Detection of Financial Time Series Turning Points: A New CUSUM Approach Applied to IPO Cycles

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Abstract.

This paper presents a new Cumulative Sum approach for the detection of turning points in financial time series that are subject to cyclical mean level and volatility regime shifts. The new CUSUM approach is applied to the problem of detecting turning points in "hot issue" markets for Initial Public Offerings (IPOs), thus providing a multi-dimensional characterization of states of the IPO cycle.

Key words: CUSUM approach, IPO cycle, turning points

JEL Classification: B41; E32; G30

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1. Introduction

An important time series problem is the detection of regime shifts in a series when the mean and volatility of the series are subject to cyclical shifts of a potentially unknown magnitude at unknown points in time. The problem is compounded when the series is serially correlated, as is often the case with financial time series data. This paper presents a new Cumulative Sum (CUSUM) control scheme approach for the detection of turning points in financial time series that are serially correlated and are subject to independent mean level and volatility regime shifts of varying magnitudes.

CUSUM procedures are designed for rapid, optimal detection of shifts in statistical process parameters and have been adapted to deal with serially correlated data. The CUSUM approach is extended in this paper to account for the ongoing cyclical nature of many financial time series applications as well as to incorporate important economic significance considerations using an NBER-style rule that requires a state of the cycle to last at least six months before it is considered to be economically meaningful. The new CUSUM approach is illustrated using an important finance example, the detection of turning points in "hot issue" markets for Initial Public Offerings (IPOs).

"Hot issue" markets for IPOs were first identified by Ibbotson and Jaffe (1975) and are characterized by an unusually high volume of new offerings with very high initial returns. The ease with which initial public offerings can be brought to market during "hot issue" markets and the difficulties associated with IPOs that arrive when market conditions are unfavourable imply that the rapid detection of turning cumulating the amount by which observed values of a variable exceed their expected level (Hawkins and Olwell, 1998; Montgomery, 1991; Lucas, 1985). An unanticipated upwards or downward parameter shift will soon result in a uni-directional drift of the cumulative sum over time. The CUSUM procedure then gives an out-of-control signal when the absolute value of the cumulative sum exceeds a critical value, thus indicating that the variable's recent values are significantly different from their previously expected levels. When a significant out-of-control signal is received, the starting time when the process went out of control is determined and the magnitude of the parameter shift is also estimated. CUSUM control schemes are designed to optimally detect out-of-control states, and can therefore outperform other statistical techniques at this purpose.

CUSUM applications have generally focussed on the detection of a single significant break in a process whereas the detection of subsequent breaks in a financial time series are often as important as the detection of an initial shift. This paper shows how CUSUM schemes can be dynamically adapted with appropriately redefined parameters following a significant break to a new state, thus allowing subsequent breaks to also be detected. The approach is shown to be an efficient and conceptually simple technique for rapidly detecting and determining economically important structural breaks in the volatility and mean level of financial time series, such as IPO data series, when the timing and extent of the breaks are unknown. Another advantage is the ex-ante nature of the procedure which means that an entire data set does not have to be examined before states can be decided upon, so the structure and characteristics of breaks need not be known before the analysis is conducted.

IPO underpricing and volume series are analysed independently and are then combined to define overall hot issue, cold issue, and transition states of the IPO market. Volatility shifts detected using the CUSUM approach are used to provide a multi-dimensional characterization of each IPO market state. The new CUSUM approach's detection of significant structural breaks in the IPO series volatility is important because it is the first time a study has identified economically important, independent volatility regime shifts in IPO activity.

An important financial management result to emerge from the analysis is the finding that hot issue IPO markets are generally followed by a long transition state with fairly active volume, so financial managers who observe a hot issue market can therefore be reassured that they have a reasonable amount of time to bring an IPO to market under favourable conditions. Financial managers can quickly ascertain when market conditions are changing because the adapted CUSUM control procedure provides rapid detection of shifts to new states with few false signals. The paper's approach can also be used by investors to quickly detect time periods when IPOs tend to provide sharply higher initial returns.[1]

The following section introduces Cumulative sum control scheme techniques and outlines how the CUSUM approach is dynamically adapted following the

Y is potentially subject to regime shifts of varying magnitudes and timing, the timing and magnitude of which are unknown to the researcher and are therefore to be detected. The variable's mean can shift at mean value regime switch times $t+j$ by an amount Ä$_{t+j}$ to

$$m_{t+j} = m_{t+j-1} + \Delta_{t+j} , \qquad (1)$$

and the standard deviation can shift at volatility regime switch times $t+k$ by an amount ô$_{t+k}$ to

$$s_{t+k} = s_{t+k-1} + \boldsymbol{t}_{t+k} . \qquad (2)$$

The time t value of the variable, Y_t, is

$$Y_t = m_t + e_t , \qquad (3)$$

where

$$e_t \sim N(0, s_t^2). \qquad (4)$$

The mean of the distribution is given by equation (1) following each mean value regime switch at mean value regime switch times $t+j$, and the standard deviation is given by equation (2) following each volatility regime switch at volatility regime switch times $t+k$. The conditional distribution is therefore a mixture of normals that is closely related to the Hamilton (1989) regime-switching model, with the difference being that the regime probabilities do not deviate from unity within each state.[2]

Correctly detecting and interpreting an initial parameter shift in a regime-shifting process like the one described by equations (1) to (4) is difficult since a volatility regime shift can be misinterpreted as a shift in the mean, and the reverse scenario is also possible (Hawkins and Olwell, 1998). This problem is compounded by the need not only to detect an initial regime switch but also to quickly estimate the new parameter value in the new state so that subsequent regime switches can, in turn, be detected. CUSUM mean shift and scale shift procedures detect shifts in the mean or the standard deviation of a process, and can be dynamically adapted with appropriately re-estimated parameters following a significant break so that subsequent shifts can be detected.

Detection techniques that utilize cumulative sums are usually implemented using a two-sided procedure. A two-sided CUSUM mean shift procedure detects upwards shifts in a variable's mean using an upper control scheme that cumulates positive deviations of observed values from a reference level and a lower scheme that detects downwards shifts by cumulating negative deviations from a second, lower reference level. The procedure provides a significant "out-of-control" signal when either the upper or lower CUSUM scheme exceeds a decision interval. The reference levels and the decision interval are chosen to optimize the detection of process shifts and are a function of the volatility of the process, desired error probabilities, and the process shift to be detected. Time series dependencies in the variable of interest, such as serial correlation, can be accounted for by adjusting (at each point in time) the reference levels against which observations are compared, or by appropriately transforming the data set.

An upper CUSUM control scheme $S_H(t)$ cumulates positive deviations of a variable's observed time t value Y_t from the variable's expected time t level μ_t plus a reference value K according to the formula

$$S_H(t) = Max[0,\ Y_t - (m_t + K) + S_H(t-1)], \qquad (5)$$

where $S_H(t\text{-}1)$ is the value of the upper CUSUM scheme in the preceding time period *t-1*. Positive deviations have to exceed the variable's expected value by an amount K (specified below) before they increase the value of the upper CUSUM scheme. The scheme resets itself to zero ("zeroes") if enough smaller or negative deviations reduce its value. This feature helps the CUSUM scheme procedure to rapidly detect out-of-control states because it discards conforming observations from the analysis, thus allowing the scheme to be immediately affected by non-conforming data when the process goes out-of-control. This "reset" feature of CUSUM control schemes enhances their detection optimality properties (Hawkins and Olwell, 1998).[3]

A lower one-sided CUSUM scheme $S_L(t)$ evolves through time according to a similar formula

$$S_L(t) = Max[0,\ (m_t - K) - Y_t + S_L(t-1)]. \qquad (6)$$

Scheme S_H or S_L will randomly take on positive values from time to time but will soon "zero" as smaller or opposite-signed realizations are drawn when the process for the variable remains in control, but a shift in the mean would soon cause the value of one of the schemes to drift upwards. The CUSUM scheme procedure detects that the process for variable Y is significantly out of control when either $S_H(t)$ or $S_L(t)$ exceeds the level of a decision interval H that is approximated by the equation

$$H = \frac{-2\boldsymbol{s}_Y^3}{AD} \ln(\boldsymbol{a}), \qquad (7)$$

where á is the desired probability of incorrectly concluding that a shift in the mean has occurred, A is a scaling factor choice parameter, and D is the shift in the mean that is to be detected (Montgomery, 1991). The beginning of a break in the process corresponds to the point in time when the appropriate (upper or lower) scheme became non-negative immediately prior to the break becoming significant. Observations from this point onwards are used to calculate the new mean in the new state as soon as the significant break is detected.

