-time data ranging from V_1996:Q1 to V_2008:Q2.[1] The regression model involves regressing the *h*-period ahead change in total inflation at time *t* onto the difference between core inflation at time *t* and total inflation at time *t*, which is the exclusions-from-core measure of inflation at time *t*. If core inflation is an unbiased predictor of inflation, then the estimated vertical intercept term should jointly be zero with the estimated slope coefficient being unity.

[1] To make it easier to determine when a particular vintage of a real-time dataset as opposed to a given observation is being discussed the notation of "V_" will appear before the vintage of the real-time dataset. For instance, V_1996:Q1 refers to the vintage of the real-time dataset released in the middle of the first quarter of 1996 with the observable data ranging from 1959:Q4 to 1995:Q4.

Along the lines of Rich and Steindel (2005) and Clark (2001), two data samples are examined for inflation persistence with the first data sample beginning from 1960:Q1 and the partitioned data sample beginning from 1984:Q1, which takes into account structural breaks. The findings of this paper are that unbiasedness is sensitive to the following: inflation measure, data sample, and vintage.

Although nonparametrics is not specifically mentioned by Granger (2008), Granger states that the next forefront in non-linear research is time-varying parameters. For the nonparametric estimation of the regression model, the kernel-weighted least squares method (KWLS) method is used, and the main reason for using nonparametrics is its ability to provide time-varying local regression estimators that are easy to interpret for policy matters without the need of partitioning the dataset, which is commonly done in this literature. Another reason for using nonparametrics is that the empirical distribution of inflation is typically a fat-tailed distribution, and nonparametrics is better able to capture information in the tail regions as opposed to an ordinary least squares (OLS) model (Clark 2001).

In regards to the parametric estimation, OLS is used to capture the average behavior of the inter-relationship between the variables and is used as a benchmark comparison for its nonparametric counterparts. For instance, in an OLS framework, Johnston (1999) isolates and examines separately high and low-to-stable inflationary periods in the Canadian economy when parametric modeling is used. With nonparametrics, the partitioning of the sample period is not needed in order to isolate periods of high and low-to-stable inflationary periods. The window width, which is the smoothing parameter, along with the kernel, i.e. the smoothing function, is able to combine like-with–like by giving a higher weight to observations closer to the conditioning observation in terms of metric distance and less weight, i.e. less importance as the metric distance increases between any given observation and the conditioning observation. This is useful in the sense that the kernel automatically partitions the dataset while using the entire dataset thereby, being better able to capture the underlying trend with the inclusion of the tail regions. Within each window width, a local linear least squares (LLLS) line conditional on any given observation within the dataset is fitted with the inclusion of an intercept term that permits one to interpret the parameters of this local line as one would for its OLS counterpart.

It should be noted that while the reasons for a particular low or high inflationary period might differ, the underlying result is the same in that low inflationary periods produce a smaller measure of inflation and the alternate is true for high inflationary periods. If the general trend of core inflation is stable and does not contain periods where core inflation does not over-or-under predict the transitory nature of inflation, then this should be able to be captured both at the aggregated and local levels of core inflation. The use of nonparametrics permits one to examine potential periods of local deviations due to outliers that might be missed at the aggregate level as opposed to having the possibility of the aggregated results being outlier-driven.

Another reason for using nonparametrics follows heuristically along the same line of reasoning as Cogley (2002), which presents an adaptive measure of core inflation that permits learning with the assistance of a predetermined constant gain parameter such as the one used in recursive discounted least squares, which discounts old data while assigning new data a constant weight. Nonparametrics is able to provide an adaptive framework by providing a dynamic gain parameter that is data-driven though the use of its weighing kernel, which gives more weight, i.e. a higher importance to observations that are similar to the conditioning observation in terms of metric distance. For instance, a low measure of inflation is given more importance in a low inflationary period, and increasingly less weight as the similarity dissipates. Hence, new data is able to be accessed for importance, conditional on a given observation and incorporated appropriately. For this paper, the window width, which is the smoothing parameter of the weighting kernel that facilitates this comparison, is obtained through the use of the integrated residual squares criterion (IRSC) as proposed by Fan and Gijbels (1995).[2]

Yet another reason for using nonparametrics is its potential to explain the differing results obtained by Lafléche and Armour (2006) and Johnson (1999), which could be due to the larger sample size or due to the averaging method of OLS.[3] To account for these differing results, nonparametrics can assist through its ability by providing local analysis through tracing the conditional effect of each quarter of a vintage over time, which also happens to be a solution proposed to Elliott's (2002) call for examining the relationship across vintages thereby tracing the effect that data revisions have on parameters across time.

[2] In practice, the average residual squares criterion (ARSC) is used to approximate the IRSC.

[3] It should be noted that averaging and aggregation are not used as synonyms in this paper. For instance, the average estimators refer to the mean estimators, and aggregation refers to the use of *all* the local conditional nonparametric estimators.

Aside from examining whether core inflation is an unbiased estimator through the use of OLS, this paper also investigates unbiasedness through the use of nonparametrics by using each local, averaged as well as the aggregate nonparametric parameters. The global nonparametric parameters are the average of the local nonparametric parameters, which are able to be more readily compared to the OLS parameters. The statistical validity of the null of unbiasedness is tested through the F-test for the parametric and global nonparametric models and the likelihood ratio (LR) test for the local nonparametric model.[4]

A summary for the reasons why nonparametrics is used in this paper is as follows:[5]

(i.) Nonparametrics is able to provide both local time-varying and global regression parameters hence determining the effect of aggregation on the regression results especially when compared to the parametric OLS model,

(ii.) Nonparametrics removes the need to partition a dataset in order to isolate periods of interest due to the use of the smoothing kernel and its ability to provide local regression parameters,

(iii.) Nonparametrics provides an adaptive learning framework through the use of a data-driven dynamic gain parameter that is able to incorporate new data based on relevance in relation to the conditioning observation for each and every single data point of the dataset automatically,

(iv.) Nonparametrics is less prone to outliers and is able to use data both in the interior and boundary regions especially since the KWLS method is used,

(v.) The effect of revisions across vintages of real-time is able to be traced conditionally and across quarters, which could prove useful for monetary policy purposes in regards to the behavior of core inflation, and

(vi.) The KWLS form of nonparametrics is able to provide local conditional regression parameters that are easier to interpret for policy analysis.

To briefly summarize the empirical contributions of this paper, this paper examines the effect of the exclusions-from-core measure of inflation at the averaged levels, which refers to the parametric and global nonparametric regression estimators, aggregated levels, which simultaneously examines all the local nonparametric regression estimators, and at each individual conditional local nonparametric level. In order to analyze the effect of

[4] In much of the existing literature, such as Rich and Steindel (2005), the F-test is used.

[5] Items (i.), (ii.), (iv.), and (vi.) follow along the lines of motivation implied by Granger (2008) with Item (ii.) also being motivated by the reasoning of Cogley (2002) as is Item (iii.), and Item (v.) follows along the reasoning of Elliott (2002).

unbiasedness at the local conditional nonparametric level, this paper presents a local conditional hypothesis test based on the generalized method of moments (GMM) distance statistic.

For the first sample period, this paper finds that both the parametric and nonparametric models indicate that core inflation is a biased estimator of the trend of total inflation for both PCE and CPI at the one-, two-, and four-quarter in-sample forecasts. The only strong agreement in regards to unbiasedness is between the parametric and nonparametric models at the twelve-quarter in-sample forecast of CPI, where both models find that the core inflation measure of CPI to be an unbiased estimator of the total inflation measure of CPI. For the second sample period, the findings are more vintage-related than the first sample, which could be due to the effects of data-revision, but a clear consensus cannot be firmly made at this point since new data is incorporated with the revised data. The effect of structural breaks does impact both methodologies, but much more so in the parametric case.

The structure of this paper is of the following format: Section 2 presents the parametric and nonparametric model. The empirical results are presented in Section 3 as well as a brief discussion of the univariate data, and the conclusion is presented in Section 4.

2. The Parametric and Nonparametric Model

Without loss of generality, the discussion of the parametric and nonparametric models will be presented in reference to only one dataset, which leaves out the notion of vintages with each vintage representing a different real-time dataset that occurs with the advent of the release of new data.

2.1 The Parametric Model

One of the problems in analyzing inflation is its persistence as well as the possible presence of a unit root. The following regression model is an OLS model that permits the analysis of inflation persistence in a stationary framework with the parametric regression model being:

$$\left(\pi_{t+h} - \pi_t\right) = \alpha + \beta\left(\pi_t^{core} - \pi_t\right) + u_t \qquad (1.1)$$

where π_{t+h} is the *h*-period-ahead total inflation at time *t*, π_t is total inflation at time *t*, π_t^{core} is core inflation at time *t* with $u_t \sim (o, \sigma^2)$ being the random error term with *h* representing the in-sample forecast horizon (Clark 2001, Cogley 2002, Rich and Steindel 2005, Lafléche and Armour 2006, etc.).

To statistically test for unbiasedness, in regards to core inflation being able to predict total inflation, Equation (1.1) is tested for the joint null hypothesis of $\alpha = 0$ and $\beta = 1$ using the F-test at the 5% significance level. If the null hypothesis is rejected at the 5% significance level, then this seems to indicate that there is persistence (biasedness) present in the excluded-from-core series of inflation. In order to see if and how "fast" the short-run effects of inflation dissipates, a range of *h*-period in-sample forecast horizons is used, which is discussed in more detail in Section 3.1.

Suppose $\alpha = 0$ and $\beta = 1$, then Equation (1.1) collapses to

$$\pi_{t+h} = \pi_t^{core} + u_t . \tag{1.2}$$

In interpreting the slope coefficient with the mean of the error term being zero, if $\beta = 1$, this implies that

$$\beta_1 = \frac{\Delta(\pi_{t+h} - \pi_t)}{\Delta(\pi_t^{core} - \pi_t)} = 1$$

$$\Delta(\pi_{t+h} - \pi_t) = \Delta(\pi_t^{core} - \pi_t) \tag{1.3}$$

$$\Delta\pi_{t+h} - \Delta\pi_t = \Delta\pi_t^{core} - \Delta\pi_t$$

$$\Delta\pi_{t+h} = \Delta\pi_t^{core} . \tag{1.4}$$

Thus, Equation (1.3) refers to the changes in future inflation matching the changes in the excluded-from-core series of total inflation, which means that core inflation is an unbiased predictor of total inflation, π_t. Analogously, the changes in current core inflation is able to capture the changes in the *h*-period in-sample forecast of total inflation as demonstrated by Equation (1.4).

Furthermore, suppose $\alpha = 0$ and $\beta < 1$ with the average error term being zero, infers the following:

$$\Delta\pi_{t+h} < \Delta\pi_t^{core} . \tag{1.5}$$

Equation (1.5) implies that the excluded-from-core series of total inflation are overstated with the implication being that the changes in the *h*-period in-sample forecast of total inflation is below the changes in trend inflation as depicted by the changes of core inflation as shown by Equation (1.5) (Johnson 1999, Lafléche and Armour 2006).

Alternatively, with the average of the error term being zero as defined by the regression model, suppose $\alpha = 0$ and $\beta > 1$, then

$$\Delta\pi_{t+h} > \Delta\pi_t^{core} \quad . \tag{1.6}$$

Equation (1.6) infers that the changes in the excluded-from-core series of inflation are less than the changes of future inflation. The transitory movements from the excluded-from-core series are then said to be understated (Lafléche and Armour 2006, Johnson 1999). Analogously, the changes in the *h*-period in-sample forecast of total inflation are above the changes of trend inflation, which is what Equation (1.6) states.

Analogous to Cogley (2002) and Rich and Steindel (2005), the Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) covariance matrix is used to form the standard errors and the t-statistics for Equation (1.1) with the lags of the Bartlett kernel reflecting the length of the *h*-period in-sample forecasts.[6] Due to the construction of the variables used in the regression model, which includes the *h*-period in-sample forecast horizons, the Newey-West (1987) HAC is used to account for autocorrelations caused by the overlapping time period of variables and any potential conditional heteroskedasticity (Rich and Steindel 2005). [7]

In regards to hypothesis testing, for the parametric model the F-test is used. Pervious attempts at using the LR-test for both the parametric and nonparametric model produced some negative estimated LR-test statistics for both sample periods. This could be due to the distribution of the finite sample being different from the asymptotic distribution (Davidson and MacKinnon 1993). For the critical values the standard F-statistic critical values are used as opposed to the Dickey-Fuller F-statistic critical values since the variables in the model are stationary as is further discussed in Section 3.1.

In keeping within the framework of the literature in this area such as Cogley (2002), Johnson (1999), Lafléche and Armour (2006), and Rich and Steindel (2005), etc., the

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[6] Regarding the estimation of the Newey-West HAC variance-covariance matrix, the procedure written by Mika Vaihekoski (1998, 2004) is used and is able to be obtained from the following web address: *http://www2.lut.fi/~vaihekos/mv_econ.html#e3*.

[7] In estimation, as the in-sample forecast horizon increases, the level of autocorrelation in the residuals also increases, which further necessitates the need for the Newey-West (1987) HAC.

adjusted R-squared, $\bar{R}^2$, is used as a method for model comparison, which demonstrates how well the variation of the dependent variable is explained by the estimated model.

2.2 The Nonparametric Methodology

In this sub-section, the theoretical issues relating to the nonparametric estimation of KWLS will be addressed. Specifically, the issues of the choice of kernel, which is the smoothing function, window width, i.e. the smoothing parameter, the trade-off between bias and variance, and the curse of dimensionality as well as hypothesis testing of the cumulative local nonparametric estimators and the local conditional estimators will be discussed briefly in this section with more details being offered in the appendix.

2.2.1 The Kernel

The particular form of nonparametrics used in this paper is the KWLS, which amounts to fitting a line within the window width that is conditional on a given observation. The KWLS form of local polynomial fitting is able to provide both local conditional regression parameters as well as a set of global regression estimates by taking the average of the local conditional regression parameters. For this paper, the degree of the local polynomial is one since it is able to reduce the bias in the boundary regions without increasing the variance by much since a non-linear fit, such as a quadratic fit, increases the variance greatly due to the boundary effect (Ruppert and Wand 1994, Pagan and Ullah 1999).

Without loss of generality, let $Y = \begin{pmatrix} y_1 & \cdots & y_i & \cdots & y_T \end{pmatrix}'$ denote the regressand and $X = \begin{pmatrix} x_1 & \cdots & x_i & \cdots & x_T \end{pmatrix}'$ denote the univariate regressor. For this paper, the Gaussian kernel serves as a probabilistic smoothing function with the weights summing to unity for each local regression. In the univariate case, within the window width, the purpose of the Gaussian kernel function is to assign a weight to a given data point by measuring the metric distance between the given regressor data point, x_i, and the conditioning observation x_j, with the observations closest to the conditioning observation, x_i being given a higher weight, and thereby more importance, while observations farther from the conditioning observation, x_i being given a lower weight where *T* equals the total number of observations for *j = {1, . . . , T}* and *i = {1, . . . , T}*. So, conditional on any give value of x_j, and eventually, for all values of x_j, a window width is fitted around the conditioning observation x_j with the window width interval being $\left[\left(x_j - d_T\right),\ \left(x_j + d_T\right)\right]$ (Li and Racine, 2007). It should be noted that the window width, d_T, is also commonly referred to as a scaling parameter or bandwidth, since it scales the weighted Euclidean distance measure. Hence, the window width, d_T, is used in the kernel to help determine the "nearness" or "farness" based on the conditioning observation, x_j (Atkeson, Moore, Schaal, 1997) with the window width being discussed in more detail in the following sub-section.

The univariate Gaussian kernel is of the form:

$$K_j = \sum_{i=1}^{T} K\left(\psi_{ij}\right), \tag{2.1}$$

where $K\left(\psi_{ij}\right) = \frac{1}{(2\pi)^{\frac{1}{2}}} exp\left(-\frac{1}{2}\left(\frac{x_i - x_j}{d_T}\right)^2\right)$ with $\psi_{ij} = \left(\frac{x_i - x_j}{d_n}\right)$ and d_T referring to the window width, which is the smoothing parameter of the model. The Gaussian kernel has the Rosenblatt-Parzen properties that are beneficial for both asymptotic purposes and empirical estimation with the Rosenblatt-Parzen properties being as follows conditional on each and every x_j:

(i.) By the definition of a probability function: $\int K\left(x_j\right) dx_j = 1$

(ii.) Symmetry of the Gaussian kernel function: $\int x_j K\left(x_j\right) dx_j = 0$

(iii.) Boundedness: $\int x_j^2 K\left(x_j\right) dx_j > 0$ but less than infinity

(Wand and Jones 1995, Pagan and Ullah 1999).

