Real-Time Data Revisions and the PCE Measure of Inflation

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February 2010

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By

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April 2010

Abstract

This paper tracks data revisions in the Personal Consumption Expenditure using the exclusions-from-core inflation persistence model. Keeping the number of observations the same, the regression parameters of earlier vintages of real-time data, beginning with vintage 1996:Q1, are tested for coincidence against the regression parameters of the last vintage of real-time data, used in this paper, which is vintage 2008:Q2 in a parametric and two nonparametric frameworks. The effects of data revisions are not detectable in the vast majority of cases in the parametric model, but the flexibility of the two nonparametric models is able to utilize the data revisions.

KEY WORDS: Inflation Persistence, Real-Time Data, Monetary Policy, Nonparametrics, In-Sample Forecasting

JEL Classification Codes: E52, C14 , C53

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1. Introduction

Real-time data gives the researcher access to the lastest available information that can be used in policy analysis. The general train of thought is: the more information, the better. This would hold true, especially, if the information is being utilized. According to Croushore and Stark (2001), the revisions in real-time data are typically just a few tenths, but these small changes can be gleaned and applied if the appropriate economometric tool is used such as a flexible nonparametric model, which this paper employs.

The data revisions can come from two sources: the updating of previously released data and benchmark revisions. The updating of previously released datum can occur up to three years after the initial release and occurs when new information becomes available or an error in calculating the original statistic is remedied. Benchmark revisions occur every five years and could possibly include new data from economic censuses as well as possible methodological changes such as the switch to the chain-weighted GDP, which occurred in 1996.[1]

In regards to using quarterly data, which this paper analyzes, a maximum of twelve observations of a given real-time data set has the potential of changing at any given time, aside from the benchmark revisions. As stated by Croushore and Stark (2003), generally not all of the potential twelve observations change simultaneously.

Since 2007, the Federal Reserve has been using both total and core Personal Consumption Expenditure (PCE) for forecasting inflation due to one reason being that both time series are subject to revision (Croushore 2008).[2] Regarding previous work on the effects of data revisions and the PCE, Croushore (2008) analyzes the changes in the magnitudes and the pattern of the data revisions of PCE. This paper tracks real-time data revisions in PCE in the exclusions-from-core model of inflation persistence of Lafléche and Armour (2006) and Tierney (2009), which are based upon Cogley (2002). The purpose is to see if the data revisions, which are generally small in magnitude, have an impact on the parameters of the exclusions-from-core inflation persistence model by producing statistically different parameters, which might be of future use in policy analysis.

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[1] Please see Croushore and Stark (2001) and Croushore (2007) for more information regarding the data collection methods of the real-time dataset.

[2] In the U.S., core inflation is total inflation minus the volatile components of food and energy.

Tierney (2009) finds that the effects of data revisions are difficult to determine when a recursive framework is implemented since both new data as well as revised data is used in a new vintage, i.e. real-time dataset.[3] The estimated parameters of a model are changing, but it is difficult to determine, with any degree of certainty, whether the changes are coming from the newly incorporated data or the revised data. In this paper, instead of using just one particular vintage or one particular revision for tracking the effects of data revisions, all available vintages and all available revisions are able to be examined simultaneously as has been suggested by Elliott (2002).

In regards to denoting the vintages, each vintage will have the prefix of "V_" in order to distinguish it from a given observation. For instance, V_1996:Q1, which is the first available vintage of PCE, refers to the vintage of the real-time dataset released in the middle of the first quarter of 1996 with the data ranging being from 1983:Q4 to 1995:Q4 for this paper. The sample size increases by an increment of one with each additional vintage. The last vintage of real-time PCE used in this paper is V_2008:Q2 with the data ranging from 1983:Q4 to 2008:Q1.

To test for the effects of data revisions, each earlier vintage is tested against V_2008:Q2, while keeping the number of observations the same in each comparison. The regressions produced by the two separate vintages are then tested for coincidence. This translates into testing whether the estimated intercepts and slope coefficients are statistically equivalent between the two comparison vintages at the 5% significance level. If this is the case, then data revisions are too small to be detected and hence are not useful for implementation in policy matters in the given methodology.

Three different methodologies are used to test for coincidence. Lafléche and Armour's (2006) model of Ordinary Least Squares (OLS) is used as a benchmark comparison against two versions of the kernel weighted least squares (KWLS) method of nonparametrics.[4] The first nonparametric methodology involves using the average of *all* the local conditional nonparametric estimators, which is referred to as the global

[3] For a summary of the uses of real-time data, please see Croushore and Stark (2001) and (2003).
[4] The KWLS nonparametric model is also known as the Local Linear least Squares (LLLS) nonparametric model, which is a form of Generalized Least Squares (GLS), and thereby, efficient.

nonparametric model. It is offered as a measure of central tendency and is meant as a direct comparison against OLS.

The second methodology involves using the local results of the nonparametric regression produced conditional on just the very last observation, i.e. the T^{th} observation of each comparison vintage. As it pertains to policy, examining just the T^{th} local conditional regression is a very useful tool because it utilizes the latest available information while automatically incorporating the information in the relevant time-frame through the use of KWLS. For instance, in deciding whether to raise or lower interest rates in response to inflation, the Federal Reserve might look at historical periods that contain inflation similar to the current level of inflation. The T^{th} local conditional regression automatically incorporates related periods by placing a higher weight on observations closer to the T^{th} conditioning observation within the window width.[5]

In regards to real-time data, with only a few observations changing by a small magnitude at a given time, this paper finds that an econometric model that is aggregate-driven such as OLS is unable to utilize the subtlety of the new information, while both versions of the KWLS nonparametric model is able to do so especially at the T^{th} local conditional level. Thus, data revisions do have an impact on the exclusions-from-core measures of inflation over a five-period in-sample forecast horizon of one, two, four, eight, and twelve quarters given the proper econometric tool.

The structure of this paper is of the following format: Section II presents the theoretical methodologies. A brief discussion of the univariate data and the empirical results are presented in Section III. The conclusion is presented in Section IV.

2. Theoretical Methodologies

Before the effects of data revision of core and total inflation can be examined, a discussion of the exclusions-from-core inflation persistence model is necessary. The exclusions-from-core inflation persistence model is used in both the parametric and nonparametric case and is discussed without a loss of generality with respect to only one

[5] For more information on the nonparametric exclusions-from-core inflation persistence model, please see Tierney (2009).

vintage, i.e. real-time dataset.[6] For both the parametric and nonparametric models, the regressand, $Y_t = (\pi_{t+h} - \pi_t)$, is the h-period-ahead *change* in total inflation at time t, and the regressor, $X_t = (\pi_t^{core} - \pi_t)$, is the difference between core inflation and total inflation at time t, which is the exclusions-from-core measure of inflation. For the calculation of inflation, the PCE is used for both core and total inflation. Regarding the testing for the effects of data revisions, this is accomplished by testing for coincidence by examining the same sample period in two comparison vintages at a time in a given in-sample forecast horizon.

2.1 The Parametric and Nonparametric Inflation Persistence Models

Both the parametric and nonparametric methodologies model the conditional mean of $m(\cdot) = E(Y_t | X_t = \cdot)$ with $E(\varepsilon_t | X_t) = 0$ for the given pairs of observations $\{(X_t, Y_t)\}_{t=1}^{T}$, in the following regression function:

$$Y_t = m(X_t) + \varepsilon_t . \tag{1}$$

Regarding the parametric model, the conditional mean is denoted as $m(X_t) = m_p(X_t)$ with the subscript p referring to the parametric regression. The OLS regression model is of the following forms:

$$Y_t = m_p(X_t) + u_t \tag{2}$$

$$Y_t = \alpha + \beta X_t + u_t , \tag{3}$$

with $u_t \sim (0, \sigma_t^2)$ and where $m_p(X_t) = \alpha + \beta X_t$, which indicates that for each dataset, only one set of regression parameters is produced.

One of the main benefits of using the exclusions-from-core inflation persistence model is that it permits the study of inflation persistence in a stationary framework.[7] One problem in using the afore-mentioned model is autocorrelation, which is addressed through the use of the Newey-West (1987) heteroskedasticity and autocorrelation

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[6] For more details on the exclusions-from-core examination of inflation persistence, please see Johnson (1999), Clark (2001), Cogley (2002), Rich and Steindel (2005), Lafléche and Armour (2006), Tierney (2009).

[7] For more information regarding the stationarity of the exclusions-from-core-inflation persistence model, please see Johnson (1999), Clark (2001), Cogley (2002), Rich and Steindel (2005), Lafléche and Armour (2006), Tierney (2009).

consistent (HAC) covariance matrix in the parametric and nonparametric model as has been implemented by Cogley (2002), Rich and Steindel (2005), and Tierney (2009). The Newey-West (1987) HAC covariance matrix is used to form the standard errors and the t-statistics for the exclusions-from-core inflation persistence model with the lags of the Bartlett kernel reflecting the length of the *h*-period in-sample forecast horizons.[8]

Similarly for the nonparametric regression, the conditional mean is denoted as $m(X_t) = m_{np}(X_t)$, with the subscript *np* referring to the nonparametric regression. For any given *x* and for $\upsilon_t \sim (0, \sigma^2(x))$, the KWLS nonparametric model, which produces *T* sets of time-varying regression parameters, is:

$$Y_t = m_{np}(X_t) + \upsilon_t \tag{4}$$

$$Y_t = \alpha(x) + \beta(x) X_t + \upsilon_t. \tag{5}$$

with $m_{np}(X_t) = \alpha(x) + \beta(x) X_t$.

The KWLS nonparametric model differs from the parametric model in its flexibility, which enables the small changes of data revisions to be more readily incorporated and utilized. The flexibility as well as the minmax properties of the KWLS regression model comes from fitting a line within a certain bandwidth, i.e. window width conditional on each and every observation, *x* in the dataset, which helps to balance the bias-variance trade-off and produce *T*-sets of time-varying coefficients.[9]

In addition, the KWLS nonparametric regression model provides an adaptive learning framework through the use of the window width. It is able to automatically incorporate new data based on relevance in relation to the conditioning observation for each and every single *x*. In regards to the incorporation of data revisions, this flexibility permits the gleaning of new, small-in-magnitude information, which can be lost in an aggregate-driven model such at the OLS.

