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Recent Trends in Trading Activity and Market Quality

Tarun Chordia
Emory University - Department of Finance

Richard Roll
University of California, Los Angeles (UCLA) - Finance Area

Avanidhar Subrahmanyam
University of California, Los Angeles (UCLA) - Finance Area

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Recent Trends in Trading Activity and Market Quality

by

Tarun Chordia, Richard Roll, and Avanidhar Subrahmanyam

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We explore the sharp uptrend in recent trading activity and accompanying changes in market efficiency. Higher turnover has been associated with more frequent smaller trades, which have progressively formed a larger fraction of trading volume over time. Evidence indicates that secular decreases in trading costs have influenced the turnover trend. Turnover has increased the most for stocks with the greatest level of institutional holdings, suggesting professional investing as a key contributor to the turnover trend. Variance ratio tests suggest that more institutional trading has increased information-based trading. Intraday volatility has decreased and prices conform more closely to random walk in recent years. The sensitivity of turnover to past returns has increased and cross-sectional predictability of returns has decreased significantly, revealing a more widespread use of quantitative trading strategies that allow for more efficient securities prices.

Contacts

	Chordia	Roll	Subrahmanyam
Voice:	1-404-727-1620	1-310-825-6118	1-310-825-5355
Fax:	1-404-727-5238	1-310-206-8404	1-310-206-5455
E-mail:	Tarun_Chordia@bus.emory.edu	Rroll@anderson.ucla.edu	asubrahm@anderson.ucla.edu
Address:	Goizueta Business School Emory University Atlanta, GA 30322	Anderson School UCLA Los Angeles, CA 90095-1481	Anderson School UCLA Los Angeles, CA 90095-1481

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We explore the sharp uptrend in recent trading activity and accompanying changes in market efficiency. Higher turnover has been associated with more frequent smaller trades, which have progressively formed a larger fraction of trading volume over time. Evidence indicates that secular decreases in trading costs have influenced the turnover trend. Turnover has increased the most for stocks with the greatest level of institutional holdings, suggesting professional investing as a key contributor to the turnover trend. Variance ratio tests suggest that more institutional trading has increased information-based trading. Intraday volatility has decreased and prices conform more closely to random walk in recent years. The sensitivity of turnover to past returns has increased and cross-sectional predictability of returns has decreased significantly, revealing a more widespread use of quantitative trading strategies that allow for more efficient securities prices.

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I. Introduction

Intense trading activity is a conspicuous aspect of financial markets. For example, the New York Stock Exchange (NYSE) website reports that the share turnover rate on the NYSE in 2008 is well in excess of 100%, corresponding to a volume in excess of 800 billion shares. The investing public paid several billion dollars for these transactions. In his AFA presidential address, French (2008) suggests that the cost of price discovery via trading was about $99 billion in 2006.[1]

Trading activity in equities is not only at high levels, but also has increased dramatically over the past few years.[2] The value-weighted average monthly share turnover (on the NYSE) increased from about 5% to about 26% from the beginning of 1993 to the end of 2008, and the average daily number of transactions increased about ninety-fold during that same period.[3] The aim of this paper is to empirically explore this strong upswing and accompanying changes in market efficiency. Although examining an unusual pattern in trading and accompanying shifts in market efficiency measures are worthwhile pursuits in themselves, our study attains further significance because recent research has found that increases in trading activity are associated with decreases in the cost of equity capital.[4]

There have been previous time-series studies of volume, many of which have focused on the contemporaneous links between volume and other variables such as returns and volatility. For example, a number of empirical papers have documented a positive correlation between volume and absolute price changes (see Karpoff, 1987, Schwert, 1989, and Gallant, Rossi, and

[1] French (2008) includes trading commissions as well as the fees charged by mutual funds and hedge funds in his cost measure, and documents that U.S. investors spent an average of 0.67% of the aggregate value of the market each year over the period 1980-2006 in searching for superior returns.

[2] Apart from the NYSE, a dramatic increase in trading volume is evident in a number of markets, including Nasdaq, the London Stock Exchange and the Tokyo Stock Exchange, among others. See World Federation of Exchanges (http://www.world-exchanges.org/statistics/annual/equity-markets).

[3] In contrast to the trend from 1993 to 2008, turnover remained virtually unchanged at around 4.5% per month during the decade prior to 1993 (NYSE.com).

[4]See Datar, Naik, and Radcliffe (1998), Brennan, Chordia and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001).

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Tauchen, 1992). Other papers document calendar regularities in volume. Amihud and Mendelson (1987, 1991) find that volume is higher at the market's open, while Foster and Viswanathan (1993) demonstrate a U-shaped intraday volume pattern and also find that trading volume is lower on Mondays. Lakonishok and Maberly (1990) observe that volume from institutions is smaller but individual investor volume is larger at the beginning of the week. In another stream of research, Campbell, Grossman, and Wang (1993) and Llorente, Michaely, Saar, and Wang (2002) analyze the dynamic relation between returns and volume levels.

This paper examines the *trend* in trading activity and the impact of this trend on market efficiency measures. Trading costs have declined substantially and this decline has contributed significantly to the volume trends. For example, French (2008) and Chakravarty, Panchapagesan, and Wood (2005) argue that institutional commissions have declined over time, and it is well known (e.g., Chordia, Roll, and Subrahmanyam, 2001) that bid-ask spreads have also decreased substantially. Further, the advent of technology has made it easier for institutions to execute automated algorithmic trading (Hendershott, Jones, and Menkveld, 2008) and online brokerage accounts have made trading easier for retail investors. With lower trading costs, the demand for trading activity has gone up, and with the advent of technology, it has become easier for exchanges to accommodate large trading volumes.

