NON-STATIONARITY IN BID-ASK SPREADS: THE ROLE OF TICK SIZE REDUCTION

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ABSTRACT

Mean-reversion of spreads follows directly from an error correction quote adjustment process plus a random walk theory of the quote midpoint as an implicit efficient price. In such a model, buys and sells are equally likely, and the trade direction is informationless. With asymmetric information and strategic trading, however, order flow is serially correlated, and the spread incorporates a time-varying adverse selection component that conditions on trade direction (or more generally, on order flow imbalance). We test the mean reversion of trade-to-trade spreads for every NYSE stock for each year 1993-2006 and find that tick size reduction in 1997 and 2001 substantially reduced the incidence of mean-reverting NYSE spreads. We attribute this growing non-stationarity of spreads to "legging" in the bid and ask quotes, and relate the reduced resiliency of the NYSE book to arbitrage threshold bounds relative to the radically declining tick size. In addition, we show that mean-reversion tests are very sensitive to lag structure misspecification and evaluate three approaches to selecting an optimal lag structure. ***(KEYWORDS: spread, mean-reversion, stationarity, tick size)***

1.1 Introduction

The trading behavior of market makers and institutional participants in modern capital markets is pivotally affected by the stochastic properties of the data generating process for asset prices. For example, it is well-known that, apart from regulatory affirmative obligations, both market makers and several types of liquidity suppliers seek net neutral positions ("go flat") when markets begin to trend but otherwise, in mean-reverting markets, are quite content to take inventory risk and earn the quoted spread. Whether or not security prices mean-revert therefore determines in large part whether liquidity providers are active or temporarily move to the sidelines. Their decision has immediate implications for the availability of liquidity and thereby for the largest component of execution costs, the quoted bid-ask spread.

Detecting in real time whether a particular security price is mean-reverting or not is both an art and a science. Practitioner knowledge of this matter is broad and deep, state-of-the-art, and insightful. In this paper, we investigate the importance of specifying an optimal lag structure for the detection of mean reversion in thickly-traded U.S. equity markets.

Using trade-to-trade data for the period 1993-2006, we document and then offer an explanation for the growing non-stationarity of quoted price midpoints and quoted spreads. Two radical reductions in minimum tick size from eighths to sixteenths in 1997 and from sixteenths to pennies in 2001 play a key role in our analysis. In short, the massive erosion of minimum tick size has markedly reduced one expense of executing a round trip transaction but has imposed an unfortunate consequence – i.e., the collapse of depth posted at the BBO. The resulting increase in price impact, as larger orders no longer find sufficient counterparties at the BBO but instead "walk the book," is directly related to the increased incidence of non-stationary spreads.

1.2 Related Literature

Several existent methods are available for distinguishing stochastic trends in economic and financial time series where the data generating process contains a unit root from mean-reverting series with possible deterministic trends or structural breaks. The most widely-adopted is the augmented Dickey-Fuller test statistic, a non-normal distribution for testing the autoregressive parameter in AR(p) models (Dickey and Fuller 1979,1981). If the autoregressive coefficient rho in detrended AR(1) models or the sum of the autoregressive coefficients tau in detrended AR(p) models is insignificantly different from 1.0, the series is non-stationary exhibiting unit roots and stochastic trends. Such a series does not mean-revert and instead exhibits non-constant variance, growing through time. If one can reject the null hypothesis of a unit root (H_0: $\rho = 1$) against a one-tailed alternative in the first differences – i.e., H_A: $(\rho - 1) < 0$,

$$\Delta P_t = \alpha + \lambda t + (\rho - 1) P_{t-1} + \sum \beta_i \Delta P_{t-i} + \nu_t \qquad (1)$$

the price series is dynamically stable, and its detrended version does mean-revert.

Numerous pivotal complications arise in this testing. First, unit root and mean-reversion testing must be conditioned on pretesting for deterministic time trends and drift. Perron (1988) and Enders (1995 and 2004, pp. 207-214) present nested ADF tests of equation (1) that accommodate the possible inclusion of drift α and a deterministic time trend t in the d.g.p. Harris (1995) cautions that detrending a trend stationary d.g.p. or misspecifying a drift term in a simple random walk reduces the power of the Dickey-Fuller statistic and increases the probability that a false hypothesis of a unit root will be accepted. If one initially fails to reject the unit root null, testing continues to the more restricted specifications without deterministic trends or drift and only then should the null hypothesis of a unit root be accepted.