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[8] 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.

[9] For more information regarding the nonparametric methodology, please refer to Ruppert and Wand (1994), Wand and Jones (1995), Fan and Gijbels (1996), Atkeson, Moore, and Schaal (1997), Pagan and Ullah (1999) and Tierney (2009).

A set of global nonparametric regression parameters are formed by taking the average of all the local conditional nonparametric regression parameters of Equation (5). This permits one to compare the averaged OLS parameters with a set of averaged nonparametric parameters.

For this paper, conditional on any given x, the univariate Gaussian kernel is used as the smoothing, i.e. weighting function, which is of the form:

$$K = \sum_{t=1}^{T} K(\psi), \tag{6}$$

where $K(\psi) = \frac{1}{(2\pi)^{\frac{1}{2}}} exp\left(-\frac{1}{2}\left(\frac{x_t - x}{d_T}\right)^2\right)$ with $\psi = \left(\frac{x_t - x}{d_T}\right)$ and d_T referring to the window width, which is the smoothing parameter of the model. Within the realm of the window width, the closer any given x_t is to the conditioning observation, x, the higher the weight and vice versa.

The flexibility provided by nonparametrics is due to its window width, and it is also its weakness since the choice of window width can severely affect the estimation of the local conditional regression parameters.[10] For this paper, the pre-asymptotic, data-driven residual-based window width approach of Fan and Gijbels (1995), which is the integrated residual squares criterion (IRSC) method, is used to obtain the window width. As previously noted by Fan and Gijbels (1995), Marron (1988), and Härdle and Tsybakov (1997), the use of the IRSC also minimizes the squared bias and the variance of the regression parameters, which provides a constant window width for each dataset, but it is not constant across the fifty vintages of real-time data.[11]

Robinson (1998) notes that the nonparametric methodology takes into account heteroskedasticity but not autocorrelation. Even though the parameters are not affected, autocorrelation needs to be addressed since it produces standard errors that could be underestimated. This would then produce test statistics that are overestimated. Härdle, Lütkepohl, and Chen (1997) state that the principle of 'whitening by window width' does

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[10] The Curse of Dimensionality is a non-issue since a univariate model is used in this paper (Cleveland and Devlin 1988, Härdle and Linton 1994).

[11] For other papers that use the residual-based window, please see Cai (2007), Cai and Chen (2006), Cai, Fan, and Yao (2000), Chauvet and Tierney (2008), Fan and Yao (1998), Fujiwara and Koga (2004), Wand and Jones(1995).

not apply since it pertains to removing autocorrelation within the window width only. Hence, due to the formation of the leading variables used in the nonparametric regressions, the Newey-West (1987) HAC covariance matrix is needed to removed the autocorrelation. and to form the standard errors and the test statistics.[12]

The parametric OLS model of inflation persistence using the exclusions-from-core measure of inflation of Equation (3) is of the following form:

$$\left(\pi_{t+h} - \pi_t\right) = \alpha + \beta\left(\pi_t^{core} - \pi_t\right) + u_t \tag{7}$$

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*, $m_p\left(X_t\right) = \alpha + \beta\left(\pi_t^{core} - \pi_t\right)$, and $u_t \sim \left(o, \sigma_t^2\right)$ being the distribution of the random error term, u_t with *h* representing the in-sample forecast horizon.[13]

The KWLS nonparametric regression model of inflation persistence using the exclusions-from-core measure of inflation of Equation (3) is of the following form:

$$\left(\pi_{t+h} - \pi_t\right) = \alpha\left(x\right) + \beta\left(x\right)\left(\pi_t^{core} - \pi_t\right) + \upsilon_t \tag{8}$$

where $x = \pi^{core} - \pi$ and $m_{np}\left(X_t\right) = \alpha\left(x\right) + \beta\left(x\right)\left(\pi_t^{core} - \pi_t\right)$. Equation (8) is calculated conditional on each and every single observation of the regressor in the dataset thereby producing a total of *T* local conditional nonparametric regressions. In regards to the local analysis, only the T^{th} local conditional nonparametric regression of Equation (8) is used.

2.2 Testing for the Effects of Data Revisions

The general idea for testing for the effects of data revisions necessitates analyzing the same sample period in the three previously mentioned methodologies and to testing for coincidence. As noted by Kleinbaum and Kupper (1978) and Howell (2007), when two regressions have coincidence, in this case, this means that the intercepts and slopes produced by the two comparison vintages, Vintages *K* and *L* are statistically equivalent. Vintage *K* ranges from {V_1996:Q1, V_1996:Q2, …, V_2008:Q2}, and Vintage *L* refers to the very last vintage examined in this paper, which is V_2008:Q2.

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[12] For more on the use of the Newey-West HAC covariance matrix in the parametric methodology, please see Cogley (2002) and Rich and Steindel (2005), and for the nonparametric methodology, please see Tierney (2009). For the use of the t-statistic in nonparametrics, please see Wasserman (2006).

[13] For more information regarding the interpretation of the exclusions-from-core-inflation persistence model, please see Johnson (1999), Clark (2001), Cogley (2002), Rich and Steindel (2005), Lafléche and Armour (2006), Tierney (2009), etc.

The parametric OLS model of inflation persistence using the exclusions-from-core measure of inflation of Equations (7) is used to explain the test for coincidence. In the parametric model, the regression coefficients from the regression from Vintages *K* and *L* are compared and are denoted respectively as the following:

$$\left(\pi_{Kt+h}-\pi_{Kt}\right)=\alpha_K+\beta_K\left(\pi_{Kt}^{core}-\pi_{Kt}\right)+u_{Kt} \qquad (9)$$

and

$$\left(\pi_{Lt+h}-\pi_{Lt}\right)=\alpha_L+\beta_L\left(\pi_{Lt}^{core}-\pi_{Lt}\right)+u_{Lt} \qquad (10)$$

The hypothesis test of the parametric regression for coincidence is of the following form:

H_o: $\alpha_K=\alpha_L$ and $\beta_K=\beta_L$ (Regressions have coincidence)

versus

H_1: $\alpha_K\neq\alpha_L$ or $\beta_K\neq\beta_L$ (Regressions do not have coincidence) (11)

A t-statistic using a pooled variance term, assuming dependence, that takes into account autocorrelation within each dataset as well as the correlation between Vintages *K* and *L* is used to separately compare the intercepts and slopes of Vintages *K* and *L*. Since a pooled variance is utilized, the question of which degrees of freedom (df) to use in the calculation of the critical value arises. To determine the *df*, an F-test at the 5% significance level comparing the unconditional variance of the error terms of Vintage *K* and Vintage *L* is used and is as follows:

H_o: $\sigma_L^2=\sigma_K^2$ versus H_1: $\sigma_L^2\neq\sigma_K^2$ (12)

as noted by Kleinbaum and Kupper (1978) and Howell (2007). If the null fails to be rejected then the *df* for the t-test becomes:

$$df=T_L+T_K-2. \qquad (13)$$

If the null is rejected, then the df for the t-test becomes:

$$df=T_L-1 \text{ or } df=T_K-1. \qquad (14)$$

Since the total number of observations, which is denoted as T_K and T_L for Vintages *K* and *L* respectively, are the same, then $T_L = T_K$.

Assuming dependence, the t-test for both the intercept and the slopes are of the following form:

$$t_\alpha = (\alpha_L - \alpha_K) \Big/ \left(\sqrt{\left(\sigma^2_{\alpha_L} + \sigma^2_{\alpha_K} - 2 * \rho \sigma_{\alpha_L} \sigma_{\alpha_K} \right)} \right) \quad (15)$$

and

$$t_\beta = (\beta_L - \beta_K) \Big/ \left(\sqrt{\left(\sigma^2_{\beta_L} + \sigma^2_{\beta_K} - 2 * \rho \sigma_{\beta_L} \sigma_{\beta_K} \right)} \right) \quad (16)$$

where ρ refers to the covariance of the error terms of the regressions of Vintage K and Vintage L. The Newey-West (1987) standard errors of the intercepts of Vintages K and L are σ_{α_K} and σ_{α_L} respectively, and the Newey-West (1987) standard errors of the slope coefficients of Vintages K and L are σ_{β_K} and σ_{β_L}. In the case of assuming correlated data, the *df* is that of Equation (14) and is confirmed by rejecting the null of equal variances. The covariance of the error terms is used since many observations are identical in each of the comparisons of Vintages K and L since only a maximum of twelve observations of a given dataset can change due to data revisions with the exclusion of the benchmark years.

In regards to analyzing the effects of data revisions from V_1996:Q1 to V_2008:Q2, a recursive methodology that keeps the same sample size for Vintages K and L with the sample size being that of Vintage K is as follows:

(i.) The OLS parameters from Equations (7) and the global nonparametric parameters, which is the average of all the T_K and T_L nonparametric parameters for Vintages K and L from Equation (8) are obtained for each of the two vintages and tested for coincidence within each respective methodology. Regarding the local nonparametric model, *only* the T^{th}_K local conditional KWLS nonparametric parameters from Vintage K and the T^{th}_L local conditional KWLS nonparametric parameters from Vintage L of Equation (8) are tested for coincidence. This will be done for all five in-sample forecast horizons since the updating of data can occur for a maximum of three years excluding the benchmark revisions.

(ii.) Repeating Item (i.) with Vintages $(K+1)$ and L, the OLS, global nonparametric, and the local nonparametric regression parameters conditional on $T^{th}_{(K+1)}$ and $T^{th}_{(L+1)}$ are again obtained and are tested for coincidence.

(iii.) This iterative method is done for all remaining vintages while holding each of the observations and in-sample forecast horizons constant for each dataset until Vintage *K* equals Vintage *L*.

