Stale or Sticky Stock Prices?
Non-Trading, Predictability, and Mutual Fund Returns

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Abstract

The observed predictability in indexes and domestic mutual funds has been attributed to stale prices. Market timing of mutual funds exploits this predictability. We show that there are few stale prices for stocks in the top few deciles of market value and that mutual funds concentrate their holding in these deciles. Still, we observe predictability in the returns of portfolios and mutual funds holding these stocks. Much of this predictability is due to stickiness, or momentum, in market returns and not stale prices. Thus, the often suggested use of "fair-value" accounting will not eliminate the profitability of market timing.

Stale or Sticky Stock Prices? Non-Trading, Predictability, and Mutual Fund Returns

It has long been known that the returns on many indexes or portfolios display positive first order serial correlation. Larry Fisher (1966) may have been the first to attribute this predictability to stale prices. By a stale price, Fisher meant that the current value of a security was based upon a price from a trade that occurred earlier in time and thus did not incorporate any new information from the time of the trade to the current time. Because of this lag, the change in the price of the next trade from the stale price may be predictable.

More recently, Chalmers, Edelen, and Kadlec (2001), Boudoukh, Richardson, Subrahmanyam and Whitelaw (2002), Goetzmann, Ivkovic, and Rouwenhorst (2001), Greene and Hodges (2002) and Zitzewitz (2003) have reported sufficient predictability in the returns of mutual funds to suggest that "market timing" strategies would be profitable. "Market timing" strategies involve purchases and sales of mutual funds conditioned on past information. Like Fisher, these authors attribute this predictability to stale prices. Chalmers, Edelen, and Kadlec (2001) and Zitzewitz (2003) find predictability in the returns of both funds investing in international securities and those investing in domestic securities, while the other studies report predictability only in international funds. In practice, such market timing has been profitable: *The Wall Street Journal* (2006) reports that numerous mutual funds and individuals have paid at least $4.25 billion dollars in restitution and fines, plus legal and distribution costs, in settlements of charges that they colluded in facilitating market timing activities.[1]

The argument that returns of mutual funds are predictable is based on the industry practice of determining the NAV (net asset value) of a fund at 4:00 pm Eastern Time. At 4:00 pm, a fund typically values each asset in its portfolios as the product of the number of shares or units and the closing price on the primary market (the price of the last trade on that market), and then calculates the NAV as the total value of the portfolio divided by the number of shares owned by it mutual fund stockholders.[2] Because foreign markets outside of the Americas close

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[1] Some of these charges involved "late trading," the practice of entering trades after the markets had closed to be executed at the closing prices. Such late trading allowed these timers to benefit from information not reflected in the closing prices, even when these closing prices were not stale.

[2] That mutual funds typically use the official closing price, which in the U.S. is usually the last price on the primary market rather than a composite price, was confirmed in a telephone conversation with Peter Salmon of the Investment Company Institute on June 28, 2005. There is another form of staleness in the calculation of the NAV for day t. As described in Tufano, Quinn and Taliaferro (2006), U.S. mutual funds often use "t+1" accounting to account for portfolio purchases and sales. Shares purchased or sold on day *t* are not recognized as changes in share holdings until day *t*+1.

many hours before 4:00 pm, the closing prices from these markets are stale as of 4:00 pm when mutual funds calculate their NAVs. The closing prices of domestic securities can also be stale if the last trade did not occur near 4:00 pm. Because the closing prices of foreign securities are for the most part stale, this paper focuses on the predictability of U.S. equities whose prices are not always stale, thereby allowing us to disentangle predictability due to stale prices from other sources of predictability. This focus also provides more general insight into the predictability of the returns of US equities. To adjust for stale prices and thereby mitigate the possibility for profit, several of the papers cited above recommend that the value of the assets in a fund's portfolio be estimated with "fair value" prices. This paper examines this proposition for diversified portfolios of US equities.

The paper is organized as follows: First, there is a description of the data used in this study that cover the years from 1993 through 2004. Second, we show that there are few stale prices associated with larger-cap stocks in the sample period, but a substantial number of stale prices associated with smaller-cap stocks. Third, we analyze return predictability in a controlled environment and find that even when prices are not stale, returns are still predictable. It appears that much of this predictability comes from stickiness of, or momentum in, the market as a whole. Fourth, we show that mutual funds concentrate their holdings in stocks with minimal stale prices. Still, the returns of mutual funds display predictability which varies over time in a manner that suggests that stale prices are not the primary cause of this predictability.

I. Data

The data used in this study are the Trade and Quote (TAQ) data provided by the NYSE, the CRSP daily stock return files, the CRSP Survivor-Bias Free Mutual Fund File, the mutual fund holdings from the S12 filings as compiled by Thomson/CDA, and tick data for the S&P 500 futures contract from TickData. Wharton Research Data Services (WRDS) was the ultimate source for these data with the exception of the futures data. We include in the analysis all common stocks listed on registered US exchanges and NASDAQ except REITs, ADRs, and limited partnerships, as determined by a share code of 10 or 11 in the CRSP stock file. We also exclude the two classes of Berkshire Hathaway stock as there are many errors in TAQ in the recording of the trade prices of the two classes. We include only diversified domestic equity mutual funds, as determined by an S&P objective code in the CRSP Mutual Fund File of AGG

(Equity US Aggressive Growth), GMC (Equity US Mid-Cap Companies), GRI (Equity US Growth and Income), GRO (Equity US Growth), and SCQ (Equity US Small Companies).

The TAQ data used in this study begin in January 1993 and end in December 2004. For each stock, we record for each day *t* whether the stock traded on its primary market and if so, the last price on the primary market and the time of that price, as well as the last bid and offer on the primary market, where primary is defined as market on which the stock is listed. We merge our TAQ data with data from the CRSP daily stock return file using a mapping file (based on matching cusips) developed by WRDS. We eliminate daily stock observations where the absolute value of the percentage difference between the last trade price from TAQ and the closing price from CRSP exceeded 10% for stock prices less than \$5, 5% for stock prices between \$5 and \$10, and 1% for stock prices greater than \$10. For each stock, we record from CRSP its market value on both day t–1 and day t–2 as the product of the shares outstanding at the end of the day and the closing price from CRSP. The daily stock returns on CRSP are based on consolidated prices that are not always prices from the primary market. To determine the return based upon prices from the primary market, we multiply the CRSP return (plus one) for day *t* by the product of the following ratios: the ratio of last price from CRSP to last price from TAQ for day t–1 and the ratio of last price from TAQ to last price on CRSP for day *t*.

Finally, we merge the holdings of the mutual fund portfolios in the S12 filings from Thompson/CDA and the daily returns from the CRSP Mutual Fund File with our TAQ/CRSP stock data. The S12 filings contain the name, cusip and number of shares of each US stock owned by each domestic equity mutual fund from January 1992 through October 2004, as well as the fund identification number ("fundno") and fund name. The file provides holdings data at quarterly intervals, although most funds report their holdings during these years semiannually as required by the SEC under provisions of the Investment Company Act of 1940.[3] Daily returns, NAVs, names, identification codes ("icdi"), total net assets (TNA), and Standard & Poor Investment Objective Codes of U.S. equity mutual funds for the period January 2001 to December 2004 are from the CRSP Mutual Fund File, originally developed by Carhart (1996). The CRSP mutual fund file reports returns and TNA separately for each share class for each fund. In section IV below, we estimate regressions of daily returns on lagged returns for each

[3] See Wermers (1999) for an excellent discussion of the Thomson/CDA database and the initial analysis of these data. Prior to 1985 mutual funds were required to report their holdings quarterly. Beginning in 1985 the requirement was changed to semiannual reporting, although some funds continued to voluntarily report quarterly. See Wermers (1999) and Alexander, Cici and Gibson (2005) for further discussion about mutual fund reporting practice.

individual share class for each year, and we average the slope coefficients for each class to obtain an overall slope coefficient for the fund. This average weights the slope coefficient for each class by the beginning-of-year TNA for that class. We merge the mutual funds in the CRSP Mutual Fund File with the funds in the S12 filings file using a linking file originally developed by Wermers (2000) and updated by WRDS.[4] We then merge our mutual fund data with the TAQ/CRSP stock data on the basis of the concurrent CUSIP number.

II. Stale Prices and US Equity Portfolios

A necessary condition for stale prices to be the source of predictability in the returns of mutual funds, indexes, or other portfolios is that those portfolios do indeed contain stale prices. This section examines the incidence of stale prices through an update of the findings in Kadlec and Patterson (1999), who analyze NYSE and American Stock Exchange stocks for the years from 1988 through 1992. They find that almost all large-cap stocks trade within the last 15 minutes of the close, but find that a substantial number of small-cap stocks have last trades prior to the last 15 minutes. For the more recent period 1993 to 2004, we find even less evidence of stale prices for both large-cap and small-cap stocks.

For each trade day t, we rank all stocks on their day t–1 market capitalization and partition the stocks into ten deciles. For each stock in a cap-decile, we record for day t the time of its last trade on its primary market and calculate the number of minutes between the trade and the time of the market close. For most days the closing time was 4:00 pm Eastern Time, but on some days the market closed earlier.[5] To permit aggregation across days with different closing times we convert all early closing times to 4:00 pm. This simplifies the reporting of results with no loss of accuracy because our analysis focuses on the number of minutes between last trade and the close. For each cap decile for each day t, we assign each stock, based on its last trade, to a time interval measured relative to the close and compute the market value of all the stocks in

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[4] See Wermers (2000) for details regarding the matching of funds across the two files. The difficulty of the matching arises from the use of different fund identifiers in the two files. The linking file creates a unique identifier for each fund ("wficn") that links "fundno" from Thomson/CDA and "icdi" from CRSP. The matching process uses an algorithm involving fund names, investment objectives, management company names and total net assets.