Scaling parameter A should lie within the range of one to two standard deviations in order to enhance the performance of the CUSUM procedure, and the reference value K in equations (5) and (6) is set equal to half the level of D, the shift in the process mean to be detected (Montgomery, 1991). The potential size of the shift in the mean is often unknown, as in equation (1). In this situation an approximate value for D is required, and the design of the CUSUM procedure is then close to optimal for detecting mean shifts that are close in size to D (Hawkins and Olwell, 1998).[4] Winsorizing observations (editing outliers to more central values) prevents outliers from causing false signals of structural breaks.

Mean CUSUM schemes are not designed to detect volatility shifts, but sharp and somewhat temporary upward moves in the upper and lower mean CUSUM schemes can indicate that a volatility shift has occurred. Scale CUSUM schemes are specifically designed to detect volatility shifts. The scale CUSUM approach first standardizes observations and then takes their absolute square root, thus creating observations that tend to be normally distributed with a mean of .822 and a variance of .119 (see Hawkins and Olwell, 1998, p 67). The scale CUSUM procedure therefore involves the utilization of upper and lower CUSUM schemes (5) and (6) on transformed observations W_t, where

$$W_t = \frac{\sqrt{\frac{|Y_t - m|}{s}} - 0.822}{\sqrt{0.119}}, \qquad (8)$$

in order to determine whether the volatility of process (3) and (4) has shifted.

The CUSUM schemes are restarted with appropriately re-estimated parameters in this paper's application when a statistically and economically significant structural break in the IPO series is detected. Economic significance considerations can often be important when evaluating financial economic time series such as IPO cycles because it is often not economically meaningful to consider a state that lasts for only a short time (see, e.g., Harding and Pagan, 1999). A National Bureau of Economic Research (NBER) style six-month rule is therefore applied which requires the appropriate CUSUM scheme to stay positive for at least six months before a significant break is established as being both economically and statistically significant. This rule corresponds to the "six month rule" employed by Bry and Boschan (1971) in their algorithm for quantifying NBER business cycle dating rules. The six-month rule requires that a recession or recovery phase of the business cycle must last for at least six months before it is recognized.

Scale and mean CUSUM schemes are run concurrently since the mean parameter or the volatility parameter has to be updated in both sets of schemes when a shift in the mean or volatility is detected.[5] IPO underpricing and volume data display high measured serial correlation, so the data series are transformed using a first order autoregressive (AR1) transformation before CUSUM schemes are applied to the series (see Hawkins and Olwell, 1998; Yashchin, 1993; Lowry and Schwert, 2000). This prevents the detection of signals of parameter regime switches caused by serial correlation alone, a problem to which CUSUM procedures could otherwise be sensitive. Mean level CUSUMs are also run on the non-transformed data to identify "hot issue" market states that are caused by serial correlation.

3. Hot Issue Markets and IPO Cycles

"Hot issues" are IPOs that are extremely underpriced (the offering price is considerably below the first day or first month trading price), so Ibbotson and Jaffe (1975) labelled time periods with a considerable number of highly underpriced IPOs as "hot issue" markets. They used an IPO initial return series to identify hot issue markets in the early and late sixties, and found no overall contemporaneous relationship between IPO underpricing and volume. Ritter (1984) identified a further hot issue market in 1980, and argued that extreme IPO underpricing tends to lead to a heavy subsequent volume of new issues. Researchers have also found that the IPO initial return and volume series are highly serially correlated (Ibbotson et al, 1994; Lowry and Schwert, 2000). Over the time period 1960 to 1992, the first-order autocorrelation coefficient for average monthly initial returns to IPOs was .66, and the first-order autocorrelation coefficient for monthly volume was an even higher .89, thus indicating that the current level of IPO activity is a good predictor of next period's level (Ibbotson et al, 1994).

The level of the stock market also appears to play an important role in IPO cycles (Loughran et al, 1994), perhaps indicating that private companies contemplating IPOs tend to "time" the market during "windows of opportunity" by issuing shares when stock market and IPO market conditions are favourable. Cycles in IPO underpricing are therefore highly relevant to financial managers. Figures 1 and 2 illustrate the cyclical nature of the monthly IPO underpricing and volume series. The value-weighted and equally-weighted underpricing series in Figure 1 reveal large, short-lived spikes around 1979, 1980, 1981, and 1983, thus creating a challenge for any technique that attempts to objectively assign the underpricing series into economically significant states. Figure 2 shows a clear pattern of heavy and light activity periods prior to 1991, with spikes around 1981, 1984, and 1987. The series becomes more volatile after 1991.

[Figures 1 and 2 about here]

Autocorrelation results and graphical analysis provide strong evidence of the existence of IPO cycles, but they do not objectively identify the turning points of IPO cycles using quantitative procedures that statistically determine significant structural breaks in IPO series. Objective identification of significant turning points in IPO cycles would be useful for financial managers attempting to understand hot issue markets and researchers attempting to explain them, so quantitative detection and determination of the timing, duration, and volatility characteristics of IPO underpricing and volume cycles is an important exercise.

Brailsford, Heaney, Powell and Shi (2001) objectively determine IPO cycles in four underpricing and activity measures using a regime switching analysis that assumes IPOs switch from a low mean, low volatility state to a high mean, high volatility state, with each state having constant parameters. This paper's CUSUM approach focuses on ex-ante detection and determination of IPO cycle states, and it can detect independent mean level or volatility regime shifts of potentially varying magnitudes. The new CUSUM approach detects and identifies structural breaks using an objective procedure that allows the volatility characteristics as well as mean level shifts of IPO cycles to be illustrated, thus helping to more fully characterize and define states of the IPO cycle and to indicate the level of uncertainty associated with each state of the cycle.

4. Data

IPO data are initially collected from the Securities Data Corporation (SDC). SDC maintains files on all registered security issues using information from the Securities and Exchange Commission (SEC) and other sources. Share price data are obtained from SDC, the Center for Research in Security Prices (CRSP), and Datastream International.

The following sample selection criteria were employed:

a) The IPO must be a common stock IPO. Issues under Rule 144A, Private Placements and Shelf Registrations are excluded;

b) Closed-end mutual funds and Real Estate Investment Trusts (REITs) are excluded;[6]

c) Unit offerings are excluded;[7]

d) A US-based company must issue the IPO.

A final sample of 7,559 IPOs is obtained for the period January 1976 to December 2000.

Table 1 presents descriptive statistics for the sample on a year-by-year basis. The number of offerings has increased sharply over the sample period and peaked in 1996, with the average offering size increasing from US$7.0 million in 1976 to US$138.6 million in 2000. The equally-weighted average initial return on the first day of listing ranges from 0.77% in 1976 to 71.29% in 1980, with the overall sample average being close to 15%. The value-weighted average initial return for the overall sample is slightly lower (12.41%), and has a range between 0.43% in 1976 and 57.91% in 2000.

[Table 1 about here]

A value-weighted measure of underpricing (VWUP) is utilized in the paper because traditional arithmetic average (equal-weighted) measures of underpricing are strongly affected by small stock IPO underpricing (Ibbotson and Ritter, 1995). VWUP weights each issue's contribution to monthly underpricing by the relative size of the issue according to the formula

$$VWUP_t = \frac{\sum_{i=1}^{N} (\text{proceeds})_{i,t} \times (\text{IPO Underpricing})_{i,t}}{\sum_{i=1}^{N} (\text{proceeds})_{i,t}} \times 100, \tag{9}$$

where

t = month 1, 2, ..., T where T = 270;

i = company 1, 2, …, N where N is the number of IPOs in month t;

$(\text{proceeds})_{i,t}$ = [(number of shares issued) $_{i,t}$ * (offer price) $_{i,t}$];

$(\text{IPO Underpricing})_{i,t}$ = [(first trading day closing price)$_{i,t}$–(offer price)$_{i,t}$] / (offer price)$_{i,t}$].

The VWUP measure avoids the problem whereby high underpricing of small companies in a particular month can lead to extreme measured underpricing even though larger, more important IPOs might be less underpriced (Ritter, 1984).[8] Figure 1, which illustrates the differences between value-weighted and equally weighted underpricing, indicates that the two underpricing measures are highly correlated (the correlation coefficient is 0.9019), so results are generally reported for VWUP only.