Testing the T^{th} local conditional nonparametric regression model and the global nonparametric model for coincidence is analogous to the testing of the parametric model. Using the parameters from the T^{th} local conditional nonparametric regression model from Equation (8), the hypothesis test for the T^{th} local conditional nonparametric regression model for coincidence is of the following form:

H$_0$: $\alpha\left(x_{T_K}\right)=\alpha\left(x_{T_L}\right)$ and $\beta\left(x_{T_K}\right)=\beta\left(x_{T_L}\right)$

versus

H$_1$: $\alpha\left(x_{T_K}\right)\neq\alpha\left(x_{T_L}\right)$ or $\beta\left(x_{T_K}\right)\neq\beta\left(x_{T_L}\right)$. (17)

The hypothesis test of Equation (17) is of particular interest because it directly compares the last observation of Vintage *K* with its counter-part in Vintage *L*, which is the observation that is most likely to be updated. This permits one to see if the parameters of the T^{th} local conditional nonparametric regression model are affected by data revisions. The t-test is analogous to that of Equations (15) and (16) except for using the Newey-West (1987) standard errors of the intercepts and slope coefficients of Vintages *K* and *L* that are obtained from the T^{th} local conditional nonparametric regression from each comparison vintage.

Regarding the test for coincidence of the global nonparametric model, the average of all the local conditional nonparametric parameters is used to form the hypothesis test of Equation (17) instead of using just the T^{th} local conditional nonparametric regression parameters. The Newey-West (1987) standard errors from *all* the *T* local nonparametric regressions are used to form the t-statistic for the global nonparametric regression model since these residuals are obtained my minimizing the sum of squared errors. Lastly, the t-test is formed in the same manner as that of Equations (15) and (16). The Newey-West (1987) standard errors of the intercepts and slope coefficients are obtained from the KWLS nonparametric regression of Equation (8) and are used to form the t-statistic.

3. EMPIRICAL RESULTS

Table 1 is provided to help with the interpretation of the tables and the presentation of the empirical results since three different methodologies, which are the parametric, global nonparametric, and local conditional nonparametric methodologies are used as well as five in-sample forecast horizons.

The regression results for V_1999:Q4, a benchmark year, and V_2000:Q1 are not presented because the results are unreliable due to problems that stem from the data. V_1999:Q4 is problematic because much of the dataset would have to be interpolated since the real-time data of V_1999:Q4 actually begins with observation 1994:Q1 instead of 1983:Q4, which is the starting observation for all the other vintages. The interpolation needed for V_1999:Q4 distorts the size of the window width compared to the other regressions and is therefore not included in the analysis of this paper. The data in V_2000:Q1 is inconsistent due to the data being collected from a variety of sources that the nonparametric model is able to detect as evidenced by the abnormally small window width.[14]

In regards to inflation persistence, Tierney (2009) finds that the nonparametric model has greater explanatory power when compared to OLS. Concerning data revisions, this paper finds the nonparametric models to outperform OLS by being able to detect differences in the estimated parameters of the comparison vintages as indicated by rejecting the null of coincidence in many more instances than OLS.

The designation of an asterisk and bold print accompanying the t-statistic or the p-value in Tables 2 to 7 denotes rejection of the null of coincidence at the 5% significance level meaning that the regressions produced by Vintages K and L produce statistically different intercepts *and* slopes coefficients. Items that are marked in bold print in Tables 2 to 7 indicate statistically different estimators in either the intercepts or the slope coefficients, but not both at the 5% significance level. It should be noted that the window width for all five in-sample forecast horizons range from 0.22 to 0.05.[15]

[14] The information regarding V_2000:Q1 has been kindly provided by Dean Croushore.
[15] A complete table of the window widths for all five in-sample forecast horizons is available upon request.

3.1 Data and Univariate Analysis

The measures of core PCE and PCE are obtained in real-time and are available from the Philadelphia Federal Reserve. The real-time dataset begins with the first vintage of V_1996:Q1 and ends with vintage V_2008:Q2. Only 48 vintages are examined with the exclusions of V_1999:Q4 and V_2000:Q1 as has been previously discussed.

After the calculation of inflation has been computed, the dataset of the last vintage, V_2008:Q2 ranges from 1984:Q1 to 2008:Q1. 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-quarters 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 in each regression is presented in Table 1.

By the construction of the regressand and the regressor, the regression models of Equations (7) and (8) are stationary. Clark (2001), Cogley (2002), Rich and Steindel (2005), and Tierney (2009) have found, which this paper has verified, that the regressand, regressor, and residuals of the regression model are I(0) by both the Augmented Dickey-Fuller Test and the Phillips-Perron Test.

3.2 Empirical Results with Respect to Data Revisions

In regards to the hypothesis test for the equality of variances as is found in Equation (12), the p-values of the F-test for the parametric model are all greater than 0.05, which means that the null of statistically equivalent unconditional variances of the residuals fails to be rejected. This also is the case with a few exceptions for the global nonparametric model, which is presented as a comparison of central tendency to the parametric model.[16] A few of the p-values are less than 0.05 for each of the five in-sample forecast horizons for the local nonparametric model, but the vast majority fail to reject the null of statistically equivalent unconditional variances as well.[17]

Concerning the parametric model, the p-values of the pooled t-test for the estimated intercepts and slopes of Vintages K and L, assuming dependence, are presented in Table 2, and the t-statistics are presented in Table 3. All of the p-values for the estimated intercepts

[16] The global nonparametric model rejects the null for the two-quarter in-sample forecast horizon for the following vintages: V_1997:Q4 to V_1998:Q2 and V_1998:Q4 to V_1999:Q3, and the null is also rejected for the twelve-quarter in-sample forecast horizon for the following vintages: V_1996:Q1 to V_1997:Q1.

[17] The tables of the F-statistic are not presented in the paper but are available upon request.

are much greater than 0.05 and are closer to unity in a great number of instances, which means that the null of statistically equivalent estimated intercepts strongly fails to be rejected. This is also true for the p-values of the pooled t-test for the estimated slope coefficients of Vintages *K* and *L*. Except for h_3, the four-quarter in-sample forecast horizon, for vintages V_2002:Q2 to V_2003:Q4 and for h_1, the one-quarter in-sample forecast horizon, for vintage V_2006:Q4, the null of statistically equivalent estimated slope coefficients is not rejected. This is not a surprising finding because the differences between the parametric slopes for Vintage *K* and *L* are very close to zero and range between -0.20 and 0.15 as is shown in Graphs 1 and 4.[18]

So, in regards to the OLS form of the exclusion-from-core inflation persistence model, the pooled t-test finds for coincidence of the regressions with respect to Vintages *K* and *L* for all five in-sample forecast horizons with a few previously noted exceptions in the estimated slopes. Thus, the effects of data revisions are essentially lost in this aggregate-driven regression model.

Concerning the global nonparametric model, Table 4 shows the p-values for the pooled t-test of the estimated intercepts and estimated slope coefficients, and Table 5 shows the corresponding t-statistics. Comparing Table 4 to Table 2, which is a summary of the p-values of the parametric model, there are more p-values that are less than 0.05 in the h_1, h_2, h_3, and h_4 in-sample forecast horizons, which range from one-quarter to eight-quarters. Hence, there are more instances where we reject that the null of coincidence when using the global nonparametric model as a measure of central tendency especially in the h_1, h_2, and h_3, in-sample forecast horizons, which ranges from one-quarter to four-quarters. This indicates that data-revisions are able to be detected, which can be of use for policy matters in the earlier in-sample forecast horizons even in a model of central tendency as captured by the global nonparametric regression model.

It should be noted that the Newey-West (1987) standard errors from *all* the *T* local nonparametric regressions are used to form the t-statistic for the global nonparametric regression model since these residuals are obtained my minimizing the sum of squared

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[18] The shaded areas in Graphs 1 to 6 represent recessions as declared by the NBER and the bold vertical lines denote benchmark years.

errors.[19] When examining Graphs 2 and 5, one can see that the differences between the slopes are relatively larger than its parametric counterpart and range between -2.5 and 1.5.

The flexibility of the nonparametric model is able to capture the nonlinearity in inflation, which is within the current vein of research that finds significant nonlinearity present in inflation such as Nobay, Paya, and Peel (2007), Chauvet and Tierney (2008), Choi (2009), and Tierney (2009). In addition, the local conditional nonparametric model is more efficient than the parametric model, which leads to a better gleaning of information as it pertains to data revisions as noted by Tierney (2009).

In regards to the effect of data revisions, the strongest effects are captured in the T^{th} local conditional nonparametric model as is demonstrated in Tables 6 and 7. With a few exceptions in each of the in-sample forecast horizons, the p-values of the pooled t-test for both the estimated intercept and estimated slopes are generally 0.00, which means that the null of coincidence is strongly rejected with respect to Vintages K and L.[20] As is shown in Graphs 3 and 6, the range in the difference between the T^{th} local conditional estimated slopes of Vintage L and Vintage K are larger in magnitude when compared to either the parametric or global nonparametric model. The range of the observations in Graph 6 is between -12 and 8, but this is mainly due to the regressions involving the two-quarter in-sample forecast horizon.[21] The majority of the differences hover between 1 and -1.

The fact that data revisions are able to be picked up at the local level has important policy implications because nonparametrics removes the need to partition a dataset in order to isolate periods of interest. The T^{th} conditioning observation in the local nonparametric regression is automatically incorporated in related periods through the use of the window width, which functions as a dynamic gain parameter in the weighting function of Equation (6) by placing a higher weight on observations closer to the

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[19] The global nonparametric regression model is offered as a comparison of central tendency to the parametric model, but there is no exact equivalent to the parametric model in the nonparametric methodology.

[20] For Tables 1 to 6, regardless of the model, the p-value for V_2008:Q2 are all 1.00, and this is due to Vintage K and Vintage L being one in the same.

[21] The difference in the estimated slopes for the local conditional nonparametric model is not included for the eight-quarter in-sample forecast horizon in Graph 6 for V_2005:Q2 in order for the scale to be easier to interpret.

conditioning observation as has been previously stated by Tierney (2009). Thus, as the results of Tables 6 and 7 have shown, the use of revised data is warranted.

In summary, the flexibility and the efficiency of the local conditional and the global nonparametric models are able to detect the effects of data revisions, while the parametric model is unable to do so with just a handful of exceptions.