Secondly, Schwert (1989) investigates the presence of learning behavior with moving average effects -- i.e., with parametric influence on pricing of serially uncorrelated prior error disturbances ν_{t-1} as in (2),

$$\Delta P_t = \alpha + \lambda t + (\rho - 1) P_{t-1} + \sum \beta_t \Delta P_{t-i} + \theta \nu_{t-1} + \nu_t \qquad (2)$$

where $\nu_t \sim$ i.i.d. $N(0, \sigma^2)$. Simulating Dickey-Fuller and other tests for mixed auto-regressive integrated moving average models, Schwert's Monte Carlo experiments show that ARIMA (1, 0, 1) models lead to numerous false negatives (overrejecting unit root processes) as the moving average parameter θ approaches the autoregressive parameter ρ. With smaller positive or negative θ, the augmented Dickey-Fuller test leads to valid inference. For quoted prices and spreads, because $\rho \approx 1$ and θ could be as large as 0.8 or 0.9, one approach is to estimate the ARIMA model to assess the magnitude of θ before proceeding to unit root tests.

Third, deterministic seasonal patterns or regime changes (structural breaks) in an otherwise covariance stationary d.g.p. can be difficult to distinguish from the non-stationarity of a unit root process. Gordon and St Amour (2000) showed that shifts in risk-aversion alone can trigger hidden Markov model (HMM) regime switching in stock returns. Timmermann (2001) derived skewness, kurtosis, volatility clustering, and positive serial correlation in stock returns from HMM regime switching of dividends. Empirical evidence of HMM regime switching does arise in monthly stock returns that otherwise appear to random walk (Hardy 2001). In a parallel paper, we investigate the possibility of HMM regime switching for daily stock prices (Harris, Wood, Zhao 2007). Intraday stock price data (the subject of the current paper) does not appear to exhibit structural breaks.

Finally, valid statistical inference in VAR models is entirely dependent on specifying an autoregressive lag structure that matches the dynamics of adjustment in the data generating process. Too few lags results in autocorrelation of the error terms which affects the distributions of the ADF test statistics and thus invalidates inference. Too many lags results in reduced power of the ADF test, underrejecting the null hypothesis of a unit root when it is false.

Ng and Perron (1995) recommend a general-to-specific lag structure test, beginning with a generously chosen k_{max} autoregressive lag in an ADF model and truncating and reestimating if that longest lag (which we refer to as the longest "continuous lag") fails to meet conventional critical values. Harris (1992) showed that minimizing the Akaike information criterion (AIC) is a satisfactory method for picking the longest continuous lag structure. In the empirical work that follows, we compare and contrast the unit root inferences for intraday stock prices under three competing specifications of the lag structure -- ten lags, longest AIC-minimizing continuous lags, and optimal lags where the latter minimizes the AIC across all possible continuous and discontinuous lag structures.

The rationale for our 'optimal lag' structure can be understood in terms of equation (1). Suppose that the coefficient β_2 on ΔP_{t-2} is highly significant while β_1 is clearly not significant. A researcher would want to include ΔP_{t-2} in the Dickey-Fuller test to control for serial correlation. However, the general-to-specific method of using continuous lags entails a loss of power since an unnecessary coefficient is included in the testing regression. An *F*-test for the joint significance of both coefficients is also inappropriate since only β_2 belongs in the regression. The use of the AIC to select the specific lagged terms to include in the regression allows us to balance the need to control for serial dependence with the need to maintain the power of the Dickey-Fuller testing methodology.

2. Hypothesis Development

We begin by assuming that the sequence of quote midpoints m_t is an implicit efficient (semi-martingale) price of the security $\mathscr{P}_t$ plus a mean-zero tracking error ε_t. $\mathscr{P}_t$ evolves as a simple random walk $\mathscr{P}_t = \mathscr{P}_{t-1} + u_t$ where the $u_t \sim$ i.i.d.$(0, \sigma_u^2)$ may be thought of as common value information arrivals with a mean-zero expectation. The quote midpoint may therefore be written .

$$(3) \qquad \mathbf{m_t} = \mathbf{m_{t-1}} + \mathbf{u_t} + \boldsymbol{\varepsilon_t} = \sum \mathbf{u_t} + \boldsymbol{\varepsilon_t}.$$

The dynamic properties of this quote midpoint clearly depend upon the autocovariance Cov $(\varepsilon_t, \varepsilon_{t-1})$ and the covariance Cov (u_t, ε_t). Provisionally, we assume $\varepsilon_t \sim$ i.i.d.$(0, \sigma_E^2)$ and Cov $(u_t, \varepsilon_t) = 0$.