Summary statistics for the IPO series are reported in Table 2. The average VWUP per month is 12.79%. Monthly VWUP ranges from 133.13% to an overpricing of 15.56%. In the last column of Table 2, test statistics for the Dickey-Fuller test for stationarity are presented. These results suggest that the series are stationary, and also suggest that the CUSUM schemes do not have to be adjusted for a time trend.

[Table 2 about here]

5. Results

The first striking feature to emerge from the CUSUM procedure analysis of IPO series is the absence of mean value parameter regime switches in the underpricing and volume series once an AR1 transformation of the data is undertaken to account for serial correlation. This is a surprising result, given the clearly cyclical nature of the IPO underpricing and volume series (see Figures 1 and 2). It tends to indicate that the patterns of heavy and light activity periods apparent in the series are due to momentum effects associated with strong serial correlation rather than distinct mean value regime switches in the underlying IPO series statistical processes. The non-detection of mean parameter structural regime shifts is robust to alterations in the size of the shift to be detected, *D* (results not reported). Figures 3 and 4 indicate the reason for the transformed data mean CUSUM results: the AR1 transformation creates an essentially random series with clearly time-varying volatility.

[Figures 3 and 4 about here]

Time-varying volatility of the IPO series is also evident in the scale CUSUM results which provide a strong indication that changes through time in the volatility of IPO series are generated by statistically and economically significant volatility regime switches. Table 3 reveals that IPO underpricing volatility is initially high during the time period February 1978 until August 1983. A shift to very low underpricing volatility occurs in September 1983 and again in February 1987 and May 1993, with most of the remainder of the underpricing series displaying somewhat moderate volatility. The end of the sample (August 1998 to December 2000) displays extremely high volatility. Table 4 presents the scale CUSUM results for IPO volume. Volatility of the IPO volume series is high in the mid-eighties and very high in late 1996, and has two extremely low periods (in the late seventies and 1982).

[Tables 3 and 4 about here]

Mean and scale CUSUM analysis of the AR1 transformed IPO data series provides an overall indication of distinct regime switches in IPO series volatility and ongoing momentum effects in the mean level of IPO activity that are associated with strong serial correlation. This latter possibility is further explored using mean CUSUM schemes applied to the original, non-transformed IPO series.

The well-known patterns of heavy and light cycles in the mean level of IPO market activity that are often apparent from a visual analysis of IPO series (see Figures 1 and 2) are clearly detected by mean CUSUM analysis of the original series. Eleven distinct time periods for the level of IPO underpricing are detected (see Figure 5 and Table 5). Figure 5 creates a confidence interval around the mean level states in order to indicate the uncertainty associated with each state of the IPO underpricing cycle.[9] The confidence interval changes whenever a break to a new mean occurs as well as when significant volatility breaks are detected. High volatility during the time period February 1978 until August 1983 explains why the underpricing spikes at the beginning of the data set generally stay within the confidence intervals of each state, since the confidence intervals are considerably wider during this high volatility period. A shift to low volatility in September 1983 narrows the underpricing confidence intervals considerably during the middle third of the data set. The state means fit the data fairly closely from this point onwards, even when volatility once again rises and the confidence intervals widen during the nineties.[10]

[Figure 5 and Table 5 about here]

Underpricing volatility during most of the nineties (until August, 1998) was generally much lower than the level of volatility during the initial hot issue markets of the early eighties, thus indicating that financial managers and investors could be much more confident about the hot issue state of the markets during the nineties than during the earlier hot markets. The tight confidence interval bands during most of the time period from mid-1983 until the end of the eighties indicate that observers could be extremely confident about the cold market state of the market at this time.

The distinct IPO underpricing states illustrated in Figure 5 can be categorized into hot and non-hot underpricing markets, as indicated in column 4 of Table 5. Hot markets initially correspond to time periods following an upwards break in underpricing, and non-hot underpricing markets correspond to a significant break downwards, until September 1984 when a significant upwards break increases underpricing from an extremely cold state to a moderately cold state. Underpricing increases three more times during the nineties to moderately hot, hot, and very hot underpricing states.

The average level of underpricing is 20% for hot periods and 3.6% for non-hot periods. Non-hot underpricing periods have almost the same average duration as hot periods during the sample (26 months versus 29 months). Hot periods for IPO underpricing do not necessarily correspond to high volatility states because the mean and standard deviation of the IPO underpricing series break together on three occasions only (see Figure 6). This finding would be important for fine-tuning a regime-switching analysis of the data since regime-switching analysis often utilizes the simplifying assumption that the standard deviation and the mean of the process switch states together.

[Figure 6 about here]

There are only two "false" breaks in the underpricing series where the CUSUM scheme signals a break to a new state but the break is not considered to be economically meaningful because it lasts less than 6 months. A signal of a break to a new state takes, on average, only 3.3 months to be detected as statistically significant and almost always less than six months, an especially short detection period in relation to the average duration of each state of 26 months. These results, taken together, suggest that changes of state in the IPO underpricing cycle are rapidly detected by the CUSUM procedure, with the signal being highly reliable, so financial managers concerned about the state of the IPO market can be confident a change of state has occurred when a signal is received.

Figure 7 indicates that the CUSUM procedure mean estimates for the original (non-transformed) IPO volume series provide a very good fit of the IPO volume observations due to sharp distinctions between states and a lack of idiosyncratic spikes.[11] All t tests for differences in means between adjacent states are significant (see Table 6). The effect of the crash of October 1987 on IPO volume is picked up immediately by the CUSUM procedure, for example, with a sharp drop in new issues due to the crash leading to the immediate detection of a significant downwards break in IPO volume. The CUSUM procedure also indicates that the important falloff in IPO volume during September and October 1998 is part of a sharp downward break that begins in August 1998.[12]

[Figure 7 and Table 6 about here]

Figure 8 highlights the degree to which the mean and standard deviation of IPO volume break together. The break dates are somewhat correlated, but the IPO volume mean level tends to change much more sharply than the volatility parameter.

[Figure 8 about here]

The volume series results can be used to determine active and inactive periods of IPO volume, where active states follow a significant break up and inactive states follow a significant break down for all but the beginning and end of the time period (see Table 6). The monthly average number of IPOs issued in an active market is 42 whereas 15 IPOs are issued in an average month during an inactive market, with 25 IPOs per month being the average of the means in all IPO volume states. Active markets have an average duration of 24 months whereas the duration of inactive markets tends to be just slightly shorter (23 months, on average). There were no "false" breaks in the mean level of IPO volume, with all cumulative sum sequences that exceeded the critical H value from equation (7) eventually satisfying the six-month economic significance rule. The average number of months before a break in the mean number of IPOs per month becomes statistically significant is 4.67 months. Breaks can often be picked up with reasonable certainty before the six month rule is applied: there was only one instance in each of the volume and underpricing series where seven months were required for a break to become statistically significant.

The study's overall results indicate that financial managers could use the CUSUM procedure to quickly and reliably detect a change in the state of the IPO cycle. The mean CUSUM results for the transformed and non-transformed underpricing and volume series create an overall impression that that shifts in the mean level of IPO activity are generated by IPO market trends that are perpetuated by strong serial correlation momentum (see also Lowry and Schwert, 2000).

The volume and underpricing results can also be combined to categorize overall hot issue markets that have a high level of underpricing and a heavy volume of IPOs. The findings, detailed in Table 7, indicate the existence of four such overall "hot issue" markets (with the final hot issue market becoming "very hot" in September, 1999). This table also identifies numerous transitional periods where there was either high underpricing or a high volume of issues, but not both. Cold periods are the five periods that have cold underpricing and inactive volume. Each period lasts just over a year, on average. Cold issue periods last slightly longer than 16 months, on average, with the shortest lasting ten months. Overall hot issue markets tend to be of a shorter duration. Interestingly, there is always a transition market between hot and cold issue markets, with only three of the transitions being relatively short-lived. Overall IPO cycles tend to take a very long time, with barely three full cycles (cold to overall hot back to cold) occurring over a twenty-four year period.[13]

[Table 7 about here]

Figure 9 presents the active/inactive volume markets overlaid on the hot/non-hot underpricing markets. This figure shows that in the early eighties and latter nineties, volume tends to "chase" hot underpricing, with all four overall hot issue market periods tending to follow this pattern, thus providing comfort to financial managers who can be confident that they have time to bring an IPO to market under favourable (active) conditions if they observe a hot issue market (Ritter, 1984).[14] This evidence supports Ibbotson, Sindelar, and Ritter (1988) who interpreted their results as implying that underpricing leads volume. This hypothesis is theoretically compelling since bringing an IPO to market generally takes at least a few months.