5 During our sample period the markets closed at 1:00 pm Eastern Time on the following days: Nov 26, 1993, Nov 25, 1994, Jul 3 1995, Nov 24,1995, Jul 5, 1996, Nov 29 ,1996, Dec 24, 1996, Jul 3, 1997, Nov 28, 1997, Dec 24, 1997, Dec 26, 1997, Nov 27, 1998, Dec 24, 1998, Nov 26, 1999, Dec 31, 1999, Jul 3, 2000, Nov 24, 2000, Jul 3, 2001, Nov 23, 2001, Dec 24, 2001, Jul 5, 2002, Nov 29, 2002, Dec 24, 2002, Jul 3, 2003, Nov 28, 2003, Dec 24, 2003, Dec 26, 2003 and Nov 26, 2004. In addition, the markets closed at 2:30 pm Eastern Time on Feb 11, 1994 and at 2:00 pm Eastern Time on Jan 8, 1996

each interval as a percentage of the market value of all stocks in that cap-decile on that day. The intervals varied from short intervals of 5, 10 and 15 minutes at the end of the trading day to two-hour intervals earlier in the trading day. We also compute the percentage of stocks in each cap-decile that did not trade at all during the day. We average these daily percentages over all days from 1993 through 2004 and report the results in Table I.

Consistent with prior studies, Table I shows a monotonic inverse relation between market capitalization and the probability that the last trade is near the end of the day: 99.5 percent of the total capitalization of the largest cap-decile traded within the last 5 minutes of the day; 60.6 percent for the fifth cap decile; 48.1 percent for the sixth cap-decile; and only 13.3 percent of the smallest cap-decile. However, due to the skewed distribution of market capitalization, 96.0 percent of all stocks, weighted by market capitalization, trade within 5 minutes of the close. A similar pattern exists for the percent that traded within the last half hour. Finally, in all but the smallest cap deciles, most stocks trade every day. In the largest-cap decile, virtually every stock traded every day. The percent not trading increases to 2.3 percent for the fifth decile and 21.9 percent for the smallest-cap decile. [6]

There are clear time trends in these percentages. The percentage of stocks that traded at least once during a trading day increased from 1993 through 2004 with the exception of the largest-cap stocks, everyone of which trades virtually every day throughout the sample period (Figure 1). By the end of the period even the smallest stocks were trading almost every day, with a trading percentage of about 88%. There is a marked increase in the percentage of stocks in the smallest-cap decile that trade at the end of the calendar year—a pattern previously identified by Lakonishok and Smidt (1984) for the 1970-1981 period, Keim (1989) for 1972-1987, and Foerster and Keim (2000) for 1926-1990. The percentage of stocks trading near the end of the trade day also increased during the sample period for all cap-deciles (Figures 2 and 3). By the end of 2004, virtually every stock in the largest cap-decile, and 90 percent of the sixth cap-decile, traded within five minutes of the close. At the end of 2004, however, there is still a substantial number of stale prices in small-cap stocks. In the smallest cap-decile, for example, only 25 percent traded within five minutes of the close and only 42 percent with thirty minutes of the close.

[6] This 21.9% value is only slightly lower than the 24.8% value for small-cap stocks reported in Foerster and Keim (2000) for the 1973-1990 period, but their number is computed for NYSE and AMEX stocks only. The Nasdaq stocks in our sample have higher incidence of non-trading.

These results lead to two conclusions. First, the last trade for a non-trivial percentage of small stocks occurs well before the close of trading. Second, the last trade for most stocks, when aggregated by market capitalization, occurs within the five-minute interval before the close of trading, particularly in the latter part of the sample period.

III. Predictability of Returns

As mentioned above, Chalmers, Edelen and Kadlec (2001) (hereafter CEK) and Zitzewitz (2003) identify significant predictability in domestic equity mutual fund returns. In this section we ask whether such predictability is due to stale prices. Because domestic equity mutual funds might hold foreign securities (the prices of which can indeed be stale) and because the composition of their portfolios changes over time, we replicate the CEK and Zitzewitz analyses using daily returns for ten portfolios of US stocks formed on market capitalization (cap-decile portfolios) that are not subject to such potential experimental shortcomings. In the first set of tests we use lagged price changes in S&P 500 futures to predict portfolio returns and the results confirm the findings in CEK and Zitzewitz.[7] We then use the lagged returns of cap-decile portfolios to predict their subsequent returns and find that the lagged returns predict at least as well as, and usually better than, lagged S&P futures price changes. However, we develop a model of predictability resulting from stale prices and find that the incidence of stale prices explains little if any of the observed patterns and magnitudes of predictability from lagged returns over time. We conclude this section with tests of an econometric model that indicates that much of any stickiness in prices of individual securities stems from the stickiness in the return of the market itself.

A. Construction of the Cap-Decile Portfolios

To construct the cap-decile portfolios, we rank all US common stocks on December 31 of each year by their December 31 market capitalization and partition these stocks equally into ten deciles. For each decile for the following year, we compute value-weighted daily portfolio

[7] Zitzewitz regresses daily returns of domestic equity mutual funds on lagged S&P 500 futures price changes measured 2:00 to 4:00 pm on the prior trade day and CEK on lagged futures from 2:00 to 3:55 pm. CEK exclude the last five minutes to allow sufficient time for a trader to place an order with a mutual fund before 4:00 pm. In an analysis not reported here, we find that the regressions results are virtually identical whether the last five minutes of the futures returns are included or not. Thus, the analysis below excludes the last five minutes of trading to allow time for trading.

returns for each day t using the market values of the stocks as of day t–2 as an instrument to measure the market value as of t–1. We use an instrument because the calculated market value-weight at t–1 is based on the same possibly stale price used in the denominator of the return for day t. Blume and Stambaugh (1983) show that in a value weighted portfolio, the stale price in the weight cancels the stale price in the denominator of the return, neutralizing any biases that might arise from stale prices. Any stock that is delisted during the year is dropped from the portfolio as of the date of delisting and the proceeds are reinvested proportionally to the market value of each remaining stock. Any stock that is newly listed during the year is not added to the portfolios until the following year.

B. Futures as Predictors

In conformity with CEK and Zitzewitz, we estimate the following regression for each of the cap-decile portfolios

$$R_{i,t} = a_0 + a_1 R_{SP500,t-1} + e_{i,t} \, , \qquad (1)$$

where $R_{i,t}$ is the daily return for cap-decile portfolio i for day t and $R_{SP500,t-1}$ is the S&P 500 futures price change over the interval from 2:00 to 3:55 pm for day t–1. The results for the overall 1993-2004 period are generally consistent with the results reported by CEK and Zitzewitz for mutual fund returns (Table II, Panel A). For the second through the tenth decile, the slope coefficients are positive and significant, ranging from 0.189 to 0.254. These estimates are similar to the CEK estimates, which range from 0.098 (large-cap domestic equity mutual funds) to 0.213 (small-cap domestic equity mutual funds) for February 1998 to March 2000, and the Zitzewitz estimate of 0.29 (mid- and small-cap domestic equity mutual funds) for January 1998 to October 2001. Only for the largest cap-decile portfolio do the lagged S&P 500 futures provide no predictability.

To check the sensitivity of the results to the intra-day interval over which the S&P 500 futures return is measured, we re-estimated equation (1) using the S&P 500 futures return from 9:30 am until 3:55 pm for day t–1 (Table II, Panel B).[8] For the second through the tenth decile,

[8] CEK find that the return on the S&P futures from 2:00 to 3:55 is a better predictor of mutual fund returns than the return on the S&P futures for the full day. Their sample was from February 1998 through March 2000. We replicated our results for our cap-decile portfolios over their sample period. We still find that the regression using

the futures return for the longer intra-day interval has uniformly more predictive power as measured by the adjusted R^2.

The significant predictability in Panels A and B for the larger cap-decile portfolios that contain few stocks with stale prices requires explanation (especially deciles 2 and 3). One possible explanation is that the stale prices of these few stocks are sufficient to cause predictability at the portfolio level. To rule out this possibility, we reconstruct the cap-decile portfolios to include only those stocks whose last price on day $t-1$ occurred within the last five minutes of trading, on the assumption that any trade price within the last five minutes of trading is not stale. The security returns in these modified cap-decile portfolios are weighted, as above, by their market values two days before. Even with returns computed with non-stale end-of-day prices the slope coefficients for the second through tenth cap-decile portfolios are positive and significant (Table II, Panel C), indicating that stale prices are not the reason for the observed predictability. We recognize that investing in this type of portfolio may be infeasible as it would involve buying and selling a possibly large number of stocks within the last five minutes of each day. Yet, it does provide a valid statistical test of predictability.

C. Fair-value Price Adjustments

To eliminate the impact of stale prices, CEK, Zitzewitz and others including the SEC have recommended using "fair-value" prices for the fund's securities when computing the end-of-day NAV. In this section, we analyze the efficacy of two versions of fair value pricing. The first version, employed by CEK, adjusts the last price on day *t* by changes in S&P futures prices from the time of the stock's last trade to the close. For example, if the last transaction price is at 11:05 am, we multiply this price by one plus the return on the S&P futures from 11:05 am until 4:00 pm. Using stock returns calculated with these adjusted prices, we recomputed the cap-decile portfolio returns and re-estimate equation (1). The results show that this adjustment does eliminate some of the portfolio return predictability (Table II, Panel D). The coefficient estimates for the second and third largest cap- decile portfolios are slightly lower than in panels A to C, but significant predictability remains. These results for large-cap stocks are not surprising in view of the limited number of stale prices in these deciles. There is, however, a greater reduction in the predictability for the fourth through seventh cap-decile portfolios,

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the return on the S&P future for the full day has greater adjusted R^2 values than the regressions using S&P futures beginning at 2:00, although the differences are less for this subperiod than for the 1993-2004 period in Table II.

although most of these coefficients are still significant. The slope coefficients for the eighth through tenth cap-decile portfolios are now negative, suggesting that this version of "fair-value" pricing over-adjusts prices for small-cap stocks, although the t-values are close to zero.

In the second fair-value adjustment, we replace each last-trade price on day *t* with the midpoint of the bid and ask prices at the end of the day. This approach has been used by others in estimating intraday returns (e.g., Chordia, Roll and Subramanyam (2005)). Using the same example as above, we take a last-trade price at, say, 11:05 am and multiply it by the ratio of the closing mid-point to the price at 11:05. The results in Panel E of Table II show that this adjustment does not reduce predictability but rather increases it in comparison to the results in Panel C.