4. Conclusion

This paper examines the effects of data revisions in the exclusions-from-core inflation persistence model in five in-sample forecast horizons in 48 vintages. This amounts to examining 240 hypothesis tests for coincidence.

Concerning the parametric model, both the estimated intercepts and slopes are not simultaneously statistically different from zero between Vintage L and Vintage K in any of the five in-sample forecast horizons. The effects of data revisions are only detected in 16 out of the 240 hypothesis tests of the estimated slope coefficients and in none of the estimated intercepts. So, in an overwhelming number of regressions, the regressions produced by OLS are statistically equivalent regardless of vintage. Thus, the effects of data revisions are essentially lost when using OLS.

With respect to the global nonparametric model, the regressions of the comparison vintages do not have coincidence as evidenced by having both statistically different intercepts and slopes in 85 out of the 240 hypothesis tests. This does not include the results of the comparison where there is only a difference in either the intercept, which would increase the total by 35, or the slope, which would increase the total by 15. Concerning the results of the T^{th} local conditional nonparametric model, the comparisons find for statistically different intercepts *and* slopes in 209 out of the 240 regressions.

Thus, data revisions, which are subtle changes in magnitude, can be lost in aggregation or when outliers dominate such as in the parametric model. With the proper measuring tool such as the global nonparametric model and especially the T^{th} local conditional nonparametric model, which are flexible and able to provide local time-varying estimators, data revisions can be gleaned for used in policy analysis.

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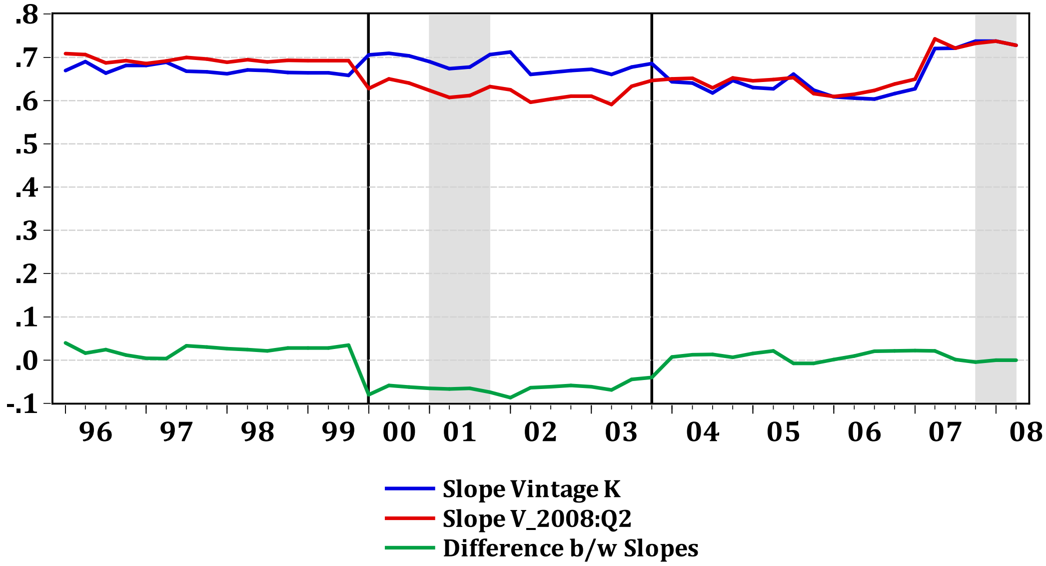
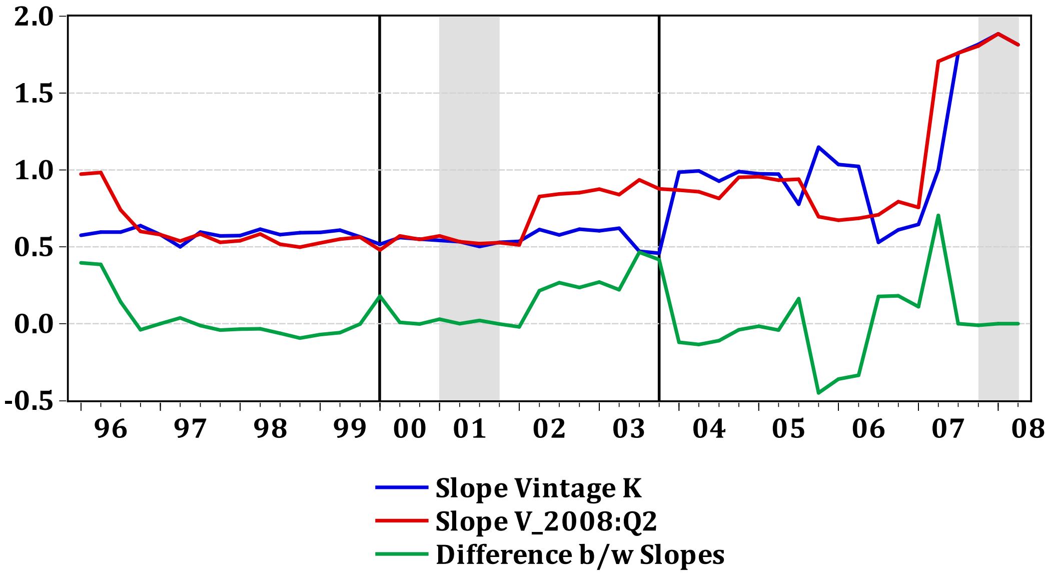
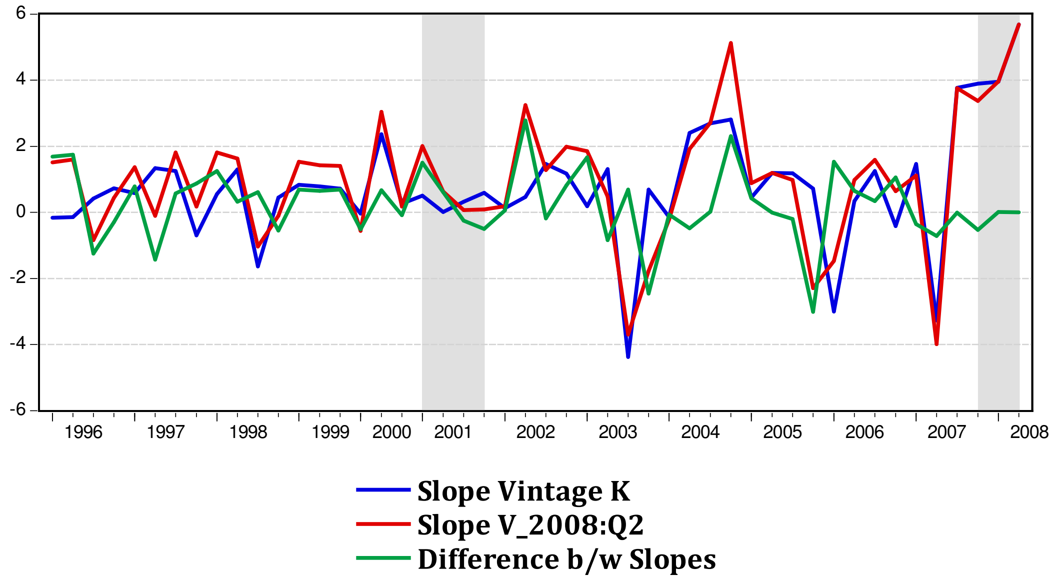
Graph 1: Parametric Model
In-Sample Forecast Horizon--1 Quarter



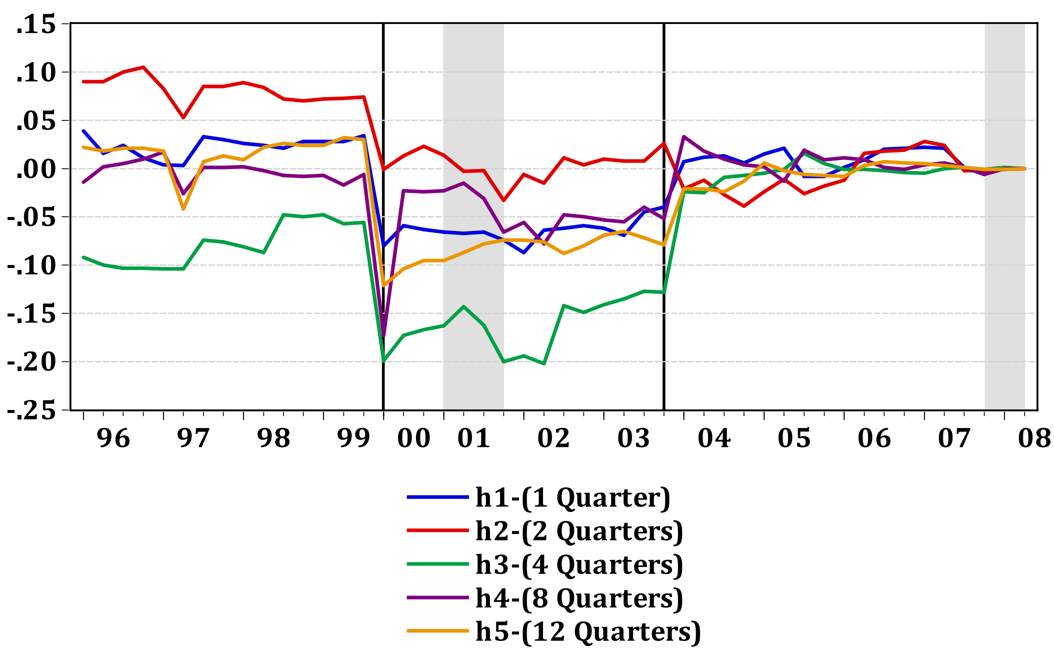
Graph 2: Global (Averaged) Nonparametric Model
In-Sample Forecast Horizon--1 Quarter