[Figure 9 about here]

Evidence in favour of the hypothesized lead from underpricing to volume is complicated by the long transition state prior to the 1987 crash which follows a cold issue market and contains active volume but low underpricing. Results for this period may be due to investor optimism and a lack of need to underprice IPOs, as the demand for IPOs might already have been there. The leads from underpricing to volume are also not always clear-cut, especially from the mid-eighties onwards. This finding is further supported by examining the type of transition market that precedes each hot or cold issue market, as indicated in Table 7. In the early eighties short "transition-hot" markets with hot underpricing but low volume tended to precede overall hot issue markets, and longer "transition-active" markets with high volume tended to precede cold markets. This pattern gets disrupted from 1985 onwards. The overall results suggest that the relationship between IPO underpricing and volume cycles has become much more complicated lately, providing additional challenges to researchers attempting to theoretically explain IPO cycles. Whether this could be due to overall changes in the risk characteristics of IPOs coming to market, or other underlying economic factors such as information spillovers, could be an important area of investigation for future research (see also Lowry and Schwert, 2001; Cook, Jarrell, and Kieschnik, 2001).

6. Conclusion

Financial times series, such as IPO volume and underpricing series, often contain serial correlation and also display non-synchronous shifts in their mean and variance. This paper provides a modified Cumulative Sum framework that can incorporate these time series properties, thus allowing the optimal detection and dating of persistent shifts in the underlying distribution of the series. The results obtained by applying the CUSUM procedure to IPO activity series are shown to be useful for management decisions and could aid in methodological design issues in other statistical approaches such as multi-state regime-switching. The CUSUM design utilizes ex-ante Gaussian distributional assumptions when detecting non-zero “out-of-control” sequences as well as when characterising the new “in-control” state. The framework is tractable enough to allow alternative analytical distributions to be utilized to address distributional asymmetries such as skeweness or kurtosis (see Montgomery (1991), and Hawkins and Olwell (1998) for examples), a potentially important extension that is left to future research.

The results of the CUSUM procedure application to IPO series provide challenges for future IPO research because they indicate that, while extreme IPO underpricing is subsequently associated with a considerable volume of new issues, high volume can also occur without significant underpricing, as happens during the mid-eighties. The results also imply that financial managers contemplating an IPO will tend to have a timing margin of error during a hot issue market because it generally takes a long time before conditions become unfavourable. More generally, the paper’s CUSUM procedure application rapidly identifies the current state of the IPO cycle and provides an indication of the uncertainty associated with the state as well as a quick and reliable signal if market conditions are changing, considerations that should be of especial interest to financial managers and IPO investors.

Notes

[1] Institutional investors and good brokerage clients often get a high proportion of the best IPOs, so the results regarding underpricing are somewhat more relevant to these investors relative to smaller investors who might miss out on some of the hottest IPOs. We thank an anonymous referee for pointing this out.

[2] Time series dependencies imply that the conditional expected values of the distribution parameters also vary through time due to serial correlation, GARCH effects, or other factors.

[3] Its absence in other structural change tests can imply that detection boundaries for the tests fan out, so timely detection of breaks can becomes less likely as more observations are examined (see, e.g., Greene, 1997).

[4] In this paper's application, the desired shift that is to be detected, *D*, is equal to 1.96 times the standard deviation level of each series. This is important because a constant shift *D* would ignore the consideration that, for instance, a change of 5 around a mean of 10 could be vastly different from a change of 5 around a mean of 50.

[5] Concurrent signals of mean and volatility shifts have to be interpreted with caution since a volatility shift can also temporarily affect the mean CUSUM schemes (Hawkins and Olwell, 1998).

[6] Closed-end mutual fund and REIT IPOs behave differently from corporate IPOs (Peavy, 1990; Wang et al, 1992, Nelling et al 1995, Sirmans et al 1987). Closed-end mutual funds and REIT IPOs tend to be overpriced, so closed-end mutual funds and REITs are excluded from the sample (see Ibbotson et al, 1994).

[7] Unit offerings are complex instruments that consist of a bundle of common stock offerings and other securities, typically warrants, sold together as a package. Research suggests that there is a difference in initial returns between unit and stock offerings (Schultz 1993, Jain 1994). Unit offerings are removed from the sample due to their complexity, problems in valuing unit offerings, and the possible bias arising from differences in underpricing between unit and stock IPOs.

[8] An alternative approach would be to limit the sample to IPOs with offer prices greater than $6 in an attempt to screen out smaller companies. This approach would eliminate IPOs that make an important contribution to IPO volume, however, and would also not be consistent with standard definitions of hot issue IPO markets (Ritter, 1984; Helwege and Liang, 1996). Ritter (1984), for instance, observes that the hot market of 1980 can be ascribed to small natural resource issues.

[9] A full cycle of each series is defined as the time interval between initial upward shifts in the series when there is at least one intervening downwards shift.

[10] Two sample unequal variance t tests for differences in means indicate that all but two of the estimated means are very significantly different between each successive underpricing state (see Table 5). The Cusum procedure does not (initially) have all the information that is used in a t test because of the forward-looking nature of the Cusum technique, so it would not be surprising if some of the t-tests are insignificant even though the Cusum procedure is designed to detect only significant differences in means.

[11] The volume observations cannot be negative, thus violating assumption (4). A logarithmic transformation of the volume series would overcome this problem, but the Cusum procedure is fairly robust to this transformation.

[12] We thank an anonymous referee for pointing out the importance of this second example.

[13] The final cycle in the series is incomplete, but conditions have since turned cold.

[14] A previous hot issue market in the late sixties that was not part of this paper's sample also followed this pattern, since volume did not fall until 1973 following this hot issue market. We thank an anonymous referee for pointing this out.

References

Brailsford, T., R. Heaney, J.G. Powell and J. Shi, "Hot and Cold IPO Markets", forthcoming at the *Multinational Finance Journal,* (2001).

Bry, G. and C. Boschan, *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs,* NBER Technical Paper 20, 1971.

Cook, D.O., S.L. Jarrell and R. Kieschnick, *The Role of Asymmetric Information in US IPO Cycles,* Working paper, University of Texas at Dallas, 2001.

Greene, W.H., *Econometric Analysis,* 3rd edition, Prentice Hall, 1997.

Hamilton, J.D., "A New Approach to the Economic Analysis of Nonstationary Time *Econometrica* 57, 357-384, (1989).

Harding, D. and A. Pagan, *Dissecting the Cycle: a Methodological Investigation*, Working Paper, the Australian National University, 1999.

Hawkins, D.M. and D.H. Olwell, *Cumulative Sum Charts and Charting for Quality Improvement*, Springer Verlag, New York, 1998.

Helwege, J. and N. Liang, *Initial Public Offerings in Hot and Cold Markets, working paper*, Working paper, Federal Reserve Bank of New York, 1996.

Ibbotson, R.G. and J.F. Jaffe, "'Hot Issue' Markets", *Journal of Finance* 30, 1027-1042, (1975).

Ibbotson, R.G., J.L. Sindelar and J.R. Ritter, "Initial Public Offerings", *Journal of Applied Corporate Finance* 1, 37-45 (1988).

Ibbotson, R.G., J.L. Sindelar and J.R. Ritter, "The Market's Problems with the Pricing of Initial Public Offerings*", Journal of Applied Corporate Finance* 7, 66-74, (1994).

Jain, B.A., "The Underpricing of 'Unit' Initial Public Offerings", *Quarterly Reviews of Economics and Finance* 4, 309-325, (1994).

Kahya, E. and P. Theodossiou, "Predicting Corporate Financial Distress: A Time-Series CUSUM Methodology," *Review of Quantitative Finance and Accounting* 13, 71-93, (1999).

Loughran, T., J.R. Ritter and K. Rydqvist, "Initial Public Offerings: International Insights," *Pacific-Basin Finance Journal* 2, 165-199 (1994).

Lowry, M. and W.G. Schwert, *IPO Market Cycles: An Exploratory Investigation*, Working Paper, University of Rochester, 2000.

Lucas, J.M. and R.B. Crosier, "Robust CUSUM", *Communications in Statistics, Part A - Theory and Methods* 11, 2669-2687, (1982).

Lucas, J.M., “Counted Data CUSUM’s,” *Technometrics* 27, 129-144, (1985).