Dealers and other market makers add to this midpoint a half spread c (interpreted as a minimum transaction cost recovery in competitive dealer markets with no asymmetric information) to set the transaction price at the ask P_a quoted for buy orders ($q_t = +1$) and at the bid P_b quoted for sell orders ($q_t = -1$). With buys and sells assumed to be equally likely and therefore an order flow indicator q_t that is informationless, as in the Roll (1984) model, we have:

$$(4) \qquad P_{a,t} = \mathbf{m_t} + c\,q_t \qquad \text{and} \qquad P_{b,t} = \mathbf{m_t} - c\,q_t$$

Quotes P_a and P_b in (4) are difference stationary I(1) sequences drifting up or down together based on a permanent common factor component (the cumulative information arrivals $\sum u_t$) and a transitory common tracking error ε_t in the quote midpoint. Evaluating the difference of the ask quote minus the bid quotes causes both common factors to cancel out, leaving a constant quoted half-spread equal to c. These stylized facts and simplistic assumptions lead to the following hypothesis.

H_A**: The ask-bid spread is a covariance-stationary sequence.**

Of course, there are a number of objections to the assumptions underlying H_A that suggest some refinements could prove useful in developing a testable competing hypothesis.[1] First, empirical quoted spreads exhibit apparently stochastic variation; yet, spreads in (4) are a parametric constant. We hypothesize instead that with information asymmetry and strategic trading by informed traders who have advance access to common value knowledge, spreads are time-varying. Second, at any point in time, buys and sells are not equally likely. Buys follow buys; sells follow sells Cov $(q_t, q_{t-1}) > 0$. That is, q_t is itself a stochastic order flow indicator variable, not a parameter. Third, Cov $(q_t, u_t) \neq 0$; an imbalance of buys reflects one state of the information conditions in the market; a sequence of sells reflects another. As a result, spreads should incorporate a time-varying adverse selection component λ that is triggered by the order flow indicator variable q_t. The equilibrium λ just recovers a liquidity provider or market maker's expected net losses as counterparty to informed traders minus his or her gains as counterparty to liquidity traders.

Hasbrouck (2007, chap 8) suggests the following timing. When information u_t arrives, the quote midpoint is first updated $m_t = m_{t-1} + u_t$ to reflect the new public information, and the market maker sets a symmetrical pair of tentative quotes for small size around that updated midpoint $P_{a,t} = m_t + cq_t$. Then, when an order arrives (or cumulating

[1] Most finance academics have covariance stationarity of the spread as their prior. However, we assign this a priori reasoning to the alternative hypothesis (H_A) because the ADF statistical tests of stationarity are set up to reject or fail to reject unit roots as the null hypothesis.

across a multi-order time interval, when an order imbalance of a particular size appears), market makers add a time-varying adverse selection component $\lambda_t q_t$ to the previous midpoint as in Glosten (1987),

$$(5) \qquad m_t \quad = \quad (\mathbf{m_{t-1}} + \mathbf{u_t} + \boldsymbol{\lambda_t q_t}),$$

thereby identifying the transaction price,

$$(6) \qquad P_t \quad = \quad \mathbf{m_t} + \mathbf{cq_t}.$$

Campbell, Lo, and MacKinlay (1997, section 3.2) emphasize two important differences that distinguish this Glosten framework from the Roll framework underlying H_0. Taking the first differences of (6) and using (5) rather than (3) yields

$$(7) \qquad \Delta P_t \quad = \quad \mathbf{u_t} + \boldsymbol{\lambda_t q_t} + (\mathbf{cq_t} - \mathbf{cq_{t-1}}).$$

Trade-to-trade security returns should exhibit transitory shocks u_t and negative serial correlation because of the mean-reversion that arises from bid-ask bounce, as q_t and q_{t-1} reverse signs. In contrast, the adverse selection term $\lambda_t q_t$ is time-varying but always positive, does not mean revert, and in that sense is permanent. Consequently, the half-spread S_t

$$\mathbf{(8)} \qquad \mathbf{S_t} \quad = \quad \boldsymbol{\lambda_t} + \mathbf{c}$$

is time-varying and potentially non-stationary because of the dependence of λ_t on order flow imbalances.