However, recognizing that trading frictions have decreased still leaves several unanswered research questions related to the turnover trend. For example, which types of investors have responded most to decreased frictions? One possibility is that on-line brokerages, lower trading costs, and the accompanying "illusion of control" (Barber and Odean, 2002) has intensified trading by retail investors. Another possibility is that institutional trading (induced perhaps by reduced commissions and spreads) accounts for much of the turnover trend.[5] A third possible factor is the advent of widespread algorithmic trading. Other determinants of trading

[5] Evidence indicates that assets in institutional as well as individual accounts have increased substantially over the sample period. For example, both mutual fund assets and the number of retail accounts grew fourfold from 1996 to 2001 (see Saxton, 2002, and *Charting Success: An Overview of Online Brokerage and Emerging eTrends in the Securities Industry*, 3 April 2001, JP Morgan). This observation makes it particularly intriguing to examine whether institutional or retail investing is primarily responsible for the turnover increase.

activity, such as dispersion of opinion and implied volatility, might have increased and may have contributed to the trend. These possible influences are not mutually exclusive.

A related, and arguably more important, issue involves the economic consequences of the turnover trend. If the trend is largely due to uninformed investing, then the market may have become more volatile and less efficient at incorporating information. Alternatively, trading by more informed agents may well have led to greater information production and a more efficient market with reduced short-run fluctuations.

Motivated by the above observations, we address the following questions: (i) What microstructure patterns have accompanied the sharp increase in turnover? Is the increase due to changes in transaction frequency, or trade size, or both? (ii) Who, amongst institutions or individuals is primarily responsible for the turnover trend? (iii) Is it possible to discern why trading by certain trader classes has increased? (iv) What have been the consequences of the shift in trading activity? Has information-based trading increased? Has market quality increased or decreased? Have there been changes in the cross-section of expected turnover and returns possibly due to the actions of hedge funds that trade on cross-sectional return predictability?

We examine these issues in several stages. First, we establish some basic empirical features of the recent turnover trend. In particular, we show that volume has increased substantially for both S&P 500 constituent larger stocks and non-S&P 500 smaller stocks, suggesting that neither indexation nor market capitalization are responsible for the increase in trading activity.[6] We also document that the turnover increase has principally resulted from smaller trades and a greater frequency of transactions. We then ask whether institutions or individuals are primarily responsible for the increase in turnover. We find that stocks with larger levels of institutional holdings experienced the greatest increases in turnover, indicating a possible causative role for institutions. In addition, changes in the breadth of ownership (as

[6] French (2008) shows that the fraction of US domestic equity invested passively has increased steadily for all four groups of institutions (defined benefit plans, defined contribution plans, non-profits and public funds) examined. For instance, non-profits start with 2.8% of their assets passively managed in 1986, which increased to 28.7% in 2006.

measured by the number of shareholders) are not associated with changes in turnover in the cross-section. Under the supposition that changes in ownership breadth primarily reflect changes in dispersed retail ownership (as opposed to concentrated institutional ownership), this further points to the role of institutions in causing turnover trends. Moreover, daily serial correlation in large trade imbalances have increased the most for stocks with the largest levels of institutional holdings. Since large orders are more likely to be used by institutions, this finding once again suggests that it is institutional trading that has led to the recent increases in trading volume.

While exogenous decreases in trading costs due to technological advances and declines in the tick size are well known and have undoubtedly influenced trading activity,[7] have other known determinants changed in a manner consistent with increases in institutional trading? We consider this question by looking at shifts in analysts' forecast dispersion, equity fund flows, and option-implied volatility. The evidence suggests that the shifts in these determinants during recent years are not nearly as dramatic as shifts in trading activity, and that these determinants play a very modest role in explaining the time-series variation in turnover. This suggests that a secular increase in liquidity and improvements in trading technology are mainly responsible for the increase in trading.

Finally, we turn to the link between increased trading by institutions and price formation. One possibility is that institutions are able to trade more effectively on private information in recent years, thereby contributing to increased market efficiency. A second possibility is that they are able to more effectively trade on findings about cross-sectional return predictability. Evidence supports both of these conjectures. Our analysis of open/close and close/open variance ratios (along the lines of French and Roll, 1986) indicates that increased turnover has indeed been accompanied by increased information-based trading, and this increase is most pronounced for stocks with the highest levels of institutional holdings. Further, intraday volatility has decreased and hourly/daily variance ratios indicate that prices conform more closely to random

[7] As Chakravarty, Panchagesan and Wood (2005) point out, the decline in trading commissions can be attributed to the growth of alternative, automated trading systems as well as online brokerage firms which allow institutions a greater choice of execution venues and, consequently, greater competition between providers of trading services.

walks in recent years, which indicates that increased trading activity has been accompanied by enhanced market quality. Moreover, turnover has become more sensitive in recent years to return predictors that are increasingly employed in quantitative trading strategies used by hedge funds,[8] pointing to the prominent role of these institutions in causing turnover patterns. This pattern also has been accompanied by decreased cross-sectional return predictability. Thus, overall, the most important conclusion from the analysis is that the increased trading activity has been accompanied by increased market quality.

The remainder of this paper is organized as follows. Section II describes the data. Section III presents preliminary evidence on the increase in trading activity. Section IV provides evidence that the increase in turnover is likely due to increased institutional trading. Section V analyzes the association between greater institutional trading and price formation, while Section VI concludes.

II. The Data

The sample period 1993 to 2008 was chosen because the Trade and Quote (TAQ) data are available from the New York Stock Exchange (NYSE) beginning in 1993. The sample consists of NYSE-listed stocks only. This avoids aggregating volume across exchanges with different trading protocols. [9]

Stocks are included or excluded during a calendar year depending on the following criteria:

- To be included, a stock has to be present at the beginning of the year in both the CRSP and the intraday (TAQ) databases.
- If a firm changed exchanges during a year it was excluded from the sample for that year.

[8] Fung and Hsieh (2000, 2002) discuss the hedge fund strategies based on empirical return predictors.