Montgomery, D.C., *Introduction to Statistical Quality Control*, John Wiley & Sons, New York, 1991.

Nelling, E.F., J.M. Mahoney, T.L. Hildebrand and M.A. Goldstein, “Real Estate Investment Trusts, Small Stocks and Bid-Ask Spreads”, *Real Estate Economics* 22, 45-64, (1995).

Peavy, J.W., "Returns on Initial Public Offerings of Closed-End Funds," *Review of Financial Studies* 3, 695-709, (1990).

Ploberger, W. and W. Kramer, "The Local Power of the CUSUM and CUSUM of Squares Tests," *Econometric Theory* 6, 335-347, (1990).

Ritter, J.R., “The ‘Hot Issue’ Market of 1980”, *Journal of Business* 57, 215-240, (1984).

Schultz, P., “Unit Initial Public Offerings: A Form of Staged Financing”, *Journal of Financial Economics* 34, 199-229, (1993).

Sirmans, C.W. and C.F. Sirmans, “The Historical Perspective of Real Estate Returns”, *Journal of Portfolio Management* 13, 2-31, (1987).

Wang, K., S.H. Chan and G.W. Gau, “Initial Public Offerings of Equity Securities: Anomalous Evidence Using REITs”, *Journal of Financial Economics* 31, 381-410, (1992).

Yashchin, E., "Statistical Control Schemes: Methods, Applications and Generalizations," *International Statistical Review* 61, 41-66, (1993).

Table 1: Descriptive Statistics of IPOs Classified by Year, January 1976 to December 2000

	Number of Offerings	Equally Weighted Underpricing	Value Weighted Underpricing	Gross Proceeds per Year (US $ Mil.)	Average Proceeds per Year (US $ Mil.)
1976	37	0.0077	0.0043	260	7.0
1977	24	0.0799	0.0273	138	5.7
1978	34	0.1210	0.1196	210	6.2
1979	58	0.0814	0.0682	377	6.5
1980	120	0.2851	0.1998	1,173	9.8
1981	291	0.1347	0.0666	2,765	9.5
1982	97	0.1046	0.1155	1,152	11.9
1983	574	0.1019	0.0744	11,662	20.3
1984	251	0.0424	0.0226	2,770	11.0
1985	270	0.0466	0.0197	5,996	22.2
1986	561	0.0613	0.0395	16,658	29.7
1987	400	0.0600	0.0512	12,399	31.0
1988	158	0.0685	0.0314	4,664	29.5
1989	135	0.0921	0.0501	4,807	35.6
1990	131	0.1079	0.0807	4,122	31.5
1991	302	0.1229	0.0945	14,203	47.0
1992	415	0.1074	0.0811	19,747	47.6
1993	525	0.1275	0.1130	26,550	50.6
1994	414	0.0922	0.0804	15,180	36.7
1995	462	0.2158	0.1795	23,947	51.8
1996	695	0.1730	0.1639	37,600	54.1
1997	471	0.1482	0.1541	26,900	57.1
1998	307	0.1965	0.1417	29,099	94.8
1999	477	0.7129	0.5791	53,223	111.6
2000	350	0.4921	0.5450	48,509	138.6
Total	**7,559**	**0.1513**	**0.1241**	**364,111**	**38.3**

Table 2: Summary Statistics of Measures of IPO Activity

	Mean	Standard Deviation	Minimum	Maximum	Dickey-Fuller Test Statistic
NOIPO	25.2575	19.7298	0.0000	90	-3.2832*
VWUP (%)	12.7794	18.6348	-15.5557	133.1311	-3.7028*

1. * denotes significance at 5% level.
2. VWUP denotes value-weighted IPO underpricing per month and NOIPO denotes number of offerings per month.

Table 3: Breaks in the Standard Deviation of Value-weighted IPO Underpricing

Period	Initially Detected Standard Deviation	Scale CUSUM Direction of Break	Length of Break (Months)	Length of Detection (Months)
Feb 78 to Aug 83	0.128		67	
Sep 83 to Aug 85	0.013	Down	24	5
Sep 85 to Jan 87	0.075	Up	17	3
Feb 87 to Jan 89	0.032	Down	24	10
Feb 89 to Apr 93	0.080	Up	51	2
May 93 to Nov 94	0.027	Down	19	4
Dec 94 to Nov 96	0.067	Up	24	2
Dec 96 to Jul 98	0.021	Down	20	4
Aug 98 to Dec 00	0.490	Up	29	2
Averages	0.104		30.6	4.0

Note that the standard deviation figures are for the initially estimated standard deviation levels when the scale Cusum procedure initially detects a break to a new volatility state.

Table 4: Breaks in the Standard Deviation of IPO Volume

Period	Initially Detected Standard Deviation	Scale CUSUM Direction of Break	Length of Break (Months)	Length of Detection (Months)
Feb 78 to Nov 79	2.167	Start	22	
Dec 79 to Nov 80	4.082	Up	12	2
Dec 80 to Jan 82	10.727	Up	14	2
Feb 82 to Nov 82	1.506	Down	10	2
Dec 82 to Jun 83	12.580	Up	7	2
Jul 83 to Apr 86	9.347	Down	34	2
May 86 to Nov 87	13.382	Up	19	6
Dec 87 to Aug 92	4.930	Down	57	2
Sep 92 to Apr 93	10.583	Up	8	2
May 93 to Sep 96	11.029	Up	41	8
Oct 96 to Mar 97	25.280	Up	6	2
Apr 97 to Dec 00	9.772	Down	45	1
Averages	9.615		20.3	2.8

Note that the standard deviation figures are for the initially estimated standard deviation levels when the scale Cusum procedure initially detects a break to a new volatility state.

Table 5: Breaks in the Mean Level of Value-weighted IPO Underpricing

Period	State Mean Level (CUSUM Mean)	Direction of Break	Identification of Periods	Tests for Differences In State Means (P-Value)	Length of Break (Months)	Length of Detection (Months)
Jan 77 to Mar 78	0.019 (0.0364)				15	
Apr 78 to Sep 78	0.187 (0.115)	Up	Hot	0.1082	6	4
Oct 78 to Oct 79	0.025 (0.026)	Down	Non-hot	0.0011**	13	1
Nov 79 to Dec 80	0.227 (0.235)	Up	Hot	0.0021**	14	2
Jan 81 to Oct 82	0.046 (0.059)	Down	Non-hot	0.0002**	22	5
Nov 82 to Jun 83	0.171 (0.143)	Up	Hot	0.0000**	8	5
Jul 83 to Aug 84	0.022 (0.021)	Down	Non-hot	0.0000**	14	2
Sep 84 to Jan 89	0.039 (0.042)	Up	Non-hot	0.1412	53	3
Feb 89 to Jan 95	0.094 (0.102)	Up	Marginal Hot	0.0000**	72	2
Feb 95 to Aug 99	0.228 (0.185)	Up	Hot	0.0000**	55	7
Sep 99 to Dec 00	0.580 (0.672)	Up	Very Hot	0.0000**	16	2
Average	0.1489 (0.1499)				26.18	3.3

1. ** significant at 1% level.
2. Figures in parentheses are the initially estimated mean levels when the mean Cusum procedure initially detects a break to a new state.

Table 6: Breaks in the Mean Level of IPO Volume

Period	State Mean Level (CUSUM Mean)	Direction of Breaks	Identification of Periods	Tests for Differences in State Means (P-Value)	Length of State (Months)	Length of Detection (Months)
Jan 77 to Aug 78	1.950 (2.083)				20	
Sep 78 to May 80	4.667 (4.000)	Up	Less Inactive	0.0001**	21	4
Jun 80 to Dec 81	20.579 (19.000)	Up	Active	0.0000**	19	4
Jan 82 to Feb 83	9.000 (8.083)	Down	Inactive	0.0003**	14	2
Mar 83 to Jan 84	52.909 (51.000)	Up	Active	0.0000**	11	4
Feb 84 to Apr 86	21.407 (18.500)	Down	Inactive	0.0000**	27	6
May 86 to Sep 87	48.882 (49.833)	Up	Active	0.0000**	17	3
Oct 87 to Apr 91	11.767 (12.750)	Down	Inactive	0.0000**	43	3
May 91 to Jan 96	36.649 (36.364)	Up	Active	0.0000**	57	7
Feb 96 to Feb 97	57.769 (58.667)	Up	Active	0.0000**	22	5
Mar 97 to Jul 98	37.941 (39.000)	Down	Less Active	0.0009**	17	11
Aug 98 to Apr 99	17.222 (20.500)	Down	Inactive	0.0003**	9	4
May 99 to Dec 00	36.600 (43.583)	Up	Active	0.0023*	20	3
Average	27.488 (27.951)				22.85	4.67

1. * significant at 5% level
   ** significant at 1% level.
2. Figures in parentheses are the initially estimated mean levels when the mean CUSUM procedure initially detects a break to a new state.