In summary, fair-value pricing methods that use intra-day S&P 500 futures returns to adjust for staleness remove most of the predictability of returns for the smaller cap-deciles, but have little effect on the larger cap-deciles, as might be expected from the limited number of stale prices in these deciles. Using the midpoint of the closing bid and ask prices to adjust for staleness does not reduce predictability for any of the cap-decile portfolios, indicating that this approach to fair-value pricing does not achieve its goals.

D. Past Returns as Predictors

If stale prices are the explanation for predictability, then S&P 500 futures price changes measured over the interval *prior to* the last trade of a stock should have no predictability. Only the futures price change occurring *after* a stock's last trade on day *t*-1 should predict returns on day *t*. And in the larger cap-deciles, where there are few stale prices, the S&P futures return over the entire day should have little or no explanatory power. The finding that the S&P futures return measured over the entire day has greater explanatory power than when measured over a shorter end-of--day interval (Table II, Panels A and B) is inconsistent with this reasoning.

If not stale prices, what can explain this predictability? In its final ruling entitled "Disclosure Regarding Market Timing and Selective Disclosure of Portfolio Holdings", the SEC concluded that a significant number of fund complexes disclosed portfolio information "that may have provided certain fund shareholders with the ability to make advantageous decisions to place orders for fund shares." If so, the past returns of the funds themselves may be useful in predicting future returns. This possibility is consistent with the predictability results in panel B of Table II.

We begin by developing a model of returns that allows for stale prices and establishes bounds on the predictability of portfolio returns with lagged portfolio returns due to these stale prices. Assume that returns for all securities are generated by the same one-factor model

$$r_{it} = \mu + \pi_t + \varepsilon_{it},$$

where μ is the expected return, π_t and ε_{it} are mean-zero independent random variables representing market and idiosyncratic components respectively, and π_t has a constant variance over time. We make the extreme assumption that if there is a stale price, the price is exactly one day old. In a portfolio of n securities with equal weights, x is the proportion of securities with stale prices. In this case, the measured return on a portfolio at time t is

$$r_{pt} = \mu + (1-x)\pi_t + x\pi_{t-1} + \overline{\eta}_t,$$

where $\overline{\eta}_t$ is an average of the appropriate ε_t's and ε_{t-1}'s.

The slope coefficient b in the regression of r_{pt} on $r_{p,t-1}$ is

$$b = \frac{Cov(r_{pt}, r_{p,t-1})}{Var(r_{pt})}$$

$$= \frac{x(1-x)\sigma^2(\pi)}{[(1-x)^2 + x^2]\sigma^2(\pi) + v(\vec{\varepsilon})},$$

where $v(\vec{\varepsilon})$ is the variance of the weighted sum of the appropriate ε's. If short sales are not allowed, $x \in [0,1]$ and b has a lower bound of zero. Since $v(\vec{\varepsilon})$ is positive, we have

$$0 \le b \le \frac{x(1-x)}{(1-x)^2 + x^2}.$$

If $v(\vec{\varepsilon})$ is close to zero, as it will be for a portfolio with a large number of securities, b will approximate the upper bound. When x is 0, the upper bound is zero. The upper bound increases with x for values of x up to 0.5. For $0 < x < 0.5$, it can be shown that the upper bound exceeds x, with the difference initially increasing and then decreasing in x. For example, when $x = 0.01$, the upper bound is 0.011; when $x = 0.30$, the upper bound is 0.36; and when $x = 0.45$, the upper bound is 0.49. At $x = 0.5$, the upper bound is at its maximum, with a value of 0.5. For $0.5 < x < 1$ we have the mirror image of $0 < x < 0.5$ with the upper bound now decreasing in x. At $x = 1.0$, the upper bound is again zero. The intuition is that at $x = 0$ there are no stale prices, and at $x = 1.0$ all prices are stale. In either case, there is no inter-day overlap in the common market factor. Similarly, the upper bound is the same for both *x* and 1–*x* as there is the same amount of inter-day overlap for both levels of non-trading.

We estimate equation (1) using the prior-day returns on the cap-decile portfolios in place of the prior-day futures price changes and compare the estimated coefficients to the bounds established above.[9] The results show that lagged returns do provide more predictability than lagged futures price changes, as measured by the adjusted R^2 (Table III, Panel A). However, the estimated coefficient for each cap-decile portfolio except the largest one greatly exceeds the corresponding upper bound reported in panel B. These upper bounds are computed using the percentage of the securities in the cap-decile portfolio that did not trade during the entire day, as reported in the bottom row of Table I, measured over the 1993-2004 period. Adding the S&P futures to the prior-day returns in the regression shows that futures returns provide additional explanatory power (Table III, Panel C).

There are clear time-trends in the coefficients on prior-day cap-decile returns when we estimate these regressions separately for each of the twelve years in our sample period (Table IV). These trends are not consistent with the trends in daily non-trading implied in Figure 1. For the larger cap-decile portfolios, the slope coefficients decline over the sample period and are generally insignificant after 1999 despite very little change in nontrading for these stocks over the period. The reverse occurs for the smaller cap-decile slope coefficients. Indeed, the smaller cap-decile coefficients are for the most part not significant from 1993 through 1996 despite the greater degree of staleness in small-cap prices during those years.

E. Stale or Sticky?

Even though the larger cap-decile portfolios contain few (if any) stale prices, the finding of significant predictability in the returns of these portfolios casts doubt on the validity of stale prices as an explanation of return predictability. Thus we consider two alternative hypotheses. The first hypothesis is that the observed prices of individual stocks – even if observed at the end of the trade day – differ from their true value by an independent random variable, giving rise to an apparent nonsynchronous adjustment of the returns of individual stocks. This is the same

[9] The analysis here is related to the large literature on sources of autocorrelation in portfolio returns. This literature examines nonsynchronous trading, market frictions and time-varying returns as possible sources of positive autocorrelation. In addition to the previously-mentioned paper by Fisher (1966), an (admittedly) incomplete list of related papers includes Atchison, Butler and Simonds (1987), Boudoukh, Richardson and Whitelaw (1994), Conrad and Kaul (1988), Kadlec and Patterson (1999), Keim and Stambaugh (1986), Lo and MacKinlay (1990a), Mech (1993), and Scholes and Williams (1977).

effect hypothesized by Fisher (1966) to explain predictability of index returns, and subsequently analyzed by Blume and Stambaugh (1983) to identify biases in portfolio returns and by Roll (1983) to estimate bid-ask spreads. In the context examined here, however, the effect is not due to staleness. The second hypothesis is that the return on the market is sticky, and returns of individual securities are randomly distributed around this sticky market return.

E.1. A Simple Model

To motivate the price dynamics that allow us to distinguish between these hypotheses, we follow Blume and Stambaugh (1983) and let $\hat{P}_{it} = P_{it}(1+\delta_{it})$, where P_{it} is the true end-of-day price of security *i* on day *t*, $\hat{P}_{it}$ is the observed end-of-day price, and the error δ_{it} is a mean-zero independent random variable with variance $\sigma(\delta)$, which is constant over time and is the same for all securities. The error could be due to a bid-ask effect or to nonsynchronous adjustments in the observed prices. Define the true return R_{it} as $P_{it}/\ P_{i,t-1}$ with constant mean μ and the observed return $\hat{R}_{it}$ as $\hat{P}_{it}\ /\hat{P}_{i,t-1}$.

With this notation, the covariance between observed returns on day *t* and day *t*–1 can be expressed as

$$Cov(\hat{R}_{i,t},\hat{R}_{i,t-1}) = E\left[R_{i,t}R_{i,t-1}\frac{1+\delta_{i,t}}{1+\delta_{i,t-2}}\right] - E\left[R_{i,t}\frac{1+\delta_{i,t}}{1+\delta_{i,t-1}}\right]E\left[R_{i,t-1}\frac{1+\delta_{i,t-1}}{1+\delta_{i,t-2}}\right]$$

After expanding the ratio denominators in a Taylor series, making the further assumption that $-1<\delta_{i,t}<1$, and dropping third and higher moments,[10] we have

$$\begin{aligned} Cov(\hat{R}_{it},\hat{R}_{i,t-1}) &\approx \left[E(R_{it}R_{i,t-1})(1+\sigma^2(\delta))\right] - \left[\mu^2(1+\sigma^2(\delta))^2\right] \\ &= (1+\sigma^2(\delta))\left[Cov(R_{i,t},R_{it-1})-\mu^2\sigma^2(\delta)\right] \\ &\approx (1+\sigma^2(\delta))\left[Cov(R_{i,t},R_{it-1})-\sigma^2(\delta)\right], \end{aligned} \qquad (2)$$

where the last approximation holds if $\left|\mu^2-1\right|$ is much smaller than $\sigma^2(\delta)$. Roll (1984) employed a similar model to estimate bid-ask spreads with the assumption that $Cov(R_{i,t-1},R_{it})$ is zero.

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[10] The ratio can be written as $E\{1/(1+\delta_{i,,t})\} = E\{1-\delta_{i,,t}+\delta^2_{i,,t}-\ldots\} \approx 1+\sigma^2\{\delta_{i,,t}\}$.

