E C O N O M I C S   B U L L E T I N

Structural change in cigarette demand: cusum tests using panel data

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Abstract

We conduct cusum tests of structural change in a rational addiction model of cigarette demand estimated using a panel of annual time series of state−level data. In contrast to the one previous application of cusum tests to the question of cigarette demand stability, our results provide strong evidence of downward shifts in demand during the modern era of health warnings and anti−smoking campaigns.

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1. Introduction

There is a significant volume of empirical research investigating the impact of anti-smoking campaigns, health warnings, taxation, and advertising bans on cigarette demand. Most of these studies produced results supporting the view that demand decreases in response to news of the harmful effects of smoking and other anti-smoking measures such as advertising restrictions.[1] The conventional, regression-based approach used in these studies involves estimating a demand equation with a qualitative variable introduced to reflect the timing of a health-warning or advertising event. A test for a significantly negative coefficient on the qualitative variable amounts to a test of the hypothesis that the corresponding event was responsible for a structural change entailing a downward shift in demand. Sloan, Smith, and Taylor (2002; SST) argue that this conventional approach is biased toward findings of structural change and advocate the use of Brown, Durbin, and Evans' (1975; BDE) "cusum" tests as an alternative means of investigating the temporal stability of cigarette demand. SST carry out cusum tests in the context of a model motivated by Becker and Murphy's (1988) "rational addiction" framework and estimated using annual U.S. cigarette consumption and price data for the entire 20th century. They interpret their results as evidence that the significant changes in the structure of cigarette demand occurred in the first half of the century, well before the modern era of "health scares" and public anti-smoking initiatives.

This paper involves another application of cusum tests, in the context of a rational addiction model, to examine the issue of cigarette demand stability. Our application uses a data set that extends Becker, Grossman, and Murphy's (1994; BGM) panel data set consisting of annual time series of state-level figures for cigarette sales and price. The main advantage of using state-level, as opposed to national, data is that state-specific cigarette excise tax rates exhibit considerable cross-sectional variation. The resulting variation in tax-inclusive cigarette prices provides statistical leverage for the identification of price effects; an advantage that is lost when state-level price variation is confounded in a national average price calculation. Significant differences in state excise tax rates also create incentives for interstate smuggling, however, creating the potential for significant differences between sales and consumption at the state level. BGM's analysis controls for these potential differences using explanatory variables that reflect the magnitude of interstate smuggling incentives. We used their definitions of these smuggling indices to extend the series to our longer timeframe.

Section 2 of this paper briefly sketches our empirical model. BDE's original formulation of cusum tests involved non-stochastic regressors and did not accommodate the combination of time series and cross-sectional data. The presence of endogenous explanatory variables in the rational addiction model and our use of panel data require some modifications to cusum testing procedures. These modifications are discussed in Section 3. Section 4 presents our results. Briefly, we find strong evidence of structural shifts in cigarette demand during the past 50 years.

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[1] Hamilton (1972) was one of the early studies of this kind. Fenn, Antonovitz, and Schroeter (2001) is a recent example. Gallet and Agarwal (1999) contains references to several similar studies.

2. The rational addiction model of cigarette demand

Building on Becker and Murphy's theory of rational addiction, BGM develop a demand equation of the following form:

$$C_t = \alpha_0 + \alpha_1 C_{t-1} + \alpha_2 C_{t+1} + \alpha_3 P_t + \alpha_4 X_t + u_t, \tag{1}$$

where C_t is per capita consumption of the addictive good in period t, P_t is the real price of the good in period t, X_t represents other exogenous variables such as income, and u_t is an error term. The presence of lagged and, especially, future consumption as explanatory variables in a demand equation is non-standard. Lagged consumption enters because, due to the good's addictiveness, "yesterday's" consumption determines how "today's" consumption will affect utility. A rationally addicted forward-looking consumer, aware of this intertemporal linkage, would also recognize that optimal consumption "today" depends on future variables. Equation (1) is a reduced form, embodying certain simplifying assumptions, in which the impact of future variables on "today's" consumption is subsumed in a dependence on "tomorrow's" consumption.