[9] During the early years of our sample, the dealer is always assumed to take the other side of every transaction on Nasdaq, as opposed to often acting as an intermediary (see Atkins and Dyl, 1997). This leads to trades being "double counted" and artificially inflates volume on Nasdaq relative to that on NYSE. However, the definition of Nasdaq volume has changed over time to include only customer-to-customer transactions (Anderson and Dyl, 2005). This change in interpretation of Nasdaq volume over time makes the dynamic analysis of Nasdaq volume, and its comparison to NYSE volume, problematic.

- Since their trading characteristics might differ from ordinary equities, assets in the following categories were also removed from the sample: certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks and REITs.
- Any stock with price greater than $999 was deleted from the sample.

Given that a stock is included in the sample, its transaction data are filtered for errors and the trades are signed as in Chordia, Roll and Subrahmanyam (2001). The Lee and Ready (1991) trade-signing algorithm is used to designate buy and sell trades, and calculate order imbalances for use later in the analysis.[10] Note that due to the filtering, a number of trades (especially for large stocks with a large number of trades), are excluded because of out of sequence recording of trades or because the trades are recorded before the open or after the close. Also, some trades cannot be signed as buy or sell trades and are excluded from the sample.[11] Due to the exclusion of trades, the turnover obtained using transactions data from TAQ is understated compared to turnover obtained from CRSP.

Two subperiods are selected to give an indication of changing conditions. They each span eight complete calendar years; Subperiod 1 includes 1993 to 2000, and Subperiod 2 covers 2001 to 2008. Data pertaining to candidate determinants of turnover are described when used.

III. Preliminary Evidence

Figure 1 presents the value-weighted monthly turnover for NYSE stocks from 1993 through 2008 inclusive. The monthly turnover for each individual stock is obtained from CRSP trading volume and shares outstanding; then a value-weighted average is computed using market

[10] The matching quote is the first quote at least five seconds prior to a trade for the period from 1993 to 1998. Due to a generally accepted decline in reporting errors in recent times (see, for example, Madhavan et al., 2002), after 1998, the matching quote is simply the first quote prior to the trade.

[11] We use the tick test going back five lags (and no more) if trades occur at the quote midpoint. This results in some trades not being assigned a sign. An exploratory analysis reveals the proportion of trades that cannot be signed to be fairly small; for example, in January 1993, 2002 and 2008, the proportions for IBM are 5.6%, 1.78%, and 1.13%, respectively.

capitalization at the end of the previous year. To examine the possible role of indexation, we present separate plots for S&P500 and non-S&P500 NYSE stocks.[12] This also indicates the effect of market capitalization, since stocks included in the S&P500 are generally larger firms. As can be seen, trading activity has increased markedly for both groups. Turnover for either group starts from below 6% (per month) at the beginning of the period (January 1993) and exceeds 40% in 2008 before falling to around 25% in December 2008.

Panel A of Table 1 presents summary statistics associated with turnover for the two subperiods.[13] There is no evidence that the turnover of index (large cap) stocks increased more or less than that of non-index (smaller cap) stocks. Indeed, an unreported test shows that the average difference in turnover between non-index and index stocks throughout both subperiods is positive and significant.[14] In Panel B of Table 1, we fit the turnover series to trend variables. Since Figure 1 demonstrates a clear non-linear trend, we include linear through quartic trend terms, represented by orthogonal Legendre polynomials.[15] Confirming the evidence in Panel A, all the trend terms are positive and significant for both the S&P 500 and the non-S&P 500 turnover series. The adjusted R^2s exceed 80% in both cases.

The increase in turnover could result from an increase in trading frequency or in the average trade size, or possibly both. To shed some light on this issue, Panel A of Figure 2 plots the daily average dollar trade size (transaction sizes are first averaged for each stock on a daily basis, and then a value-weighted mean is calculated for each trading day). After increasing from around $70,000 to $90,000 in the mid-1990s, the dollar trade size declined precipitously and is only around $7,000 in 2008. Trades are now being conducted in ever-smaller units. We also

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[12] The S&P 500 index is by far the most common benchmark for index funds (see, Fabozzi and Molay, 2000).

[13] The *NYSE Fact Book* documents that turnover in the early 1900s was also very high. For instance, the highest annual turnover to date of 319% occurred in 1901. Except for outliers such as 1929, the reported share volume has increased relatively steadily over time. After 1962 the increase in share trading volume is quite slow but it has accelerated dramatically in more recent years (see also footnote 3).

[14] The various references to significance (at the 5% level unless otherwise noted) or lack thereof across the two subperiods in this paper are based on standard difference-in-means tests.

[15] In all of the trend regressions either reported in tables or mentioned in the text, the time index runs from –1 to +1 and the Cochrane and Orcutt (1949) method adjusts for residual autocorrelation as necessary. The results are qualitatively similar in every case without the correction for autocorrelation.

plot the average number of transactions per day in Panel B of Figure 2. This quantity has increased considerably through the sample period. Note that the vertical axis uses logs, which implies that the number of transactions has been increasing at an accelerating rate.

Table 2 provides summary statistics on the average trade size and number of transactions by subperiod. It indicates that the average trade size has decreased by about 56%, whereas the average number of transactions has increased more than ten-fold across the two subperiods. Consequently, the increase in total dollar turnover is entirely driven by an increase in trading frequency, which has more than offset the decline in average trade size.

As an additional piece of evidence regarding the source of the increase in dollar turnover, Figure 3 documents the proportion of dollar volume in trades less than or more than $10,000.[16] For each stock and day, we simply add up the dollar volume of trades exceeding and falling below $10,000 then calculate the (value-weighted) average of these quantities across stocks. There is a clear pattern: the proportion of volume due to smaller (larger) trades has been growing (falling) at an accelerating pace. Further, Table 2 indicates that the proportion of small trades increased more than four-fold in the second period relative to the first. However, as Figure 3 reveals, the second subperiod's increase does not fully depict the dramatic acceleration in the fraction of small trades during the last few years.