2.2.2 The Window Width

The flexibility provided by nonparametrics is due to its window width since it is able to provide local regression parameters conditional on any given observation, x_j. This advantageous feature of nonparametrics is also the Achilles' heel since the choice of window width can severely affect the estimation of the local conditional regression parameters. If the window width is too *large*, then the variance is reduced but the bias of the regression coefficients increases. Alternatively, if the window width is too *small*, then the variance increases and the bias of the regression coefficients decreases (Pagan and Ullah 1999). Hence, it is important to balance the trade-off between bias and variance.

The most common method of choosing the window width is some form of cross-validation with one of the most common forms being the leave-one-out form of least squares cross-validation (LSCV), which is intentionally not used for this paper due to periods of instability when estimated (Fujiwara and Koga 2004). In determining the window width for each of the vintages, the LSCV method is estimated and rejected in favor of the IRSC since the LSCV does not produced stable results meaning that the same window width that minimizes the LSCV score function is not always chosen with the re-running of the LSCV method (Fan and Yao 1998, Wand and Jones 1995). This is due to the potential for more than one local minima with LSCV choosing the largest of the local minima (Wand and Jones 1995). Yet another reason for not using LSCV is that it does not automatically minimize the sum of squared errors, which is of importance since the local fit will be used for policy interpretation (Härdle 1994). In addition, the desirable characteristics in a window width, which are that as $T \to \infty$ with $d_T \to 0$ and $Td_T \to \infty$ are not obtained in estimation (Fujiwara and Koga 2004, Marron 1988). The reason that the aforementioned asymptotic characteristics are desirable in the behavior of the window width is to balance the trade-off between bias and variance as the sample size grows larger (Wand and Jones 1995).

The choice of window width used in this paper is Fan and Gijbels' (1995) IRSC method, which is a pre-asymptotic approach that is data-driven, and hence it does not rely upon unknown parameters such as the exact form of the underlying density function of the conditioning observation. The residual selection criterion (RSC) refers to normalizing the weighted residual sum of squares conditional on each and every observation, x_j and given window width, d_T.

The optimal window width for Equation (2.1) is obtained analogous to Fan and Gijbels (1995), which is as follows:

$$IRSC(d_T) = \min_{\alpha_t, \beta_t}\left[\int RSC(u_t, d_T)\, du\right] \tag{2.2}$$

where

$$RSC(x_j, d_T) = \hat{\sigma}(x_j)\{1 + (p+1)V\}$$

with $p = 1$ since the degree of the polynomial is unity and

$$\hat{\sigma}\left(x_j\right)=\frac{1}{tr\left\{K-\left(X'KX\right)^{-1}X'K^2X\right\}}\sum_{i=1}^{T}\left(y_i-\hat{y}_i\right)^2 w_i \tag{2.3}$$

where $\hat{y}_i = X\hat{\beta}\left(x_j\right)$, and $w_i = K\left(\frac{x_i - x_j}{d_T}\right) \Big/ \sum_{i=1}^{n} K\left(\frac{x_i - x_j}{d_T}\right)$ with V being the first diagonal element of

$$V=\left(X'KX\right)^{-1}X'K^2X\left(X'KX\right)^{-1} \tag{2.4}$$

where K is a $\left(T \times T\right)$ diagonal matrix with the ii^{th} element of K being $K\left(\Psi_{ij}\right)$ which is calculated conditionally on x_j for each and every single x_i. It is important to stress that for each and every x_j, a new $\left(T \times T\right)$ diagonal matrix K is formed. By minimizing the RSC, the mean squared error (MSE), which balances the bias and variance, is locally being minimized. It should be noted that the weighting function does not have a direct significant effect on the regression parameters while the window width does (Cleveland and Devlin 1988).

2.2.3 The Trade-off between Bias and Variance

The potential problem of the trade-off between bias and variance is addressed at each and every single component of the nonparametric model. For instance, the choice of the Gaussian kernel assists in bias reduction due to its symmetry around the mean and since the Gaussian kernel is a smooth function, it is able to provide "smooth" estimates (Atkeson, Moore, Schaal, 1997). The bias only concerns the estimated fit and the true fit within a given window width. If the true fit is almost linear, this would imply that the bias is small. Only if there is a great deal of curvature such as that which occurs at a maximum or a minimum, will the bias be large locally (Wand and Jones 1995).

Concerning the window width, by choosing a global window width that minimizes the ARSC, the mean squared errors is minimized thereby minimizing the squared bias and the variance of the regression parameter (Fan and Gijbels 1995, Marron 1988, Härdle and Tsybakov 1997).

2.2.4 The Curse of Dimensionality

The Curse of Dimensionality refers to the estimated nonparametric parameters tending to perform poorly, i.e. breaking down in higher dimension multivariate models that have a small amount of data. The Curse of Dimensionality is not an issue when the number of lags used in the model is small (Härdle and Linton 1994). It should also be noted that the Curse of Dimensionality is not an issue provided that the number of parameters is not a large proportion of the total number of observations, which means that having enough data can overcome the Curse of Dimensionality as stated by Cleveland and Devlin (1988). Hence, especially since this paper concerns a univariate model, after the calculation of inflation, with the smallest dataset containing 144 observations for the first sample period and 85 observations for the second sample period, the Curse of Dimensionality is a non-issue in regards to this paper.

2.2.5 The Nonparametric Model and Hypothesis Testing

For this paper, the IRSC method of Fan and Gijbels (1995) is used to obtain a constant window width. Through the use of the kernel density function, K which is a $(T \times T)$ diagonal matrix, the j^{th} conditional nonparametric coefficients based upon the j^{th} observation of the set of regressors, the local regression coefficients conditional on the x_j^{th} observation produces a $(q \times 1)$ column vector with q equaling two for this paper is denoted as

$$\beta_j = \left(X'KX \right)^{-1} X'KY \tag{2.5}$$

with K referring to the calculation of the kernel in Equation (2.1). Since the dataset contains T number of observations, then there will be T-number of regression estimates. Hence, conditional on x_j, the local regression equation is of the following form:

$$y_j = x_j \beta_j + v_j \tag{2.6}$$

where v_j is the local conditional error term. Once the local nonparametric coefficients are obtained, the global nonparametric estimates are able to be obtained by taking the average of Equation (2.5).

Just as in the OLS case, autocorrelation due to the leading dependent variable needs to be taken into account for both the global and local nonparametric models. The global nonparametric model is easier to deal with since it parallels OLS. The local error terms of

v_j for all j of Equation (2.6) are used to form the Newey-West (1987) HAC since they are obtained by minimizing the residual sum of squares.[8]

In regards to dealing with autocorrelation at the local level, Cai, Kuan, and Sun (2008) propose a way of combining nonparametrics, specifically, KWLS and GMM as does Creel (2008) except Creel's (2008) work mainly concerns general dynamic latent variable models. Creel (2008) discusses combining kernel smoothing techniques to obtain conditional moments and the Newey-West (1987) HAC, which itself involves a nonparametric kernel function, i.e. the Bartlett kernel, as is done in this paper in order to remove autocorrelation from the local conditional standard errors, which are needed for hypothesis testing.[9]

Two types of hypothesis testing based upon variations of the LR-test will be examined in this paper with the first one being a hypothesis test for testing for the goodness of fit regarding *all* the local conditional nonparametric regression estimates, and the second concerns hypothesis testing of *only the j^{th} conditional local* nonparametric estimates, which is done for all j observations in regards to policy analysis at the local level. The benefit of using the aforementioned variations of the LR-test is that the Chi-Squared critical values may be used without the need of bootstrapping, which saves computational time that can be rather extensive when bootstrapping is involved due to the need for calculating the window width for each iteration of the bootstrap.

Regarding the overall goodness of fit for all the local nonparametric regression estimates, Fan, Zhang, and Zhang's (2001) generalized nonparametric LR-test in a varying-coefficients models is used. Specifically, the generalized nonparametric LR-test is a hypothesis test that uses the weighted residual sum of squares with the same weighting matrix for both the null and alternate hypothesis being used in order to keep the comparison as similar as possible, which is important since the weighting is based on metric distance and the same observations need to be considered in the hypothesis tests.

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[8] Sometimes in nonparametrics, the average nonparametric regression parameters are used in an OLS framework to obtain the error terms, but this is not advisable since these error terms were *not* created by minimizing the residual sum of squared, and therefore, are not useful for hypothesis testing purposes.

[9] Creel (2008) does not use the Newey-West (1987) HAC variance-covariance matrix due to unreliability in the general dynamic latent variable model.

Assuming $E(v|X=x)=0$ and $E(v^2|X=x)=\sigma^2(x)$, the null hypothesis for the aggregate local nonparametric model, which includes *all* the local conditional nonparametric parameters for Equation (1.1) is of the form:

$$\text{H}_0\text{: } \alpha(x)=0 \text{ and } \beta(x)=1 \text{ for each and every } x_j, \tag{2.7}$$

with the alternate hypothesis being, H_1: Not H_0.

As provided by Fan, Zhang, and Zhang 2001, the construction of the generalized LR-statistic is of the following construction:

$$r_q'\lambda_T \xrightarrow{d} \chi^2_{a_T'} \tag{2.8}$$

where $r_q'=2.5600$ is the normalizing term for the LR-statistic of λ_T and $q=2$ for the total number of regression estimates. a_T' refers to the degrees of freedom where

$$a_T' = \left(\frac{2q+1}{2q-1}\right)\cdot\left(\frac{24q^2c^{\left(-1/2q\right)}}{24q^2+14q+1}\right)\left[\frac{\pi}{4q^2\sin\left(\frac{\pi}{2q}\right)}\right]\left(T^{\left(2/4q+1\right)}\right) \tag{2.9}$$

with c being some constant term where $c^{\left(-1/2q\right)}=0.7737$ since the Gaussian kernel is used. The LR-statistic of λ_T is of the form:

$$\lambda_T = \left[Ln(H_1)-Ln(H_0)\right]=\left(\frac{T}{2}\right)\log\left(\frac{RSS_0}{RSS1}\right) \tag{2.10}$$

where RSS_0 is the residual sum of squares under the null (the restricted model) and RSS_1 is the residual sum of squares of the estimated local nonparametric model. The RSS_0 is calculated *for all j observations* with the restricted parameters being equal to Equation (2.7) is of the following form:

$$RSS_0(x)=\sum_{j=1}^{T}\left\{y_i-\hat{\alpha}_0-\hat{\beta}_0\left(x_i-x_j\right)\right\}^2 K\left(\frac{x_i-x_j}{d_n}\right) \tag{2.11}$$

and RSS_1 is the residual sum of squares of the nonparametric model and is of the form with the nonparametric coefficients being obtained from Equation (2.5) *for all j observations*:

$$RSS_1(x)=\sum_{j=1}^{T}\left\{y_i-\hat{\alpha}_j-\hat{\beta}_j\left(x_i-x_j\right)\right\}^2 K\left(\frac{x_i-x_j}{d_n}\right) \tag{2.12}$$

Hence, a generalized nonparametric LR test produces *only* one test statistic for each dataset.

Especially if the relationship between variables is nonlinear, it is important to test for statistical significance at the local level, which could be of significance for policy implementation. By, exploiting the local nature of nonparametrics, the local conditional LR-statistic for *only the j^{th} conditional* nonparametric estimates is proposed based upon Newey and West (1987), which in this paper is referred to as the GMM distance statistic, $D_T\left(x_j\right)$. Hence, the residual sum of squares of the local unrestricted model is of the following form:

$$RSS_0'\left(x_j\right)=\sum_{i=1}^{T}\left\{y_i-\hat{\alpha}_0-\hat{\beta}_0\left(x_i-x_j\right)\right\}^2 K\left(\frac{x_i-x_j}{d_n}\right) \tag{2.13}$$

and the residual sum of squared of the j^{th} local nonparametric model is of the form:

$$RSS_1'\left(x_j\right)=\sum_{i=1}^{T}\left\{y_i-\hat{\alpha}_j-\hat{\beta}_j\left(x_i-x_j\right)\right\}^2 K\left(\frac{x_i-x_j}{d_n}\right). \tag{2.14}$$

Assuming that there is linearity in regards to the parameters under the null, then D_T is equal to the Wald statistic and is of the following form:

$$D_T\left(x_j\right)=W_T\left(x_j\right)=T\left(\frac{RSS_0'\left(x_j\right)-RSS_1'\left(x_j\right)}{RSS_1'\left(x_j\right)}\right)\xrightarrow{d}\chi_k^2 \tag{2.15}$$

where k is the number of restrictions under the null (Davidson and MacKinnon 1993).[10] $RSS_0'\left(x_j\right)$ and $RSS_1'\left(x_j\right)$ refers to the residual sum of squares of the conditional locally fitted regression produced by the KWLS method of the restricted and unrestricted models respectively for *only* the j^{th} observation. It is important to keep in mind that in a dataset with T-number of observations, there will be T-sets of locally estimated parameters to test for unbiasedness and therefore T-sets of local conditional GMM distance statistics, $D_T\left(x_j\right)$ can be interpreted.

As with its OLS counterpart, the $\bar{R}^2$ is used as a means of model comparison in determining which model is able to explain the variation of the regressand better. The global and local nonparametric models will have the same $\bar{R}^2$ since the same local conditional error terms are used. It should be noted that the same formula for the $\bar{R}^2$ is used in both the parametric and non-parametric cases which is as follows:

$$\bar{R}^2=1-\left[\frac{\hat{\sigma}^2}{\sigma_y^2}\right]=1-\left[\frac{RSS/(T-q)}{TSS/(T-1)}\right] \tag{2.16}$$

[10] It should be noted that the GMM distance function is a form of Hansen's (1982) J-statistic.

where $\hat{\sigma}^2 = RSS/(T-q)$ with RSS being the residual sum of squares and $\sigma_y^2 = TSS/(T-1)$ with TSS being the total sum of squares with q referring to the number of parameters in the model (Wooldridge 2003).[11]

3. Empirical Results

Since the empirical portion involves five in-sample forecasts for two measures of inflation PCE and CPI, which means that two regression models are estimated and discussed for three different methodologies which are the parametric, global nonparametric, and local nonparametric methodologies as well as five in-sample forecast horizons, Legend 1 to Legend 4 are provided in order to help with the interpretation of the tables.

Regarding the analysis and comparison of the parametric, global, and local nonparametric regression estimates, this section will mainly focus on the $\bar{R}^2$, the joint hypothesis test with the null of unbiasedness, and the investigation of the effects of data revision.

Concerning the real-time data set, even though the results for V_1999:Q4 and V_2000:Q1 are presented for the regressions involving the PCE measure of inflation, the results are unreliable due to issues that stem from the PCE. V_1999:Q4 is problematic because much of the dataset had to be interpolated since the real-time data of V_1999:Q4 actually begins with observation 1994:Q1, and especially in the nonparametric model, V_2000:Q1 is problematic due to inconsistencies in the data collection methodology.[12] In comparing V_2000:Q1 to other vintages, the change in data of V_2000:Q1 is picked up by the nonparametric methodology as evidenced by the smaller window width as is shown in Tables 6 and 7.

3.1 Data and Univariate Analysis

The measures of core PCE, PCE, and CPI are obtained in real-time and is available from the Philadelphia Fed. The seasonally-adjusted core CPI is obtained from the St. Louis Federal Reserve Economic Data (F.R.E.D) since it is not provided

[11] For a more generalized form of an R-squared formula, please see (Hayfield and Racine 2008), which breaks down to the same R-squared formula as the parametric case when the linear least squares model with an intercept term is used as is done in this paper.
[12] The interpolation method for V_1999:Q4 was kindly provided by Dean Croushore as was the information regarding V_2000:Q1.

in real-time.[13] Although CPI is not a revised time series, seasonally adjusted CPI does contain some small adjustments due to seasonality, which is why the real-time data of seasonally adjusted CPI is used.

The real-time dataset begins with first vintage being V_1996:Q1 and the last vintage being V_2008:Q2. Only 50 vintages are examined since these are the only available vintages of core PCE and PCE. Vintages of CPI go farther back, but in order to keep the real-time data analysis as symmetric as possible in regards to the vintages between the PCE and CPI, the shorter available time span of vintages is used. For the first sample period, each of the 50 vintages begins with 1959:Q4 before the calculation of inflation.

Regarding the first sample period, the calculation of inflation begins with 1960:Q1 to 2008:Q1 for the very last vintage used in this paper, which is V_2008:Q2. This long range of data is deliberately used in order to capture the long run trend in the core and total measures of inflation when possible and to look for patterns during recessionary times, expansionary times, and periods of economic growth (Rapach 2003, Gagnon 2008).[14] Since some observations are lost in forming the leading variables, the number of observations in each of the regressions varies according to the in-sample forecast horizons of h with h being defined as follows: $h = \{h_1, h_2, h_3, h_4, h_5\} = \{1, 2, 4, 8, 12\}$. The number of observations for each regression is presented in Legend 4.