BGM estimate a rational addiction model of cigarette demand using annual state-level data and the following embellished version of equation (1):

$$\begin{aligned} C_{it} = \sum_{j=1}^{n} \alpha_{0j} D_{jit} + \alpha_1 C_{it-1} + \alpha_2 C_{it+1} + \alpha_3 P_{it} + \alpha_4 INC_{it} + \\ \alpha_5 SDTIMP_{it} + \alpha_6 SDTEXP_{it} + \alpha_7 LDTAX_{it} + u_{it}, \end{aligned} \tag{2}$$

where the t subscript indexes years and i subscripts have been added to index states. For state i in year t, C_{it} is per capita, tax-paid cigarette sales in packs, P_{it} is the average real retail price per pack including state and federal excise taxes, and INC_{it} is real per capita disposable income. The remaining explanatory variables; $SDTIMP_{it}$, $SDTEXP_{it}$, and $LDTAX_{it}$; were developed by BGM to serve as controls for the interstate cigarette smuggling incentives. $SDTIMP_{it}$ and $SDTEXP_{it}$ measure incentives for short-distance, or "casual," import and export smuggling. They are constructed as weighted averages of the differences between the excise tax rates in state i, on the one hand, and in neighboring states, on the other. Weights are based on the states' "border" populations, a rough indication of the number of residents who might be inclined to cross state lines to take advantage of a lower excise tax rate. $LDTAX_{it}$ measures incentives for long-distance, or "commercial," smuggling from low-excise-tax states. The index is based on the difference between state i's tax rate and the tax rates in Kentucky, Virginia, and North Carolina.[2] The D_{jit}s are state-specific dummy variables (for $j = 1, 2, \ldots, n$; $D_{jit} = 1$ if $i = j$ and $D_{jit} = 0$ otherwise) included to allow the intercept term to vary across states.[3]

[2] See BGM for further details of the definitions of these variables.

[3] BGM's model also includes a set of annual dummy variables, thus allowing the regression equation's state-specific intercept terms to change, from each year to the next, by amounts that are uniform across states. These annual dummy variables are omitted from our model because equation (2) is meant to represent the null hypothesis of temporal stability.

3. Cusum tests with panel data and endogenous explanatory variables

BDE consider the model:

$$y_t = x_t \beta_t + u_t \quad t = 1, 2, \ldots, T, \tag{3}$$

where y_t is a scalar dependent variable, x_t is a row vector of k non-stochastic explanatory variables, β_t is a column vector of non-stochastic parameters, and the u_ts are independently distributed $N(0, \sigma_t^2)$. The hypothesis of stability of the model is

$$H_0: \ \beta_1 = \beta_2 = \ldots = \beta_T = \beta \ \text{ and } \ \sigma_1^2 = \sigma_2^2 = \ldots = \sigma_T^2 = \sigma^2.$$

If the model were estimated on the assumption of a stable structure, intuition suggests that the residuals would contain evidence of the validity of H_0. To develop test statistics with simple distributions, BDE work with standardized recursive residuals defined as

$$w_t = \frac{y_t - x_t \hat{\beta}_{t-1}}{\sqrt{1 + x_t (X_{t-1}' X_{t-1})^{-1} x_t'}} \quad \textit{for } t = k+1, k+2, \ldots, T;$$

where $\hat{\beta}_{t-1}$ is the ordinary least-squares (OLS) estimator of β based on the first t-1 observations,

$$\hat{\beta}_{t-1} = (X_{t-1}' X_{t-1})^{-1} X_{t-1}' Y_{t-1}, \tag{4}$$

and $X_{t\text{-}1}$ and $Y_{t\text{-}1}$ are the (t-1) x k and (t-1) x 1 matrices that obtain by stacking x_s and y_s, respectively, for s = 1, 2, . . ., t-1.

The advantage of working with the w_ts is that, on H_0, they can be shown to be *i.i.d.* $N(0, \sigma^2)$. BDE's tests are based on the cumulative sums of standardized recursive residuals and squared recursive residuals:

$$\frac{1}{\hat{\sigma}} \sum_{s=k+1}^{t} w_s \quad \textit{and} \quad \sum_{s=k+1}^{t} w_s^2 \Big/ \sum_{s=k+1}^{T} w_s^2 \quad \textit{for } t = k+1, k+2, \ldots, T;$$

where $\hat{\sigma}$ is the OLS estimate of σ. BDE derive means and confidence bounds for these statistics on the null hypothesis. The "cusum" and "cusum of squares" tests are carried out by plotting the statistics and confidence bounds, as functions of t, and observing whether the statistics' graphs cross the confidence boundaries, departing from their null-hypothesized mean values by statistically significant amounts. The location of a crossing-point, moreover, can provide at least some informal evidence of the date at which structural change begins to occur.