Table 2 also fits the number of transactions, trade size, and the percentage of trades under $10,000 to trend variables, as in Panel B of Table 1. As can be seen, all trend variables are positive and significant for both the number of transactions and the small trade percentage, confirming the non-linear upward trend for these quantities. For transaction size, the linear and quadratic terms are negative and significant, but the cubic and quartic terms are positive and significant. It is easily verified, however, that the overall trend is strongly negative for trade size.

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[16] Lee (1992) uses a cutoff of $10,000 to separate large and small traders. Barber and Odean (2000) report median trade sizes of about $5,000 for individual investors, with larger means (see also Kaniel, Saar and Titman, 2008). As a robustness check, we also experiment with a cutoff of 10,000 shares to separate large and small trades, and the results are qualitatively the same.

The next section considers the behavior of liquidity and the relative importance of investor types for the turnover trend. It also investigates whether known determinants of turnover have shifted recently in a manner consistent with the increase in turnover.

IV. Potential Causes of Recent Trends in Trading Activity Patterns

The analysis thus far indicates that the increase in turnover is due to ever-smaller trades conducted ever more frequently. There are several possible reasons for this (which are not mutually exclusive). First, illiquidity, as measured, for example, by effective spreads, may have shown a greater decline for smaller trades relative to larger ones due to exogenous shifts in ease of trading for small orders (e.g., by way of the NYSE Direct system).[17] Second, direct retail investing, consisting predominantly of smaller trades, may have increased due to the advent of online trading technologies (Barber and Odean, 2002). Third, institutions may have resorted to splitting orders to take advantage of lower trading costs in the presence of reduced depths as documented in Chakravarty, Panchapagesan and Wood (2005) as well as Jones and Lipson (2001). Fourth, other potential determinants of trading activity such as dispersion of analyst opinions and mutual fund flows may have contributed to the turnover increase. We now empirically explore these potential reasons for the turnover increase.

A. Cost of Trading

Do turnover trends mirror a pattern in liquidity? Figure 4, Panel A reports the average proportional effective spreads for large trades (>$10,000) and small trades (≤$10,000) over time. These spreads are calculated by matching prevailing quotes to each transaction in our sample of NYSE stocks from 1993 to 2008.[18] As can be seen, spreads have generally been decreasing for both large and small trades, (except for their widening in the financial crisis towards the end of

[17] The NYSE Direct system is a procedure introduced in 2000 for automated execution of small trades (less than 1,099 shares). For details, see Huang (2002).

[18] The effective spread is calculated as twice the absolute difference between the transaction price and the mid-point of the prevailing bid-ask quote for each matched transaction. This quantity is then averaged during the trading day; then value-weighted across stocks.

the sample period). Indeed, Panel A of Table 3 indicates that the average effective spread is about eight cents lower in 2001-2008 than in 1993-2000 for each type of trade, and an unreported test indicates that the difference is statistically significant at the 1% level in both cases. Further, we have verified that both the spread series (for large and small trades) exhibit a strongly significant and negative linear trend, but the difference between large and small trade spreads does not exhibit a significant trend. This indicates a secular increase in liquidity for reasons unrelated to the mix of trades.[19]

Panel B of Figure 4 as well as Table 3 reports depth at the inside quote for the two subperiods. Consistent with Chordia, Roll, and Subrahmanyam (2001), inside depth has decreased in the second subperiod. The decrease in depth can be attributed to decreases in the minimum tick size, which has reduced the willingness of market makers to display large quote sizes at the inside price quotes. Depth decreases at the inside quotes do not necessarily imply that the overall depth has decreased, because depth outside the minimum quotes may well have increased. However, the data on overall depth are available only in the limit order book, which is not available over our extended sample period. The decrease in depth likely has contributed to the shift to smaller transactions by market participants that is documented in Table 2. Even as difference between the effective spreads for large and small transactions has not diverged much, the reduced depth has it made it less cost-effective to execute large transaction sizes.

Based on the evidence in Table 3, it is tempting to attribute the overall trend in trading activity to spread decreases. But, the endogeneity between spreads and trading activity is not completely addressed by Table 3. This endogeneity arises because it is not clear whether the decrease in spreads has led to the increase in trading or whether the increase in trading volume has led to a decrease in spreads. Note, however, that spreads have decreased both for large and small orders even though the increase in volume is largely due to an increase in small orders,

[19] In addition to secular spread declines, trading commissions also have decreased steadily over the years. Indeed, French (2008) documents the dramatic reductions in trading commissions relative to trading volume from over 60 basis points in 1993 to 11 basis points in 2006. Also, given the significant decreases in computing costs, online trading has become far easier. Thus, there has been a general decrease in trading costs over and beyond liquidity decreases.

suggesting a secular trend in spreads over time. Nevertheless, in an attempt to further address this endogeneity problem, we consider the natural experiment afforded by the tick size reductions. The eighth to sixteenth shift on the NYSE occurred on June 24, 1997 and the sixteenth to decimals shift on January 29, 2001. These exogenous tick size shifts are accompanied by immediate and dramatic drops in bid-ask spreads (Chordia, Roll, and Subrahmanyam, 2001).