For this paper, annualized quarterly measures of inflation are used. Quarterly PCE and quarterly core PCE data are available but only monthly seasonally-adjusted real-time data of CPI is available from the Federal Reserve Bank of Philadelphia. The release dates of real-time CPI are different from real-time PCE and real-time core PCE in addition to the fact that real-time CPI is measured monthly. Hence, real-time CPI is adjusted accordingly to produce annualized quarterly data.[15]

To describe generally the relationship between total inflation and core inflation using both PCE and CPI as depicted in Graphs 1A and 1B using V_2008:Q2, the relationship appears to be as follows:

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[13] For a more complete description of real-time data, please see Croushore and Stark (2001), Croushore (2007), and the Federal Reserve Bank of Philadelphia.

[14] As is later shown in Sections 3.2 and 3.3, the inclusion of a long period of time with potential structural breaks dampens the effectiveness of the regression model for both the parametric and nonparametric models.

[15] For more information regarding the collection of real-time CPI, please visit the Federal Reserve Bank of Philadelphia website of *http://www.philadelphiafed.org/econ/forecast/real-time-data/data-files/CPI/*.

(i.) *Pre-1982:* Total inflation and core inflation appear to share a similar co-movement,

(ii.) *Post-1982 to 1999:* Core inflation appears to either over- or under- estimate total inflation, which shows a great deal of unique local behavior, and

(iii.) *Post-1999:* The difference between total and core inflation becomes even more pronounce and displays some local divergence.

This seems to indicate the possible presence of a structural break especially around 1982. Based upon the findings of the Bai-Quant Test for Structural Change (1997), a structural break for core PCE, PCE, core CPI, and CPI are found at the following dates: 1983:Q2, 1981:Q2, 1980:Q3, and 1981:Q4.[16] For the purposes of keeping the analysis as similar as possible, the second sample period for each vintage begins in 1983:Q4 before the calculation of inflation with the vintages examined in this paper being analogous to the first sample period.

Regarding stationarity, since the differences in inflation measures are used in the variables of the regression model, the variables are I(0) which is confirmed by the Augmented Dickey-Fuller Test and the Phillips-Perron Test for stationarity. These findings are also confirmed by Clark (2001) and Rich and Steindel (2005).

3.2 Parametric and Global Nonparametric Empirical Results

To briefly summarize the findings of this section, the conclusions one can draw are methodologically-related as well as inflation-measure related. As a method of organizing the estimation results for discussion, "A" denotes the information regarding the regression involving the PCE measure of inflation, and "B" denotes the information regarding the regression involving the CPI. The parametric methodology provides a lower $\bar{R}^2$ when compared to the nonparametric methodology for both sample periods especially when the structural break in the early 1980's is not taken into account. Clark (2001) also finds such an increase in explanatory power of the model when the dataset is partitioned to exclude the early 1980's. For instance, in this paper, when the structural break is taken into account, the explanatory power of the variability of the dependent variable in Regression A increases by 75% at the very lowest, which occurs in the twelve-quarter in-sample forecast

[16] Bruce Hansen's program for testing for structural changes is used and is able to be obtained from the following web address: *http://www.ssc.wisc.edu/~bhansen/progs/jep_01.html*. The various tests producing conflicting results with the results of the Bai-Quant Test (1997) being chosen since the test results *appears* to best fit the visual pattern of all four time series.

horizon of PCE, and by 1558% at the very most, which occurs in the four-quarter in-sample forecast horizon. Analogously, for Regression B, the lowest increase in the $\bar{R}^2$ occurs in the twelve-quarter in-sample forecast horizon of CPI with a 397% increase once the structural break has been taken into account and a maximal increase of 2571% in the $\bar{R}^2$, which occurs at the two-quarter in-sample forecast horizon.

The parametric methodology indicates that core inflation is able to capture the overall trend of total inflation for both PCE and CPI at the two- and three-year mark for the first sample period, and the results for the second sample period vary by vintage. When the global nonparametric estimates are used as a measure of central tendency, the global nonparametric model is not able to duplicate any of the results, which most likely is due to the power of the hypothesis tests being used since it is not designed for the global nonparametric estimates. Instead as a comparison to the parametric model, the aggregated local nonparametric model might be better, which is discussed further in Section 3.3.

As with the situation of the parametric model, despite the flexibility of nonparametrics, a large structural break does affect the performance of the model as demonstrated by the $\bar{R}^2$. In Regression A, the lowest increase in the explaining the variability of the *h*-period ahead change in total PCE is a 63% increase, which occurs in the four-quarter in-sample forecast horizon, and the largest increase is found in the eight-quarter in-sample forecast horizon with the increase being 96%. For Regression B, the results are more dramatic with the lowest increase in the $\bar{R}^2$ between sample periods being 152%, which occurs in the four-quarter in-sample forecast horizon, and the largest increase is in the twelve-quarter in-sample forecast horizon with the increase being 259%. Despite these seemingly large increases in the explanatory power of the nonparametric model once the structural break is taken into account, the nonparametric model still out-performs the parametric model in regards to explaining the variability of the regressand in both Regressions A and B and for both sample periods by a large margin.

3.2.1 First Sample Period: Beginning from 1960:Q1

As a means to compare central tendency for *all* fifty vintages of real-time data from V_1996:Q1 to V_2008:Q2, the parametric OLS and the global nonparametric, i.e. the average of the local nonparametric estimated regression coefficients that are obtained respectively from Equations (1.1) and (2.6), produce vastly different results. As Table 1A shows, the estimated slope coefficients of the parametric case is smaller than its global nonparametric counterpart for the first three in-sample forecast horizons of one, two, and four quarters.[17] Table 1A shows the average of the following for each in-sample forecast horizon for the parametric and global nonparametric models: vertical intercept and slope and corresponding t-statistic and p-value for each. Alternatively, the estimated parametric slopes involving the in-sample forecast horizons of eight and twelve quarters is closer to unity and larger on average when compared to its global nonparametric counterpart as shown in Table 1A. The global nonparametric vertical intercepts tend to be negative and larger in absolute value terms than its parametric counterpart with each increasing in magnitude as the in-sample forecast horizon increases. The differences in the vertical intercept are important to point out because as mentioned by Rich and Steindel (2005), the inflexibility of the vertical intercept is one of the problems of the parametric model, especially when parameter instability is suspected.

The regression estimates for Regression B, which involves the CPI measure of inflation, are similar to the results of Regression A. The vertical intercept of the global nonparametric estimated coefficients tends to be negative and larger in absolute value terms that the parametric case for the in-sample forecast horizons of one, two, and four quarters. For the remaining two in-sample forecast horizons of eight and twelve quarters, the global nonparametric vertical intercepts are much larger and positive as shown in Table 1B. The estimated parametric vertical intercept is very close to zero but also increase in magnitude as the in-sample forecast horizon increases as it does for Regression A. For the estimated slope coefficients, the global nonparametric estimated slope coefficients are larger except for the regressions involving the in-sample forecast horizons of four and eight quarters with the average estimated slope coefficient involving the twelve-quarter in-sample forecast horizons being similar to its parametric counterpart. A summary of the average behavior of the estimated regressions coefficients for both the parametric and global nonparametric cases for all in-sample forecast horizons for Regression B are presented in Table 1B.

The standard deviations, t-statistics and related p-values for both the parametric and global nonparametric case are computed using the Newey-West HAC variance-covariance (1987) in order to take into account autocorrelation. The standard deviations, t-statistics and related p-values are provided for the estimated global nonparametric

[17] Due to an attempt at limiting space, all the results are not provided in this paper but are available upon request.

coefficients as a means of comparison of central tendency against the parametric model but are not an exact analogous comparison of methodologies due to the formation of residuals. For the hypothesis test for statistical significance for the global nonparametric regression coefficients, the local nonparametric residuals from Equation (2.6) are used since they were formed by minimizing the residual sum of squares, and the standard form of variance is used in the formation of the hypothesis tests. On average, for both Regressions A and B, the estimated global nonparametric slope coefficients are more likely to be statistically significant as is shown in Tables 1A and 1B. The statistically insignificant estimates are in bold print if the p-values are greater than 0.05. If the p-values are equal to 0.05, then the estimate is italicized and in bold print.

In comparing the $\bar{R}^2$, the parametric version is compared to the local nonparametric version, which was calculated in an analogous manner as stated in Equation (2.16). A summary of the averages of the $\bar{R}^2$ across vintages and for all five in-sample forecast horizons is provided in Table 3 for Regression A and B. As the vintages increase while holding the methodology constant, the $\bar{R}^2$ varies across methodologies with the nonparametric model producing higher $\bar{R}^2$. For all methodologies, the latter vintages combined with higher in-sample forecast horizons produce an overall higher $\bar{R}^2$ as shown in Table 3, which could possibly be partly due to data revision. Rich and Steindel (2005) also find that the $\bar{R}^2$ increases as the in-sample forecast horizons increase. The effects of data revisions are difficult to trace in an averaged framework because the differences could be due to the sample size, which increases with each vintage, even though a recursive framework is used especially since each newly incorporated observation is given the same importance, i.e. weight.

For the parametric Regression A, the lowest $\bar{R}^2$ of 0.017 is for the regression involving the four-quarter in-sample forecast horizon with the highest $\bar{R}^2$ of 0.165 involving the regression for the twelve-quarter in-sample forecast horizon. For *all* in-sample forecast horizons, the nonparametric model provides a much higher $\bar{R}^2$, and in terms of explanatory power is able to, at the very least, explain 61% more of the variation in the dependent variable when compared to the parametric model which is in the case of the regressions involving the twelve-quarter in-sample forecast horizon. In some instances, as in the four quarter in-sample forecast horizon, the nonparametric model is able to explain 1329% more than the parametric model. Concerning the $\bar{R}^2$ for Regression B, Table 3 shows the same pattern of the nonparametric model being able to explain more of the variation of the dependent variable, as is establish for Regression A, with the lowest percentage increase in terms of explanatory ability being 86%, which occurs in the regressions involving the twelve-quarter in-sample forecast horizon and at the very largest, is 1214%, which occurs at the four-quarter in-sample forecast horizon.

Regards to the joint hypothesis test for unbiasedness, in Equation (1.1), it is determined that unbiasedness occurs when the null hypothesis of $\alpha = 0$ and $\beta = 1$ fails to be rejected at the 5% significance level through the use of the F-test. So, the farther away the p-value gets from 0.05, the more strongly the null is failed to be rejected. For this paper, unbiasedness refer to the exclusions-from-core measures of inflation not having an impact on the *h*-period ahead forecast of inflation, which implies that core inflation is able to be capture the overall trend of inflation. For the first three in-sample forecasts of one, two, and four quarters, the null of unbiasedness is strongly rejected with a p-value of 0.0 for both the parametric and global nonparametric cases for Regressions A and B as is shown in Tables 5A and 5B. This means that core inflation is not able to capture the trend of total inflation for either PCE or CPI. The estimated slope coefficients for Regressions A and B, which are less than unity, mean that a scenario as described by Equation (1.5) has occurred. Equation (1.5) states that the excluded-from-core series of total inflation are overstated and that the changes in the *h*-period in-sample forecast of total inflation are below the changes in trend inflation.

For the parametric case, unbiasedness is found in the eight- and twelve-quarter in-sample forecasts of PCE and CPI. Unbiasedness is not found in any of the global nonparametric regressions despite them being able to explain more of the variation in the regressand for all regressions involving PCE and CPI.

3.2.2 Second Sample Period: Beginning from 1984:Q1

In taking into account a structural break, the parametric and global nonparametric models produce different results than that of the first sample period. Table 2A presents the average estimated coefficients for the regressions involving PCE for all fifty vintages. Except for the regression involving the first in-sample forecast horizon, the estimated slope coefficients are closer to unity that the global nonparametric slope coefficients. The signs of two- and four-quarter in-sample forecast horizon are negative while in the parametric model they are positive. In absolute value terms, the estimated vertical intercept are larger in magnitude in the global nonparametric models with the average of the estimated global nonparametric slopes for the four- and eight-quarter in-sample forecast horizon being statistically insignificant.

Regarding Regression B, which concerns the CPI, all the estimated vertical intercepts for the parametric and global nonparametric models are negative except for the global nonparametric regressions involving the two-quarter in-sample forecast horizon, which is essentially zero. As with Regression A, the average estimated slope coefficients are closer to unity especially for the latter three in-sample forecast horizon. The twelve-quarter in-sample forecast horizon for both the parametric and global nonparametric regressions are extremely close in magnitude. In the two methodologies, all the estimated slope coefficients are statistically significant as is shown in Table 2B.

Once the structural break is taken into account, the $\bar{R}^2$ of the parametric model improves dramatically when compared to the first sample period as is demonstrated in Tables 3 and 4. Despite this, when compared to the parametric model, the global nonparametric model is still able to explain at a minimum 41% more of the variation in the *h*-quarter change in PCE and 26% of the variation in the *h*-quarter change in CPI the four-quarter in-sample forecast horizon. The most dramatic increase involves the one-quarter in-sample forecast horizon with the global nonparametric model being able to explain 95% more of the variation in the regressand for Regression A and 125% more of the variation in the regressand for Regression B than the parametric model.

Concerning the joint hypothesis test with a null of unbiasedness, the results of the F-test in the parametric model are vintage-related as demonstrated by Tables 5A and 5B.[18] For both Regressions A and B, the null of unbiasedness is rejected at the 5% significance level for *all* in-sample forecast horizons. Contrary to the first sample period, the parametric model, at least for the latter vintages, the null of unbiasedness fails to be rejected at the 5% significance level for *all* in-sample forecast horizons except for the one-quarter in-sample forecast horizon involving CPI. The rejection of the null of unbiasedness for the twelve-quarter in-sample forecast horizon in the global nonparametric model is most likely due to the estimated vertical intercept, which is -0.661. Thus, regarding unbiasedness, the parametric model and the global nonparametric model do not concur on unbiasedness for any of the in-sample forecast horizons in the second sample period.

[18] Regarding the parametric model for the second sample period, the null of unbiasedness also fails to be rejected at the 5% significance level for the following sporadic vintages not specifically mentioned in Table 5A: $\mathbf{h_1}$: V_1999:Q4 to V_2000:Q1 and V_2001:Q4 to V_2002:Q1, $\mathbf{h_4}$: V_1999:Q4, V_2001:Q3 toV_2001:Q4, and V_2002:Q4 to V_2003:Q2, h_5: V_1996:Q1, V_1997:Q3, V_1999:Q4, V_2003:Q3.

3.3 Local Nonparametric Empirical Results

The window widths for each vintage and for each sample period are calculated using Fan and Gijbels' (1995) IRSC method as described in Sub-Section 2.2.2. For the first sample period, the window widths for each in-sample forecast horizon and for each vintage are found in Table 6 with the window width that minimizes the aggregate residual sum of squares being the same across in-sample forecast horizons. The second sample period's window widths for each vintage are found in Table 7, shows some variability across in-sample forecast horizons while, for the first sample period, the window widths for each vintage remain constant across all in-sample forecast horizon as is shown in Table 6.

The local nonparametric estimators show a great deal of local conditional nonlinearity that the parametric model is unable to pick up for both sample periods. In some cases, the GMM distance statistics, which tests for unbiasedness at the local level, finds failure to reject the null of unbiasedness despite the estimated slope coefficient being much greater than unity at the local level and the estimated vertical intercept term being non-zero.

When $\alpha = 0$ and $\beta = 1$, then the changes in *h*-period ahead inflation is equal to the changes in current core inflation on average as is demonstrated in Equation (1.4). Heuristically, when the difference between the actual value of the regressand and the fitted value is small, then, naturally, the residual is small. In regards to the joint hypothesis test for unbiasedness, when the difference between the residual sum of squares of the restricted and estimated (unrestricted) model is small, so is the estimated test statistic, which results in a larger p-value and failure to reject the null of unbiasedness when the p-value is greater than 0.05. Thus, it is important to examine the estimated regression coefficients in their proper context in regards to deciding for statistical relevance especially when the some of the estimated local conditional nonparametric coefficients can seem "abnormally" large. This is discussed in more detail in the following two sub-sections.

3.3.1 First Sample Period: Beginning from 1960:Q1

For Regression A, for V_2008:Q2, it might seem to be a mistake that conditional on 2006:Q4, the estimated vertical intercept for the two-quarter in-sample horizon is 20.75, and the estimated slope is -5.62, but upon examining the local nonparametric fitted values, the local nonparametric fitted value is 5.027 with the parametric fitted value being 1.14 and the actual value of the two-quarter ahead in-sample forecast of inflation being 5.07. This is just one of many instances where nonparametrics is able to pick up the curvature of the data better than the parametric version, which helps to explain why the nonparametric model has smaller residuals. Hence, regarding the interpretation of nonparametric models, it is important to not only look at the estimated coefficients but more importantly at the fitted values in order to determine if the local nonparametric estimates "make sense" and are not an anomaly in the sense of being window width driven.