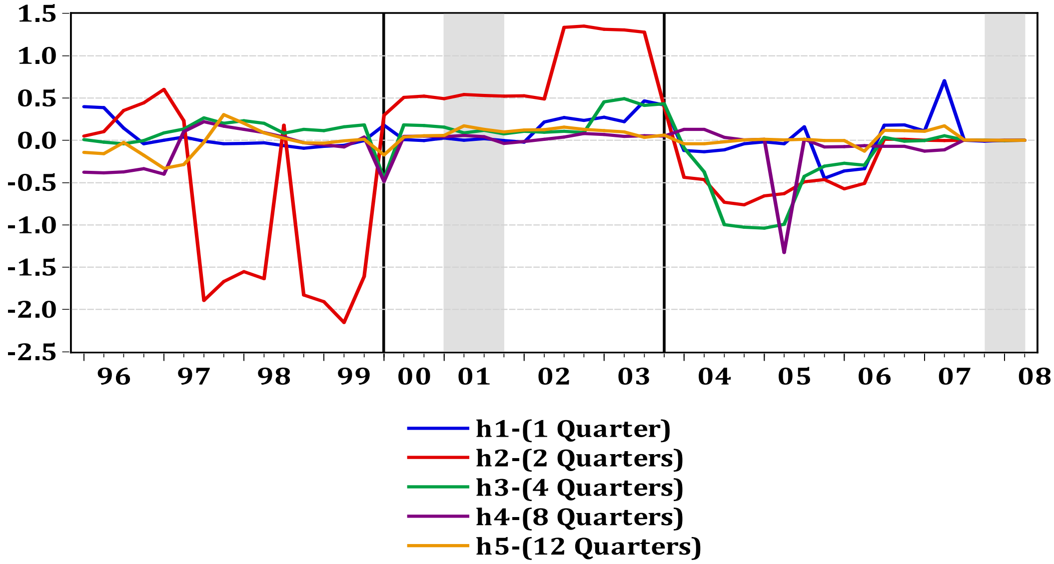
Graph 3: Local Conditional Nonparametric Model
In-Sample Forecast Horizon--1 Quarter
(Conditional on Last Obs of Vintage K)



Graph 4: Parametric Model
Difference in Slopes
(V_2008:Q2 - Vintage K)



Graph 5: Global (Averaged) Nonparametric Model
Difference in Slopes
(V_2008:Q2 - Vintage K)



Graph 6: Local Conditional Nonparametric Model
(Conditional on Last Obs of Vintage K)
Difference in Slopes
(V_2008:Q2 - Vintage K)

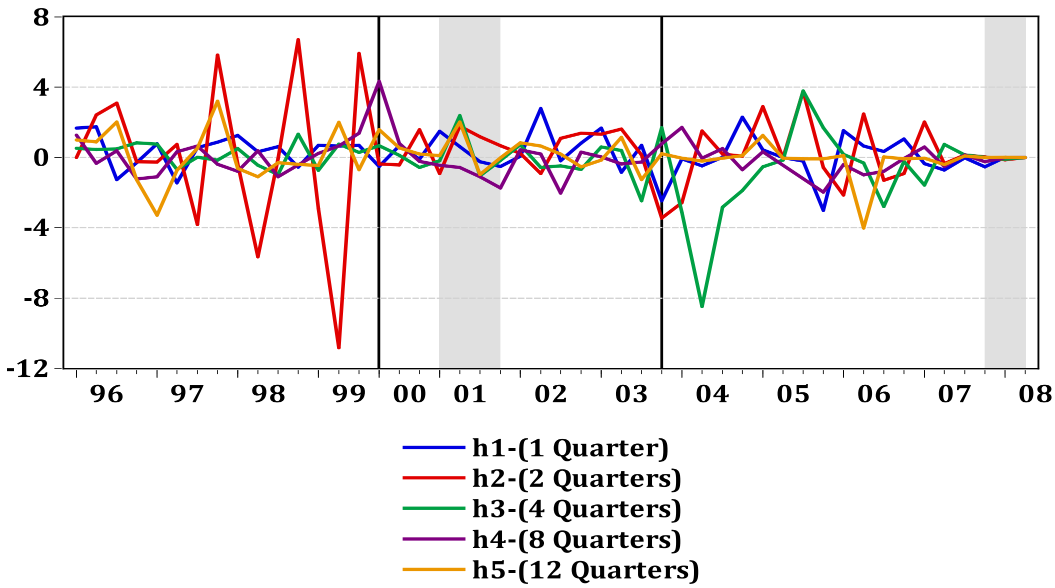


Table 1

Sample Size and In-Sample Forecast Horizons

Horizon	# of Obs.	Sample Period	Vintages
Full Sample	48 to 98	1983:Q4-2008:Q1	1996:Q1- 2008:Q2
h1 (1 quarter)	47 to 96	1984:Q1-2007:Q4	1996:Q1- 2007:Q4
h2 (2 quarters)	46 to 95	1984:Q1-2007:Q3	1996:Q1- 2007:Q3
h3 (4 quarters)	44 to 93	1984:Q1-2007:Q1	1996:Q1- 2007:Q1
h4 (8 quarters)	40 to 89	1984:Q1-2004:Q1	1996:Q1- 2006:Q1
h5 (12 quarters)	36 to 85	1984:Q1-2005:Q1	1996:Q1- 2005:Q1

Table 2

P-Values for the Hypothesis Test for Coincidence—Parametric Model

	P-Values for Estimated Intercepts					P-Values for Estimated Slopes				
Vintage	h_1	h_2	h_3	h_4	h_5	h_1	h_2	h_3	h_4	h_5
1996:Q1	0.88	0.86	0.84	0.85	0.95	0.72	0.16	0.33	0.94	0.92
1996:Q2	0.82	0.94	0.63	0.76	0.90	0.89	0.17	0.27	0.99	0.93
1996:Q3	0.95	0.73	0.64	0.80	0.93	0.83	0.10	0.22	0.98	0.91
1996:Q4	0.92	0.69	0.61	0.82	0.92	0.92	0.10	0.18	0.95	0.91
1997:Q1	0.89	0.86	0.62	0.83	0.90	0.97	0.15	0.18	0.92	0.93
1997:Q2	0.89	0.97	0.70	0.74	0.84	0.98	0.35	0.23	0.88	0.82
1997:Q3	0.99	0.68	0.96	0.90	1.00	0.78	0.13	0.38	0.99	0.97
1997:Q4	0.96	0.72	0.87	0.91	0.97	0.80	0.15	0.34	1.00	0.95
1998:Q1	0.99	0.76	0.82	0.92	1.00	0.83	0.16	0.27	0.99	0.96
1998:Q2	0.98	0.87	0.73	0.89	0.95	0.84	0.19	0.24	0.99	0.91
1998:Q3	0.93	0.83	0.76	0.76	0.85	0.86	0.27	0.48	0.97	0.89
1998:Q4	0.98	0.86	0.64	0.73	0.83	0.81	0.30	0.44	0.96	0.89
1999:Q1	0.99	0.93	0.63	0.72	0.82	0.81	0.30	0.42	0.96	0.88
1999:Q2	0.96	0.89	0.60	0.62	0.82	0.82	0.31	0.28	0.90	0.84
1999:Q3	0.95	0.80	0.66	0.60	0.83	0.77	0.29	0.36	0.97	0.87
2000:Q2	0.75	0.99	0.49	0.79	0.85	0.49	0.74	**0.00**	0.86	0.51
2000:Q3	0.88	0.97	0.55	0.85	0.92	0.59	0.84	**0.00**	0.89	0.52
2000:Q4	0.87	0.90	0.60	0.83	0.92	0.56	0.70	**0.00**	0.88	0.59
2001:Q1	0.86	0.95	0.60	0.83	0.92	0.54	0.82	**0.00**	0.88	0.59
2001:Q2	0.82	0.90	0.68	0.80	0.93	0.52	0.93	**0.00**	0.93	0.58
2001:Q3	0.70	0.60	0.62	0.88	0.90	0.52	0.97	**0.00**	0.86	0.61
2001:Q4	0.69	0.19	0.31	0.75	0.83	0.46	0.25	**0.00**	0.70	0.62
2002:Q1	0.86	0.45	0.33	0.79	0.86	0.39	0.27	**0.00**	0.74	0.61
2002:Q2	0.81	0.83	0.39	0.73	0.83	0.52	0.54	**0.00**	0.64	0.60
2002:Q3	0.80	0.84	0.68	0.80	0.88	0.51	0.52	**0.00**	0.77	0.56
2002:Q4	0.85	0.93	0.78	0.80	0.89	0.52	0.86	**0.00**	0.76	0.60
2003:Q1	0.88	0.97	0.73	0.78	0.91	0.51	0.75	**0.00**	0.75	0.64
2003:Q2	0.78	0.90	0.71	0.76	0.92	0.45	0.75	**0.00**	0.73	0.68
2003:Q3	0.90	0.86	0.73	0.82	0.89	0.61	0.80	**0.00**	0.80	0.62
2003:Q4	0.90	0.95	0.73	0.86	0.88	0.64	0.41	**0.00**	0.73	0.64
2004:Q1	0.86	0.57	0.73	0.93	0.92	0.89	0.49	0.68	0.84	0.91
2004:Q2	1.00	0.88	0.81	0.94	0.92	0.77	0.78	0.76	0.92	0.91
2004:Q3	0.89	0.86	0.83	0.92	0.94	0.73	0.62	0.91	0.96	0.90
2004:Q4	0.83	0.72	0.81	0.87	0.91	0.88	0.45	0.93	0.98	0.95
2005:Q1	0.97	0.82	0.81	0.87	0.90	0.64	0.60	0.95	0.99	0.97
2005:Q2	0.84	0.99	0.85	0.86	0.90	0.56	0.80	0.99	0.95	0.99
2005:Q3	0.97	0.98	1.00	0.99	0.98	0.78	0.61	0.85	0.93	0.97
2005:Q4	0.81	0.91	0.97	0.97	0.96	0.66	0.73	0.96	0.97	0.97
2006:Q1	1.00	0.94	0.94	0.98	0.96	0.98	0.81	0.99	0.96	0.96
2006:Q2	0.83	0.91	0.99	0.98	0.97	0.74	0.71	0.99	0.97	0.99
2006:Q3	0.97	0.98	0.99	1.00	1.00	0.09	0.69	0.99	1.00	0.97
2006:Q4	0.96	0.98	1.00	0.99	0.99	**0.03**	0.65	0.97	0.99	0.97
2007:Q1	0.97	1.00	0.99	0.99	0.99	0.66	0.73	0.96	0.99	0.98
2007:Q2	1.00	0.99	0.97	0.99	0.98	0.79	0.77	1.00	0.98	0.99
2007:Q3	0.99	1.00	1.00	1.00	1.00	0.99	0.99	0.99	1.00	1.00
2007:Q4	0.98	0.99	0.99	0.99	1.00	0.94	0.99	1.00	0.98	1.00
2008:Q1	0.99	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.00
2008:Q2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 3