The first term in brackets in equation (2), $Cov(R_{i,t-1}, R_{it})$, measures persistence in true returns and reflects stickiness or momentum induced by common factors. The second term in brackets $\sigma^2(\delta)$ is a measure of the bias induced by measurement error in observed returns from either bid-ask effects or nonsynchronous prices (Blume and Stambaugh (1993)). The relative magnitudes of these two terms will determine the magnitude and the sign of the autocovariance in observed returns. First, if $Cov(R_{i,t-1}, R_{it}) \le 0$ and $\sigma^2(\delta) > 0$, then $Cov(\hat{R}_{i,t-1}, \hat{R}_{it})$ is negative. There is ample evidence of negative autocovariance in security returns, going back at least to Niederhoffer and Osborne (1966). Second, in the case of positive covariance in true returns (induced by stickiness in the common factor), both $Cov(R_{i,t-1}, R_{it}) > 0$ and $\sigma^2(\delta) > 0$. In this case, $Cov(\hat{R}_{i,t-1}, \hat{R}_{it})$ could be positive or negative depending upon the relative magnitudes of $Cov(R_{i,t-1}, R_{it})$ and $\sigma^2(\delta)$. Third, if the influence of sticky prices in the common factor more than offsets any influence from a bid-ask effect or nonsynchronous prices, then $Cov(R_{i,t-1}, R_{it}) > \sigma^2(\delta)$ and $Cov(\hat{R}_{i,t-1}, \hat{R}_{it})$ is positive. Because the potential influence on returns of bid-ask effects and nonsynchronous prices is greater for smaller-cap stocks than for larger-cap stocks, we expect positive values of $Cov(\hat{R}_{i,t-1}, \hat{R}_{it})$, if any, to be more prevalent for larger-cap stocks for which the stickiness in true returns will dominate the effects of bid-ask spreads and nonsynchronous prices on observed returns.

E.2. Tests of the Model

To remove the effect of stale prices on observed returns, we analyze pairs of returns that are based on three consecutive non-stale prices on the primary market. A price for the last trade on the primary market is defined as non-stale if that trade occurs within five minutes of the close. Each return pair is designated by the security *i* and the date of the last return *t,* and we allocate each pair of returns to the ten market cap deciles used above. Panel D in Table V contains the number of "non-stale" pairs of returns as a percentage of the total number of observations for each market cap decile for the overall sample period, and also for three four-year subperiods. For the larger cap-deciles, this restriction does not eliminate many observations because there are few stale prices for the larger-cap stocks, especially in the 2001-2004 period. For smaller-cap deciles, this restriction eliminates a larger percentage of observations, and we need to be cognizant of this reduction in sample size when the interpreting the subsequent results.

As the first step in examining the impact of using only non-stale prices, we re-estimate the regressions of cap-decile returns on lagged cap-decile returns, but using the non-stale return pairs. For each day t, we assign each pair of adjacent-day non-stale returns, $(\hat{R}_{i,t-1}, \hat{R}_{it})$ to its proper cap-decile and average the individual security return pairs within a cap-decile to obtain pairs of "portfolio" returns, $(\hat{R}_{t-1}, \hat{R}_{t})$. It should be noted for a specific cap-decile that the securities in the pair at time t may differ from those securities in the pair at time t–1. Unlike the cap-weighted returns used in prior sections, the portfolio return pairs are equally weighted. As each pair contains possibly different securities, a capitalization weighting might give very different weights to the same security over time.

Our tests using returns based on these non-stale prices provide further confirmation that stale prices are not the reason for the predictability of portfolio returns. To begin, we concatenate within each cap-decile the portfolio return pairs for the entire sample and then regress the portfolio return for day t on the portfolio return for day t–1. The estimated slope coefficients are reported in Panel A of Table V for the 1993-2004 period, and also for three four-year subperiods. The slope coefficients for all the cap-deciles for 1993-2004 are positive and significant. The coefficients for cap-deciles 1 through 8 for 1993-2004 are, with minor differences, similar to those in Panel A of Table III. However, the coefficients for the two smallest cap-deciles for 1993-2004 are 33% and 40% higher in Table III than in Table V. These results are not unexpected given the paucity of stale prices in the larger cap-deciles, and the larger number in the smallest cap-deciles. This is evidence that the existence of stale prices in portfolios containing small-cap stocks does indeed contribute to predictability in those portfolio returns. Similar to the results in Table IV, subperiod regressions show that the predictability of portfolio returns by lagged portfolio returns declines over time for the larger cap-decile portfolios and increases for the smaller cap-deciles.

That stale prices are not the primary reason for the predictability of returns leaves us with the hypotheses that prices of individual securities are sticky or that the market itself is sticky, or a combination of both hypotheses. We try to unravel these hypotheses with two tests that focus on individual security returns rather than portfolio returns. The first test concatenates the pairs of returns for all individual securities across all days within a market cap decile and regresses the returns for day t on the returns for day t–1 (Table V, Panel B). The slope coefficients for 1993-2004 are positive with the exception of the second smallest cap-decile, and the slope coefficients for the six largest cap-deciles are all significant at the five percent level. From the above model, this finding implies that $Cov(R_{i,t-1}, R_{it}) > \sigma^2(\delta)$. Thus, at least a portion of the predictability of portfolio returns is due to predictability or momentum in the true returns. The generally smaller and even negative coefficients for the smaller cap-deciles may be attributable to some combination of larger proportional bid-ask spreads in less liquid markets and nonsynchronous adjustments effect with the result that $Cov(R_{i,t-1}, R_{it}) \leq \sigma^2(\delta)$.[11]

The second test addresses the hypothesis that $\sigma^2(\delta) > 0$. To isolate this error-related component of predictability, we first remove the component associated with predictability in the market factor from observed security returns. Specifically, we subtract from each observed security pair ($\hat{R}_{i,t-1}, \hat{R}_{it}$) the average portfolio return pair ($\hat{R}_{t-1}, \hat{R}_t$) for the cap-decile in which the security belongs on each pair of adjacent days. Note that subtracting the cap-decile returns is likely to remove most of this source of predictability, but it may not remove all of it – for instance, there may be differential stickiness or momentum between growth and value stocks in the same cap-decile portfolio. We then estimate separately for each pair of adjacent days a regression using all individual security pairs within a decile. This results in 3021 estimated slope coefficients for each decile, one for each day. Within each decile we average these coefficients and test whether the average differs from zero (Table V, Panel C). For the overall period, the average coefficients are close to zero: three of the ten deciles have negative average coefficients, and only the coefficients for the two largest deciles are significant. Provided we successfully removed the predictable component in true returns with our adjustment, these results are consistent with the hypothesis that bid-ask or nonsynchronous adjustments, $\sigma^2(\delta)$, are very close to zero and have little impact on the autocorrelations of observed returns from 1993 through 2004.

In sum, the results in this section provide strong evidence that the predictability in returns is not just due to stale prices. Using returns that are based entirely on non-stale prices, we find

[11] These results for individual securities are consistent with findings in French and Roll (1986) who find that daily autocorrelations for NYSE stocks during the period 1963-1982 are inversely related to market capitalization – autocorrelations are negative for the smallest stocks and positive for the largest stocks. Earlier, Fama (1965) found that 75% of the Dow30 stocks had significant positive autocorrelations during the period 1957-1962.

predictability in portfolio returns and in individual security returns. This predictability appears to stem more from stickiness in market returns than differential stickiness in the returns of individual securities. Of course, the existence of stale prices in portfolios containing smaller-cap stocks will contribute to predictability in those portfolio returns – whereas the estimated coefficients for cap-deciles 2 through 8 are not sensitive to the elimination of stale prices, the coefficients for the two smallest cap-deciles are substantially lower when portfolios returns are computed with non-stale prices.

IV. A Re-examination of Mutual Fund Predictability

This section shows that U.S. mutual funds investing in U.S. equities concentrate their holdings in the larger cap-deciles where there are few stale prices. Relative to aggregate market proportions, they overweight stocks in the second through fifth cap-deciles and underweight the smaller cap-deciles. Their holdings in the stocks in the largest cap-decile approximate market proportions, even though they substantially underweight the largest 50 stocks. Thus, stale prices should not be a factor in explaining predictability of mutual fund returns. Yet, we find substantial predictability in fund returns that varies over time in ways that mirror the market cap decile results in Section III. The observed patterns and magnitudes of predictability over time are largely inconsistent with the bounds implied by the model of predictability from stale prices developed in section III.D.

A. Holdings

Whether predictability of mutual fund returns is due to the effect of stale prices on the calculation of NAVs depends on the extent to which funds hold smaller stocks. To answer this question, we compare the distribution of mutual fund holdings across market cap deciles to the distribution for the entire market. To construct these distributions, we allocate mutual fund holdings at each year end to ten groups based on the decile breakpoints of the rankings of all NYSE, AMEX and Nasdaq stocks at that year end. We further separate the stocks in the largest market cap decile into 3 subgroups – the largest 50 stocks, the next largest 50 stocks, and the remainder of the decile. Within each of these twelve groups, we sum the year-end values of all the individual holdings allocated to this group across all the equity funds in the Thomson/CDA data, where the value of the individual holdings for each fund equals the year-end share price times the number of shares held in the fund as of the most recent report of that fund. We also compute the total value of all U.S. equities in each these twelve groups. Table VI summarizes these results for the first (1992) and the last (2004) year-ends in our sample.

At the end of 2004, the mutual funds in our sample owned \$1.53 trillion of U.S. stocks, compared to \$14.11 trillion for the entire market (Panel A). The bulk of mutual fund holdings was in the two largest cap-deciles — 79.2% in the largest and 11.4% in the second largest decile. Even though mutual funds tend to hold large stocks, they underweight the top 50 stocks with only 33.7% of the fund holdings in these stocks, compared to 39.8% for the market as a whole.[12] In the four smallest cap-deciles where most of the stale prices occur, mutual funds invested only 0.4% of their equity holdings at the end of 2004, compared to 1.0% for the market as a whole. And for the earlier part of our sample period when "staleness" in prices was more prevalent, equity mutual funds held an even smaller percentage of their portfolios in small-cap stocks (0.14% for the smallest four deciles at year-end 1992 compared to 0.84% for the market as a whole).

Variation in the market cap profile of mutual fund holdings over the sample period is shown in figure 4. The plot shows that over the 12-year period the major shift in investment emphasis has been an increase in tilt of mutual funds toward the largest 50 stocks in the market, with the percentage allocation increasing from 23.1% at the end of 1992 to 33.7% at the end of 2004. This is due in part to the growth of index funds that hold these larger stocks in proportion to their market value. The percentage that mutual funds invested in the smallest seven deciles decreased through 2000 and thereafter increased to about the same level in 2004 as in 1992.