Table 7: Identification of Overall Hot Issue Markets

Period	Chronology of IPO Market	Length of Break (Months)	Mean Level of IPO Underpricing	Mean Level of IPO Volume
Jan 77 to Mar 78	Cold	15	Non-hot	Inactive
Apr 78 to Sep 78	Transition-hot	6	Hot	Inactive/ Less Inactive
Oct 78 to Oct 79	Cold	13	Non-hot	Less Inactive
Nov 79 to May 80	Transition-hot	7	Hot	Less Inactive
Jun 80 to Dec 80	Hot	7	Hot	Active
Jan 81 to Dec 81	Transition-active	12	Non-hot	Active
Jan 82 to Oct 82	Cold	10	Non-hot	Inactive
Nov 82 to Feb 83	Transition-hot	4	Hot	Inactive
Mar 83 to Jun 83	Hot	4	Hot	Active
Jul 83 to Jan 84	Transition-active	7	Non-hot	Active
Feb 84 to Apr 86	Cold	27	Non-hot	Inactive
May 86 to Sep 87	Transition-active	17	Non-hot	Active
Oct 87 to Jan 89	Cold	16	Non-hot	Inactive
Feb 89 to Apr 91	Transition-hot	27	Marginal-hot	Inactive
May 91 to Jan 95	Marginal-hot	45	Marginal-hot	Active
Feb 95 to Feb 97	Hot	25	Hot	Active
Mar 97 to Apr 99	Transition-hot	26	Hot	Less Active/ Inactive
May 99 to Aug 99	Hot	4	Hot	Active
Sep 99 to Dec 00	Very Hot	16	Very Hot	Active
		Mean = 15.16		

Figure 1: Value-weighted Underpricing (VWUP) versus Equally-weighted Underpricing (EWUP), January 1977 to December 2000