Maskus (1983) showed how to extend these procedures to pooled cross-section, time series data. To this end, reinterpret (3) with y_t now an n x 1 vector dependent variable with components corresponding to each of n cross-sectional units. Similarly, x_t

becomes an *n x k* matrix of non-stochastic explanatory variables and the u_ts are *n x* 1 vectors of independent error terms with distribution $N(0, \sigma_t^2 I_n)$. Reinterpret (4) with X_{t-1} and Y_{t-1} defined, as before, as the stacked data for the first *t*-1 time periods, but now having dimensions $n(t-1)$ *x k* and $n(t-1)$ *x* 1 respectively. Then, on the null hypothesis, the recursive (*n x* 1) vector residuals:

$$\tilde{u}_t = y_t - x_t \hat{\beta}_{t-1} \quad t = m, m+1, \ldots, T,$$

are independently distributed with a common mean equal to the zero vector and covariance matrix[4]

$$\Omega_t = \sigma^2 (I_n + x_t (X_{t-1}' X_{t-1})^{-1} x_t').$$

An estimate of the covariance matrix for the t^{th} recursive vector residual, $\hat{\Omega}_t$, obtains by replacing σ^2 with an estimate based on the error sum of squares from OLS estimation using the entire panel. Let P_t be a diagonalizing matrix for $\hat{\Omega}_t$ such that $P_t' \hat{\Omega}_t P_t = I_n$. Define standardized recursive vector residuals $\tilde{w}_t = P_t' \tilde{u}_t$ for $t = m, m+1, \ldots, T$. Then $\tilde{w}_m, \tilde{w}_{m+1}, \ldots, \tilde{w}_T$ are approximately *i.i.d.* $N(0, I_n)$. Maskus proposed tests based on weighted sums of residuals across cross-sectional units:

$$\tilde{v}_t = \frac{1}{\sqrt{n}} \sum_{j=1}^{n} \tilde{w}_{tj} \quad \textit{for } t = m, m+1, \ldots, T.$$

Defined in this way, $\tilde{v}_m, \tilde{v}_{m+1}, \ldots, \tilde{v}_T$ are approximately *i.i.d.* $N(0, 1)$ on H_0, and the modified (scalar) cusum statistics

$$\tilde{s}_t = \sum_{s=m}^{t} \tilde{v}_s \quad \textit{and} \quad \tilde{z}_t = \sum_{s=m}^{t} \tilde{v}_s^2 \Bigg/ \sum_{s=m}^{T} \tilde{v}_s^2 \quad \textit{for } t = m, m+1, \ldots, T$$

have approximately the same distributions as BDE's cusum and cusum of squares statistics, respectively.[5]

The distribution theory supporting cusum tests is derived on the assumption of non-stochastic regressors. In our application to BGM's empirical model, an additional complication arises due to the presence of endogenous explanatory variables; namely, one lag and one lead of consumption. BGM estimate (2) by two stage least-squares (2SLS). One could base "cusum tests" on recursive 2SLS residuals. But because these residuals involve nonlinear functions of common stochastic variables, there is little reason to suspect that they would be either normal or independent and, therefore, little reason to suspect that the statistics' null distributions derived by BDE would still be valid.

[4] We define *m*-1 as the smallest integer greater than or equal to *k/n*. As such, it is the minimal number of time periods permitting estimation of β with non-negative degrees of freedom.

[5] Han and Park (1989) consider additional extensions of cusum tests to panel data analysis.

An alternative approach borrows a suggestion made by Dufour (1982) in a related context. If the values of α_1 and α_2 were known, one could rewrite (2) in the form of (3) with a transformed dependent variable as

$$C_{it}^{*} \equiv C_{it} - \alpha_1 C_{it-1} - \alpha_2 C_{it+1} = x_{it}\beta_t + u_{it},$$

where the remaining explanatory variables and parameters have been consolidated in the x_{it} and β_t vectors. Dufour's suggestion is to perform the above transformation of the dependent variable with consistent estimates replacing the unknown values of α_1 and α_2 and proceed using standard cusum tests based on recursive OLS residuals. This is the method that we undertake in the next section.