Graphs 2A to 2B and Graphs 3A to 3B illustrates the estimated fitted values of the parametric and local nonparametric values along with the actual values of the four-quarter change and the twelve-quarter change in total PCE and total CPI, respectively. With the inclusion of the structural break, the local nonparametric model is better able to capture the actual in-sample forecasts of total inflation despite there being a great deal of local curvature with the exception of the oils shock of the mid 1970's and the turmoil of the early 1980's, thus explaining the much higher $\bar{R}^2$ for both Regressions A and B. The nonparametric model is better able to capture the behavior of the regressands in all four regressions, but proves to be problematic especially around the early 1980's as the in-sample forecast horizon increases. The regressions involving the four-quarter in-sample forecast horizon, as is found in Graphs 2A and 2B, are shown since the difference in terms of explanatory power between the parametric and nonparametric models, as described by the $\bar{R}^2$ is the highest. Analogously, the regressions involving the twelve-quarter in-sample forecast horizon are presented since they involve the regressions with the lowest in terms of the difference of the $\bar{R}^2$ between the two methodologies.

Before beginning with the examination of the effect of data-revision quarter-by-quarter through the use of the local nonparametric regression coefficients, the issue of the joint hypothesis of unbiasedness will first be addressed using Fan, Zhang, and Zhang's (2001) generalized nonparametric LR-test in order to see the effect of the aggregate local nonparametric estimates. The same issue of unbiasedness will also be examined at the local level conditional on each j^{th} observation through the use of the conditional GMM distance statistic as represented by Equation (2.15).

Table 8A displays the results of the Fan, Zhang, and Zhang's (2001) generalized nonparametric LR-test for Regression A, with the null of conditional unbiasedness being rejected for the regressions involving all in-sample forecast horizons except for V_1999:Q4, which is problematic since much of the dataset needed to be interpolated. A summary of the joint hypothesis tests of the aggregated local nonparametric estimates for both Regressions A and B can be found in Tables 5A and 5B. Regarding Regression B, as shown in Table 8B; Fan, Zhang, and Zhang's (2001) generalized nonparametric LR-test also rejects the null of unbiasedness for all in-sample forecast horizons except for the twelve-quarter in-sample forecast horizon with the exceptions of vintages, V_2005:Q1 to V_2006:Q1. Hence, according to Fan, Zhang, and Zhang's (2001) generalized nonparametric LR-test, *only* for CPI and *only* at the three-year mark does core CPI capture the general trend of total CPI in the first sample period.

In order to demonstrate hypothesis testing for statistical significance and unbiasedness at the local level conditional on the x_j^{th} observation, the time periods from 2000:Q3 to 2000:Q4 from V_ 2000:Q4 to the last vintage of V_2005:Q2 is examined with the finding presented in Table 10.[19] In particular, the local conditional nonparametric estimated regression coefficients from both Regressions A and B are examined to see if the aggregated and averaged behavior of the estimates is captured at the local level. The twelve-quarter in-sample forecast horizon is examined since at this forecast horizon level, Regression B, which relates to CPI is able to achieve unbiasedness in both the parametric and nonparametric models, while Regression A, which relates to PCE, is only able to able to achieve unbiasedness in the parametric model.

Conditional on 2000:Q2, the GMM distance statistic for Regression A fails to reject the null of unbiasedness for vintages V_2000:Q4 to V_2004:Q2 as is shown in Table 10 with the remaining vintages being statistically biased. The null of unbiasedness is strongly rejected for all vintages for Regression B conditional on 2000:Q2. Alternatively, conditional on 2000:Q1, the null of unbiasedness is rejected for Regression A, and for Regression B, the null of unbiasedness fails to be rejected for all vintages as is also shown in Table 10.

Regarding the local conditional nonparametric estimators, one would expect a gradual changing of slope coefficients when a particular quarter is traced across vintages assuming that data revision is not a factor as new data is appropriately incorporated by the Gaussian weighting function barring the effect of a régime or a structural change. Some estimated regression coefficients are showing abrupt changes and this seems to indicate

[19] Due to the calculation of the leading dependent variable, the last vintage for the 12-quarter in-sample forecast horizon is V_2005:Q2 as is shown in Legend 4.

that this is the effect of data revision since these abrupt changes are occurring around benchmark revision years such as V_1999:Q4 and V_2003:Q4. One such example, which involves the estimated slope coefficient conditional on the data of 2000:Q3, where there is a jump in the magnitude of the estimated slope coefficient from 1.40 in V_2004:Q1 to 2.05 in V_2004:Q2 in Regression B, which involves the CPI measure of inflation in the twelve-quarter in-sample forecast horizon.

At the 5% significance level for Regression A, the estimated vertical intercept and slopes are statistically significant with the majority of the estimated slope coefficients being greater than unity, which means that the excluded-from-core series of PCE are understated with the implication being that the twelve-quarter in-sample forecast of total PCE are above the changes of trend PCE as depicted by the changes in core PCE. It should be noted that the standard deviations for the local nonparametric estimators are very small since the variance-covariance matrix for the overall nonparametric model is generally smaller, and thereby more efficient, than its parametric counterpart since the KWLS method is used, which is a form of Generalized Least Squares (GLS).

For Regression B, the scenario is not so homogenous. Conditional on the CPI measure of inflation for 2000:Q1, the estimated slope coefficients are much less than unity for V_2000:Q2 to V_2005:Q2, while for the regression conditional on the data of 2000:Q1, the estimated slope coefficients are much larger than unity for V_2000:Q3 to V_2005:Q1.

Hence, in regards to the empirical estimation of Regressions A and B, this paper finds that both the parametric and nonparametric models agree upon unbiasedness in regards to the twelve-quarter in-sample forecast of CPI *only*. Although nonparametrics is able to provided conditional local estimates, the effects of data revision are much more difficult to pinpoint with any degree of certainty because of the continual updating of the real-time dataset with new information. In order to isolate the effect of data revisions, one must keep the number of observations the same while varying *only* the vintages; this is left for future research.

3.3.2 Second Sample Period: Beginning from 1984:Q1

Graphs 4A to 4B and Graphs 5A to 5B demonstrates the estimated fitted values of both the parametric and local nonparametric values along with the actual values of the one-quarter change and the four-quarter change in total PCE and total CPI, respectively. With the removal of the structural break, the parametric model performs better, but the nonparametric model still out performs the parametric model. The regressions involving the one-quarter in-sample forecast horizon, as is found in Graphs 4A and 4B, are illustrated since the difference in terms of explanatory power between the parametric and nonparametric models, as described by the $\bar{R}^2$ is the highest. Similarly, the regressions involving the four-quarter in-sample forecast horizon are depicted since they involve the lowest in terms of the difference of the $\bar{R}^2$ between the parametric and local nonparametric models.

In regards to Fan, Zhang, and Zhang's (2001) generalized nonparametric LR-test for the aggregate nonparametric model, for Regression B, which involves CPI, for the same in-sample forecast horizon such as the eight-quarter in-sample forecast horizon, the results of the joint hypothesis test for unbiasedness are mixed, which is analogous to the finding of the parametric model with a summary of the results being provided in Tables 5A and 5B. Concerning Regression A, the earlier vintages of the four-quarter in-sample forecast horizon find unbiasedness while the vintages after and not including V_2002:Q4 find that the aggregated nonparametric model to be biased.

Interestingly, when unbiasedness is tested at the local level, there are periods of local unbiasedness as is presented in Table 10. Unbiasedness is determined at the local level for observations 2000:Q3 and 2000:Q4 except for the vintage, V_2005:Q2 for Regression A, which involves PCE.

4. Conclusion

The contributions of this paper are the strongest on the two main fronts of methodology and empirical results and the third front of real-time data analysis being inconclusive.

Concerning the methodology, the contributions of this paper is as follows:

1. The innovation of a nonparametric GMM method is used to account for autocorrelation at the local level through the use of the Newey-West HAC estimator,
2. Global nonparametric estimators, which are the average of the local nonparametric estimates, are presented as a measure of central tendency but hypothesis tests based on using these measures are inadequate since the residuals that are not formed by minimizing the residual sum of squares.

The aggregate local nonparametric estimates produce vastly difference results in regards to hypothesis testing. Thus, instead of comparing the parametric benchmark with the average local nonparametric estimators, a better comparison in regards to hypothesis testing and overall model fit would be to use the aggregate local nonparametric model, and

3. A hypothesis test at the local nonparametric level that takes a weighted least squares approach by using the Newey-West (1987) GMM distance statistic, which is a conditional Wald test statistic, is implemented in order to test for unbiasedness at the local level that to the best of the author's knowledge has not been proposed or used in application.

Regarding the empirical results of the exclusions-from-core measures of inflation capturing inflation persistence, the results are as follows:

1. The findings of unbiasedness especially in the second sample period can possibly be vintage-related, which could be due to the incorporation of new data or data-revisions. This is an argument in favor of using real-time data as opposed to the continually updated data of other sources,
2. In the presence of a large structural break such as the one that occurs in the early 1980's for PCE, core PCE, CPI, and core CPI, the ability of the parametric model to explain the variability of the *h*-period ahead change in total inflation is dramatically decreased when compared to the sub-sample period with the removal of the structural break,
3. The local nonparametric model fares better in the presence of a large structural break, but still once the structural break is taken into account, the explanatory power of the local nonparametric model as captured by the $\bar{R}^2$ also increases dramatically, but not as drastically as the parametric model, and
4. Even at the local level, unbiasedness is not obtained with any degree of recursion in regards to the vintage in the local nonparametric case except for eight-quarter in-sample forecast horizon for the second sample period. Alternatively, the parametric model is more likely to be unbiased meaning that core inflation is able to predict the *h*-period ahead changes in total inflation for both PCE and CPI but is also vintage-related and sample-related

in spite of being able to explain less of the variation in the regressand which makes one question the findings of unbiasedness.

The contribution of this paper is regards to the exact effect of data-revision on measuring the persistence of inflation is uncertain. The use of a recursive methodology in a parametric and non-parametric framework is not enough to isolate the effects of data-revision. In the presence of data revision, even when new data is incorporated by using a dynamic gain parameter, it is not clear whether the change produced in the local conditional regression is from the incorporation of new data or due to data revision. Hence, this paper finds that it is important to isolate the effect of data revisions by keeping the dataset constant and varying only the vintages, in order to see the effect of data revision and only data revisions, which is left for future research.

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Appendix:
Additional Information regarding the Nonparametric Methodology

A1. The Kernel

In regards to the weighting, the weights are obtained from the height of the kernel, conditional on any given x_j. If the given observation and the conditioning observation are the same, i.e. $x_i == x_j$ then the Euclidean distance is zero, which is one of the minimax properties with the conditional maximal value of the weighting function occurring at this point (Wand and Jones 1995, Atkeson, Moore, and Schaal 1999, and Fan and Gijbels 1996). According to Atkeson, Moore, and Schaal (1999) and to Pagan and Ullah (1999), one of the benefits of the Gaussian kernel is its symmetrical nature, which helps in bias reduction. Furthermore, since the Gaussian kernel is not bounded such as the Epanechnikov or the tricubed kernel, the Gaussian kernel has an infinite extent, which avoids many boundary problems and is actually better able to incorporate information in the tail region, but it does not entirely eliminate the boundary problems (Atkeson, Moore, and Schaal 1999). The boundary problems that are not entirely eliminated is the potential for the conditional variance being large when there is a sparsity of data and the KWLS estimators not being asymptotically orthogonal as they are at the interior points, which increases the conditional bias (Fan and Gijbels 1992, Rupert and Wand 1994).

A more heuristic explanation of the importance of metric distance is that it takes into account the scale of measurement or the level of measurement, as it is commonly referred to in the field of statistics. The scale of measurement refers to the classification and description of a variable, which generally varies depending on the interval being examined (Stevens, 1946). In nonparametrics, the classification is based upon interval measurement, i.e. metric distance, which is what the kernel function measures by considering whether x_i conditional on x_j occurs within the window width and if so, what is the conditional relational relationship in regards to the regressand y_j. An analogous example might be to describe the use of metric distance in the kernel in the framework of a recession. One definition of a recession is a decline in economic activity that is spread across all sectors of the economy that lasts for a few months. Hence, by definition, the one thing in common that all recessions share is that they must have a decline in economic activity, but as to the specific cause of the recession or in regards to which sector of the economy was the impetus of any given recession are entirely different questions with entirely different answers. To re-iterate, this paper examines the conditional probability of whether x_i given x_j occurs in relation to y_j and not the underlying reason or reasons why x_i given x_j occurs in relation to y_j, which is analogous to the underlying credo of nonparametrics of "Let the data speak," which it does in terms of the metric distance and not in regards to the "timeliness" or time period of the occurrence of an economic statistic.

An alternative to using metric distance as a conditioning measurement is the use of time. Some time-varying parameter models such as Primiceri (2005), which uses a Monte Carlo Markov Chain model, or Cogley and Sargent (2005), which uses a Bayesian approach to the Monte Carlo Markov Chain model, emphasize "timeliness" as opposed to metric distance. The main reason why "timeliness" is not used in this paper is that generally there is a gradual change in inflation, which the weighting function is able to utilize through the window width. For instance, based on the conditioning observation, x_j, generally the observations x_{j-1} and x_{j+1} are not only close x_j in terms of time but also metric distance. If the conditioning observation, x_j, is an outlier in the sense that the adjacent observations are near in terms of time and not metric distance, then this is important to note because this generally indicates an outlier for both the parametric and nonparametric model provided that there are not other observations in the range of x_j at an alternate sub-sample of time. An outlier of this form is easier to identify and isolate in the nonparametric model since the local conditional estimate will be abnormally and relatively larger. This is an indication that the results are window width driven.[20]

Furthermore, it should be noted that the metric distance is important in regards to nonparametrics being able to capture the local curvature conditional on the x_j^{th} observation. If there is a great deal of curvature within any given interval as defined by the window width, then it is important to give a greater importance, i.e. weight to observations closer to the conditioning observation, which aids in bias reduction of the nonparametric estimator (Ruppert and Wand, 1994).

[20] In addition, models such as the Monte Carlo Markov Chain require that additional assumptions be made, while this paper wants to place as few prior restrictions or assumptions as possible on the model so that the "data can speak".

As is stated in Sub-Section 2.2.3, the link between the bias and curvature depends upon the metric distance characteristic of the Gaussian kernel, the notions of conditional bias and curvature are *local attributes*. Suppose that the true fit of the model within the window width is very close to linear, this would imply that the bias is small. Generally, only if there is a great deal of curvature such at that which occurs at a maximum or a minimum of a curve will the bias be very large locally (Wand and Jones, 1995).

A2. The Window Width

A potential explanation by Wasserman (2006) could shed some light on why cross-validation has typically been the preferred method of obtaining the window width in practice over the residual-based selection of window width such as Cai and Chen (2005), Cai (2007), Fan and Yao (1998), and Chauvet and Tierney (2008). Wasserman (2006) refers to the mean squared errors as the training error and states that this will cause the regression coefficients to have a downward bias and will generally lead to under-smoothing, i.e. over-fitting. Typically, if the nonparametric regression is under-smoothed, this will cause the variance to be large, but this is not the case with the findings of this paper. This paper finds that the estimated variances formed from the residuals of the local KWLS regressions are smaller than their parametric counterpart, which is what one would expect since the KWLS is a from of Weighted Least Squares (WLS), i.e. a form of Generalized Least Squares (GLS) and thereby, efficient.