Bertsimas and Lo (1998) also posit a model of quote midpoints that drift with the beliefs of strategic trader agents about order flow imbalance. The tracking error ε_t in $\mathbf{m_t}$ (see equation (3)) is another way to motivate time-varying spreads that potentially are non-stationary because of possible correlation between ε_t and the order flow imbalances triggered by public information arrivals u_t. We therefore hypothesize,

H_0: The ask-bid spread is a non-stationary sequence.

In the next section, we investigate the importance of optimal lag length in testing these hypotheses about these dynamic properties of the spread and provide an explanation for the non-stationarity and lack of time-scale invariance in recent data.

Engle and Patton (2004) model the log bid price quotes and the log ask price quotes as a VECM system with log spreads as a mean-reverting I(0) error correction term. Consistent with H_A above, they were able to confirm the stationarity of spreads for 100 NYSE stocks from a stratified random sample in 1997-1998 using ten lags and ADF test statistics at alpha = 0.01. Our results reported below show however that, starting in 1998, some NYSE spreads began to exhibit I(1) stochastic trends and thereafter spread series are neither time scale invariant nor stationary.

3. Empirical Results

3.1 Arbitrage Thresholds and the Tick Size

The two-step reduction in minimum tick sizes in the years 1997 and 2001 has had a profound effect on the incidence of mean-reverting quote sequences. Table 1 shows that in Dow Jones Industrial Average (DJIA) stocks in 1996 at one-eighth minimum tick size, 200 quotes required 10,173 seconds, approximately one quote per minute. With this much time to identify counterparties and execute against standing offers, depth at the best bid and offer (BBO) exceeded depths elsewhere on the book. Huge volume at the BBO was posted as market-makers earned this exceptionally wide spread on bid-ask bounce. Consequently, relatively few orders from liquidity traders seeking to sector rebalance their insurance company portfolios or mutual funds responding to redemption demand were of sufficient size to exhaust immediate liquidity supply at the BBO. Hence, in such information-neutral states of the market, not many orders needed to walked up or down one-side of the book, increasing the spread in a so-called "legging" pattern, in order to execute.

However, when a major order imbalance did widen the spread by the enormous \$0.125 tick (relative to the \$0.01 minimum tick size today), limit order placers almost always quickly refreshed the book, resulting in a very high incidence of mean-reversion to a 1/8th spread. Table 2 displays the percentage of quote sequences that were mean-reverting with three types of lag structures, with five intervals of time aggregation for each of fourteen years from 1993-2006. It shows that over the last years of the 1/8th tick size (1993-1996) in 150 quote sequences of DJIA stocks estimated with optimal lag structures, no fewer than 99.8% of the spread sequences mean-reverted. In 75 quote sequences, no fewer than 96.7% mean-reverted. To put it in arbitrage terms, whenever liquidity suppliers saw orders walk the book by as much as an 1/8th, they presumed that the quote midpoint had moved beyond the arbitrage trading threshold bounds on the minimum efficient price. Consequently, unless a price trend was developing in the stock, these liquidity suppliers would quickly step in to refresh the book, and earn the spread in a mean-reverting market.

Subsequent reduction in tick sizes to teenies (1/16th) in 1997-1998 and to decimal pennies in 2001-2002 has resulted in much faster quote processes and much lower depth at the BBO. Table 1 again shows the effect on elapsed time of this finer-grained pricing process. Two hundred quotes occurred in 1998 in 4,113 seconds (approximately one every 20 seconds). 200 quotes occurred in 2002 seconds in 1,084 seconds, which halved to 571 seconds in 2003, and halved again to 291 seconds by 2006 (approximately one per second). In addition, spreads in DJIA stocks collapsed over the period of these shrinking tick sizes to just \$0.043 in 2003 from \$0.126 in 1998 and \$0.165 in 1995.

After 2002, not only did quote frequency rise and spreads collapse, but more significantly, those order imbalances that increased the comparatively small 4 cent spreads did so without triggering a refresh of the book. We interpret these findings to mean that the finer-grained quotation grid allows small changes in the implicit efficient price (inside arbitrage threshold bounds) to induce spread increases (i.e., from $0.04 to $0.05) without triggering arbitrage-motivated liquidity supply.