To examine the effect of the tick size shift on trading activity, we run cross-sectional regressions of changes in average turnover between one month prior and one month after the change in the tick size as a function of the change in the average relative quoted spread (quoted spread divided by the quote midpoint)[20] and the change in daily volatility (i.e., the change in the daily standard deviation of returns) across the same period. The inclusion of the latter control variable is based on the evidence in Karpoff (1987) and Chordia, Huh, and Subrahmanyam (2007) that volatility bears an important relation with volume. Results from the regression appear in Table 4. The table shows that the coefficient on spreads is negative and significant around both exogenous tick size decreases even after accounting for the effect of volatility. In economic terms, a one standard deviation decline in relative spreads due to the tick size change from 1/8 to 1/16 results in a 0.033% increase in turnover and a one standard deviation decrease in relative spreads due to decimalization results in a 0.036% increase in turnover. The results accord with the notion that a decline in the cost of a product (trading activity) leads to an increase in its consumption.[21] In the next subsection, we try to ascertain the influences of individual and institutional investing on share turnover.

B. Retail vs. Institutional Trading

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[20] We present results with the quoted (rather than effective) spread because traders respond to the posted quotes, while the effective spread is established *after* trades have been executed. In any case, results are essentially unchanged if the effective spread is used.

[21] Note that in general trading volumes are high in markets with lower trading costs. For instance, volume in the foreign exchange market is over $3 trillion per day with small bid-ask spreads. Thus, a typical quote in the Dollar-Euro market may be 1.2960-1.2965 with a typical trade size of $10 million. In fact, trade sizes of $50 million-$250 million are not uncommon (authors' personal communication with a currency trader).

One possible influence on the turnover trend is that retail investors are participating to a greater extent because of enhanced access to online trading (Barber and Odean, 2000), and lower trading costs arising from technological improvements and decreases in the tick size. Though French (2008) shows that direct holdings of individuals have declined (from about 47% in 1980 to about 22% in 2006), the enhanced ease of trading may have increased trading by individual investors, thus influencing the turnover trend. An alternative possibility is that institutions are able to trade more frequently and more cheaply, and their increased activity is the predominant cause of the turnover patterns.

To provide some evidence on the preceding possibilities, stocks are sorted into five groups by institutional holdings, measured by the percentage of shares held by institutions in the immediately preceding quarter. The average turnover for these groups is plotted in Figure 5. Group 5 has the highest institutional holdings and Group 1 the lowest. As shown in the figure, turnover has increased the most in absolute terms for stocks that are held most by institutions, and there is a monotonic relation in the turnover trends across the groups. This pattern is confirmed in Panel A of Table 5, which provides the mean values of turnover in the two subperiods across the five institutional holdings groups. The average turnover increases by twelve percentage points for the highest holdings quintile in the second subperiod, but only by three percentage points for the lowest holdings quintile.[22]

Table 5 also presents turnover due to large and small trades separately for the two subperiods across the institutional holdings quintiles. It can be seen that for the group with the largest institutional holdings, small trade turnover has increased by about 0.2% to 6.3% across

[22] A question that arises here is whether the increase in turnover is due to general increases in the level of institutional holdings (for example, due to growth in the mutual fund industry driven in part by increased participation in 401(k) plans—Cf. Saxton, 2002 or Poterba, Venti, and Wise, 2001) or is due to increases in trading activity orthogonal to changes in institutional holdings. To distinguish between these possibilities, stocks are sorted into quintiles by the average change in institutional holdings across the two subperiods, and then by average level of holdings across the full sample period. The average change in turnover across the two subperiods is then calculated for each of the 25 portfolios. Within each holdings change quintile, the change in turnover increases monotonically and significantly across the five holdings groups. This indicates that even after controlling for changes in institutional holdings, stocks with greater levels of institutional holdings have experienced greater increases in turnover.

the two sub-periods, whereas the corresponding increase is only from 0.4% to 1.9% for the lowest holdings group. The corresponding numbers for large trade turnover are 8.3% to 14.6% and 3.7% to 5.6%, respectively.

In Panel B of Table 5, we provide trend fits to the time-series of the *difference* in turnover between highest and lowest institutional ownership groups. We perform the trend fits for the differences in overall, small trade, and large trade turnover. For the overall turnover differential, three of the four trend variables are positive and significant, and the regression explains 57% of the variation in the difference. The trend variables are all positive and significant for the small trade turnover differential, and the adjusted R^2 of the regression is 81%. However, for the large trade turnover differential across the extreme holdings quintiles, the trend regression explains only 27% of the variation in the dependent variable and the significance of the trend variables is considerably weaker. Thus, the evidence suggests that during recent years, turnover in stocks with high institutional holdings has positively and significantly diverged from that in stocks with low levels of institutional holdings, and this divergence is driven by the increase in small trade turnover.

Another perspective on the trade size patterns across institutional holdings groups is provided by the average ratios of turnover across the extreme holdings quintiles. Specifically, we use the raw data for Table 5 to calculate the daily ratio of turnover in the quintile with the largest institutional holdings to that in the quintile with the smallest level of holdings, separately for small and large trades. We then average these ratios for the two subperiods. For small trades, the average ratios of turnover in the largest quintile relative to the smallest are respectively 0.497 and 3.34 for the first and second subperiods. Thus, small trade turnover in the largest holdings quintile relative to that in the smallest one is about half in the first subperiod but increases to more than 300% in the second subperiod. The corresponding ratios for large trade turnover across the extreme holdings quintiles are 2.24 and 2.62, so that the change in the large trade turnover ratio across the subperiods is much smaller relative to that for small trades. A trend analysis (not reported for brevity) confirms a significant and positive trend for the small trade ratio but an insignificant trend for the large trade ratio. This confirms that the proclivity of institutions to execute small trades has increased in recent years.

It is possible that institutional holdings are a proxy for firm size, thus contaminating inferences. To address this, we independently sort firms into institutional holdings and market capitalization-based quintiles and document total turnover, and turnover for large and small trades. The general pattern is preserved even within size quintiles (unreported.) Specifically, turnover generally is higher for the firms with greater institutional holdings, regardless of the size quintile. The difference in total turnover across quintiles with the largest and smallest holdings is statistically greater (at the 1% level) in the second sub-period within every size quintile. It is also easily verified that in 14 out 15 cases (five each for total, small, and large trade turnover), the ratio of average turnover in the second sub-period to that in the first is greater for the quintile representing the largest level of institutional holdings relative to the quintile with the lowest holdings.