4. Test results

Fenn, Antonovitz, and Schroeter (2001; FAS) estimate a cigarette demand model similar to equation (2) using data that extends BGM's by nine years. The methods described in the previous section and the data employed in FAS are used here to test for structural change in equation (2). Because the methods are most readily applied to a balanced panel, nine states with incomplete time series were dropped.[6] The result is a data set consisting of 42 cross-sectional units (the remaining 41 states plus the District of Columbia) and 38 annual observations spanning 1957 through 1994.

The first step is to estimate (2) by 2SLS, treating past and future consumption as endogenous variables and using an appropriate set of instrumental variables. Common practice in time series applications would restrict the instrument set to consist of only current and lagged values of exogenous variables. Nonetheless, BGM present two arguments for using actual future prices and tax rates as instruments for future consumption. First, BGM note that changes in price are largely the result of changes in state-level excise tax rates. Tax rate changes, moreover, are authorized by legislative actions that become public information months before the tax changes actually take effect. Thus, future prices do contain information available to consumers while they make current choices. Second, as BGM further note, lagged prices and tax rates alone are relatively poor predictors of future consumption.

These considerations lead BGM to use instrument sets both with and without future variables. Correspondingly, we carry out our 2SLS estimation of equation (2) using two different instrument sets. "Instrument set 1" includes the exogenous explanatory variables in equation (2) (P_{it}, INC_{it}, $SDTIMP_{it}$, $SDTEXP_{it}$, $LDTAX_{it}$, and the state-specific dummy variables); T_{it}, the sum of state and federal excise taxes in state *i* in year *t* in cents per pack; and two lags and one lead of the price and tax variables (P_{it-2}, P_{it-1}, P_{it+1}, T_{it-2}, T_{it-1}, and T_{it+1}). This corresponds to the most inclusive set of instruments used in BGM and to the instrument set used to obtain the results in column *iv* in Table 1 in FAS. "Instrument set 2" is the same as instrument set 1 except that it omits the lead

[6] These states are Alaska, California, Colorado, Hawaii, Maryland, Missouri, North Carolina, Oregon, and Virginia.

values of price and tax (P_{it+1} and T_{it+1}). This corresponds to the instrument set used in "Model *iv*" of Table 5 in BGM.[7]

Once 2SLS estimates of the parameters of equation (2) were obtained, using one instrument set or the other, the estimates of α_1 and α_2 were used to carry out the transformation of the dependent variable: $C^*_{it} \equiv C_{it} - \hat{\alpha}_1 C_{it-1} - \hat{\alpha}_2 C_{it+1}$. The transformed model,

$$C^*_{it} = \sum_{j=1}^{n} \alpha_{0j} D_{jit} + \alpha_3 P_{it} + \alpha_4 INC_{it} + \alpha_5 SDTIMP_{it} + \alpha_6 SDTEXP_{it} + \alpha_7 LDTAX_{it} + u_{it},$$

was then estimated recursively by OLS to generate the recursive vector residuals from which Maskus' modified cusum and cusum of squares statistics were computed. These statistics, and their confidence boundaries corresponding to significance levels of 0.01, 0.05. and 0.10, are plotted in Figures 1, 2, 3, and 4. Figures 1 and 2 contain cusum and cusum of squares statistics calculated using Instrument set 1 in the 2SLS estimation of α_1 and α_2. Figures 3 and 4 plot the statistics based on the use of Instrument set 2.

Inspection of Figure 1 reveals strong evidence of structural change: Cusum statistic values first exit the 99% confidence "megaphone" in 1968 and, after a brief return, exit for good in 1979. The evidence of structural change is only slightly less compelling in Figure 3's plot of the cusum statistics calculated using Instrument set 2 in the first stage. Calculated values of the statistic fall outside of the 99% confidence boundary for years 1970 through 1986. Little evidence of structural change can be seen in the plots of cusum of squares statistics in Figures 2 and 4.[8] Evidently, the nature of structural change is such that its manifestations appear in the sign pattern rather than the absolute values of recursive residuals.