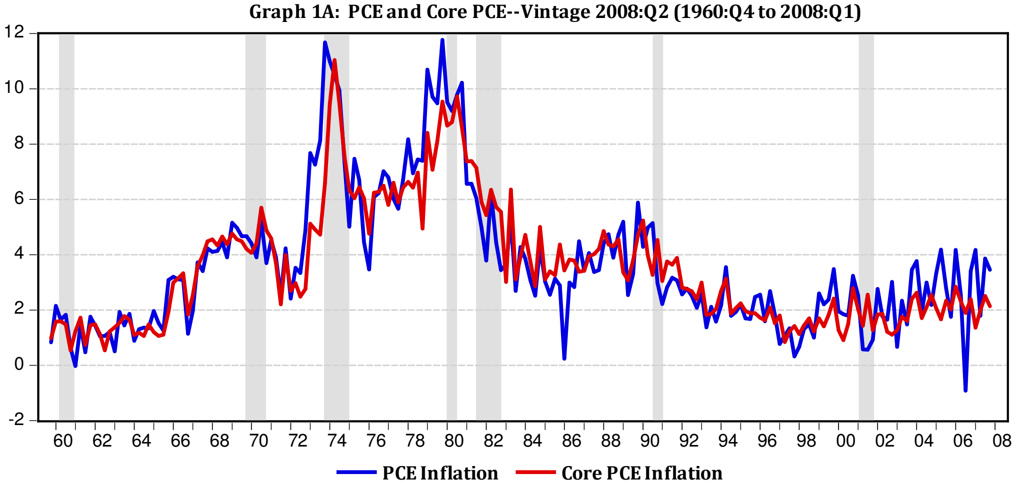
Regarding this paper, the window width is obtained through a grid search that produces an optimal global constant window width, d_T, by minimizing the residual sum of squares for each and every vintage, i.e. dataset and for each and every in-sample forecast horizon with the starting value being 0.01 and is incremented by 0.01 with the number of iterations being 300 (Fan and Gijbels 1995).[21] Since there are fifty vintages and five in-sample forecast horizons with two measures of inflation examined in this paper, *five hundred* window widths are obtained for the nonparametric portion of this paper. For each of the values of d_T, conditional weighted residual sum of squares on d_T are obtained and the optimal d_T is the one the produces the minimum IRSC, which in estimation is the ARSC. This is analogous to the approach suggested by Marron (1988) since by minimizing the ARSC, the variance and bias of the KWLS are balanced without sacrificing one for the other (Fan

[21] The global constant window width refers to the notion that the same window width in terms of metric distance is fitted around each and every single conditioning observation of x_j.

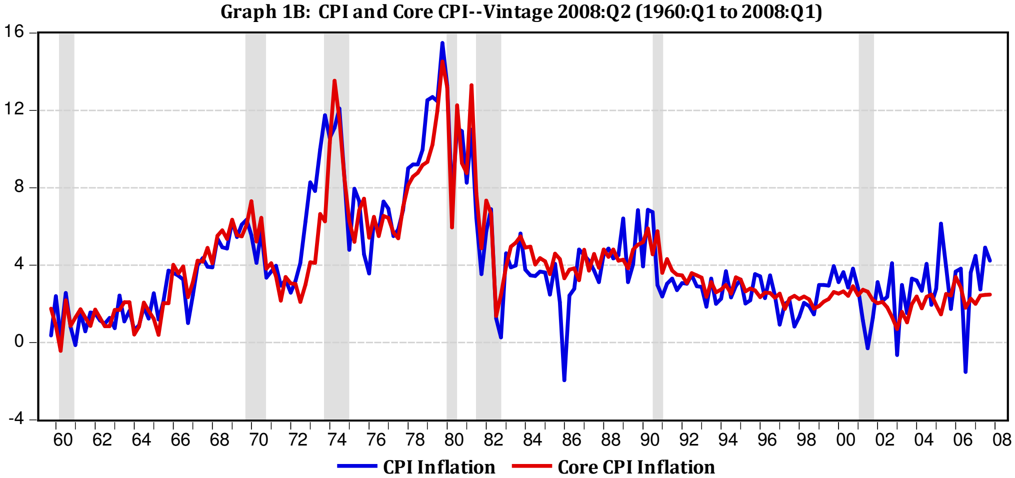
and Gijbels 1995). One of the main reasons behind the use of a global constant window width, distinctive to each dataset, is that it balances the trade-off between bias and variance and hence is able to guard against either over- or under-fitting the model. The main problem with using a global constant window width is that the asymptotic convergence is slow and abnormally large local nonparametric estimates can be produced when they are window width driven, which occurs when there is a sparsity of data locally (Härdle 1994, Härdle and Tsybakov 1997, Fan and Gijbels 1992, Fan and Gijbels 1995).

As a method of testing the robustness of the local nonparametric results, window widths of 1.5 times the window width provided by the ARSC is used, does not change the average of the local nonparametric estimators by very much. Most likely the reason for this is that when the ARSC is used, there generally is a gradual change in the residual sum of squares for a range of window widths before a significant jump is found in the value of the residual sum of squares.

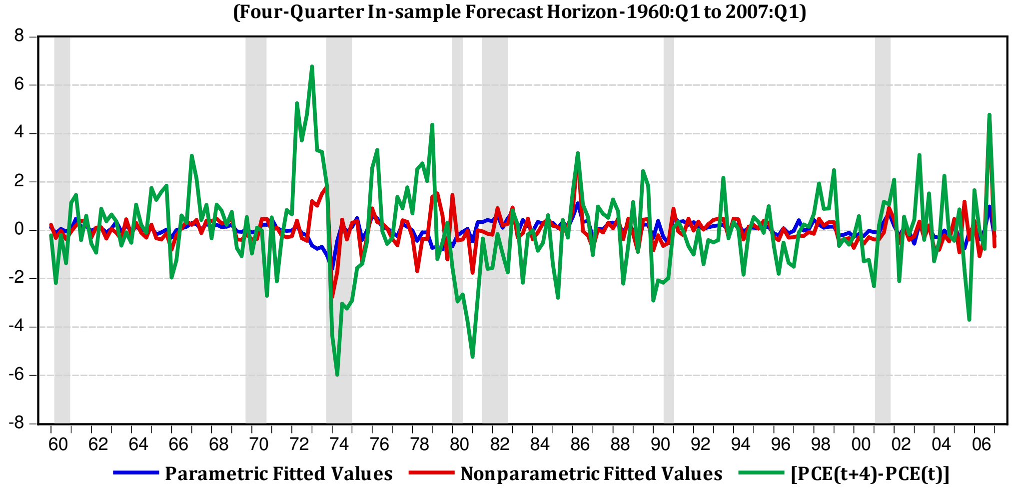
Graph 1A: PCE and Core PCE--Vintage 2008:Q2 (1960:Q4 to 2008:Q1)



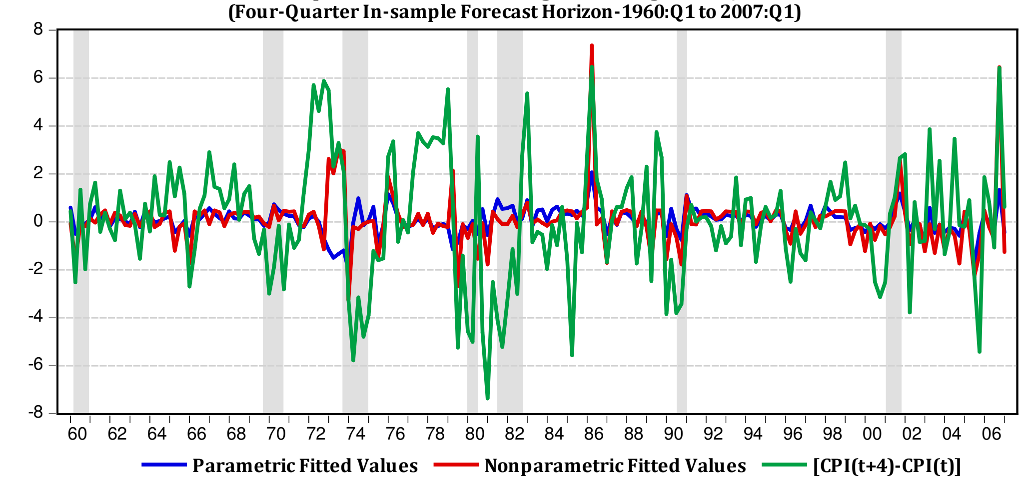
Graph 1B: CPI and Core CPI--Vintage 2008:Q2 (1960:Q1 to 2008:Q1)



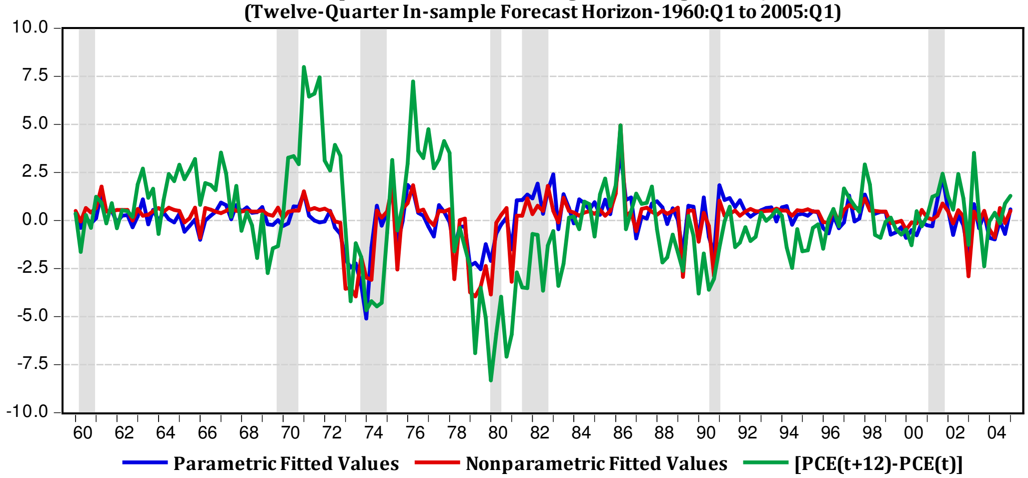
Graph 2A: Fitted Values using PCE--Vintage 2008:Q2
(Four-Quarter In-sample Forecast Horizon-1960:Q1 to 2007:Q1)



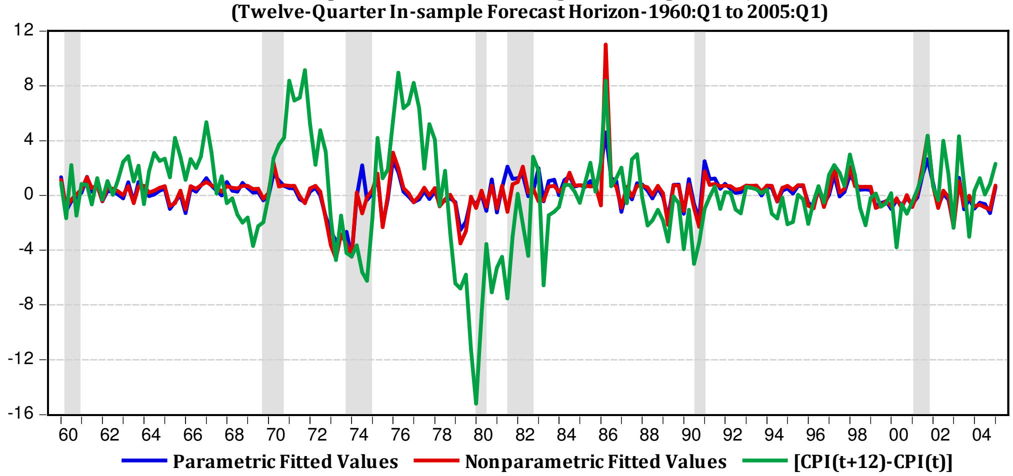
Graph 2B: Fitted Values using CPI--Vintage 2008:Q2
(Four-Quarter In-sample Forecast Horizon-1960:Q1 to 2007:Q1)



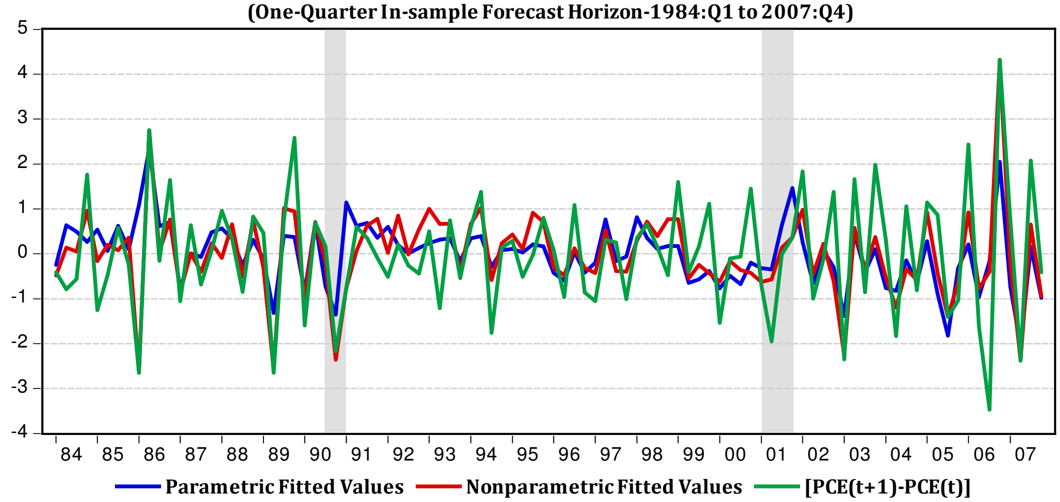
Graph 3A: Fitted Values using PCE--Vintage 2008:Q2
(Twelve-Quarter In-sample Forecast Horizon-1960:Q1 to 2005:Q1)



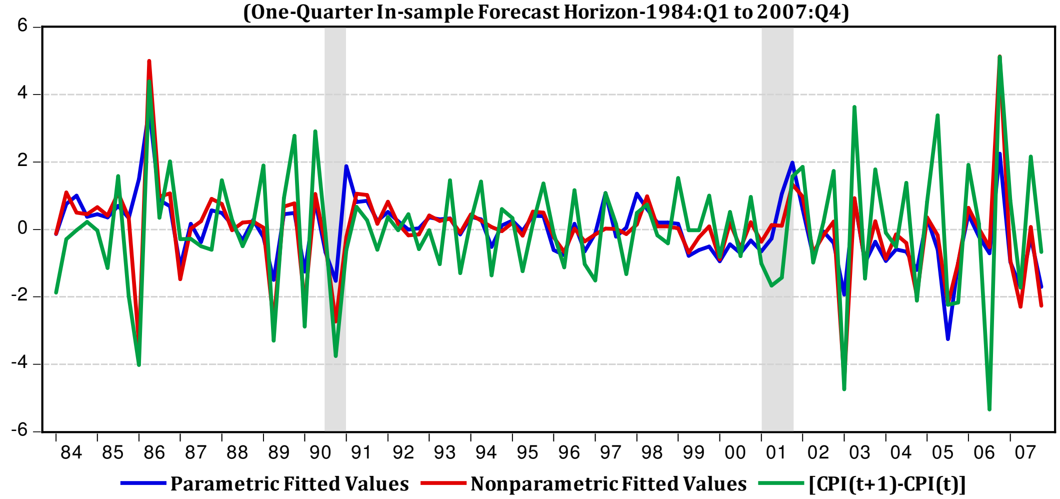
Graph 3B: Fitted Values using CPI--Vintage 2008:Q2
(Twelve-Quarter In-sample Forecast Horizon-1960:Q1 to 2005:Q1)



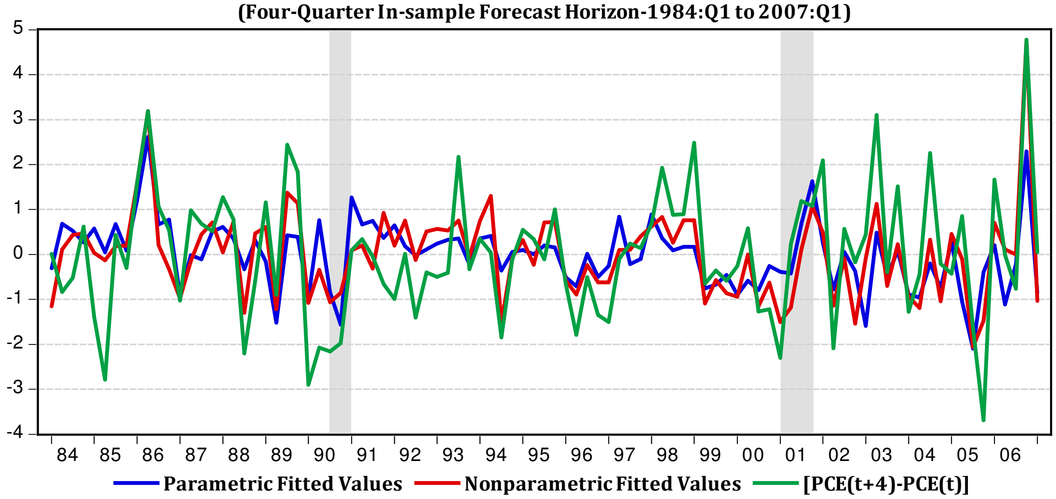
Graph 4A: Fitted Values using PCE--Vintage 2008:Q2
(One-Quarter In-sample Forecast Horizon-1984:Q1 to 2007:Q4)