Overall, the findings support the notion that the increase in turnover is driven more by institutions rather than by retail investors. However, direct data on institutional and retail trading are not available over the extended sample period of this study. Therefore, we now present additional evidence to support the link between turnover increases and increased institutional trading.

First, in order to distinguish retail from institutional trading, we examine the change in the number of shareholders over time.[23] Such a change may be attributed to changes in the breadth of ownership, and may be linked to changes in the number of retail investors holding, and thus trading, stocks. We obtain the number of shareholders from Compustat and calculate the value-weighted number of shareholders for NYSE firms each year. This quantity actually

[23] It would be desirable to have direct data on retail trading. However, these data are not available for our sample period because the standard discount brokerage dataset used, for example, by Odean (1998) does not extend beyond the year 2000.

shows a modest decrease during the sample period; thus, the average annual numbers of shareholders are 190,230 and 181,141 in the 1993-2000 and 2001-2008 periods, respectively.

Further light on the number of shareholders is shed by the following exercise. For each stock listed in both the former and latter subperiods, we calculate the change in its average turnover across the periods and the change in the average annual number of registered shareholders (as listed in Compustat).[24] The change in average turnover is then regressed on the change in the number of shareholders. The coefficient in this regression is insignificant with a t-value of 0.47, indicating that trends in the shareholder base have not had a significant impact on turnover. This suggests that increased trading by existing shareholders, rather than changes in breadth of ownership is the stronger determinant of turnover.

Next, we consider serial correlation in trade imbalances as a way to distinguish trends in retail and institutional trading. Previous research indicates that first order serial correlations in trade imbalances are strongly positive (Chordia, Roll, and Subrahmanyam, 2002). Lee et al. (2005) attribute these serial correlations to both reputational herding (Scharfstein and Stein, 1990) as well as order splitting (Kyle, 1985) by investors. An overall increase in the serial correlation of imbalance in more recent years would be consistent with the increase in turnover and would signify either increased herding or increased frequency of split orders. While a change in the serial correlation of small trades can be attributed to retail investors as well as institutional investors, an increase in the serial correlation of large trades is more likely to be driven by institutional trades.

Table 6 presents the first order serial correlations for daily share trade imbalance, calculated as the daily buy volume minus sell volume, scaled by total volume. We compute the serial correlations for the overall sample as well as for the five institutional holdings quintiles. The correlations are first calculated stock-by-stock, and then averaged across stocks. We also

[24] The Compustat variable is understated because many shares are held in street name by brokers on behalf of individuals (Knewtson and Sias, 2008). Nonetheless, the variable should be strongly correlated with the breadth of ownership.

present the correlations separately for large and small trades. The results in Table 6 reveal that the overall serial correlation increased in the second subperiod for the full sample as well as for every holdings quintile. In addition, serial correlations for both small and large trades increased in the second subperiod; the point estimate of the increase is greatest for the largest holdings quintile.[25] This again supports the notion that increased trading by institutions drives the overall trend in turnover.[26]

Another way to distinguish the roles of retail versus institutional traders is to look at turnover patterns in low- and high-priced stocks. Indeed, Falkenstein (1996) shows that mutual funds are reluctant to hold low-priced stocks. We therefore stratify all sample stocks into two groups: group 1 consists of those stocks whose monthly average closing price was less than $10 throughout the sample period, and group 2 consists of the complementary set. Across the two subperiods, average monthly turnover for the first group increased from 6.9% to 14.5%, whereas that for the second group increased from 7.4% to 16.5%. It can be seen that the relative increase in turnover is larger for the second group of stocks, and we have verified that the increase in the turnover difference between the two groups is statistically significant. This further bolsters the role of institutions in causing the turnover trend.

We also consider the correlation between the change in institutional holdings and turnover. We first calculate the absolute value of the change in institutional holdings for each stock and each quarter within our sample (institutional holdings from the Thomson database are only available for the quarterly horizon). We then calculate the time-series average of the cross-sectional correlation between turnover and the absolute change in holdings separately for the 1993-2000 and 2001-2008 subperiods. The average correlation is positive and increased from 0.187 to 0.213 in the second subperiod, suggesting increased representation of institutional

[25] Of all the changes in serial correlations in the second subperiod relative to the first, only the increases listed in the second columns of Panels A and C (i.e., those for the overall sample, representing the combined and large trade imbalances) are significant at the 10% level. All other changes are insignificant.

[26] Earlier we argued that institutions have increasingly been reducing transaction sizes in recent years, possibly due to order splitting. However, at least some agents would continue to use large orders, especially if they possess perishable private information. Such agents are more likely to be institutions.

trading in the latter period's turnover. Note, however, that the quarterly change in institutional holdings is a noisy proxy for institutional trading because it misses trades that may occur within the quarter.

Overall, the evidence suggests that increased trading by institutions in recent years, due to enhanced liquidity and decreased trading commissions, has materially influenced the increase in turnover. The evidence in this subsection and that from Tables 2 and 3 also accords with the notion that institutions have increasingly resorted to splitting orders in response to decreased market depth at the prevailing quotes. In addition to secular decreases in trading costs, other turnover determinants could also have played a role in the increased turnover. We next explore the role of these other potential influences.

C. The Roles of Dispersion of Opinion, Expected Volatility, and Fund Flows

Previous literature has pointed to three important determinants of trading activity, divergence in analysts' forecasts, return volatility, and money flows into equity funds.[27] Greater analyst forecast dispersion and higher uncertainty (return volatility) are likely to be positively related to agents' differences of opinion, which, in turn, is related to volume (Harris and Raviv, 1993). Return volatility may also lead to more portfolio rebalancing and thus higher trading volumes.