At the end of 2004, the mutual funds classified as Growth and Income, Growth, and Aggressive Growth are, as expected, concentrated in larger cap stocks, with 99.4%, 97.3%, and 89.3% of their portfolios invested in stocks in the two largest cap-deciles, respectively, with virtually no investments in the four smallest cap-deciles. Consistent with their name, the Midcap mutual funds have 45.7% of their portfolios invested in stocks in deciles 2 to 4 at the end of 2004, but inconsistent with their name, they invested 53.5% of their portfolios in the largest cap decile 1. The Midcap mutual funds invested only 0.82% of their portfolios in deciles 6 through 10 – the smaller end of the size spectrum. Despite their name, small-cap mutual funds do not own many small-cap stocks with only 7.2% of the portfolios invested in stocks in the sixth

[12] This underweighting is largely due to the expected extreme underweighting of the largest stocks by the small-cap and mid-cap funds. Indeed, the Growth and Income and Growth funds, which make up 76.0% of the market value of our mutual fund sample at the end of 2004, have an equal or even larger investment in the top 50 stocks compared to the overall market.

through tenth deciles. These same patterns are also evident for year-end 1992 and throughout the sample period.

In sum, most of the mutual funds in our sample – even the self-professed Small Company funds – do not hold stocks from the smallest five cap-deciles. Because stale prices are primarily concentrated in the smallest three or four size deciles, stale prices are unlikely to be the explanation for the previously observed predictability in mutual fund returns. Yet, we can not rule out the remote possibility that the few stale prices that remain (less than 0.5% of the value of holdings across all funds at year end 2004) could lead to the predictability in mutual fund returns that others have observed and from which market timers have profited.

B. Predictability

In this section, we compare the predictability of mutual funds returns to the bounds established in section III.D. Although we find evidence of significant predictability in mutual fund returns for the years 2001 through 2004, this predictability for the most part violates our predicted bounds. The conclusion is that stale prices are not the dominant reason for predictability for the bulk of mutual funds as measured by market value.

We first estimate the slope coefficient of daily returns on lagged daily returns for each equity mutual fund in our sample in each of the years that it appeared in the CRSP Mutual Fund file. [13] We then compute for each fund the variable *Last5* defined as the within-year average of the daily percentage of the market value of the fund's holdings (as reported in the Thomson/CDA database) that *did not* have a final trade price on the primary market during the last 5 minutes before the close. We use the value of *Last5* to compute the upper bound for the estimated slope coefficient for each fund under the extreme assumption that the price of any stock that did not trade in the last five minutes was stale for that entire day. We also record from Thompson/CDA the total value of the holdings of each fund as of the beginning of each year.

[13] We also estimated the model with lagged S&P500 futures price changes, estimated over the intervals 2:00 to 3:55pm and 9:30am to 3:55pm Eastern Time on day *t*-1. Those results are available on request. Like the results for the decile portfolios in section III, the regressions estimated here with lagged fund returns generally have greater explanatory power than the regressions with lagged S&P500 futures.

We also performed the same analysis for international mutual funds and domestic high-grade and low-grade bond funds. As in Zitzewitz, we find strong evidence of predictability for international funds and low-grade bond funds. Because the emphasis of this paper is on U.S. equity returns and because the Thomson/CDA holdings data is restricted to fund holdings of U.S. equities, we do not report these results.

Because there are a large number of funds with virtually zero stale prices, we chose predetermined intervals of *Last5* to partition the data into five stale price groups. The lower end breakpoints for the intervals for each year are: 0, 0.0001, 0.0005, 0.0025, and 0.0150. For each interval within each year we compute the mean of our predicted upper bound for the slope coefficients, the mean of the estimated slope coefficients, the percentage of estimated slope coefficients that are positive, the number of funds, and the sum of the total value of the holdings of all funds in that category. We also compute these statistics across all funds for each year. The results are reported in Table VII.[14]

Although the total holdings of all mutual funds are concentrated in the large cap deciles, where there are few stale prices, there are possibly smaller funds with many stale prices. Using 2001 as an example, only 257, or 23.1 percent, of the funds in our sample have a *Last5* greater than 1.5 percent (Table VII, Panel D). In terms of dollars, the holdings of these funds are $86.0 billion, or 5.5 percent of the total mutual fund holdings of $1,573.2 billion, confirming that these funds are smaller funds (Table VII, Panel E). But even for these 257 funds, the average value of *Last5* was only 7.8% (not shown), which translates into a mean predicted upper bound for the slope coefficient of 0.085.

The average slope coefficients vary across years in sign and magnitude in ways inconsistent with the predictability that stale prices would induce. In 2001 and 2004, the average slope coefficients are positive and considerably larger than the predicted upper bounds with just one exception (Table VII, Panel B). In 2002 and 2003, the average slope coefficients are negative with just two exceptions. Consistent with these averages, 99 percent of the funds had positive slope coefficients in 2001 and 81 percent had positive slope coefficients in 2004. In both 2002 and 2003, only 29 percent are positive (Table VII, Panel C). This pattern in average slope coefficients is similar to the year-by-year variation in estimated coefficients for the five largest cap-deciles portfolios in Table IV. This similarity is expected: Because most of the holdings of mutual funds are in the top five cap-deciles, their portfolios can be viewed as random samplings of these stocks.

Finally, note the average slope coefficients reported by CEK (see their Table III) and Zitzewitz (see his Table I) are larger than our estimated coefficients in 2001, which are the

[14] Because the average values of *Last5* for our sample of mutual funds are small, the average value of the upper bound is in almost every instance equal to *Last5* to three decile places. In only three cases (in the largest *Last5* quintile) is the average upper bound larger to three decile places than *Last5*, the largest difference being 0.007. Therefore, we report only the average values of the upper bound in the table.

largest in our sample. There are two possible reasons for their larger coefficients. First, there may be more stale prices in their sample periods, February 1998 through March 2000 for CEK and January 1998 through October 2001 for Zitzewitz. Second, there may be more stickiness or momentum in the market factor in their sample period. Because there is little difference in the percentage of stale prices in the larger cap-deciles between their sample periods and ours (see figure 4), their evidence of greater predictability is likely due to the second reason.

In summary, the estimated mutual fund coefficients violate the bounds developed in the previous section in almost every *Last5* interval in every year. Thus, it is unlikely that stale prices are the principal cause of predictability in mutual fund returns. Rather, the stickiness or momentum in the market returns that was examined in Section III. E. is the dominant source of this predictability.

VI. Conclusion

For our sample period 1993 to 2004 we find that stale prices are not the reason for predictability in returns of portfolios of US equities in the top half of market capitalization. We confirm the existence of predictability for these large-cap portfolios, but present evidence that this predictability is due primarily to stickiness, or momentum, in the returns of the market factor and not to stickiness in non-stale prices of individual securities. We provide evidence of stale prices for stocks in the bottom half of market capitalization and find that these stale prices augment the stickiness in the market factor in increasing the predictability of the returns of portfolios of these stocks.

Because U.S. mutual funds as a group concentrate their domestic stock holdings in the larger half of market capitalization, stale prices cannot explain predictability in mutual fund returns. Thus, fair-value price adjustments will not eliminate the profitability of market-timing strategies designed to exploit these predictable returns or the resulting wealth transfers from the other mutual fund investors to these market-timers.

One alternative to the ineffective fair-pricing that some funds have used is to limit the number of transactions per year. In our mind, this approach can be gamed, except perhaps in something like a 401(k) plan where the number of funds is limited.. An investor could do short-run trading until the limit is reached and then switch to another fund. If all market-timers employed this strategy, the overall level of market timing might remain unchanged.

Another alternative is a redemption fee, a fee that is returned to the fund and not the management company. A judiciously-set redemption fee that exceeds the expected profits of the market timer would eliminate any benefits to the strategy. In principle, such a fee would be indefinite, but the drawback of an indefinite fee is that it penalizes non-timing investors when they redeem their shares. A way to mitigate this penalty is to eliminate this fee after a period of time. Thus, there is thus a tradeoff between the discouragement of market timing and the liquidity needs of other investor. In economic terms, the optimal policy for setting a redemption fee and a time interval is one where the marginal benefit of deterring the market timer equals the marginal cost of penalizing the non-timer investors when they redeem.

Parallel to this argument, the SEC has recently required that the boards of all mutual funds determine whether a redemption fee of up to 2 percent would be appropriate for their funds. In this regard, Vanguard now places on some of its funds redemption fees of from 0.5 to 2 percent that apply from 2 month to five years after a purchase, and other funds are doing the same.

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Table I

Percent Distribution of Last-Trade Times (Eastern Standard Time) by Market Cap Deciles

Values reported in a column are the percent of the total market capitalization of the stocks represented in that column that traded during the interval associated with that row. For example, 13.31% of the stocks (weighted by market cap) in the smallest market cap decile traded during the last 5 minutes of the day. Daily values are averaged over all days during the period January 1993 to December 2004.

	Market Capitalization Decile										All
Trade Interval	**Largest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Smallest**	**Stocks**
15:55 until closing	99.46	89.73	80.72	71.10	60.62	48.10	35.39	25.70	19.00	13.31	**96.02**
15:45 - 15:55	0.34	5.17	8.21	10.74	12.92	14.28	14.90	14.03	12.48	10.24	1.60
15:30 - 15:45	0.11	2.29	4.17	5.87	7.40	8.92	10.05	10.25	9.87	8.86	0.78
15:30 until closing	99.90	97.19	93.10	87.71	80.95	71.30	60.34	49.98	41.35	32.42	**98.40**
13:30 - 15:30	0.08	2.31	5.37	8.68	12.38	17.03	21.30	24.33	25.81	26.36	1.07
11:30 - 13:30	0.01	0.26	0.77	1.60	2.75	4.34	6.13	7.77	9.19	10.63	0.21
09:30 - 11:30	0.00	0.11	0.35	0.86	1.63	2.78	4.29	5.83	7.11	8.66	0.12
Traded at Least Once	100.00	99.87	99.59	98.86	97.70	95.45	92.06	87.92	83.45	78.07	**99.80**
Did Not Trade	0.00	0.13	0.41	1.14	2.30	4.55	7.94	12.08	16.55	21.93	**0.20**

Table II
Stock Return Predictability by Market Capitalization Decile, January 1993 - December 2004

The table reports estimated slope coefficients from variations on the following model:

$$R_{i,t} = a_0 + a_2 R(SP\ fut)_{t-1} + e_{i,t}$$

where $R_{i,t}$ is the return on cap-decile portfolio i (reconstructed annually) for day t (unadjusted in panels A and B, and adjusted in panels C - D for potential staleness in the prices for the stocks in each decile), and $R(SP\ fut)_{t-1}$ is the S&P 500 futures price change over the specified interval on day t-1. We use three adjustments to portfolio returns to account for nonsynchronous trading. In Panel C, portfolios include only stocks that traded during the last 5 minutes on day t-1. In Panel D, individual stock returns on day t are adjusted for nontrading at the end of both days t and t-1 with SP500 future price changes over the periods of nontrading. In Panel E, individual stock returns are computed with end-of-day mid-spread prices on days t and t-1. T-values are computed with heteroskedasticity-consistent standard errors. Regressions are estimated over the period Jan 1993 to Dec 2004.