Consequently, we would predict that many fewer quote sequences mean revert after the minimum tick size reductions (comparing 1996 and earlier to 2002 and later years). Again referring to Table 2 and referencing optimal lag structures, in 1996 at 1/8th tick sizes (and $0.14 spreads), 96.7% of the 75 quote spread sequences mean reverted. In 1999 at teenies for the tick size, only 86.3% of the 75 quote spread sequences mean reverted. After 2002 with pennies for the tick size, 58.2% of the 75 quote sequences and less than half (35.9% to 47.9%) of the 50 quote spread sequences (especially relevant to algorithmic trading) mean reverted. Similar before and after results are apparent at longer time intervals of 100 quotes (see Table 2 above and below the shaded horizontal bars for the tick size changes in 1997 and 2001).[2] We conclude that legging happens on the finer-grained price grid today in large part because of much less triggering of arbitrage-based liquidity supply.

3.2 A Striking Result on Time Scale Invariance

Under the alternative hypothesis for the dynamics of the spread that we developed in section 2, as the difference between two semi-martingales plus a constant, even with tracking error, we would expect the spread sequence to be white noise around a constant. Such a sequence exhibits time scale invariance. In fact, referring again to Table 2 and reading from

[2] At 150 and especially at 200 quotes, the incidence of mean reversion approaches 100% for essentially all the years. These time intervals are much longer than the trading behavior being modeled.

right to left across the columns in row 1, we find the autoregressive structure of the spread sequence is quite different at longer and shorter time intervals.

At 150 quotes (occurring over an elapsed time of 216 seconds in 2006), we reject the null hypothesis of a unit root in the data in favor of a mean-reverting process 92.4% of the time. On the other hand, at half that elapsed time (over a 106 second interval), only 67.0% of the 75 quote sequences are mean-reverting. In the still shorter trading time intervals relevant to algorithmic trading, with 50 quotes, a majority (50.3%) of the quote sequences are unit root processes.

This lack of time scale invariance may reflect the declining power of the test as the number of observations declines from 150 to 75 to 50 quotes. However, another interpretation altogether is that time-varying spreads reflect order imbalance, perhaps in much the same way that random walk processes characterize the effect of public information arrivals on quote midpoints in equation (5) above and Glosten (1987). Chakravarty, Harris and Wood (2003) explore an error correction model of spreads and depth quotes under that assumption.

A third possibility altogether is that spread sequences are non-stationary because of hidden Markov model regime switching (Hamilton 1989) in the implicit efficient price $\mathscr{P}_t$ underlying the quote process. Hardy (2001) shows that S&P monthly returns are not distributed independent lognormal. Rather she finds that the fat tails and positive autocorrelation fit a HMM mixture of normals with switching regimes which are not time scale invariant. These investigations on monthly returns may hold key insights for further research on daily closing prices or even on trade-to-trade data.

3.3 The Effect of Excessive Lag Length on the Estimated Frequency of Mean-Reversion

To develop these conclusions about the lack of time scale invariance in the data generating process and about the effect of minimum tick size reduction on the mean-reversion of spreads requires careful attention to the optimal lag structure. Enders (2004, p. 229) warns that too many lags (or too few) reduces the power of the augmented Dickey-Fuller test to reject false positives of a unit root process. The percentage mean-reversion listed in Table 2 arises from nested ADF tests that incorporate the possible inclusion of drift and deterministic time trends (Enders, 2004, pp. 207-214).

We display three columns of results for each time interval (i.e., for 50, 75, 100, and 150 quotes). The first column in these tuples labeled “optimal lags” employs the lag structure that minimizes the Akaike Information Criterion for the log (ask minus bid). This estimation employs whatever discontinuous permutation of lags minimizes the AIC. The second column in each tuple labeled “best continuous lags” employs F tests to test shorter against a null hypothesis of longer lag structures, beginning with ten lags. The final column specifies a ten lags structure.

Figure 1 displays the lag structure lengths for the optimal lag length procedure in DJIA stock quotes. Three quotes is the modal lag length with 27.28% of the cases. Two and four quotes are almost equally highly probable, at 23.28% and 20.18%, respectively. Overall the distribution of optimal lag lengths appears lognormal, with one lag having only a 3.42% frequency, and 5 through 9 lags declining monotonically from 13.18% to less than 1% frequency. Altogether, ten and more lags occur in the analysis of optimal lag lengths for DJIA stock data with a frequency of 4%.