The fact that the cusum statistic values breach the confidence boundaries on the low side implies a systematic tendency for the model's one-step-ahead out-of-sample forecasts to *overestimate* actual consumption. This tendency is consistent with demand decreasing over time. SST applied cusum tests to a model estimated using annual nation-wide data for the entire 20th century. They interpret their results as evidence that there were no significant structural shifts in demand during the second half of the century corresponding to the modern era of health warnings and anti-smoking campaigns. Our results, obtained from a model estimated using state-level panel data to exploit cross-sectional variation in price, are quite different from theirs. We find strong evidence of downward shifts in demand during the past 50 years.

[7] The instrument sets used in BGM and FAS also included the annual dummy variables that entered those models. The model in FAS allows for structural change in parameter values by interactions of all explanatory variables with a qualitative variable denoted "$INFO_t$." In the present model, these interaction variables play no role and, hence, are also excluded from the set of instruments.

[8] In the case of estimates based on Instrument set 2, however, the calculated values lie outside of the 90% confidence band for several years in the 1970s.

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Figure 1: CUSUM STAT & Confidence Bounds (Instrument set 1)

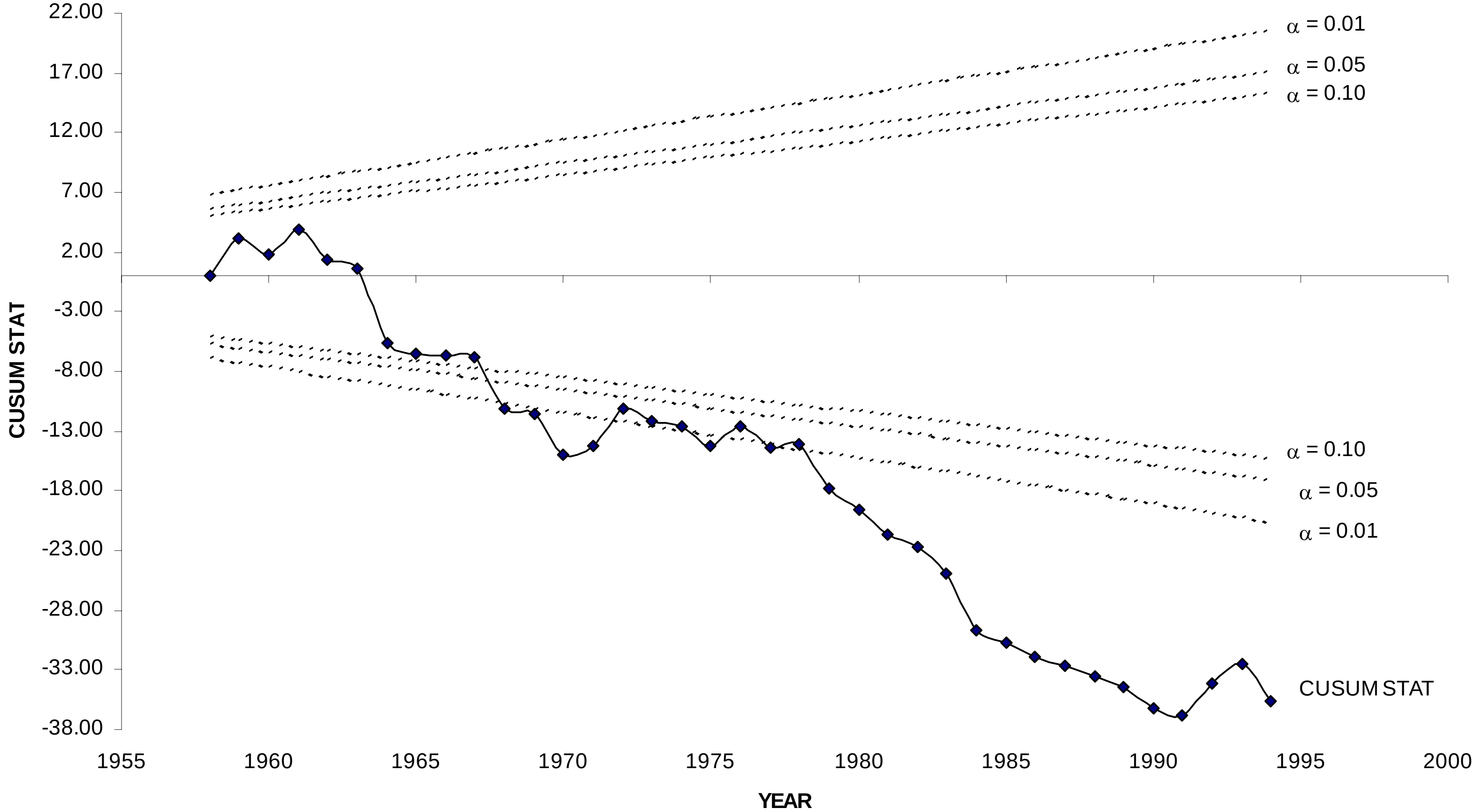

Figure 2: CUSUM SQUARE STAT & Confidence Bounds
(Instrument set 1)