While the previous section suggests that institutions and not individuals may be the driving force behind turnover, individual investor behavior may have changed over time in a way that may have influenced institutional turnover. Indeed, the participation of investors in defined contribution retirement plans has increased considerably (Poterba, Venti, and Wise, 2001). This implies that changes in equity fund flows may have contributed to an increase in turnover.

To examine the role of these determinants in the turnover trend, we consider the following empirical constructs: (a) the monthly forecast dispersion, defined as the standard

[27] See Edelen and Warner (2001) and Chordia, Huh, and Subrahmanyam (2007) for discussions on the importance of these determinants in the cross-section of turnover.

deviation of earnings per share (EPS) forecasts from two or more analysts, divided by the previous month's price,[28] (b) the value-weighted average dispersion for the aggregate market, where the weights are based on market capitalization at the end of the previous year; (c) the VIX, a measure of the implied volatility of the S&P 500 index published by the Chicago Board Options Exchange;[29] (d) aggregate monthly flows to equity mutual funds from 1993 to 2008 obtained from AMG Data Services.

The average values of the dispersion index, VIX, and equity fund flows across the two subperiods are presented in Panels A and B of Table 7. Dispersion and VIX both increased in the second subperiod. Unreported tests indicate that the change in dispersion is significant while that in VIX is not. However, the proportional differences in means across the subperiods for these two potential determinants of turnover are small relative to the corresponding turnover statistics documented in Table 1. Further, mean fund flows actually decreased in the later subperiod, and the change is significant. The decrease in the mean level may be due to the aftermath of the stock price rise and fall in the tech sector and the recent financial crisis.[30] Overall, changes in either of the three turnover determinants are either not large enough or are of the wrong sign, thus indicating that they likely cannot justify the dramatic increase in turnover in recent years.

Nonetheless, to further explore the role of these determinants in the turnover increase, we perform a regression analysis in which value-weighted monthly NYSE turnover is the dependent variable and the potential turnover determinants in Table 7 are the right-hand variables. In addition to these variables, we also include trend variables. We present regressions both

[28] Obtained from the I/B/E/S database disseminated by the firm Thomson Financial.

[29] We use implied option volatility because the speculative activity that sparks turnover would likely respond to expected volatility, rather than realized volatility. We are grateful to Bob Whaley for providing the VIX data.

[30] Even though the mean flow into equities decreased in the second subperiod, the volatility of fund flows increased. The magnitude of the increase across the two subperiods is a substantial 43%, and an F-test indicates that the change is statistically significant at the 5% level. This is consistent with asset allocation frequency increasing in recent years. Indeed, the technology to switch between asset classes has improved substantially in that it now just takes a few clicks of the mouse to switch into a new mix of assets (Brunnermeier and Nagel, 2006). Thus, individuals may be prone to changing asset mixes more frequently in recent years.

including and excluding the Table 7 variables to clarify the explanatory power of these variables vis-à-vis the trend variables.

The regression results appear in Table 7. The second and third columns contain results for the trend variables alone while the last two columns report the outcomes of including the additional determinants. The table clearly demonstrates the role of the trend variables. About 88% of the time-series variation in turnover can be explained by these variables alone, and these variables are all positive and significant, confirming the dramatic up-trend in trading activity. Among the potential determinants in Table 7 only VIX is significant (and positive, as conjectured). However, the explanatory power of the regression increases by just 2% when these potential determinants are added to the regression. Overall, therefore, it seems reasonable to surmise that secular improvements in trading technology and decreases in trading costs are the principal contributors to the dramatically increased turnover in recent years.[31]

V. Trading Activity Trends and Price Formation

The previous section pointed to evidence suggesting that institutional trading, as opposed to retail investing, is more responsible for the dramatic increase in turnover in recent year. This section examines the potential association between such an increase in trading and price formation and the cross-section of turnover and returns.

A. Price Formation

As the previous section indicates, institutions may be trading more frequently on their own account due to exogenous factors such as lower tick sizes, decreased commissions and

[31] Is the implied elasticity of turnover to trading costs within our sample in line with estimates in previous literature? The following back-of-the-envelope calculation sheds light on this issue. The value-weighted NYSE turnover in the first and second subperiods (1993-2000 and 2001-2008) is 6.50 % and 13.02%, respectively. Further, the NYSE quoted spread declined from 16.03 cents to 3.59 cents across the two subperiods. These numbers imply an elasticity estimate of –1.29, which is comparable to, but higher than, the estimate of –1.13 in Jones (2002), and the –0.25 to –1.00 range cited in the studies discussed by Schwert and Seguin (1993). Our calculation, of course, is merely illustrative and does not account for the fact that transactions frequently take place within and outside the spread.

improvements in trading technology. Such phenomena may enable them to trade on private information more effectively because decreased trading frictions may increase returns from information-based trading. However, if institutions only pass along individual investors' asset allocation decisions to the financial markets, one would not expect much change in information-based trading. Variance ratios computed using open-to-close and close-to-open returns can shed light on these competing hypotheses.

French and Roll (1986) relate these ratios to the amount of information incorporated into prices. They show that the hourly open-to-close return variances are greater than the hourly close-to-open variances and offer three potential explanations for this finding: (i) incorporation of private information during trading hours, (ii) mispricing caused by investor misreaction or market frictions and microstructure noise induced by bid-ask bounce, and (iii) greater incorporation of public information into prices during trading hours. They reject (iii) because the variance ratios are not significantly different on business days when the stock market is closed. They conclude that the other two components help explain the higher ratio during market trading hours, with (i) being the dominant factor.[32]

Panel A of Table 8 documents the average values of the variance ratios across the 1993-2000 and 2001-2008 periods. The mean variance ratios in the former and latter periods are 9.92 and 12.46, respectively. Thus, variance ratios increased by about 26% in the second subperiod on average. This change is statistically significant at the 5% level. Thus, increased turnover, possibly due to lower trading costs, has been accompanied by an increase in the variance ratio based on open-to-close and close-to-open returns.[33]

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[32] More recently, Chordia, Roll, and Subrahmanyam (2008) argue that these variance ratios reveal the degree of private information produced by the trading process.