T-Statistics for the Hypothesis Test for Coincidence—Parametric Model

	T-Statistics for Estimated Intercepts					T-Statistics for Estimated Slopes				
Vintage	h_1	h_2	h_3	h_4	h_5	h_1	h_2	h_3	h_4	h_5
1996:Q1	0.15	0.18	0.20	0.19	0.06	0.36	1.42	0.98	0.07	0.11
1996:Q2	0.23	0.08	0.48	0.30	0.13	0.14	1.39	1.12	0.01	0.09
1996:Q3	0.06	0.34	0.48	0.26	0.09	0.21	1.66	1.25	0.03	0.11
1996:Q4	0.10	0.41	0.52	0.23	0.10	0.10	1.69	1.35	0.06	0.12
1997:Q1	0.14	0.18	0.49	0.22	0.12	0.04	1.47	1.37	0.10	0.09
1997:Q2	0.14	0.04	0.38	0.33	0.21	0.02	0.94	1.23	0.15	0.23
1997:Q3	0.02	0.42	0.06	0.13	0.00	0.28	1.56	0.89	0.01	0.04
1997:Q4	0.05	0.35	0.16	0.12	0.04	0.26	1.44	0.97	0.01	0.07
1998:Q1	0.02	0.31	0.23	0.10	0.01	0.22	1.42	1.11	0.01	0.05
1998:Q2	0.02	0.16	0.35	0.14	0.06	0.20	1.31	1.19	0.01	0.12
1998:Q3	0.08	0.21	0.31	0.31	0.19	0.18	1.12	0.71	0.04	0.14
1998:Q4	0.02	0.18	0.47	0.34	0.22	0.24	1.06	0.78	0.05	0.14
1999:Q1	0.01	0.09	0.49	0.36	0.23	0.24	1.06	0.81	0.05	0.15
1999:Q2	0.05	0.14	0.53	0.50	0.22	0.23	1.03	1.09	0.12	0.20
1999:Q3	0.06	0.26	0.44	0.53	0.21	0.29	1.08	0.92	0.04	0.17
2000:Q2	0.32	0.01	0.70	0.27	0.19	0.69	0.33	**3.39**	0.18	0.66
2000:Q3	0.15	0.03	0.61	0.19	0.11	0.55	0.21	**4.93**	0.14	0.65
2000:Q4	0.16	0.13	0.53	0.22	0.10	0.59	0.38	**6.44**	0.15	0.54
2001:Q1	0.17	0.06	0.52	0.22	0.10	0.62	0.23	**10.91**	0.15	0.54
2001:Q2	0.23	0.13	0.41	0.25	0.09	0.64	0.09	**6.61**	0.09	0.55
2001:Q3	0.39	0.52	0.50	0.15	0.13	0.65	0.04	**3.03**	0.18	0.51
2001:Q4	0.40	1.31	1.01	0.32	0.22	0.75	1.16	**4.57**	0.40	0.49
2002:Q1	0.17	0.76	0.98	0.27	0.18	0.86	1.10	**5.58**	0.34	0.51
2002:Q2	0.24	0.22	0.86	0.35	0.22	0.65	0.61	**4.39**	0.47	0.54
2002:Q3	0.26	0.20	0.42	0.26	0.16	0.66	0.65	**3.42**	0.29	0.59
2002:Q4	0.19	0.09	0.28	0.25	0.13	0.64	0.17	**3.48**	0.30	0.52
2003:Q1	0.15	0.03	0.34	0.28	0.11	0.65	0.32	**5.29**	0.32	0.47
2003:Q2	0.28	0.12	0.37	0.31	0.11	0.76	0.32	**3.26**	0.34	0.42
2003:Q3	0.13	0.17	0.34	0.22	0.14	0.51	0.26	**3.16**	0.26	0.49
2003:Q4	0.12	0.06	0.35	0.18	0.15	0.46	0.83	**3.42**	0.34	0.47
2004:Q1	0.18	0.57	0.35	0.09	0.10	0.14	0.69	0.41	0.20	0.12
2004:Q2	0.00	0.15	0.25	0.07	0.10	0.30	0.28	0.31	0.11	0.12
2004:Q3	0.14	0.18	0.21	0.10	0.08	0.35	0.49	0.11	0.05	0.12
2004:Q4	0.21	0.35	0.24	0.17	0.12	0.15	0.76	0.09	0.02	0.07
2005:Q1	0.03	0.23	0.24	0.17	0.13	0.46	0.52	0.07	0.01	0.04
2005:Q2	0.20	0.01	0.19	0.18	0.12	0.59	0.25	0.01	0.07	0.01
2005:Q3	0.04	0.03	0.00	0.01	0.03	0.28	0.52	0.19	0.09	0.03
2005:Q4	0.24	0.11	0.04	0.03	0.05	0.44	0.35	0.06	0.04	0.04
2006:Q1	0.00	0.08	0.07	0.03	0.05	0.02	0.25	0.01	0.05	0.05
2006:Q2	0.22	0.11	0.02	0.02	0.03	0.33	0.38	0.01	0.04	0.02
2006:Q3	0.04	0.03	0.02	0.00	0.01	1.74	0.40	0.02	0.01	0.04
2006:Q4	0.05	0.03	0.01	0.01	0.01	**2.29**	0.46	0.04	0.01	0.04
2007:Q1	0.04	0.00	0.01	0.02	0.01	0.44	0.34	0.05	0.02	0.03
2007:Q2	0.00	0.02	0.04	0.02	0.02	0.27	0.29	0.00	0.03	0.02
2007:Q3	0.01	0.01	0.00	0.00	0.00	0.01	0.02	0.01	0.01	0.01
2007:Q4	0.03	0.02	0.01	0.01	0.00	0.07	0.02	0.01	0.03	0.00
2008:Q1	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00
2008:Q2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 4

P-Values for the Hypothesis Test for Coincidence—Global Nonparametric Model

	P-Values for Estimated Intercepts					P-Values for Estimated Slopes				
Vintage	h_1	h_2	h_3	h_4	h_5	h_1	h_2	h_3	h_4	h_5
1996:Q1	0.31	0.15	0.00	0.06	0.06	0.00	0.52	0.89	0.00	0.17
1996:Q2	0.37	0.18	0.00	0.10	0.07	0.00	0.17	0.70	0.00	0.11
1996:Q3	0.65	0.97	0.00	0.08	0.05	0.10	0.00	0.40	0.00	0.79
1996:Q4	0.03	0.21	0.00	0.05	0.06	0.65	0.00	0.96	0.00	0.06
1997:Q1	0.02	0.00*	0.00	0.05	0.05	0.99	0.00*	0.05	0.00	0.00
1997:Q2	0.00	0.66	0.00*	0.75	0.22	0.55	0.00	0.00*	0.32	0.06
1997:Q3	0.00	0.00*	0.00*	0.74	0.49	0.86	0.00*	0.00*	0.02	0.89
1997:Q4	0.00	0.00*	0.00*	0.75	0.35	0.54	0.00*	0.00*	0.05	0.03
1998:Q1	0.00	0.00*	0.00*	0.74	0.27	0.62	0.00*	0.00*	0.11	0.13
1998:Q2	0.00	0.00*	0.00*	0.64	0.22	0.65	0.00*	0.00*	0.28	0.51
1998:Q3	0.00	0.22	0.00*	0.12	0.16	0.38	0.00	0.00*	0.68	0.87
1998:Q4	0.00	0.00*	0.00*	0.40	0.13	0.20	0.00*	0.00*	0.71	0.82
1999:Q1	0.00	0.00*	0.00*	0.34	0.11	0.34	0.00*	0.00*	0.50	0.78
1999:Q2	0.00	0.00*	0.00*	0.50	0.09	0.43	0.00*	0.00*	0.29	0.94
1999:Q3	0.00	0.00*	0.00*	0.22	0.07	0.98	0.00*	0.00*	0.64	0.90
2000:Q2	0.02	0.00*	0.00*	0.08	0.00	0.61	0.00*	0.00*	0.60	0.14
2000:Q3	0.07	0.00*	0.00*	0.10	0.01	0.90	0.00*	0.00*	0.66	0.63
2000:Q4	0.05	0.00*	0.00*	0.10	0.02	0.98	0.00*	0.00*	0.63	0.54
2001:Q1	0.14	0.00*	0.00*	0.09	0.02	0.68	0.00*	0.00*	0.65	0.53
2001:Q2	0.17	0.00*	0.00*	0.17	0.10	0.99	0.00*	0.00*	0.59	0.06
2001:Q3	0.09	0.00*	0.00*	0.41	0.07	0.78	0.00*	0.02*	0.70	0.15
2001:Q4	0.06	0.00*	0.00	0.32	0.04	0.98	0.00*	0.10	0.75	0.25
2002:Q1	0.04	0.00*	0.00*	0.28	0.03	0.77	0.00*	0.01*	0.89	0.15
2002:Q2	0.00	0.00*	0.00*	0.45	0.02	0.32	0.00*	0.03*	0.92	0.13
2002:Q3	0.00*	0.00*	0.00*	0.50	0.02	0.00*	0.00*	0.02*	0.75	0.06
2002:Q4	0.00*	0.00*	0.00*	0.62	0.03	0.00*	0.00*	0.04*	0.51	0.12
2003:Q1	0.00*	0.00*	0.00*	0.61	0.03	0.00*	0.00*	0.00*	0.56	0.15
2003:Q2	0.00*	0.00*	0.00*	0.60	0.05	0.00*	0.00*	0.00*	0.69	0.26
2003:Q3	0.00*	0.00*	0.00*	0.46	0.06	0.00*	0.00*	0.00*	0.63	0.68
2003:Q4	0.00*	0.00*	0.00*	0.39	0.05	0.00*	0.00*	0.00*	0.67	0.49
2004:Q1	0.00*	0.00*	0.01	0.42	0.93	0.00*	0.00*	0.07	0.20	0.69
2004:Q2	0.00*	0.00*	0.00*	0.46	0.95	0.00*	0.00*	0.00*	0.23	0.68
2004:Q3	0.00*	0.00*	0.00*	0.90	0.89	0.00*	0.00*	0.00*	0.76	0.85
2004:Q4	0.02	0.00*	0.00*	0.77	0.88	0.06	0.00*	0.00*	0.97	0.96
2005:Q1	0.03	0.00*	0.00*	0.77	0.88	0.33	0.00*	0.00*	0.92	0.87
2005:Q2	0.00	0.00*	0.00*	0.00*	0.86	0.05	0.00*	0.00*	0.00*	0.95
2005:Q3	0.00*	0.00*	0.00*	0.65	0.94	0.00*	0.00*	0.00*	0.91	0.90
2005:Q4	0.00*	0.00*	0.00*	0.78	0.90	0.00*	0.00*	0.00*	0.58	0.97
2006:Q1	0.00*	0.00*	0.00*	0.79	0.89	0.00*	0.00*	0.00*	0.60	0.97
2006:Q2	0.00*	0.00*	0.00*	0.83	0.46	0.00*	0.00*	0.00*	0.64	0.25
2006:Q3	0.00*	0.81	0.50	0.84	0.49	0.00*	0.72	0.70	0.62	0.26
2006:Q4	0.00*	0.78	0.97	0.83	0.48	0.00*	0.70	0.87	0.61	0.26
2007:Q1	0.01*	0.90	0.95	0.72	0.48	0.00*	1.00	0.97	0.36	0.29
2007:Q2	0.00*	0.94	0.95	0.74	0.36	0.00*	0.97	0.54	0.43	0.10
2007:Q3	0.96	0.91	0.97	0.98	0.99	0.97	0.96	0.96	0.96	0.96
2007:Q4	0.54	0.93	0.98	0.98	0.99	0.68	0.96	0.98	0.98	0.99
2008:Q1	0.99	0.93	0.96	1.00	0.99	0.97	0.96	0.98	1.00	0.99
2008:Q2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 5