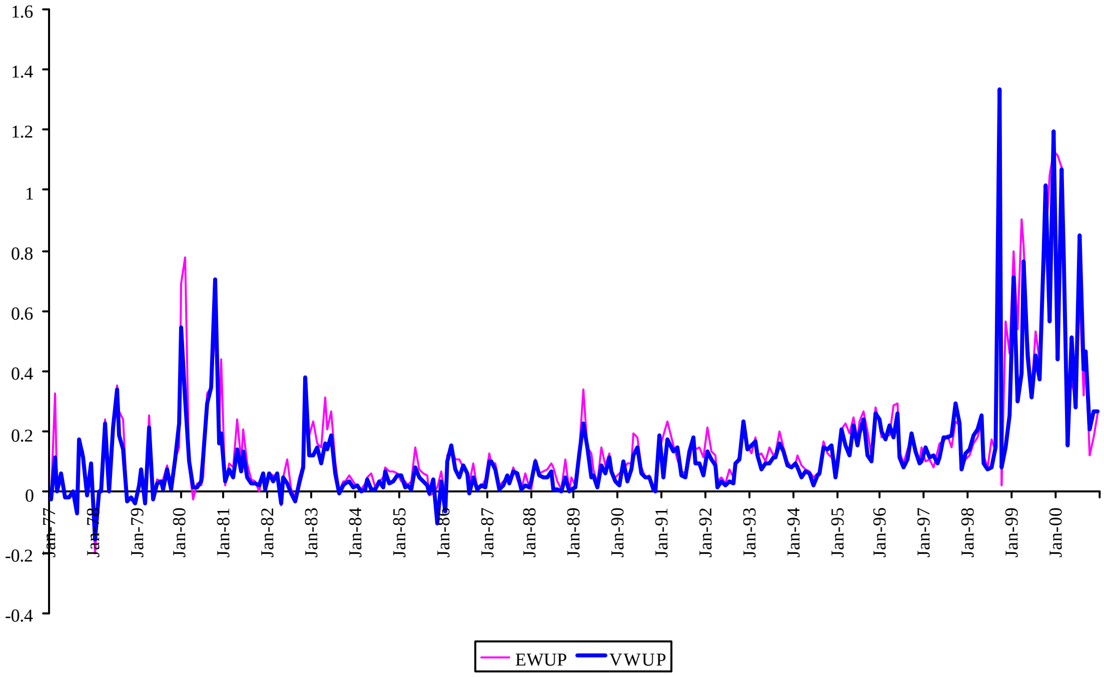

Figure 2: IPO Volume during the Period January 1977 to December 2000

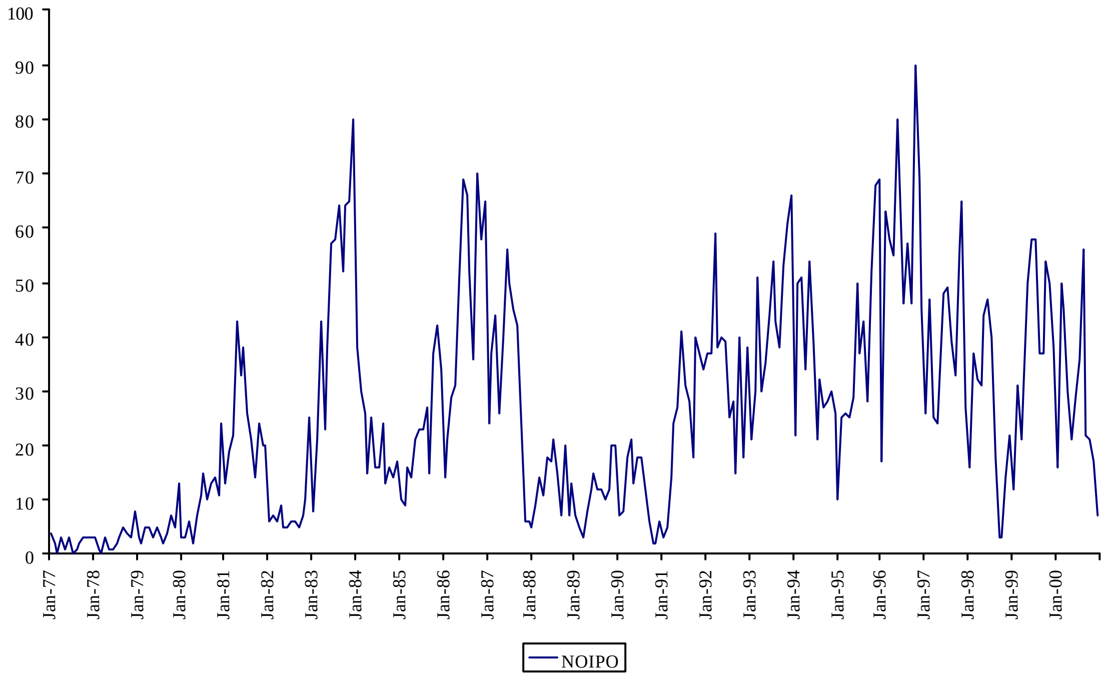

Figure 3: Windsorised AR(1) Transform on Value-weighted IPO Underpricing

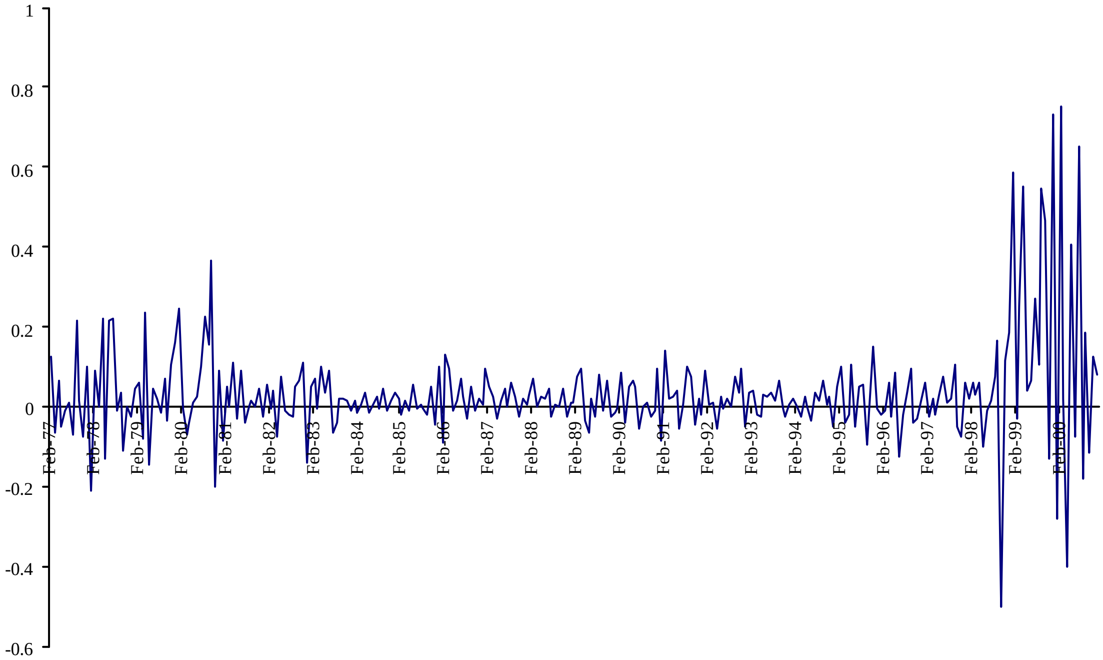

Figure 4: Windsorised AR(1) Transform on IPO Volume

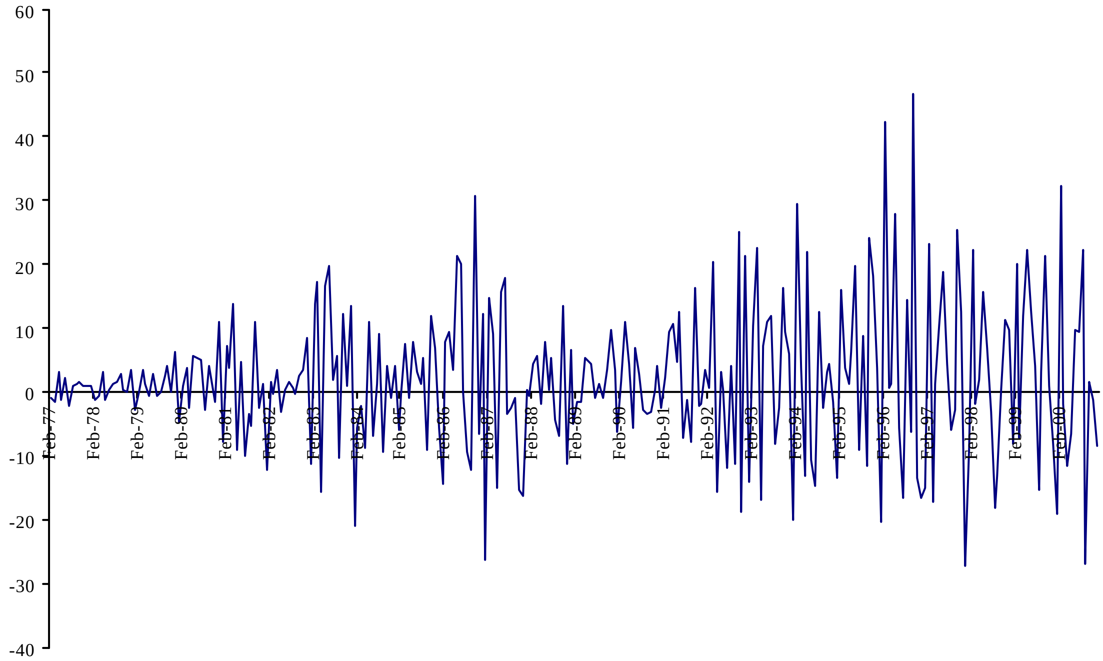

Figure 5: CUSUM Result for Value-weighted IPO Underpricing

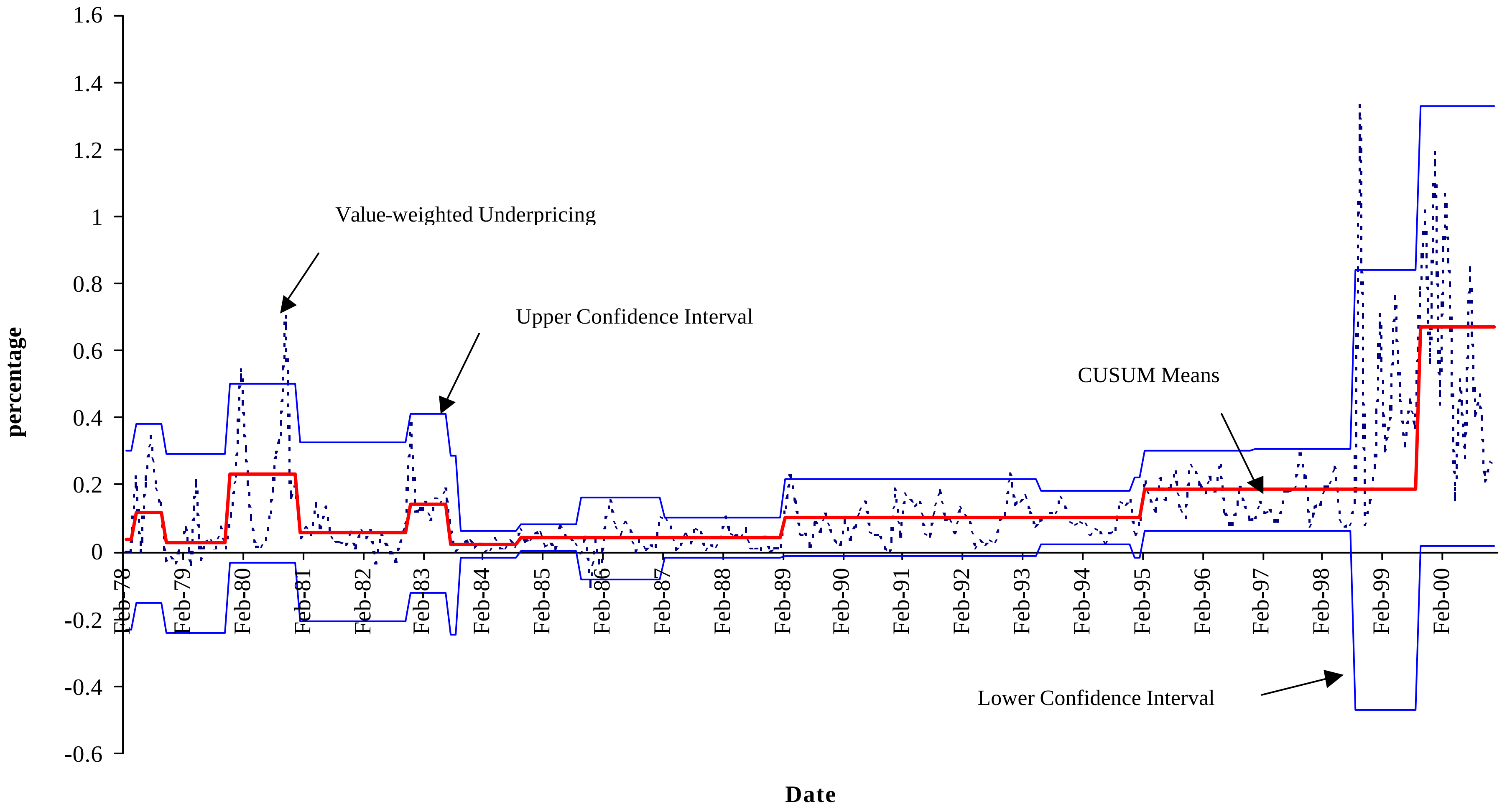

Figure 6: Breaks in CUSUM Mean Level and Standard Deviation of Value-weighted IPO Underpricing