	Market Capitalization Decile									
	Largest	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Smallest**
A *. $R_{i,t}$ is the value-weighted cap - decile returns, rebalanced at year-end*										
$R(SP\ fut)_{t-1}$ is the price change from 2 pm - 3:55 pm on day t - 1										
Slope Coef	-0.023	0.210	0.189	0.202	0.205	0.254	0.253	0.238	0.240	0.253
T-value	(-0.44)	(4.32)	(3.58)	(4.21)	(4.58)	(6.51)	(7.37)	(6.68)	(7.67)	(6.57)
Adj R^2	-0.02%	1.28%	0.94%	1.13%	1.36%	2.92%	3.58%	3.51%	3.54%	2.60%
B *. $R_{i,t}$ is the value-weighted cap-decile returns, rebalanced at year-end*										
$R(SP\ fut)_{t-1}$ is the price change from 9:30 am - 3:55 pm on day t - 1										
Slope Coef	0.014	0.152	0.133	0.148	0.153	0.179	0.192	0.175	0.176	0.183
T-value	(0.47)	(5.32)	(4.38)	(5.32)	(6.19)	(8.69)	(10.22)	(8.94)	(9.39)	(7.81)
Adj R^2	-0.02%	1.79%	1.24%	1.62%	2.03%	3.85%	5.48%	5.06%	5.07%	3.61%
C *. $R_{i,t}$ is the VW return for decile i on day t, computed only with stocks that traded during the last 5 minutes on day t-1*										
$R(SP\ fut)_{t-1}$ is the price change from 9:30 am - 3:55 pm on day t - 1										
Slope Coef	0.0131	0.1520	0.1356	0.1577	0.1736	0.2096	0.2176	0.1889	0.1778	0.1970
T-value	(0.44)	(5.25)	(4.31)	(5.17)	(5.78)	(7.45)	(8.15)	(6.53)	(7.45)	(6.97)
Adj R^2	-0.02%	1.70%	1.17%	1.52%	1.82%	3.11%	3.70%	2.96%	2.90%	2.50%
D *. $R_{i,t}$ is the VW decile return adjusted for nontrading at end of days t and t-1 using S&P 500 futures price changes.*										
$R(SP\ fut)_{t-1}$ is the price change from 9:30 am - 4:00 pm on day t - 1										
Slope Coef	0.0175	0.1354	0.1026	0.0962	0.0723	0.0566	0.0289	-0.0115	-0.0310	-0.0417
T-value	(0.59)	(4.87)	(3.49)	(3.54)	(2.92)	(2.66)	(1.42)	(-0.53)	(-1.46)	(-1.65)
Adj R^2	-0.0001	1.49%	0.77%	0.69%	0.43%	0.34%	0.08%	-0.01%	0.10%	0.14%
E *. $R_{i,t}$ is the VW decile return computed with end-of-day mid-spread prices for individual stocks on days t and t-1.*										
$R(SP\ fut)_{t-1}$ is the price change from 9:30 am - 4:00 pm on day t - 1										
Slope Coef	0.0251	0.1609	0.1519	0.1794	0.1920	0.2135	0.2220	0.2103	0.2108	0.2304
T-value	(1.22)	(8.25)	(7.51)	(9.15)	(10.52)	(13.57)	(14.96)	(14.21)	(13.91)	(12.36)
Adj R^2	0.0002	2.19%	1.81%	2.69%	3.53%	5.77%	6.93%	6.29%	6.04%	4.83%

Table III
Stock Return Predictability by Market Capitalization Decile, January 1993 - December 2004

The table reports estimated slope coefficients from variations on the following model:

$$R_{i,t} = a_0 + a_1 R_{i,t-1} + a_2 R(SP\ fut)_{t-1} + e_{i,t}$$

where $R_{i,t}$ is the return on cap-decile portfolio i (reconstructed annually) for day t, and $R(SP\ fut)_{t-1}$ is the S&P 500 futures price change (9:30am to 3:55pm) on day t-1. The predicted upper bound of the estimated a_1 is from the model in section III.D. T-values are computed with heteroskedasticity-consistent standard errors. The regressions are estimated over the period Jan. 1993 to Dec. 2004.

		Market Capitalization Decile									
		Largest	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Smallest**
A.	$\boldsymbol{a_1}$	0.004	0.121	0.094	0.116	0.148	0.229	0.309	0.321	0.318	0.341
	T-value	(0.17)	(4.63)	(3.52)	(4.61)	(5.92)	(8.10)	(10.52)	(10.02)	(10.45)	(10.97)
	Adj R2	-0.03%	1.43%	0.85%	1.31%	2.16%	5.20%	9.53%	10.28%	10.07%	11.73%
B.	**Predicted Upper Bound of Estimated** $\boldsymbol{a_1}$	0.000	0.001	0.004	0.012	0.024	0.048	0.086	0.135	0.191	0.260
C.	$\boldsymbol{a_1}$	-0.017	0.052	0.036	0.060	0.098	0.174	0.255	0.275	0.273	0.313
	T-value	(-0.37)	(1.45)	(1.05)	(1.87)	(3.18)	(5.08)	(7.51)	(7.60)	(8.29)	(9.35)
	a2	0.031	0.111	0.105	0.106	0.094	0.099	0.101	0.092	0.107	0.110
	T-value	(0.59)	(2.80)	(2.72)	(3.00)	(3.06)	(3.86)	(4.56)	(4.10)	(5.35)	(4.89)
	Adj R2	(-0.00)	1.89%	1.28%	1.81%	2.65%	6.07%	10.73%	11.43%	11.71%	12.96%

Table IV

Time Variation in Stock Return Predictability, by Market Capitalization Decile

Estimated slope coefficients from the following model estimated separately in each of the 12 sample annual periods:

$$R_{i,t} = a_0 + a_1 R_{i,t-1} + e_{i,t}$$

where $R_{i,t}$ is the value-weighted return for cap-decile portfolio i for day t. Portfolios are rebalanced annually. Values in **bold** indicate significance at the .05 level. Significance levels are computed with heteroskedasticity-consistent standard errors.

	Market Capitalization Decile									
year	**Largest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Smallest**
1993	**0.1338**	**0.2956**	**0.3193**	**0.2982**	**0.2600**	**0.1892**	**0.2024**	0.0941	0.0939	0.0326
1994	0.0925	**0.3084**	**0.2580**	**0.2079**	**0.2208**	0.1091	0.1713	0.1322	**0.1581**	0.0908
1995	0.0750	**0.2515**	**0.2224**	**0.2010**	**0.1713**	**0.1710**	0.1583	**0.2052**	0.0563	0.0553
1996	**0.1513**	**0.2218**	**0.2154**	**0.2312**	**0.2418**	**0.1935**	0.1625	**0.1844**	0.1451	**0.1872**
1997	0.0791	**0.2301**	**0.3139**	**0.3358**	**0.3357**	**0.3141**	**0.3249**	**0.3619**	**0.2774**	**0.2538**
1998	0.0239	**0.2130**	0.2102	**0.2536**	**0.2927**	**0.3185**	**0.2970**	**0.2382**	**0.2826**	**0.2678**
1999	-0.0233	**0.1111**	**0.1497**	**0.1697**	**0.2138**	**0.2359**	**0.3595**	**0.2032**	**0.2094**	**0.2605**
2000	-0.0233	0.0744	**0.1027**	**0.1395**	**0.2155**	**0.3243**	**0.3578**	**0.3423**	**0.3933**	**0.4777**
2001	0.0137	0.1164	0.0938	**0.1348**	**0.2212**	**0.2939**	**0.3495**	**0.4460**	**0.4512**	**0.5506**
2002	-0.0222	0.0155	-0.0631	-0.0689	-0.0699	0.1248	**0.2653**	**0.3762**	**0.3269**	**0.3133**
2003	**-0.1187**	0.0425	0.0245	0.0792	0.0935	**0.1522**	**0.3143**	**0.4117**	**0.2993**	**0.2539**
2004	0.0035	**0.1322**	0.0031	0.0025	0.0049	0.0710	**0.2553**	**0.3652**	**0.3652**	**0.3107**

Table V

Sticky Individual Stock Returns or Sticky Market Returns? Tests of Hypotheses

To remove the effect of stale prices on observed returns, we analyze pairs of returns that are based on three consecutive non-stale prices on the primary market. A price for the last trade on the primary market is defined as non-stale if that trade occurs within five minutes of the close. Each return pair is designated by the security i and the date of the last return t, and we allocate each pair of returns to the ten market cap deciles used above. In Panel A we re-estimate the regressions of cap-decile returns on lagged cap-decile returns, but using the non-stale return pairs. For each day t, we assign each pair of adjacent-day non-stale returns $(R_{i,t-1}, R_{i,t})$ to its proper cap-decile and average the individual security return pairs within a cap-decile to obtain pairs of "portfolio" returns (R_{t-1}, R_t). For a specific cap-decile, the securities in the pair at time t may differ from those securities in the pair at time $t-1$. The portfolio return pairs are equally weighted. In Panel B we concatenate the pairs of returns for all individual securities across all days within a market cap decile and regress the returns for day t on the returns for day $t-1$. In panel C we remove the component associated with predictability in the market factor from observed security returns to isolate the error-related component of predictability. Specifically, we subtract from each observed security pair $(R_{i,t-1}, R_{i,t})$ the average portfolio return pair (R_{t-1}, R_t) for the cap-decile in which the security belongs on each pair of adjacent days. We then estimate separately for each pair of adjacent days a regression using all individual security pairs within a decile. This results in 3021 estimated slope coefficients for each decile, one for each day. Panel D contains the number of "non-stale" pairs of returns as a percentage of the total number of observations for each market cap decile for the overall sample period, and also for three four-year subperiods. Values in bold indicate significance at the .05 level. Significance levels in Panels A and B are computed with heteroskedasticity-consistent standard errors.