Even at 150 quotes (an extremely long time interval today), Table 2 displays a consistent result. In every year, the use of ten lags rather than a set of best continuous lags or the optimal lag structure understates the incidence of mean-reversion and overstates the presence of a unit root. In 2006, I(1) spreads are falsely identified as occurring with 43.5% (1- 0.565) frequency. In fact, optimal lag structures identify I(1) spread sequences only 7.6% of the time in 2006.

As the time scale interval becomes shorter, this estimation of large numbers of false positive unit roots resulting from misspecifying an excessive number of lags is ever more pronounced. At 75 quotes, ten lags understates mean reversion as 22.9% when optimal lags identifies 67.0%. And at the 50 quote sequences most relevant to algorithmic trading in electronic markets, ten quotes misestimates mean-reversion at only 14.9 % when in fact mean-reversion has more nearly 49.7% frequency. All other years in Table 2 show the same pattern of understating the incidence of mean reversion in stock price quotes when excessively long lag structures are employed in ADF tests.[3] In Table 3, we have demeaned the spreads data by each trading day, so that the optimal lag structure regressions could be estimated with no intercept. The qualitative results are virtually identical.

4. Conclusion

The mean-reverting stochastic property of spreads that makes for net position taking by liquidity suppliers is now less probable than unit root processes for the spread. The reduction of minimum tick sizes in 1997 and 2001 appear responsible. Alongside the benefit of massive reductions in the spread, the markets have experienced the costs arising from less mean-reversion in spreads. Many more trades must now be executed to accomplish the same position as before tick size reduction, but total volume is much higher. Liquidity in the sense

[3] In Table 2, best continuous lags are subject to the same understatement of the incidence of mean-reversion relative to the optimal lag structure but the specification bias in all years and at all time intervals appears to be small.

of cumulative trading volume over some time frame is substantially higher fundamentally because net trading costs are substantially lower.

After each tick size reduction, we have documented an increase in the non-stationarity of spreads. On the one hand, this is a desirable development because it represents more accurate price discovery with the finer grid. On the other hand, non-stationary spreads have discouraged market makers and limit order traders providing liquidity from posting substantial depth at the BBO. To accurately understand the magnitude of these tradeoffs requires a correctly-specified lag structure for the stationarity tests. Long (ten lag) model structures underreject the null hypothesis of a unit root in spreads when it is false. Too few lags have the opposite effect. In NYSE quote data, post-tick size reduction, we find the bias from mis-specified lag structures is very substantial.

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Elapsed Time in Seconds by Quote Lag Length						
Year	**Tick Regime**	**50**	**75**	**100**	**150**	**200**
2006	0.01	73	106	143	216	291
2005	0.01	85	128	169	258	345
2004	0.01	110	166	222	334	446
2003	0.01	141	213	284	428	571
2002	0.01	268	404	540	812	1084
2000	1/16	619	935	1250	1881	2508
1999	1/16	846	1278	1709	2573	3434
1998	1/16	1740	1538	2057	3092	4113
1996	1/8	2667	4004	5290	7763	10173
1995	1/8	3662	5413	7100	10320	12729
1994	1/8	4110	6063	7927	11385	13788
1993	1/8	4382	6459	8435	11625	13323

Percent of runs of quotes that are stationary by run length--AIC. Optimal lag regression and sas code contain both trend