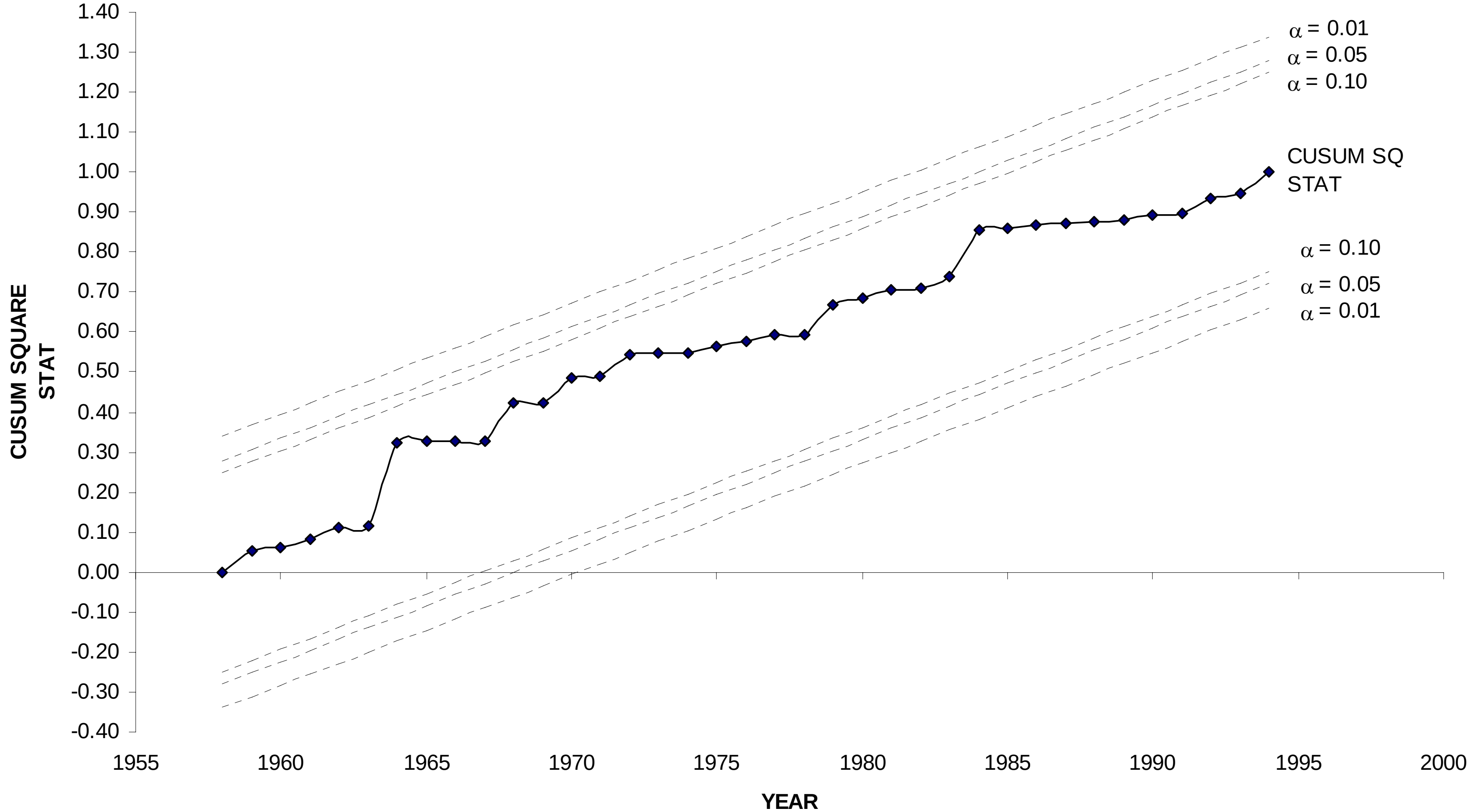

Figure 3: CUSUM STAT & Confidence Bounds (Instrument set 2)