T-Statistics for the Hypothesis Test for Coincidence—Global Nonparametric Model

	T-Statistics for Estimated Intercepts					T-Statistics for Estimated Slopes				
Vintage	h_1	h_2	h_3	h_4	h_5	h_1	h_2	h_3	h_4	h_5
1996:Q1	1.03	1.47	**9.80**	1.91	2.01	**4.95**	0.65	0.14	**4.57**	1.42
1996:Q2	0.90	1.37	**10.82**	1.68	1.91	**4.74**	1.39	0.39	**5.02**	1.67
1996:Q3	0.46	0.04	**11.37**	1.81	***2.12***	1.70	**4.75**	0.86	**5.00**	0.27
1996:Q4	**2.24**	1.28	**12.16**	***2.02***	1.97	0.46	**6.07**	0.05	**4.55**	2.02
1997:Q1	**2.42**	**4.05***	**11.32**	***2.00***	***2.11***	0.01	**8.91***	1.98	**5.37**	**4.01**
1997:Q2	**10.60**	0.44	**9.63***	0.32	1.25	0.60	**4.77**	**3.47***	1.02	1.92
1997:Q3	**7.90**	**127.58***	**8.21***	0.33	0.70	0.18	**11.04***	**5.24***	**2.57**	0.14
1997:Q4	**7.09**	**106.32***	**9.11***	0.32	0.95	0.62	**9.59***	**4.26***	***2.03***	**2.21**
1998:Q1	**6.68**	**94.35***	**10.14***	0.34	1.11	0.50	**9.00***	**5.38***	1.64	1.53
1998:Q2	**6.59**	**86.44***	**10.42***	0.47	1.25	0.45	**9.44***	**4.64***	1.10	0.66
1998:Q3	**7.95**	1.23	**8.75***	1.60	1.41	0.89	**3.14**	**3.38***	0.42	0.17
1998:Q4	**5.88**	**82.64***	**10.87***	0.85	1.56	1.31	**10.74***	**3.44***	0.37	0.23
1999:Q1	**5.95**	**77.00***	**11.61***	0.97	1.61	0.96	**11.15***	**3.21***	0.68	0.28
1999:Q2	**6.09**	**72.06***	**12.35***	0.68	1.71	0.79	**12.44***	**5.26***	1.07	0.07
1999:Q3	**6.32**	**77.08***	**9.84***	1.24	1.85	0.03	**9.38***	**4.80***	0.47	0.12
2000:Q2	**2.43**	**14.09***	**11.48***	1.80	**3.37**	0.51	**8.98***	**3.10***	0.53	1.50
2000:Q3	1.87	**12.53***	**14.00***	1.68	**2.63**	0.13	**7.71***	**13.49***	0.45	0.49
2000:Q4	***1.96***	**11.63***	**13.90***	1.69	**2.48**	0.03	**8.28***	**18.51***	0.49	0.61
2001:Q1	1.48	**11.29***	**15.17***	1.72	**2.46**	0.41	**7.95***	**14.10***	0.46	0.64
2001:Q2	1.40	**18.74***	**12.86***	1.40	1.71	0.02	**11.60***	**4.05***	0.55	1.94
2001:Q3	1.70	**19.09***	**11.13***	0.83	1.90	0.28	**11.52***	**2.31***	0.39	1.47
2001:Q4	1.92	**53.18***	**12.51**	1.02	**2.20**	0.03	**14.75***	1.69	0.32	1.17
2002:Q1	**2.05**	**39.96***	**13.62***	1.10	**2.21**	0.29	**14.50***	**2.79***	0.14	1.46
2002:Q2	**13.23**	**24.71***	**11.65***	0.76	**2.36**	1.00	**11.47***	**2.24***	0.10	1.56
2002:Q3	**11.12***	**89.07***	**11.39***	0.68	**2.43**	**3.96***	**37.87***	**2.48***	0.33	1.94
2002:Q4	**11.49***	**72.44***	**11.13***	0.50	**2.33**	**3.50***	**36.74***	**2.06***	0.67	1.59
2003:Q1	**11.61***	**56.29***	**28.87***	0.52	**2.30**	**3.94***	**35.82***	**11.31***	0.59	1.46
2003:Q2	**11.81***	**66.80***	**24.51***	0.54	***2.04***	**3.30***	**37.91***	**10.40***	0.41	1.14
2003:Q3	**4.28***	**54.07***	**24.48***	0.75	1.98	**7.34***	**33.82***	**8.44***	0.48	0.42
2003:Q4	**4.03***	**6.10***	**24.90***	0.88	***2.04***	**6.84***	**20.29***	**9.17***	0.43	0.70
2004:Q1	**16.18***	**29.47***	**2.80**	0.81	0.08	**4.11***	**17.37***	1.84	1.31	0.41
2004:Q2	**20.81***	**20.34***	**8.39***	0.74	0.06	**6.15***	**12.41***	**6.14***	1.22	0.42
2004:Q3	**4.45***	**25.14***	**16.33***	0.13	0.14	**5.14**	**18.74***	**15.21***	0.31	0.18
2004:Q4	**2.38**	**27.39***	**17.31***	0.29	0.15	1.91	**21.37***	**16.65***	0.03	0.04
2005:Q1	**2.24**	**26.64***	**16.55***	0.30	0.15	0.98	**20.52***	**16.47***	0.10	0.16
2005:Q2	**3.43**	**27.06***	**16.63***	**12.16***	0.18	***2.00***	**20.06***	**16.44***	**11.46***	0.06
2005:Q3	**12.44***	**18.88***	**5.44***	0.45	0.07	**10.01***	**11.52***	**5.99***	0.12	0.12
2005:Q4	**58.68***	**17.11***	**4.58***	0.28	0.12	**39.88***	**10.22***	**3.80***	0.56	0.04
2006:Q1	**33.87***	**20.65***	**4.36***	0.27	0.13	**25.26***	**13.50***	**3.45***	0.52	0.04
2006:Q2	**28.78***	**19.66***	**4.64***	0.22	0.75	**20.59***	**14.05***	**3.75***	0.47	1.16
2006:Q3	**13.13***	0.24	0.67	0.21	0.69	**26.81***	0.37	0.38	0.50	1.14
2006:Q4	**20.65***	0.28	0.04	0.21	0.71	**31.55***	0.39	0.16	0.51	1.14
2007:Q1	**2.77***	0.13	0.06	0.36	0.71	**3.42***	0.00	0.04	0.93	1.06
2007:Q2	**12.75***	0.07	0.06	0.34	0.93	**22.38***	0.04	0.62	0.80	1.67
2007:Q3	0.05	0.12	0.04	0.02	0.02	0.03	0.05	0.06	0.05	0.05
2007:Q4	0.62	0.08	0.03	0.02	0.01	0.41	0.05	0.02	0.02	0.01
2008:Q1	0.01	0.09	0.06	0.00	0.01	0.04	0.05	0.03	0.00	0.01
2008:Q2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 6

P-Values for the Hypothesis Test for Coincidence—T^{th} Local Conditional Nonparametric Model