Quote run length	50			75			100			150			
Year	optimal lags	best continuous lags	10 lags	optimal lags	best continuous lags	10 lags	optimal lags	best continuous lags	10 lags	optimal lags	best continuous lags	10 lags	c
2006	49.7%	48.7%	14.9%	67.0%	62.6%	22.9%	79.9%	72.9%	34.9%	92.4%	85.0%	56.5%	9
2005	46.5%	48.2%	15.4%	66.9%	64.1%	24.2%	80.7%	75.0%	36.9%	93.7%	87.2%	59.0%	9
2004	48.7%	49.7%	15.4%	69.1%	65.2%	24.2%	82.8%	76.1%	36.1%	95.2%	88.3%	58.6%	9
2003	48.0%	49.9%	15.6%	69.1%	65.9%	24.1%	83.3%	77.1%	35.5%	95.5%	89.3%	58.1%	9
2002	35.9%	43.1%	15.3%	58.2%	61.8%	23.1%	76.0%	75.5%	33.8%	92.8%	89.4%	56.3%	9
2001													
2000	57.3%	61.2%	16.7%	80.1%	77.7%	27.4%	90.6%	86.0%	40.9%	97.3%	93.4%	64.9%	9
1999	64.6%	67.5%	17.4%	86.3%	82.8%	28.4%	95.1%	90.0%	42.7%	99.2%	95.6%	67.4%	9
1998	68.0%	70.0%	17.6%	88.1%	84.1%	29.3%	95.7%	90.4%	44.2%	99.1%	95.4%	68.3%	9
1997													
1996	87.4%	83.0%	19.7%	96.7%	91.4%	35.1%	98.9%	94.6%	52.6%	99.8%	96.9%	75.1%	9
1995	90.9%	85.4%	20.1%	98.0%	92.2%	36.9%	99.2%	94.8%	54.7%	100.0%	96.3%	77.7%	1
1994	89.3%	84.9%	20.2%	97.4%	92.7%	36.0%	99.4%	95.2%	54.6%	100.0%	96.6%	74.7%	1
1993	87.2%	84.4%	20.0%	97.0%	91.9%	36.4%	99.2%	94.5%	53.0%	100.0%	97.1%	75.5%	1

Table 3 Specification: Asymmetric Testing -- Data Demeaned By Day

Percent of runs of quotes that are stationary by run length--AIC. Optimal lag regression contains no trend or intercept; ADF te and trend

	50 quotes			75 quotes			100 quotes			150 quotes			
Year	optimal lags	best continuous lags	10 lags	optimal lags	best continuous lags	10 lags	optimal lags	best continuous lags	10 lags	optimal lags	best continuous lags	10 lags	c
2006	70.1%	62.3%	27.3%	84.2%	74.3%	42.2%	91.5%	82.3%	57.4%	97.1%	91.4%	79.1%	9
2005	70.3%	65.4%	28.5%	85.9%	78.3%	45.9%	93.3%	86.0%	61.7%	98.3%	94.3%	83.4%	9
2004	72.2%	65.7%	28.1%	87.7%	78.9%	45.3%	94.7%	86.9%	61.4%	98.9%	94.9%	83.5%	9
2003	72.0%	66.4%	28.5%	88.2%	80.2%	44.9%	95.2%	88.2%	61.3%	99.2%	95.5%	83.7%	9
2002	62.1%	62.9%	27.2%	82.7%	79.3%	43.0%	92.5%	88.1%	59.0%	98.4%	95.4%	82.0%	9
2001													
2000	81.8%	77.0%	31.4%	93.4%	87.3%	50.7%	97.3%	92.4%	68.0%	99.3%	97.1%	88.5%	9
1999	86.9%	80.9%	32.6%	96.5%	90.1%	52.5%	99.1%	94.4%	70.3%	99.9%	98.0%	90.5%	9
1998	88.5%	82.6%	39.3%	97.0%	91.1%	62.3%	99.1%	94.6%	71.8%	99.8%	98.1%	91.1%	1
1997													
1996	96.5%	89.5%	41.0%	99.2%	94.5%	65.0%	99.8%	97.0%	83.0%	99.9%	98.7%	95.1%	1
1995	97.9%	91.1%	43.1%	99.6%	96.0%	80.5%	99.9%	97.4%	84.8%	100.0%	99.1%	96.5%	1
1994	97.4%	91.2%	43.2%	99.5%	95.7%	68.3%	99.9%	97.6%	84.1%	100.0%	99.2%	95.4%	1
1993	96.7%	91.0%	42.1%	99.4%	95.3%	67.2%	99.8%	97.4%	83.9%	99.9%	99.2%	96.2%	1

```
                 Histogram of the Length of Optimal Lags                                     Percent
   |
   |*********                                                                                   3.42
   |
   |*****************************************************************                          23.28
   |
   |****************************************************************************               27.28
   |
   |********************************************************                                   20.18
   |
   |*************************************                                                      13.18
   |
   |***********                                                                                 4.14
   |
   |*******                                                                                     2.61
   |
   |***                                                                                         1.08
   |
   |**                                                                                          0.84
   |
   |***********                                                                                 4.00
```