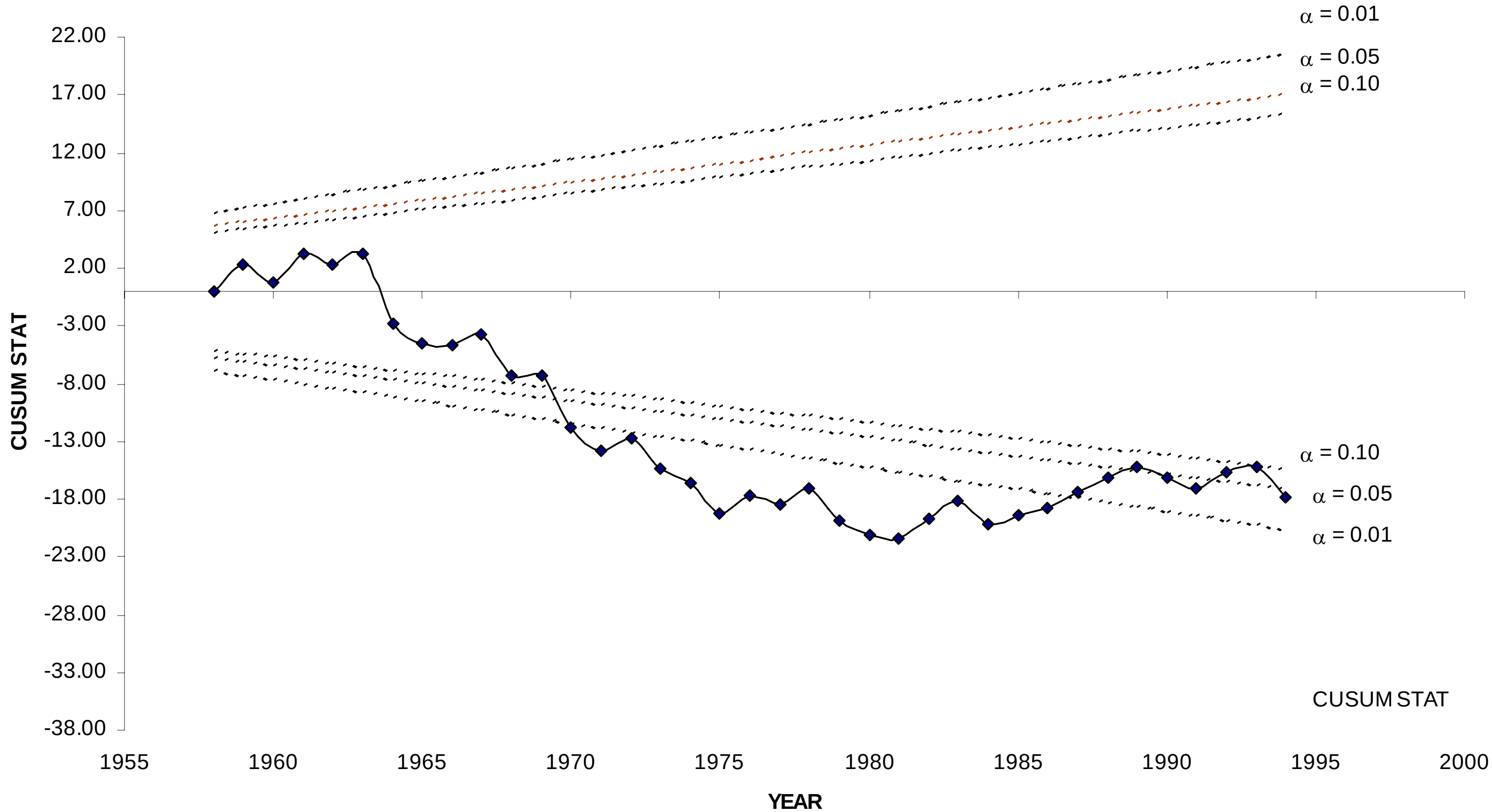

Figure 4: CUSUM SQUARE STAT & Confidence Bounds (Instrument set 2)