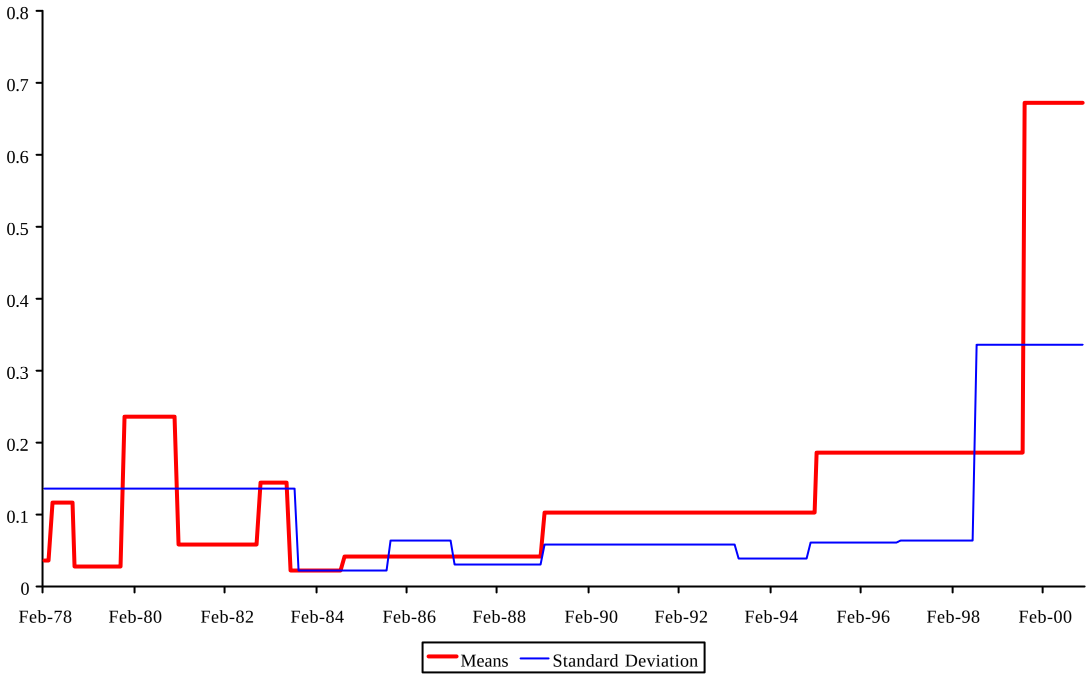

Figure 7: CUSUM Result for IPO Volume

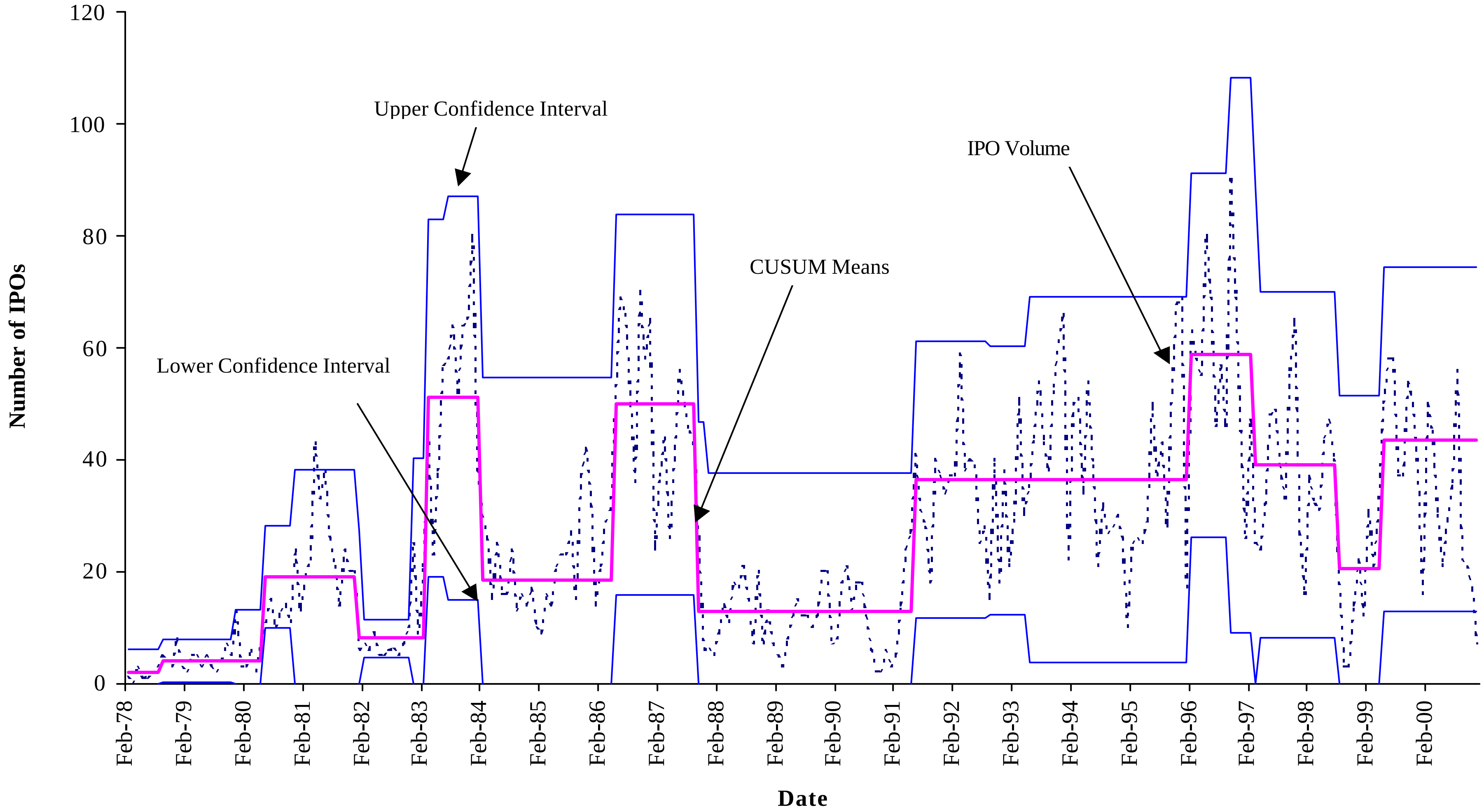

Figure 8: Breaks in CUSUM Mean Level and Standard Deviation of IPO Volume

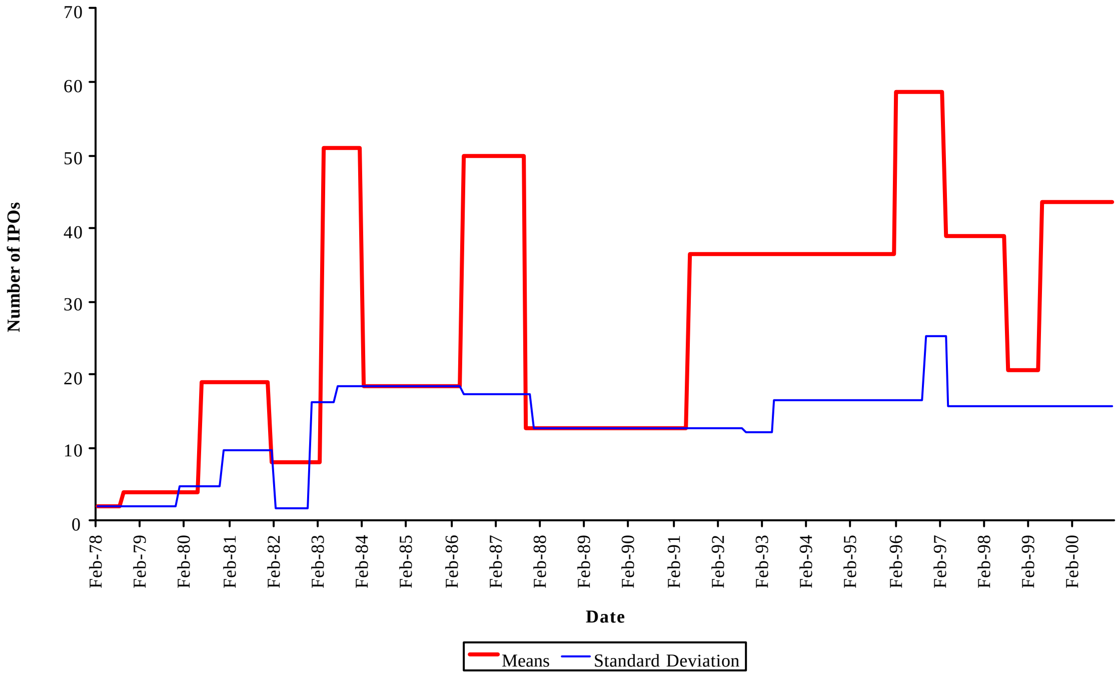

Figure 9: Comparison of Breaks in CUSUM Mean Levels between Scaled Volume, Equally-weighted and Value-weighted IPO Underpricing