A. *Portfolio Returns on Lagged Portfolio Returns with no Stale Prices*

	Largest	2	3	4	5	6	7	8	9	Smallest
1993-2004	**0.0638**	**0.1266**	**0.1098**	**0.1527**	**0.2223**	**0.2658**	**0.3290**	**0.3377**	**0.2386**	**0.2429**
1993-1996	**0.1706**	**0.3057**	**0.2853**	**0.2531**	**0.2339**	**0.1120**	**0.1400**	0.0674	-0.0110	0.0012
1997-2000	**0.0914**	**0.1607**	**0.1892**	**0.2454**	**0.3280**	**0.3442**	**0.3662**	**0.3372**	**0.2521**	**0.2584**
2001-2004	0.0287	0.0649	0.0183	0.0554	**0.1109**	**0.2275**	**0.3334**	**0.3795**	**0.2347**	**0.2153**

B. *Security Returns on Lagged Security Returns with no Stale Prices*

	Largest	2	3	4	5	6	7	8	9	Smallest
1993-2004	**0.0081**	**0.0171**	**0.0103**	**0.0066**	**0.0109**	**0.0109**	**0.0120**	**0.0044**	**-0.0092**	**0.0074**
1993-1996	**0.0067**	**0.0232**	**0.0095**	**0.0169**	**-0.0108**	**-0.0089**	**0.0245**	0.0015	-0.0068	-0.0419
1997-2000	**-0.0006**	**0.0130**	**0.0211**	**0.0218**	**0.0241**	**0.0137**	**0.0161**	**0.0275**	**0.0164**	**0.0361**
2001-2004	0.0185	0.0203	-0.0003	-0.0074	**0.0051**	**0.0119**	**0.0059**	**-0.0121**	**-0.0283**	**0.0031**

C. *Mean-Adjusted Security Retuns on Lagged Mean-Adjusted Security Returns with no Stale Prices*

	Largest	2	3	4	5	6	7	8	9	Smallest
1993-2004	**-0.0063**	**0.0050**	**0.0022**	**0.0037**	**-0.0017**	**0.0005**	**0.0045**	**-0.0036**	**0.0010**	**-0.0323**
1993-1996	**-0.0054**	**0.0125**	**0.0016**	**0.0128**	**-0.0134**	**-0.0108**	**0.0032**	-0.0109	-0.0077	-0.0645
1997-2000	**-0.0175**	**0.0039**	**0.0173**	**0.0173**	**0.0117**	**0.0117**	**0.0113**	**0.0006**	**0.0204**	**-0.0075**
2001-2004	0.0040	-0.0015	-0.0126	-0.0191	**-0.0035**	**0.0006**	**-0.0011**	**-0.0006**	**-0.0097**	**-0.0247**

D. *"Non-Stale" Returns as a Percentage of Total Observations*

	Largest	2	3	4	5	6	7	8	9	Smallest
1993-2004	**0.9376**	**0.7240**	**0.5611**	**0.4350**	**0.3260**	**0.2174**	**0.1449**	**0.1096**	**0.1078**	**0.1230**
1993-1996	**0.8579**	**0.4426**	**0.2149**	**0.1328**	**0.0950**	**0.0763**	**0.0688**	0.0801	0.1076	0.1655
1997-2000	**0.9568**	**0.7476**	**0.5228**	**0.3124**	**0.1813**	**0.1161**	**0.0904**	**0.0747**	**0.0798**	**0.0865**
2001-2004	0.9986	0.9838	0.9483	0.8624	**0.7039**	**0.4614**	**0.2765**	**0.1744**	**0.1360**	**0.1170**

Table VI

Distributions of Holdings of US Equities for U.S. Equity Mutual Funds and the Entire U.S. Equity Market (Year End 1992 and 2004)

To construct these distributions, we allocate mutual fund holdings at each year end to ten groups based on the decile breakpoints of the rankings of all NYSE, AMEX and Nasdaq stocks at that year end. We further separate the stocks in the largest market cap decile into 3 subgroups – the largest 50 stocks, the next largest 50 stocks, and the remainder of the decile. Within each of these twelve groups, we sum the year-end values of all the individual holdings allocated to this group across all the equity funds in the Thomson/CDA data, where the value of the individual holdings for each fund equals the year-end share price times the number of shares held in the fund as of the most recent report of that fund. We also report the total value of all U.S. equities in each these twelve groups.

	Decile of Market Value													
	Largest													Total Value
	Top 50 Stocks	Next 50	The Rest	Entire Decile	2nd	3rd	4th	5th	6th	7th	8th	9th	Smallest	($billions)
December 31, 2004														
Value ($billions)														
Equity Mutual Fund Holdings	516.79	202.01	496.13	1,214.93	174.31	73.55	38.17	17.96	8.65	4.09	1.66	0.64	0.13	1,534.09
Entire Equity Market	5,609.30	1,720.53	4,014.07	11,343.90	1,337.62	611.74	343.98	201.01	121.32	74.52	44.09	23.25	8.71	14,110.14
% Holding by Mkt Cap Decile														
All Equity Mutual Funds	33.69	13.17	32.34	79.20	11.36	4.79	2.49	1.17	0.56	0.27	0.11	0.04	0.01	
Growth and Income	45.62	18.20	32.00	95.83	3.56	0.43	0.14	0.03	0.01	0.00	0.00	0.00	0.00	533.71
Growth	39.34	14.74	34.95	89.03	8.26	1.73	0.61	0.25	0.07	0.03	0.01	0.01	0.00	631.54
Aggressive Growth	28.41	9.20	37.29	74.90	14.43	5.59	2.52	1.48	0.76	0.20	0.07	0.01	0.04	83.81
Mid-Cap Companies	0.88	2.11	50.54	53.54	37.23	6.81	1.61	0.44	0.24	0.10	0.03	0.01	0.00	103.94
Small Companies	0.06	1.05	11.49	12.60	28.92	26.82	16.45	8.03	4.01	1.99	0.81	0.31	0.06	181.09
Entire Equity Market	39.75	12.19	28.45	80.40	9.48	4.34	2.44	1.42	0.86	0.53	0.31	0.16	0.06	
All Mutual Funds - Market	-6.07	0.97	3.89	-1.20	1.88	0.46	0.05	-0.25	-0.30	-0.26	-0.20	-0.12	-0.05	
December 31, 1992														
Value ($billions)														
Equity Mutual Fund Holdings	48.59	29.31	87.54	165.44	28.10	9.39	4.06	1.91	0.87	0.24	0.04	0.01	0.00	210.07
Entire Equity Market	1404.59	494.51	1425.04	3324.13	420.30	162.99	83.84	47.63	28.86	17.22	9.97	5.36	2.05	4102.35
% Holding by Mkt Cap Decile														
All Equity Mutual Funds	23.13	13.95	41.67	78.75	13.38	4.47	1.93	0.91	0.41	0.11	0.02	0.01	0.00	
Growth and Income	29.50	16.64	43.88	90.02	7.49	1.67	0.56	0.20	0.04	0.01	0.00	0.00	0.00	84.69
Growth	22.43	14.36	43.95	80.74	13.31	3.87	1.28	0.53	0.20	0.06	0.01	0.00	0.00	87.12
Aggressive Growth	18.30	12.05	41.67	72.02	19.95	4.40	2.18	0.94	0.41	0.11	0.01	0.00	0.00	20.91
Mid-Cap Companies														
Small Companies	1.37	1.10	19.40	21.87	34.52	21.25	11.65	6.24	3.30	0.89	0.20	0.07	0.02	17.35
Entire Equity Market	34.24	12.05	34.74	81.03	10.25	3.97	2.04	1.16	0.70	0.42	0.24	0.13	0.05	
All Mutual Funds - Market	-11.11	1.90	6.93	-2.28	3.13	0.50	-0.11	-0.25	-0.29	-0.31	-0.22	-0.12	-0.05	

Table VII

Mutual fund return predictability by year and by quintile of percentage of portfolio holdings that didn't trade during the final 5 minutes of trade day t-1. *Last5* categories are computed for each year by computing the within-year average of the percentage of holdings that didn't trade during the final 5 minutes of each day (*Last5*) for each fund, and assigning funds to *Last5* intervals based on fixed breakpoints. Estimated coefficients are from the following regression:

$$R_{i,t} = a_0 + a_1 R_{i,t-1} + e_{i,t}$$

where $R_{i,t}$ is the return for equity mutual fund i for day t. The table organizes the results by year and then by the *Last5* quintile for funds within that year. For the funds within each quintile we report means of the estimated slope coefficients and the predicted upper bound of the slope coefficients for each year, the percentage of positive slope coefficients, the number of funds, and the sum of the total net assets for the funds (from Thompson/CDA) for each year. Results are for the period Jan 2001 to Dec 2004.