	P-Values for Estimated Intercepts					P-Values for Estimated Slopes				
Vintage	h_1	h_2	h_3	h_4	h_5	h_1	h_2	h_3	h_4	h_5
1996:Q1	0.00*	0.00	0.00*	0.00*	0.00*	0.00*	0.14	0.00*	0.00*	0.00*
1996:Q2	0.00*	0.00*	0.02*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1996:Q3	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1996:Q4	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1997:Q1	0.13	0.42	0.00*	0.00*	0.00*	0.00	0.00	0.00*	0.00*	0.00*
1997:Q2	0.00*	0.00*	0.00*	0.23	0.00*	0.00*	0.00*	0.00*	0.00	0.00*
1997:Q3	0.00*	0.00*	0.00	0.02*	0.00*	0.00*	0.00*	0.49	0.00*	0.00*
1997:Q4	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1998:Q1	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1998:Q2	0.00*	0.00*	0.00*	0.14	0.00*	0.00*	0.00*	0.00*	0.00	0.00*
1998:Q3	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1998:Q4	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1999:Q1	0.00*	0.00*	0.00*	0.01*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1999:Q2	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
1999:Q3	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2000:Q2	0.00*	0.00*	0.04*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2000:Q3	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2000:Q4	0.00*	0.00*	0.00*	0.32	0.00*	0.00*	0.00*	0.00*	0.00	0.00*
2001:Q1	0.00*	0.00*	0.00*	0.07	0.31	0.00*	0.00*	0.00*	0.00	0.00
2001:Q2	0.02*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2001:Q3	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2001:Q4	0.00*	0.00*	0.00*	0.00*	0.00	0.00*	0.00*	0.00*	0.00*	0.16
2002:Q1	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2002:Q2	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2002:Q3	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2002:Q4	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2003:Q1	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2003:Q2	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2003:Q3	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2003:Q4	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2004:Q1	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2004:Q2	0.00*	0.00*	0.00*	0.52	0.36	0.00*	0.00*	0.00*	0.00	0.00
2004:Q3	0.00*	0.02*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2004:Q4	0.00*	0.00*	0.00*	0.00*	0.11	0.00*	0.00*	0.00*	0.00*	0.00
2005:Q1	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2005:Q2	0.00*	0.00*	0.00*	0.00*	0.25	0.00*	0.00*	0.00*	0.00*	0.00
2005:Q3	0.00*	0.00*	0.00*	0.00*	0.14	0.00*	0.00*	0.00*	0.00*	0.00
2005:Q4	0.00*	0.00*	0.00*	0.00*	0.01*	0.00*	0.00*	0.00*	0.00*	0.00*
2006:Q1	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2006:Q2	0.00*	0.00*	0.47	0.00*	0.00*	0.00*	0.00*	0.00	0.00*	0.00*
2006:Q3	0.00*	0.00*	0.00*	0.00*	0.57	0.00*	0.00*	0.00*	0.00*	0.02
2006:Q4	0.00*	0.00*	0.00*	0.69	0.23	0.00*	0.00*	0.00*	0.00	0.00
2007:Q1	0.00*	0.00*	0.00*	0.00*	0.74	0.00*	0.00*	0.00*	0.00*	0.00
2007:Q2	0.00*	0.00*	0.07	0.00*	0.00*	0.00*	0.00*	0.00	0.00*	0.00*
2007:Q3	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
2007:Q4	0.00*	0.00*	0.35	0.00*	0.57	0.00*	0.00*	0.36	0.00*	0.99
2008:Q1	0.62	0.00*	0.00*	0.81	0.66	***0.05***	0.00*	0.00*	0.36	0.79
2008:Q2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 7

T-Statistics for the Hypothesis Test for Coincidence—T^{th} Local Conditional Nonparametric Model

	T-Statistics for Estimated Intercepts					T-Statistics for Estimated Slopes				
Vintage	h_1	h_2	h_3	h_4	h_5	h_1	h_2	h_3	h_4	h_5
1996:Q1	20.43*	52.60	6.25*	32.27*	21.43*	100.83*	1.55	23.25*	111.51*	130.00*
1996:Q2	20.88*	52.11*	2.53*	23.61*	6.97*	75.69*	476.44*	42.09*	34.48*	30.64*
1996:Q3	39.44*	209.97*	5.91*	5.16*	26.22*	40.95*	794.65*	106.42*	49.13*	83.75*
1996:Q4	9.61*	8.12*	12.09*	207.80*	22.51*	8.41*	7.18*	110.58*	199.25*	111.71*
1997:Q1	1.52	0.83	11.15*	11.87*	109.66*	50.02	6.47	79.56*	130.69*	771.55*
1997:Q2	74.71*	45.21*	15.69*	1.22*	8.93*	91.16*	136.99*	44.09*	17.76	32.96*
1997:Q3	7.12*	156.33*	7.36	2.43*	22.96*	43.43*	298.32*	0.70	43.89*	28.34*
1997:Q4	53.90*	188.27*	18.11*	4.03*	40.58*	57.37*	608.54*	14.03*	26.39*	269.39*
1998:Q1	17.24*	15.74*	23.42*	12.20*	17.37*	146.76*	32.47*	43.74*	84.38*	47.17*
1998:Q2	5.45*	183.36*	13.86*	1.51	14.05*	29.94*	417.36*	39.27*	21.79	70.26*
1998:Q3	73.73*	8.59*	72.29*	39.26*	17.47*	43.08*	3.11*	101.01*	40.50*	30.07*
1998:Q4	38.38*	3762.98*	69.03*	3.32*	9.60*	20.81*	2938.13*	163.53*	17.32*	70.29*
1999:Q1	6.83*	390.69*	10.30*	2.68*	38.00*	61.98*	952.49*	62.36*	9.19*	22.46*
1999:Q2	4.21*	79.72*	273.63*	6.06*	54.24*	46.69*	1181.02*	186.17*	23.56*	100.42*
1999:Q3	3.43*	176.83*	20.63*	36.37*	51.03*	63.69*	678.95*	186.33*	44.66*	87.05*
2000:Q2	61.05*	23.20*	2.14*	309.70*	6.69*	85.77*	87.92*	79.41*	274.96*	32.65*
2000:Q3	49.01*	81.87*	33.05*	30.41*	13.86*	68.60*	103.40*	14.59*	35.29*	10.27*
2000:Q4	16.71*	234.35*	41.72*	1.01	4.61*	7.17*	255.76*	102.43*	8.33	33.82*
2001:Q1	143.52*	100.99*	57.27*	1.85	1.04	292.34*	128.81*	53.05*	14.79	14.23
2001:Q2	2.45*	413.01*	390.06*	5.10*	96.56*	146.59*	416.90*	381.06*	20.80*	65.17*
2001:Q3	36.94*	68.31*	73.09*	23.99*	17.62*	40.36*	342.65*	138.88*	31.25*	18.98*
2001:Q4	72.31*	65.57*	42.20*	59.40*	4.21	93.58*	115.02*	2023.50*	134.17*	1.43
2002:Q1	28.94*	15.95*	102.71*	20.82*	6.73*	11.68*	59.26*	237.85*	37.50*	41.26*
2002:Q2	1022.67*	225.27*	41.67*	32.73*	4.04*	841.02*	165.99*	138.48*	7.87*	33.49*
2002:Q3	65.04*	304.81*	65.11*	38.50*	22.71*	41.30*	274.33*	152.90*	66.85*	8.11*
2002:Q4	153.36*	63.17*	40.89*	45.77*	22.32*	258.79*	451.63*	125.77*	52.27*	47.58*
2003:Q1	16.79*	466.42*	152.50*	12.74*	25.15*	325.05*	601.62*	131.86*	12.45*	19.66*
2003:Q2	76.46*	120.58*	31.06*	12.56*	91.38*	223.98*	1016.60*	114.66*	116.46*	66.04*
2003:Q3	135.73*	10.14*	463.11*	108.57*	47.01*	124.42*	94.30*	2322.48*	108.49*	69.91*
2003:Q4	292.80*	2335.03*	37.53*	43.69*	28.53*	595.52*	1673.31*	324.50*	212.78*	36.59*
2004:Q1	30.54*	447.22*	154.09*	800.55*	9.19*	19.61*	1274.97*	766.14*	727.23*	14.11*
2004:Q2	4.01*	280.30*	1619.32*	0.66	0.92	191.74*	639.45*	1220.92*	4.13	23.73
2004:Q3	10.95*	2.37*	159.07*	62.70*	10.31*	9.82*	72.27*	432.40*	102.59*	6.55*
2004:Q4	1094.68*	23.11*	155.92*	7.32*	1.66	1266.21*	17.24*	427.71*	76.41*	38.47*
2005:Q1	40.36*	773.36*	25.45*	15.92*	513.39*	198.27*	870.74*	152.88*	45.81*	545.51*
2005:Q2	16.53*	11.12*	20.13*	4473.18*	1.16	3.27*	6.31*	19.06*	3496.68*	5.73
2005:Q3	15.63*	653.70*	483.27*	3.75*	1.49	84.18*	893.25*	547.39*	19.49*	15.92
2005:Q4	2395.63*	22.80*	20.27*	51.43*	2.66*	2352.23*	105.09*	165.75*	151.00*	7.20*
2006:Q1	1160.62*	606.00*	20.33*	3.68*	4.59*	2214.05*	494.24*	20.80*	39.62*	15.49*
2006:Q2	363.51*	948.62*	0.72	56.42*	493.01*	1391.48*	1165.47*	57.77	72.55*	374.53*
2006:Q3	41.28*	226.52*	468.77*	63.75*	0.57	734.90*	1037.28*	525.68*	73.49*	2.47
2006:Q4	1737.54*	20.54*	37.54*	0.40	1.23	2090.51*	400.18*	50.66*	3.74	5.40
2007:Q1	34.68*	668.08*	117.19*	30.05*	0.33	550.76*	923.52*	573.51*	40.90*	2.92
2007:Q2	2872.60*	16.40*	1.87	5.48*	21.70*	2424.25*	121.58*	122.61	30.97*	25.37*
2007:Q3	4.27*	178.84*	26.15*	9.66*	4.65*	4.25*	166.20*	42.78*	10.80*	5.98*
2007:Q4	434.21*	9.88*	0.95	28.69*	0.57	300.06*	10.10*	0.92	36.01*	0.01
2008:Q1	0.50	84.70*	127.20*	0.24	0.44	*2.03*	58.74*	108.97*	0.93	0.27
2008:Q2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00