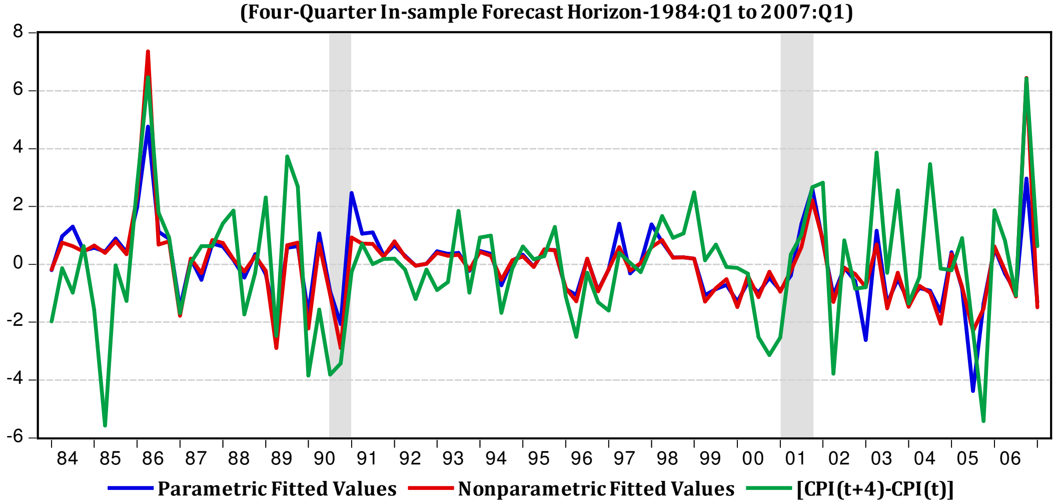
Graph 4B: Fitted Values using CPI--Vintage 2008:Q2
(One-Quarter In-sample Forecast Horizon-1984:Q1 to 2007:Q4)



Graph 5A: Fitted Values using PCE--Vintage 2008:Q2
(Four-Quarter In-sample Forecast Horizon-1984:Q1 to 2007:Q1)



Graph 5B: Fitted Values using CPI--Vintage 2008:Q2
(Four-Quarter In-sample Forecast Horizon-1984:Q1 to 2007:Q1)



Legends and Tables

Legend 1

Regression Model--Equation (1.1)		
Regression	**Dependent Variable**	**Independent Variable**
REG A	$(PCE_{t+h}\text{-}PCE_t)$	$(PCE_t^{core}\text{-}PCE_t)$
REG B	$(CPI_{t+h}\text{-}CPI_t)$	$(CPI_t^{core}\text{-}CPI_t)$

Legend 2

Regression Model A	Regression Model B	Forecast Horizon: h
REG A:h_1	REG B:h_1	1 quarter
REG A:h_2	REG B:h_2	2 quarters
REG A:h_3	REG B:h_3	4 quarters
REG A:h_4	REG B:h_4	8 quarters
REG A:h_5	REG B:h_5	12 quarters

Legend 3

Est. Regression Coefficients	Parametric (REG A)	Parametric (REG B)	Global Nonparametric (REG A)	Global Nonparametric (REG B)
Vertical Intercept	a_{AP}	a_{BP}	a_{AG}	a_{BG}
Slope Coefficient	b_{AP}	b_{BP}	b_{AG}	b_{BG}

Legend 4

	Data Samples		
Forecast Horizon: h	**1960:Q1-2008:Q1**	**1984:Q1-2008:Q1**	**Ending Data Period**
h_1	192	96	2007:Q4
h_2	191	95	2007:Q3
h_3	189	93	2007:Q1
h_4	185	89	2006:Q1
h_5	181	85	2005:Q1

Table 1A: REG A -Average Regression Results (Starting in1960:Q1)

	PARAMETRIC REGRESSION								GLOBAL NONPARAMETRIC REGRESSION							
h_m	a_{AP}	S.D.	T-Stat	PV	b_{AP}	S.D.	T-Stat	PV	a_{AG}	S.D.	T-Stat	PV	b_{AG}	S.D.	T-Stat	PV
h_1 = 1Q	0.025	0.08	0.31	0.76	0.220	0.14	1.59	0.12	-0.047	0.07	-0.57	0.33	0.360	0.07	4.94	0.00
h_2 = 2Q	0.025	0.12	0.21	0.83	0.237	0.19	1.28	0.23	-0.248	0.11	-2.28	0.14	0.418	0.09	4.60	0.00
h_3 = 4Q	0.029	0.22	0.13	0.89	0.272	0.25	1.09	0.28	-0.039	0.19	-0.23	0.61	0.395	0.15	2.50	0.02
h_4 = 8Q	0.101	0.39	0.26	0.79	0.814	0.21	3.87	0.00	0.488	0.35	1.38	0.21	0.465	0.17	2.70	0.07
h_5 = 12Q	0.134	0.51	0.27	0.79	1.067	0.25	4.28	0.00	0.517	0.45	1.15	0.30	0.660	0.17	4.01	0.00

Table 1B: REG B-Average Regression Results (Starting in 1960:Q1)

	PARAMETRIC REGRESSION								GLOBAL NONPARAMETRIC REGRESSION							
h_m	a_{BP}	S.D.	T-Stat	PV	b_{BP}	S.D.	T-Stat	PV	a_{AG}	S.D.	T-Stat	PV	b_{AG}	S.D.	T-Stat	PV
h_1 = 1Q	0.009	0.12	0.07	0.92	0.264	0.13	2.11	0.05	-0.171	0.11	-1.55	0.22	0.456	0.09	5.10	0.00
h_2 = 2Q	0.012	0.17	0.07	0.93	0.200	0.19	1.08	0.31	-0.375	0.16	-2.44	0.05	0.448	0.11	3.94	0.00
h_3 = 4Q	0.022	0.31	0.07	0.94	0.257	0.26	1.01	0.33	-0.054	0.27	-0.20	0.78	0.215	0.13	1.67	0.31
h_4 = 8Q	0.053	0.54	0.10	0.92	0.621	0.17	3.58	0.00	0.345	0.50	0.70	0.50	0.478	0.16	3.06	0.06
h_5 = 12Q	0.072	0.66	0.11	0.91	0.834	0.18	4.59	0.00	0.101	0.63	0.15	0.81	0.894	0.16	5.59	0.00

Table 2A: REG A -Average Regression Results (Starting in 1984:Q1)																
	PARAMETRIC REGRESSION								GLOBAL NONPARAMETRIC REGRESSION							
h_m	a_{1AP}	S.D.	T-Stat	PV	b_{1AP}	S.D.	T-Stat	PV	a_{1AG}	S.D.	T-Stat	PV	b_{1AG}	S.D.	T-Stat	PV
$h_1 = 1Q$	-0.123	0.10	-1.13	0.35	**0.672**	0.13	5.07	0.00	**-0.105**	0.09	-1.60	0.19	**0.734**	0.09	9.76	0.00
$h_2 = 2Q$	-0.174	0.14	-1.16	0.32	**0.828**	0.13	6.31	0.00	**-1.601**	0.12	-18.80	0.07	**-0.145**	0.13	-8.28	0.00
$h_3 = 4Q$	-0.242	0.18	-1.30	0.28	**0.931**	0.14	6.55	0.00	**-1.854**	0.17	-18.28	0.24	**-0.397**	0.10	-12.88	0.09
$h_4 = 8Q$	-0.385	0.24	-1.61	0.21	**1.024**	0.19	5.40	0.00	**1.308**	0.21	11.05	0.42	**1.392**	0.11	17.97	0.16
$h_5 = 12Q$	-0.446	0.34	-1.29	0.27	**1.052**	0.19	5.67	0.00	**-0.023**	0.28	0.50	0.19	**0.702**	0.09	8.76	0.00

Table 2B: REG B-Average Regression Results (Starting in 1984:Q1)																
	PARAMETRIC REGRESSION								GLOBAL NONPARAMETRIC REGRESSION							
h_m	a_{1BP}	S.D.	T-Stat	PV	b_{1BP}	S.D.	T-Stat	PV	a_{1BG}	S.D.	T-Stat	PV	b_{1BG}	S.D.	T-Stat	PV
$h_1 = 1Q$	-0.217	0.14	-1.53	0.21	**0.654**	0.14	4.72	0.00	**-0.155**	0.12	-1.29	0.30	**0.912**	0.07	12.49	0.00
$h_2 = 2Q$	-0.293	0.20	-1.41	0.22	**0.844**	0.12	6.94	0.00	**0.004**	0.18	-0.16	0.05	**1.209**	0.08	15.19	0.00
$h_3 = 4Q$	-0.388	0.26	-1.48	0.21	**1.003**	0.15	6.56	0.00	**-0.147**	0.23	-0.69	0.45	**0.712**	0.09	7.57	0.00
$h_4 = 8Q$	-0.494	0.33	-1.49	0.19	**1.039**	0.15	7.22	0.00	**-0.188**	0.30	-0.68	0.56	**0.757**	0.10	7.66	0.00
$h_5 = 12Q$	-0.484	0.35	-1.38	0.22	**1.114**	0.15	7.46	0.00	**-0.661**	0.33	-2.17	0.17	**1.151**	0.13	10.28	0.00

	Table 3: Average of Adjusted R-Squared Term (Starting in 1960:Q1)					
	REG A			REG B		
h_m	Parametrics	Global/Local Nonparametrics	% Change	Parametrics	Global/Local Nonparametrics	% Change
$h_1 = 1Q$	**0.029**	0.254	776%	0.038	0.190	400%
$h_2 = 2Q$	**0.023**	0.229	896%	0.012	0.155	1,192%
$h_3 = 4Q$	**0.017**	0.243	1,329%	0.014	0.184	1,214%
$h_4 = 8Q$	**0.110**	0.221	101%	0.054	0.143	165%
$h_5 = 12Q$	**0.165**	0.266	61%	0.086	0.160	86%

	Table 4: Average of Adjusted R-Squared Term (Starting in 1984:Q1)					
	REG A			REG B		
h_m	Parametrics	Global/Local Nonparametrics	% Change	Parametrics	Global/Local Nonparametrics	% Change
$h_1 = 1Q$	**0.230**	0.448	95%	0.253	0.568	125%
$h_2 = 2Q$	**0.268**	0.394	47%	0.321	0.416	30%
$h_3 = 4Q$	**0.282**	0.397	41%	0.368	0.464	26%
$h_4 = 8Q$	**0.300**	0.433	44%	0.346	0.450	30%
$h_5 = 12Q$	**0.289**	0.463	60%	0.427	0.574	34%

	Table 5A: REG A-Summary of Tests for Unbiasedness					
	Parametrics		**Global Nonparametrics**		**Local Nonparametrics**	
h_m	**1960:Q1**	**1984:Q1**	**1960:Q1**	**1984:Q1**	**1960:Q1**	**1984:Q1**
h_1 = 1Q	Biased (β_{ave} = 0.220)	Unbiased: After V_2007:Q1 (β_{ave} = 0.672)	Biased (β_{ave} = 0.360)	Biased (β_{ave} =0.734)	Biased	Biased
h_2 = 2Q	Biased (β_{ave} = 0.237)	Unbiased: All Vintages (β_{ave} = 0.828)	Biased (β_{ave} =0.418)	Biased (β_{ave}=-0.145)	Biased	Biased[♦] (some exceptions)
h_3 = 4Q	Biased (β_{ave} = 0.272)	Unbiased: All Vintages (β_{ave} = 0.931)	Biased (β_{ave} =0.395)	Biased (β_{ave} =-0.397)	Biased	Biased V_2000:Q1 & after V_2002:Q4
h_4 = 8Q	Unbiased (β_{ave} = 0.814)	Unbiased: After V_2003:Q3 (β_{ave} =1.024)	Biased (β_{ave} =0.465)	Biased (β_{ave} =1.392)	Biased except V_1999:Q4	Biased except V_1999:Q4
h_5 =12Q	Unbiased (β_{ave}=1.067)	Unbiased: After V_2003:Q4 (β_{ave} =1.052)	Biased (β_{ave} =0.660)	Biased (β_{ave} =0.702)	Biased not valid in V_1999:Q4	Biased

	Table 5B: REG B-Summary of Tests for Unbiasedness					
	Parametrics		**Global Nonparametrics**		**Local Nonparametrics**	
h_m	**1960:Q1**	**1984:Q1**	**1960:Q1**	**1984:Q1**	**1960:Q1**	**1984:Q1**
h_1 = 1Q	Biased (β_{ave} 0.264)	Biased (β_{ave} =0.654)	Biased (β_{ave}=0.456)	Biased (β_{ave}=0.912)	Biased	Biased except V_2007:Q1 to V_2007:Q2
h_2 = 2Q	Biased (β_{ave} 0.200)	Unbiased[+]: After V_2000:Q2 (β_{ave} =0.844)	Biased (β_{ave}=0.448)	Biased (β_{ave}=1.209)	Biased	Biased
h_3 = 4Q	Biased (β_{ave} 0.257)	Unbiased[+]: After V_2000:Q2 (β_{ave} =1.003)	Biased (β_{ave}=0.215)	Biased (β_{ave}=0.712)	Biased	Biased
h_4 = 8Q	Unbiased All Vintages (β_{ave}=0.621)	Unbiased[+]: After V_2000:Q2 (β_{ave} =1.039)	Biased (β_{ave}=0.478)	Biased (β_{ave}=0.757)	Biased	Unbiased for V_2001:Q1, V_2001:Q3 to V_2001:Q4, & after V_2006:Q2
h_5 = 12Q	Unbiased All Vintages (β_{ave} 0.834)	Unbiased[+]: After V_2000:Q1 (β_{ave} =1.114)	Biased (β_{ave}=0.894)	Biased (β_{ave}=1.151)	Unbiased except V_2005:Q3 to V_2006:Q1	Biased

[♦] In the local nonparametric model, there is sporadic unbiasedness during the following vintages for the following in-sample forecast horizon: **h_2**: V_1996:Q1 to V_1997:Q1, V_1999:Q4, and V_2000:Q2 to V_2002:Q2.

[+] Regarding the parametric model for the second sample period, the null of unbiasedness is rejected for the following vintages at the 5% significance level: **h_2**: V_1998:Q2 to V_2000:Q1 and V_2002:Q2, **h_3**: V_1997:Q4 to V_2000:Q1, **h_4**: V_1997:Q3 to V_2000:Q2, V_2002:Q2, and V_2003:Q3 to V_2004:Q2 **h_5**: V_1997:Q3 to V_2000:Q2, V_2002:Q2 to V_2002:Q3, and V_2004:Q1.

	Table 6: ARSC Nonparametric Window Widths (Starting in1960:Q1)									
Vintage	**REG A: h1**	**REG B: h1**	**REG A: h2**	**REG B: h2**	**REG A: h3**	**REG B: h3**	**REG A: h4**	**REG B: h4**	**REG A: h5**	**REG B: h5**
1996:Q1	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29
1996:Q2	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29
1996:Q3	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29
1996:Q4	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29
1997:Q1	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29	0.27	0.29
1997:Q2	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1997:Q3	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1997:Q4	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1998:Q1	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1998:Q2	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1998:Q3	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1998:Q4	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1999:Q1	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1999:Q2	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1999:Q3	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29	0.20	0.29
1999:Q4	0.21	0.29	0.21	0.29	0.21	0.29	0.21	0.29	0.21	0.29
2000:Q1	0.06	0.29	0.06	0.29	0.06	0.29	0.06	0.29	0.06	0.29
2000:Q2	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2000:Q3	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2000:Q4	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2001:Q1	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2001:Q2	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2001:Q3	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2001:Q4	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2002:Q1	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2002:Q2	0.22	0.28	0.22	0.29	0.22	0.29	0.22	0.29	0.22	0.29
2002:Q3	0.22	0.28	0.22	0.28	0.22	0.29	0.22	0.29	0.22	0.29
2002:Q4	0.22	0.28	0.22	0.28	0.22	0.29	0.22	0.29	0.22	0.29
2003:Q1	0.22	0.28	0.22	0.28	0.22	0.28	0.22	0.29	0.22	0.29
2003:Q2	0.22	0.25	0.22	0.25	0.22	0.25	0.22	0.29	0.22	0.29
2003:Q3	0.22	0.25	0.22	0.25	0.22	0.25	0.22	0.29	0.22	0.29
2003:Q4	0.22	0.25	0.22	0.25	0.22	0.25	0.22	0.29	0.22	0.29
2004:Q1	0.20	0.25	0.20	0.25	0.20	0.25	0.20	0.25	0.20	0.29
2004:Q2	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.29
2004:Q3	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.29
2004:Q4	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.29
2005:Q1	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26
2005:Q2	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26
2005:Q3	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26
2005:Q4	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26
2006:Q1	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26	0.20	0.26
2006:Q2	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28
2006:Q3	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28
2006:Q4	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28
2007:Q1	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28
2007:Q2	0.20	0.18	0.20	0.28	0.20	0.28	0.20	0.28	0.20	0.28
2007:Q3	0.20	0.18	0.20	0.18	0.20	0.28	0.20	0.28	0.20	0.28
2007:Q4	0.20	0.18	0.20	0.18	0.20	0.28	0.20	0.28	0.20	0.28
2008:Q1	0.20	0.24	0.20	0.24	0.20	0.24	0.20	0.28	0.20	0.28
2008:Q2	0.20	0.24	0.20	0.24	0.20	0.24	0.20	0.28	0.20	0.28