Last5 **Interval Breakpoints**	**2001**	**2002**	**2003**	**2004**
A. *Mean Predicted Upper Bound of Slope*				
0 ≤ x ≤ .0001	0.0000	0.0000	0.0000	0.0000
.0001 < x ≤ .0005	0.0002	0.0002	0.0002	0.0002
.0005 < x ≤ .0025	0.0012	0.0013	0.0013	0.0013
.0025 < x ≤ .0150	0.0072	0.0070	0.0070	0.0073
.0150 < x	0.0850	0.0761	0.0735	0.0687
All Funds	0.0209	0.0128	0.0099	0.0073
B. *Mean Slope Coefficients*				
0 ≤ x ≤ .0001	0.0721	-0.0189	-0.0924	0.0249
.0001 < x ≤ .0005	0.0996	-0.0171	-0.0326	0.0513
.0005 < x ≤ .0025	0.1186	-0.0088	-0.0051	0.0562
.0025 < x ≤ .0150	0.1353	-0.0134	0.0158	0.0530
.0150 < x	0.1425	-0.0115	0.0399	0.0517
All Funds	0.1080	-0.0156	-0.0475	0.0386
C. *% Positive Coefficients*				
0 ≤ x ≤ .0001	97.3	20.3	8.1	72.6
.0001 < x ≤ .0005	100.0	26.3	27.2	91.2
.0005 < x ≤ .0025	100.0	35.8	47.1	89.9
.0025 < x ≤ .0150	99.4	36.2	64.8	87.0
.0150 < x	99.2	41.1	68.0	83.5
All Funds	99.3	28.5	28.6	80.5
D. *Number of Funds*				
0 ≤ x ≤ .0001	365	467	558	486
.0001 < x ≤ .0005	190	171	92	148
.0005 < x ≤ .0025	144	106	119	99
.0025 < x ≤ .0150	156	163	125	131
.0150 < x	257	163	122	85
All Funds	1112	1070	1016	949
E. *Sum of Total Net Assets ($Bill)*				
0 ≤ x ≤ .0001	804.7	809.5	831.6	1,069.3
.0001 < x ≤ .0005	366.4	270.1	105.6	218.3
.0005 < x ≤ .0025	208.7	115.9	124.3	109.8
.0025 < x ≤ .0150	107.4	101.0	83.9	119.5
.0150 < x	86.0	62.3	56.3	65.5
All Funds	1,573.2	1,358.8	1,201.8	1,582.4

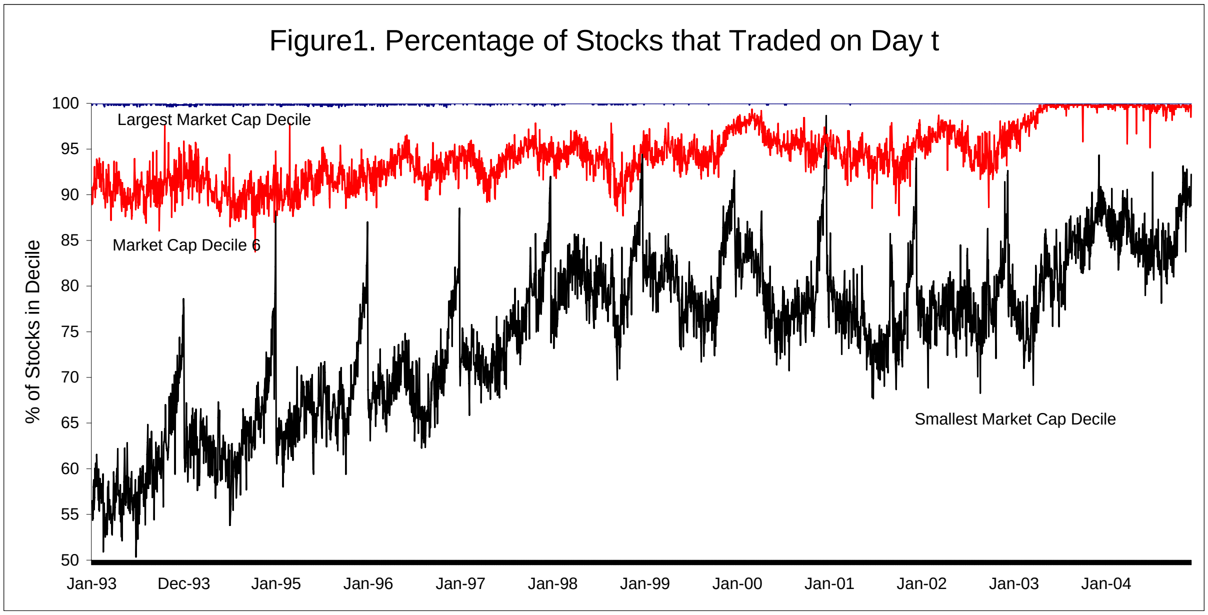

Figure1. Percentage of Stocks that Traded on Day t
% of Stocks in Decile
100
95
90
85
80
75
70
65
60
55
50
Largest Market Cap Decile
Market Cap Decile 6
Smallest Market Cap Decile
Jan-93
Dec-93
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99
Jan-00
Jan-01
Jan-02
Jan-03
Jan-04

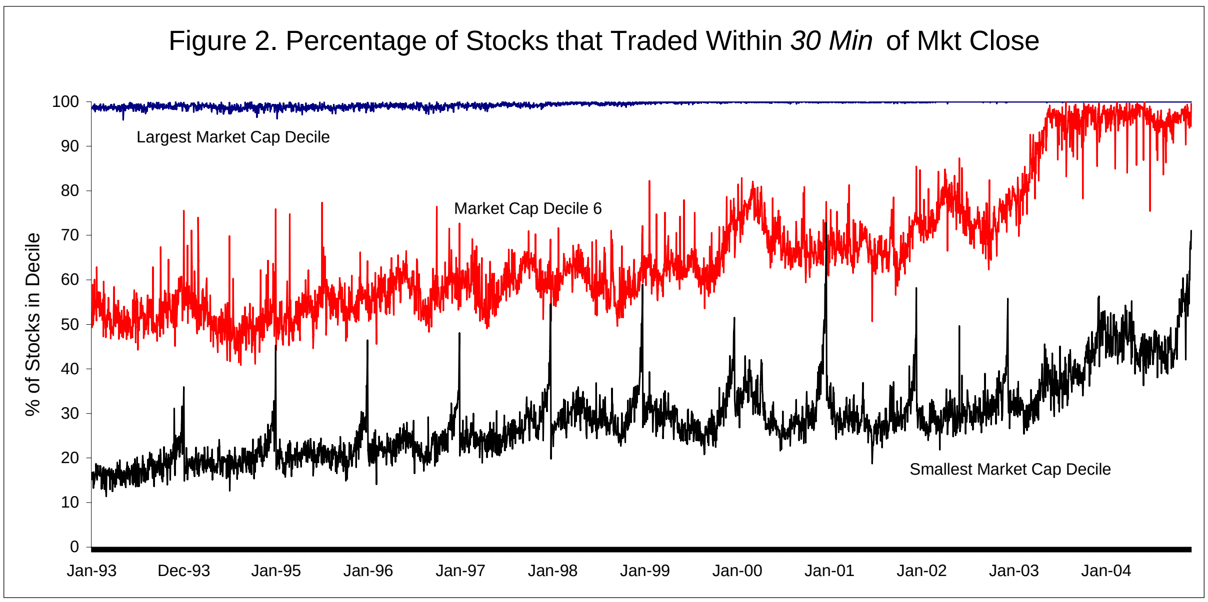

Figure 2. Percentage of Stocks that Traded Within 30 Min of Mkt Close
% of Stocks in Decile
100
90
80
70
60
50
40
30
20
10
0
Largest Market Cap Decile
Market Cap Decile 6
Smallest Market Cap Decile
Jan-93
Dec-93
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99
Jan-00
Jan-01
Jan-02
Jan-03
Jan-04

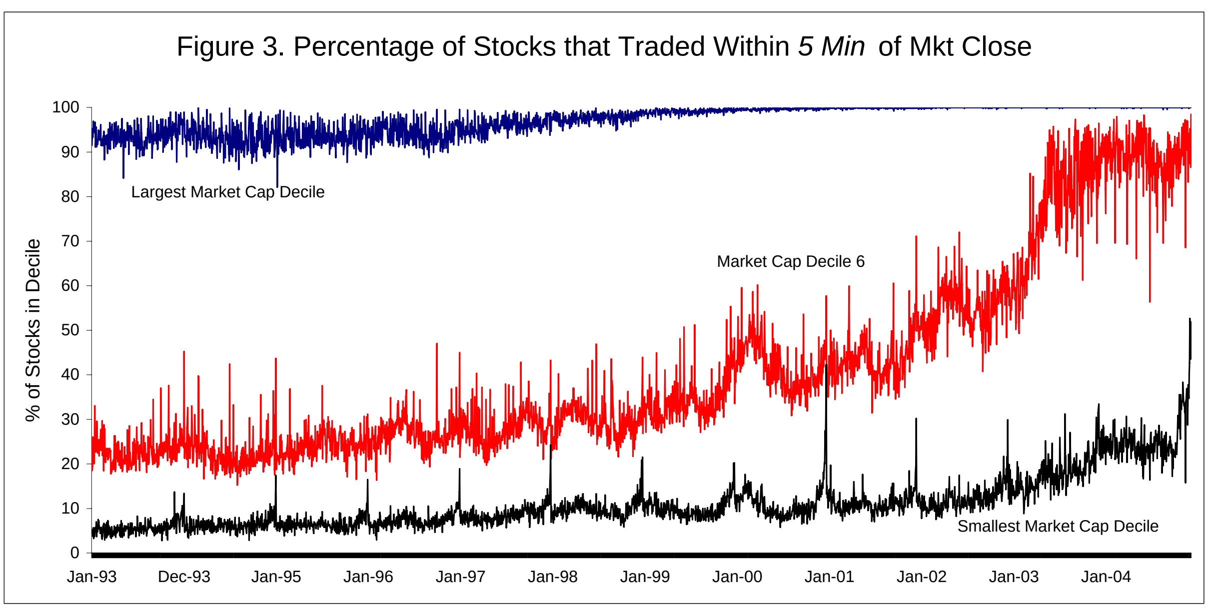

Figure 3. Percentage of Stocks that Traded Within 5 Min of Mkt Close
% of Stocks in Decile
100
90
80
70
60
50
40
30
20
10
0
Largest Market Cap Decile
Market Cap Decile 6
Smallest Market Cap Decile
Jan-93
Dec-93
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99
Jan-00
Jan-01
Jan-02
Jan-03
Jan-04

Figure 4
Distribution of Value of Holdings of U.S. Equities by U.S. Equity Mutual Funds
(Year-end 1992 to Year-end 2004)