	Table 7: ARSC Nonparametric Window Widths (Starting in 1984:Q1)									
Vintage	**REG A: h1**	**REG B: h1**	**REG A: h2**	**REG B: h2**	**REG A: h3**	**REG B: h3**	**REG A: h4**	**REG B: h4**	**REG A: h5**	**REG B: h5**
1996:Q1	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.46
1996:Q2	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.46
1996:Q3	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.46
1996:Q4	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.46
1997:Q1	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.46
1997:Q2	0.20	0.30	0.20	0.30	0.20	0.30	0.20	0.30	0.21	0.46
1997:Q3	0.21	0.30	0.05	0.30	0.21	0.30	0.21	0.30	0.21	0.46
1997:Q4	0.21	0.30	0.05	0.30	0.21	0.30	0.21	0.30	0.21	0.46
1998:Q1	0.21	0.30	0.05	0.30	0.21	0.30	0.21	0.30	0.21	0.46
1998:Q2	0.21	0.30	0.05	0.30	0.21	0.30	0.21	0.30	0.21	0.46
1998:Q3	0.20	0.30	0.20	0.30	0.20	0.30	0.20	0.30	0.21	0.46
1998:Q4	0.21	0.30	0.05	0.30	0.21	0.30	0.21	0.30	0.21	0.46
1999:Q1	0.21	0.30	0.05	0.30	0.21	0.30	0.21	0.30	0.21	0.46
1999:Q2	0.21	0.30	0.05	0.30	0.21	0.30	0.21	0.30	0.21	0.46
1999:Q3	0.21	0.30	0.05	0.30	0.21	0.30	0.21	0.30	0.21	0.30
1999:Q4	0.23	0.30	0.23	0.30	0.23	0.30	0.23	0.30	0.24	0.30
2000:Q1	0.04	0.30	0.04	0.30	0.04	0.30	0.04	0.30	0.04	0.30
2000:Q2	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30
2000:Q3	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30
2000:Q4	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30
2001:Q1	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30
2001:Q2	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30
2001:Q3	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30
2001:Q4	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30
2002:Q1	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30	0.22	0.30
2002:Q2	0.16	0.29	0.22	0.31	0.22	0.31	0.22	0.31	0.22	0.31
2002:Q3	0.16	0.29	0.16	0.29	0.22	0.31	0.22	0.31	0.22	0.31
2002:Q4	0.16	0.29	0.16	0.29	0.22	0.31	0.22	0.31	0.22	0.31
2003:Q1	0.16	0.29	0.16	0.29	0.16	0.29	0.22	0.31	0.22	0.31
2003:Q2	0.16	0.25	0.16	0.25	0.16	0.25	0.22	0.31	0.22	0.31
2003:Q3	0.16	0.25	0.16	0.25	0.16	0.25	0.22	0.31	0.22	0.31
2003:Q4	0.16	0.25	0.16	0.25	0.16	0.25	0.22	0.31	0.22	0.31
2004:Q1	0.14	0.25	0.14	0.25	0.14	0.25	0.14	0.25	0.20	0.31
2004:Q2	0.14	0.26	0.14	0.26	0.14	0.26	0.14	0.26	0.20	0.31
2004:Q3	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26	0.20	0.31
2004:Q4	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26	0.20	0.31
2005:Q1	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26
2005:Q2	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26
2005:Q3	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26
2005:Q4	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26
2006:Q1	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26	0.15	0.26
2006:Q2	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.29
2006:Q3	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.29
2006:Q4	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.29
2007:Q1	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.29
2007:Q2	0.07	0.20	0.15	0.28	0.15	0.28	0.15	0.28	0.15	0.29
2007:Q3	0.06	0.20	0.06	0.20	0.15	0.28	0.15	0.28	0.15	0.29
2007:Q4	0.06	0.19	0.06	0.20	0.15	0.28	0.15	0.28	0.15	0.29
2008:Q1	0.06	0.24	0.06	0.24	0.06	0.24	0.15	0.28	0.15	0.29
2008:Q2	0.06	0.24	0.06	0.24	0.06	0.24	0.15	0.28	0.15	0.29

Table 8A: Fan, Zhang, and Zhang's (2001) LR-Statistic and P-Values (Starting in 1960:Q1)										
	REG A: h1		REG A: h2		REG A: h3		REG A: h4		REG A: h5	
Vintage	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value
1996:Q1	144.12	0.00	95.88	0.00	73.66	0.00	29.60	0.00	21.15	0.02
1996:Q2	143.68	0.00	96.32	0.00	74.11	0.00	30.02	0.00	20.92	0.02
1996:Q3	143.08	0.00	96.52	0.00	74.14	0.00	30.11	0.00	20.91	0.02
1996:Q4	141.63	0.00	96.89	0.00	74.65	0.00	29.28	0.00	20.99	0.02
1997:Q1	141.67	0.00	97.54	0.00	75.00	0.00	29.58	0.00	21.11	0.02
1997:Q2	127.00	0.00	103.78	0.00	100.67	0.00	34.53	0.00	23.75	0.01
1997:Q3	129.45	0.00	103.05	0.00	98.38	0.00	35.04	0.00	23.45	0.01
1997:Q4	130.38	0.00	103.90	0.00	98.90	0.00	35.00	0.00	22.78	0.01
1998:Q1	131.18	0.00	104.65	0.00	98.80	0.00	34.97	0.00	22.25	0.01
1998:Q2	132.08	0.00	105.34	0.00	99.08	0.00	34.01	0.00	21.81	0.02
1998:Q3	131.40	0.00	104.17	0.00	100.56	0.00	32.73	0.00	21.15	0.02
1998:Q4	132.52	0.00	104.38	0.00	101.26	0.00	32.65	0.00	20.90	0.02
1999:Q1	133.24	0.00	104.95	0.00	101.75	0.00	32.45	0.00	20.77	0.02
1999:Q2	134.09	0.00	105.58	0.00	101.45	0.00	32.11	0.00	20.68	0.02
1999:Q3	133.34	0.00	105.53	0.00	101.52	0.00	31.45	0.00	21.04	0.02
1999:Q4	24.19	0.01	22.89	0.01	**12.72**	**0.25**	**4.50**	**0.93**	**-0.80**	**-1.00**
2000:Q1	181.31	0.00	139.35	0.00	138.56	0.00	47.95	0.00	54.73	0.00
2000:Q2	130.14	0.00	100.60	0.00	80.32	0.00	24.40	0.01	22.92	0.01
2000:Q3	129.92	0.00	101.06	0.00	81.60	0.00	24.39	0.01	23.83	0.01
2000:Q4	130.28	0.00	101.55	0.00	82.21	0.00	24.52	0.01	24.25	0.01
2001:Q1	131.18	0.00	102.09	0.00	82.67	0.00	24.58	0.01	24.41	0.01
2001:Q2	131.10	0.00	102.70	0.00	82.55	0.00	24.90	0.01	23.57	0.01
2001:Q3	129.51	0.00	103.66	0.00	84.15	0.00	25.52	0.00	24.59	0.01
2001:Q4	127.89	0.00	100.75	0.00	83.30	0.00	25.24	0.01	24.14	0.01
2002:Q1	128.37	0.00	101.82	0.00	83.81	0.00	25.48	0.01	23.85	0.01
2002:Q2	129.00	0.00	102.30	0.00	83.67	0.00	24.81	0.01	23.53	0.01
2002:Q3	131.83	0.00	103.78	0.00	84.69	0.00	25.66	0.00	23.98	0.01
2002:Q4	131.76	0.00	104.01	0.00	83.48	0.00	26.28	0.00	24.33	0.01
2003:Q1	132.18	0.00	104.67	0.00	84.22	0.00	26.23	0.00	24.55	0.01
2003:Q2	132.38	0.00	104.65	0.00	84.42	0.00	26.27	0.00	24.83	0.01
2003:Q3	131.92	0.00	105.23	0.00	84.63	0.00	26.42	0.00	24.89	0.01
2003:Q4	131.13	0.00	105.33	0.00	85.01	0.00	25.49	0.01	25.41	0.01
2004:Q1	133.28	0.00	103.77	0.00	82.67	0.00	22.75	0.01	25.35	0.01
2004:Q2	132.66	0.00	104.95	0.00	83.63	0.00	22.81	0.01	25.68	0.00
2004:Q3	134.44	0.00	103.61	0.00	81.52	0.00	23.61	0.01	26.07	0.00
2004:Q4	133.57	0.00	103.22	0.00	82.15	0.00	23.35	0.01	26.02	0.00
2005:Q1	133.89	0.00	103.71	0.00	82.55	0.00	23.76	0.01	25.42	0.01
2005:Q2	134.34	0.00	103.56	0.00	82.78	0.00	22.56	0.02	25.30	0.01
2005:Q3	131.17	0.00	102.55	0.00	84.15	0.00	23.38	0.01	25.85	0.00
2005:Q4	131.40	0.00	102.49	0.00	83.92	0.00	23.93	0.01	26.24	0.00
2006:Q1	130.85	0.00	102.43	0.00	84.60	0.00	24.14	0.01	26.64	0.00
2006:Q2	132.22	0.00	98.81	0.00	85.05	0.00	24.00	0.01	25.82	0.00
2006:Q3	132.17	0.00	97.87	0.00	84.79	0.00	23.71	0.01	25.56	0.01
2006:Q4	131.65	0.00	98.30	0.00	78.84	0.00	24.02	0.01	25.76	0.01
2007:Q1	128.27	0.00	95.25	0.00	77.50	0.00	22.85	0.01	25.20	0.01
2007:Q2	129.96	0.00	94.85	0.00	77.58	0.00	22.91	0.01	25.35	0.01
2007:Q3	130.85	0.00	96.91	0.00	78.47	0.00	22.20	0.02	26.02	0.00
2007:Q4	131.96	0.00	96.14	0.00	78.75	0.00	21.78	0.02	25.96	0.00
2008:Q1	131.63	0.00	100.41	0.00	80.49	0.00	22.26	0.02	26.69	0.00
2008:Q2	133.00	0.00	100.51	0.00	80.98	0.00	22.56	0.02	26.71	0.00

Table 8B: Fan, Zhang, and Zhang's (2001) LR-Statistic and P-Values (Starting in 1960:Q1)										
	REG B: h1		REG B: h2		REG B: h3		REG B: h4		REG B: h5	
Vintage	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value
1996:Q1	87.74	0.00	68.40	0.00	62.55	0.00	22.70	0.01	**12.62**	**0.23**
1996:Q2	88.03	0.00	68.76	0.00	62.94	0.00	22.78	0.01	**12.61**	**0.23**
1996:Q3	88.57	0.00	68.87	0.00	63.31	0.00	22.99	0.01	**12.63**	**0.23**
1996:Q4	89.08	0.00	69.32	0.00	63.73	0.00	22.92	0.01	**12.65**	**0.23**
1997:Q1	89.27	0.00	69.75	0.00	64.07	0.00	23.00	0.01	**12.53**	**0.24**
1997:Q2	89.35	0.00	70.81	0.00	64.36	0.00	23.23	0.01	**12.59**	**0.24**
1997:Q3	90.19	0.00	71.22	0.00	64.42	0.00	22.70	0.01	**12.34**	**0.26**
1997:Q4	90.72	0.00	71.62	0.00	64.82	0.00	22.60	0.01	**12.64**	**0.24**
1998:Q1	91.28	0.00	72.05	0.00	64.93	0.00	22.42	0.01	**12.50**	**0.25**
1998:Q2	91.36	0.00	72.60	0.00	65.49	0.00	22.92	0.01	**12.46**	**0.25**
1998:Q3	91.53	0.00	72.95	0.00	65.72	0.00	23.30	0.01	**12.25**	**0.27**
1998:Q4	92.06	0.00	72.95	0.00	66.14	0.00	23.10	0.01	**12.17**	**0.27**
1999:Q1	92.67	0.00	73.32	0.00	66.44	0.00	23.25	0.01	**12.02**	**0.28**
1999:Q2	94.13	0.00	74.85	0.00	66.96	0.00	22.66	0.01	**11.61**	**0.31**
1999:Q3	93.44	0.00	74.80	0.00	67.20	0.00	22.26	0.01	**12.18**	**0.27**
1999:Q4	94.26	0.00	75.04	0.00	67.49	0.00	22.48	0.01	**12.11**	**0.28**
2000:Q1	94.79	0.00	75.13	0.00	67.78	0.00	22.51	0.01	**12.34**	**0.27**
2000:Q2	95.79	0.00	76.75	0.00	68.01	0.00	22.18	0.02	**14.59**	**0.15**
2000:Q3	96.82	0.00	76.76	0.00	68.13	0.00	22.12	0.02	**14.40**	**0.16**
2000:Q4	97.43	0.00	77.35	0.00	68.51	0.00	22.16	0.02	**14.42**	**0.16**
2001:Q1	98.01	0.00	76.94	0.00	68.86	0.00	22.08	0.02	**14.41**	**0.16**
2001:Q2	98.36	0.00	77.70	0.00	70.12	0.00	23.30	0.01	**14.97**	**0.14**
2001:Q3	98.67	0.00	78.08	0.00	70.54	0.00	23.65	0.01	**14.84**	**0.14**
2001:Q4	98.06	0.00	76.79	0.00	69.72	0.00	23.49	0.01	**14.75**	**0.15**
2002:Q1	100.98	0.00	76.59	0.00	69.44	0.00	23.48	0.01	**14.48**	**0.16**
2002:Q2	100.21	0.00	79.16	0.00	69.78	0.00	22.97	0.01	**14.79**	**0.15**
2002:Q3	99.98	0.00	78.23	0.00	70.24	0.00	23.12	0.01	**15.37**	**0.13**
2002:Q4	99.96	0.00	78.70	0.00	70.69	0.00	23.19	0.01	**15.53**	**0.12**
2003:Q1	100.29	0.00	78.83	0.00	70.61	0.00	23.25	0.01	**16.04**	**0.11**
2003:Q2	102.67	0.00	84.23	0.00	76.23	0.00	22.94	0.01	**16.46**	**0.10**
2003:Q3	101.30	0.00	84.82	0.00	76.18	0.00	22.80	0.01	**16.58**	**0.09**
2003:Q4	100.56	0.00	85.23	0.00	76.59	0.00	22.76	0.01	**16.97**	**0.08**
2004:Q1	100.40	0.00	85.59	0.00	77.19	0.00	26.34	0.00	**16.86**	**0.09**
2004:Q2	98.23	0.00	83.72	0.00	73.72	0.00	25.13	0.01	**17.02**	**0.08**
2004:Q3	99.88	0.00	82.77	0.00	73.29	0.00	24.68	0.01	**17.34**	**0.08**
2004:Q4	100.35	0.00	81.66	0.00	73.62	0.00	24.91	0.01	**16.98**	**0.08**
2005:Q1	99.73	0.00	82.38	0.00	73.97	0.00	25.20	0.01	18.86	***0.05***
2005:Q2	97.18	0.00	83.05	0.00	77.21	0.00	25.37	0.01	18.86	***0.05***
2005:Q3	96.89	0.00	83.69	0.00	78.36	0.00	26.11	0.00	19.34	0.04
2005:Q4	97.30	0.00	83.67	0.00	78.51	0.00	26.39	0.00	19.46	0.04
2006:Q1	93.88	0.00	84.70	0.00	78.79	0.00	26.93	0.00	19.61	0.04
2006:Q2	95.71	0.00	74.82	0.00	70.39	0.00	24.41	0.01	**17.23**	**0.08**
2006:Q3	94.78	0.00	74.67	0.00	70.98	0.00	24.02	0.01	**17.44**	**0.08**
2006:Q4	94.20	0.00	74.96	0.00	67.51	0.00	24.18	0.01	**17.78**	**0.07**
2007:Q1	92.55	0.00	66.95	0.00	65.50	0.00	23.91	0.01	**17.46**	**0.08**
2007:Q2	112.23	0.00	66.85	0.00	67.21	0.00	26.53	0.00	**16.70**	**0.10**
2007:Q3	114.34	0.00	94.44	0.00	67.30	0.00	27.98	0.00	**17.14**	**0.09**
2007:Q4	108.26	0.00	94.60	0.00	67.63	0.00	27.83	0.00	**17.16**	**0.09**
2008:Q1	99.99	0.00	90.99	0.00	79.64	0.00	24.39	0.01	**17.46**	**0.08**
2008:Q2	100.75	0.00	90.71	0.00	79.58	0.00	24.35	0.01	**17.55**	**0.08**

Table 9A: Fan, Zhang, and Zhang's (2001) LR-Statistic and P-Values (Starting in 1984:Q1)										
	REG A: h1		**REG A: h2**		**REG A: h3**		**REG A: h4**		**REG A: h5**	
Vintage	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value
1996:Q1	22.97	0.00	14.45	**0.06**	11.24	**0.17**	23.38	0.00	34.39	0.00
1996:Q2	20.50	0.01	14.53	**0.06**	11.72	**0.15**	24.70	0.00	35.14	0.00
1996:Q3	20.64	0.01	14.92	**0.06**	13.06	**0.10**	24.52	0.00	36.11	0.00
1996:Q4	20.17	0.01	14.96	**0.06**	13.36	**0.09**	25.42	0.00	36.63	0.00
1997:Q1	19.73	0.01	14.84	**0.06**	13.00	**0.10**	25.64	0.00	36.58	0.00
1997:Q2	28.65	0.00	16.38	0.04	12.40	**0.13**	25.28	0.00	23.41	0.00
1997:Q3	29.81	0.00	26.99	0.00	12.67	**0.12**	25.06	0.00	23.66	0.00
1997:Q4	30.59	0.00	27.25	0.00	12.30	**0.13**	25.52	0.00	23.98	0.00
1998:Q1	31.07	0.00	27.89	0.00	13.08	**0.11**	26.15	0.00	23.82	0.00
1998:Q2	31.32	0.00	28.64	0.00	14.04	**0.08**	26.73	0.00	24.67	0.00
1998:Q3	28.40	0.00	18.05	0.02	14.03	**0.08**	29.05	0.00	27.15	0.00
1998:Q4	29.21	0.00	31.38	0.00	14.49	**0.07**	29.97	0.00	28.27	0.00
1999:Q1	29.52	0.00	31.51	0.00	14.47	**0.07**	30.64	0.00	29.04	0.00
1999:Q2	30.01	0.00	31.69	0.00	14.29	**0.08**	31.52	0.00	29.64	0.00
1999:Q3	28.96	0.00	30.26	0.00	13.48	**0.10**	28.35	0.00	29.37	0.00
1999:Q4	10.65	**0.24**	7.40	**0.52**	10.23	**0.26**	10.83	**0.22**	22.12	0.00
2000:Q1	74.49	0.00	45.04	0.00	67.96	0.00	57.99	0.00	87.88	0.00
2000:Q2	23.19	0.00	12.25	**0.16**	16.00	***0.05***	20.95	0.01	25.18	0.00
2000:Q3	23.58	0.00	11.95	**0.17**	13.37	**0.11**	19.55	0.01	25.48	0.00
2000:Q4	24.53	0.00	11.86	**0.18**	12.91	**0.13**	19.69	0.01	25.76	0.00
2001:Q1	25.47	0.00	11.94	**0.18**	13.06	**0.13**	19.78	0.01	26.26	0.00
2001:Q2	25.59	0.00	13.21	**0.12**	11.94	**0.18**	19.58	0.01	22.71	0.00
2001:Q3	25.56	0.00	13.49	**0.12**	13.35	**0.12**	18.21	0.02	24.32	0.00
2001:Q4	22.80	0.00	11.70	**0.19**	14.67	**0.08**	21.03	0.01	25.87	0.00
2002:Q1	22.69	0.01	12.06	**0.18**	14.95	**0.07**	21.85	0.01	26.23	0.00
2002:Q2	16.93	0.04	12.10	**0.18**	16.06	**0.05**	24.09	0.00	26.84	0.00
2002:Q3	34.10	0.00	18.55	0.02	14.12	**0.10**	22.13	0.01	25.26	0.00
2002:Q4	33.55	0.00	18.41	0.02	12.19	**0.17**	20.59	0.01	25.41	0.00
2003:Q1	33.61	0.00	18.48	0.02	20.84	0.01	21.01	0.01	25.68	0.00
2003:Q2	33.64	0.00	18.54	0.02	19.88	0.01	21.07	0.01	24.19	0.00
2003:Q3	34.03	0.00	19.03	0.02	20.96	0.01	21.42	0.01	24.56	0.00
2003:Q4	32.57	0.00	21.69	0.01	21.46	0.01	18.06	0.03	24.68	0.00
2004:Q1	61.90	0.00	26.79	0.00	29.51	0.00	30.44	0.00	22.82	0.00
2004:Q2	61.00	0.00	27.76	0.00	31.25	0.00	28.41	0.00	23.13	0.00
2004:Q3	56.62	0.00	25.84	0.00	29.59	0.00	26.55	0.00	21.98	0.01
2004:Q4	57.86	0.00	25.85	0.00	29.90	0.00	26.72	0.00	22.27	0.01
2005:Q1	57.44	0.00	26.67	0.00	29.97	0.00	24.76	0.00	28.93	0.00
2005:Q2	57.83	0.00	24.28	0.00	29.88	0.00	24.79	0.00	27.62	0.00
2005:Q3	56.79	0.00	21.42	0.01	28.67	0.00	22.72	0.01	27.50	0.00
2005:Q4	56.20	0.00	21.70	0.01	28.24	0.00	21.59	0.01	26.26	0.00
2006:Q1	58.77	0.00	22.54	0.01	28.51	0.00	21.75	0.01	26.51	0.00
2006:Q2	60.04	0.00	23.57	0.00	28.47	0.00	22.37	0.01	25.28	0.00
2006:Q3	55.76	0.00	22.46	0.01	24.07	0.00	19.70	0.02	21.66	0.01
2006:Q4	54.97	0.00	22.76	0.01	25.06	0.00	19.81	0.02	22.02	0.01
2007:Q1	48.78	0.00	22.96	0.01	26.91	0.00	19.08	0.02	22.50	0.01
2007:Q2	65.51	0.00	22.21	0.01	27.04	0.00	19.39	0.02	21.49	0.01
2007:Q3	75.51	0.00	52.68	0.00	29.53	0.00	18.04	0.03	21.61	0.01
2007:Q4	76.62	0.00	53.37	0.00	29.60	0.00	18.21	0.03	21.82	0.01
2008:Q1	76.87	0.00	60.45	0.00	58.68	0.00	18.00	0.03	23.27	0.01
2008:Q2	76.17	0.00	61.38	0.00	58.07	0.00	18.45	0.03	22.42	0.01

Table 9B: Fan, Zhang, and Zhang's (2001) LR-Statistic and P-Values (Starting in 1984:Q1)										
	REG B: h1		**REG B: h2**		**REG B: h3**		**REG B: h4**		**REG B: h5**	
Vintage	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value
1996:Q1	53.39	0.00	22.95	0.00	18.71	0.01	17.24	0.02	18.03	0.01
1996:Q2	53.46	0.00	22.98	0.00	18.94	0.01	17.09	0.02	18.08	0.01
1996:Q3	53.91	0.00	22.54	0.00	19.03	0.01	16.90	0.03	17.48	0.02
1996:Q4	54.66	0.00	22.85	0.00	19.58	0.01	17.34	0.02	17.70	0.02
1997:Q1	54.50	0.00	21.12	0.01	19.54	0.01	17.47	0.02	17.64	0.02
1997:Q2	56.44	0.00	19.67	0.01	20.19	0.01	17.04	0.03	18.13	0.02
1997:Q3	56.91	0.00	20.68	0.01	20.86	0.01	17.18	0.02	19.26	0.01
1997:Q4	56.80	0.00	20.95	0.01	21.19	0.01	17.27	0.02	20.75	0.01
1998:Q1	57.89	0.00	21.49	0.01	21.51	0.01	17.45	0.02	21.08	0.01
1998:Q2	57.97	0.00	23.98	0.00	21.49	0.01	19.65	0.01	22.08	0.00
1998:Q3	47.46	0.00	24.34	0.00	21.92	0.01	19.22	0.01	22.91	0.00
1998:Q4	48.32	0.00	24.62	0.00	22.20	0.00	19.49	0.01	23.64	0.00
1999:Q1	49.23	0.00	25.04	0.00	22.51	0.00	20.04	0.01	24.43	0.00
1999:Q2	61.57	0.00	26.17	0.00	23.81	0.00	20.52	0.01	26.82	0.00
1999:Q3	57.98	0.00	25.49	0.00	23.23	0.00	18.59	0.02	33.13	0.00
1999:Q4	58.34	0.00	25.28	0.00	23.56	0.00	17.99	0.02	32.89	0.00
2000:Q1	59.08	0.00	25.35	0.00	23.51	0.00	17.84	0.02	32.71	0.00
2000:Q2	59.81	0.00	22.25	0.01	21.69	0.01	17.02	0.03	31.51	0.00
2000:Q3	59.99	0.00	20.70	0.01	18.23	0.02	16.19	0.04	30.07	0.00
2000:Q4	61.86	0.00	21.09	0.01	18.55	0.02	16.25	0.04	28.31	0.00
2001:Q1	61.98	0.00	20.46	0.01	18.24	0.02	15.88	***0.05***	27.79	0.00
2001:Q2	59.61	0.00	20.81	0.01	16.56	0.04	15.55	0.06	25.22	0.00
2001:Q3	60.34	0.00	20.55	0.01	16.87	0.04	13.44	**0.11**	25.12	0.00
2001:Q4	56.90	0.00	19.30	0.02	17.40	0.03	14.27	**0.09**	26.26	0.00
2002:Q1	62.14	0.00	18.82	0.02	16.97	0.04	16.37	0.04	28.11	0.00
2002:Q2	63.69	0.00	21.49	0.01	19.27	0.02	20.13	0.01	32.86	0.00
2002:Q3	63.47	0.00	20.75	0.01	19.03	0.02	19.32	0.02	30.88	0.00
2002:Q4	63.68	0.00	21.18	0.01	19.29	0.02	19.81	0.01	31.33	0.00
2003:Q1	63.96	0.00	21.38	0.01	18.59	0.02	20.06	0.01	31.49	0.00
2003:Q2	68.53	0.00	22.92	0.01	22.38	0.01	18.69	0.02	35.32	0.00
2003:Q3	69.85	0.00	23.64	0.00	22.20	0.01	19.90	0.01	36.15	0.00
2003:Q4	67.36	0.00	23.63	0.00	22.14	0.01	20.13	0.01	36.51	0.00
2004:Q1	67.08	0.00	23.57	0.00	22.73	0.01	24.99	0.00	36.70	0.00
2004:Q2	61.08	0.00	21.47	0.01	23.63	0.00	23.23	0.00	34.82	0.00
2004:Q3	61.69	0.00	19.27	0.02	21.37	0.01	23.19	0.00	32.71	0.00
2004:Q4	61.82	0.00	18.66	0.03	21.42	0.01	23.64	0.00	32.11	0.00
2005:Q1	61.31	0.00	17.90	0.03	21.44	0.01	22.68	0.01	34.87	0.00
2005:Q2	58.37	0.00	19.51	0.02	24.24	0.00	22.46	0.01	35.81	0.00
2005:Q3	58.28	0.00	20.22	0.02	23.22	0.01	22.49	0.01	37.01	0.00
2005:Q4	50.72	0.00	19.85	0.02	23.24	0.01	19.76	0.02	33.01	0.00
2006:Q1	53.22	0.00	18.84	0.03	22.80	0.01	19.85	0.02	33.31	0.00
2006:Q2	61.43	0.00	19.50	0.02	18.98	0.02	16.95	0.04	29.00	0.00
2006:Q3	59.10	0.00	18.69	0.03	18.50	0.03	16.49	***0.05***	23.63	0.00
2006:Q4	57.83	0.00	18.77	0.03	19.75	0.02	16.23	**0.06**	23.22	0.00
2007:Q1	49.27	0.00	12.42	**0.19**	20.11	0.02	16.46	***0.05***	23.29	0.00
2007:Q2	60.63	0.00	11.86	**0.22**	19.57	0.02	14.60	**0.10**	23.42	0.00
2007:Q3	62.22	0.00	27.45	0.00	20.23	0.02	14.54	**0.10**	24.79	0.00
2007:Q4	64.23	0.00	28.22	0.00	20.21	0.02	14.77	**0.09**	25.19	0.00
2008:Q1	64.02	0.00	30.84	0.00	22.57	0.01	15.92	**0.07**	29.76	0.00
2008:Q2	64.43	0.00	28.47	0.00	21.73	0.01	15.74	**0.07**	27.79	0.00

Table 10: GMM Distance Statistic–(In-Sample Forecast Horizon, h_5: 12 Quarters)									
		(Starting in 1960:Q1)				(Starting in 1984:Q1)			
		REG A		REG B		REG A		REG B	
Vintage	**Cond Obs.**	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value	LR-Stat	P-Value
2000:Q4	2000:Q3	5.786	0.055	0.251	0.882	0.135	0.935	2.728	0.256
2001:Q1	2000:Q3	3.490	0.175	0.199	0.905	0.475	0.789	3.413	0.181
2001:Q2	2000:Q3	3.516	0.172	0.130	0.937	0.492	0.782	3.151	0.207
2001:Q3	2000:Q3	3.809	0.149	0.229	0.892	0.624	0.732	1.291	0.524
2001:Q4	2000:Q3	3.821	0.148	0.231	0.891	0.613	0.736	1.309	0.520
2002:Q1	2000:Q3	3.844	0.146	0.177	0.915	1.594	0.451	1.581	0.454
2002:Q2	2000:Q3	3.867	0.145	0.160	0.923	1.616	0.446	2.103	0.349
2002:Q3	2000:Q3	5.212	0.074	0.208	0.901	3.677	0.159	3.562	0.168
2002:Q4	2000:Q3	5.211	0.074	0.209	0.901	3.680	0.159	3.597	0.166
2003:Q1	2000:Q3	5.283	0.071	0.213	0.899	3.742	0.154	3.455	0.178
2003:Q2	2000:Q3	5.322	0.070	0.256	0.880	3.795	0.150	1.594	0.451
2003:Q3	2000:Q3	5.621	0.060	0.258	0.879	4.205	0.122	1.614	0.446
2003:Q4	2000:Q3	5.737	0.057	0.347	0.841	4.305	0.116	1.465	0.481
2004:Q1	2000:Q3	5.743	0.057	0.348	0.840	4.329	0.115	1.501	0.472
2004:Q2	2000:Q3	6.150	0.046	0.294	0.863	4.560	0.102	2.984	0.225
2004:Q3	2000:Q3	8.028	0.018	0.264	0.876	6.898	0.032	3.393	0.183
2004:Q4	2000:Q3	8.025	0.018	0.263	0.877	6.946	0.031	3.310	0.191
2005:Q1	2000:Q3	9.878	0.007	0.132	0.936	10.642	0.005	5.568	0.062
2005:Q2	2000:Q3	9.983	0.007	0.133	0.936	10.853	0.004	5.634	0.060
2001:Q1	2000:Q4	8.640	0.013	0.630	0.730	0.451	0.798	1.595	0.450
2001:Q2	2000:Q4	8.950	0.011	0.626	0.731	0.200	0.905	1.347	0.510
2001:Q3	2000:Q4	9.305	0.010	0.760	0.684	0.092	0.955	0.621	0.733
2001:Q4	2000:Q4	9.327	0.009	0.765	0.682	0.092	0.955	0.630	0.730
2002:Q1	2000:Q4	9.382	0.009	0.866	0.649	0.919	0.632	0.257	0.880
2002:Q2	2000:Q4	9.439	0.009	0.836	0.658	0.932	0.627	0.322	0.851
2002:Q3	2000:Q4	9.958	0.007	0.846	0.655	0.954	0.621	0.313	0.855
2002:Q4	2000:Q4	10.164	0.006	0.895	0.639	1.086	0.581	0.206	0.902
2003:Q1	2000:Q4	10.612	0.005	1.003	0.606	1.751	0.417	0.238	0.888
2003:Q2	2000:Q4	10.749	0.005	1.121	0.571	1.903	0.386	0.337	0.845
2003:Q3	2000:Q4	10.887	0.004	1.128	0.569	2.058	0.357	0.354	0.838
2003:Q4	2000:Q4	11.010	0.004	1.175	0.556	2.199	0.333	0.298	0.862
2004:Q1	2000:Q4	10.729	0.005	1.079	0.583	2.100	0.350	0.030	0.985
2004:Q2	2000:Q4	10.771	0.005	1.300	0.522	2.119	0.347	0.009	0.996
2004:Q3	2000:Q4	10.870	0.004	1.308	0.520	2.143	0.342	0.009	0.996
2004:Q4	2000:Q4	10.597	0.005	1.296	0.523	1.920	0.383	0.010	0.995
2005:Q1	2000:Q4	10.759	0.005	1.135	0.567	2.129	0.345	0.096	0.953
2005:Q2	2000:Q4	10.820	0.004	1.142	0.565	2.155	0.340	0.099	0.951