[33] Our analysis of open/close to close/open variance ratios does not account for after-hours trading (e.g., Barclay and Hendershott, 2004) that has become prevalent in the second subperiod. But, if such trading contributes to volatility, it would increase the close-open variance and thus tend to *reduce* the variance ratio we compute. But, we find that the variance ratio *increases* in the later subperiod. This indicates that our inference that the trading process creates more volatility in the second subperiod is unaffected by the consideration of after-hours trading.

We have argued that the increase in trading activity in recent years is driven primarily by institutions. If this is the case, and variance ratios capture trading on private information (as suggested by French and Roll, 1986), then one would expect a greater shift in the variance ratios in stocks more widely held by institutions. This should be revealed by variance ratio shifts for stocks divided into groups by institutional holdings. Results appear in Panel B of Table 8. It can be seen from the table that the increase in the variance ratios is most pronounced for stocks with the highest levels of institutional holdings. Indeed, the percentage changes in the variance ratios in the second subperiod relative to the first are –7.9%, 13.5%, 30.9%, 58.3%, and 35.2% for the smallest to the largest holdings groups, respectively, and only the latter three increases are statistically significant at the 5% level. Thus, the increase in variance ratios is most evident in stocks with the higher levels of institutional holdings. In Panel C, we present a trend fit for the difference in variance ratios between the highest and lowest holdings quintiles. The difference exhibits a significantly positive linear trend (and an insignificant quadratic trend).[34] Thus, in recent years, the variance ratio for stocks with the highest institutional representation has diverged positively and significantly from that in stocks with the lowest levels of institutional holdings. The overall evidence, coupled with the conclusions of French and Roll (1986), thus supports the dual notions that institutions are trading more actively and trading on private information more effectively in recent years.[35]

While French and Roll (1986) show that much of the variance due to the trading process arises from private information, it is still possible that increased uninformed noise trading may be driving the increased variance ratios during trading hours relative to non-trading ones. As French and Roll (1986) argue, such noise trading should be associated with inefficiencies such as

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[34] Only linear and quadratic terms are included in this trend fit as well as that in Tables 13 and 14 to follow, because higher order terms are statistically insignificant. In any event, the less parsimonious specification which includes the cubic and quartic terms does not alter the qualitative conclusions; results are available upon request.

[35] The reader may wonder how the increased variance ratios in recent years, implying increased private information production are consistent with the increased liquidity documented, for example, in Jones (2002), Brennan, Chordia, Subrahmanyam, and Tong (2008) or in our Table 3, given that adverse selection due to informed trading reduces liquidity (Kyle, 1985). However, equilibrium liquidity may also be influenced by greater uninformed trades due to indexation or greater frequency of asset allocation by individual investors (as discussed in the previous section). Further, greater information production that is due to exogenous decreases in trading costs is likely associated with an increase in the number of informed traders, and this phenomenon may further increase equilibrium liquidity due to enhanced competition between the informed (Admati and Pfleiderer, 1988).

serial dependence in stock returns. To investigate this issue, we computed the value-weighted average daily first order return serial correlations for the entire sample of NYSE stocks and for the five holdings groups in both the first and second subperiods. To mitigate the problem of bid-ask bounce, these correlations are obtained from mid-quote returns, using the last quote of a trading day that can be matched to a transaction.

The results (not reported) show that the absolute serial correlation falls from 2.22% to 0.01% in the second subperiod relative to the first. The average serial correlation is 3.68% for the largest holding quintile in the first subperiod, which, interestingly, is the highest absolute correlation amongst all of the holdings quintiles. This correlation falls to 0.19% in the second subperiod, forming the biggest drop in absolute serial correlations across all of the holdings groups. While the decrease in serial correlations is modest (their values in the first subperiod are low to begin with), the point estimates suggest that increased trading has been accompanied by an increase in market efficiency.

We now investigate trends in the degree of intraday price fluctuations. If indeed the extra activity is primarily uninformed, i.e., it emanates principally from "noise" traders, more volatile prices may result (Black, 1986). To test whether this is indeed the case, we calculate intradaily volatility, measured as the standard deviation of five-minute returns for each stock. In order to mitigate bid-ask bounce concerns, we use prevailing quote midpoints at five-minute intervals, rather than transactions prices.

An alternative approach to measuring market quality involves the comparison of short- and long-horizon variance ratios. For a random walk price process, the variance of long-horizon returns is q times the variance of short horizon returns, where q is the number of short horizon intervals in the longer horizon. Deviations from a random walk can arise because noise trading can cause return serial correlation (Grossman and Miller, 1988). Our notion is that there should be smaller deviations from random walk benchmarks in recent years if the higher trading activity has improved market quality. We consider the ratio of mid-quote return variances computed from hourly intervals and from open-to-close of trading days as in Bessembinder (2003). In computing this variance ratio, the hourly return variance is multiplied by the number of hourly intervals in a trading day.

Panel A of Table 9 reports intraday volatility and hourly to daily variance ratios for the two subperiods. The variables are computed monthly for each stock and then averaged across stocks for each month in the sample period. It can be seen that the intraday volatility drops substantially in the second subperiod. Furthermore, consistent with intuition, the variance ratios are closer to unity in the later period, indicating that prices in recent years conform more closely to random walks. Panel B fits linear and quadratic trends to the two time-series, and confirms the decline in both series (the linear term is negative and strongly significant; while the quadratic term is positive, it is easily confirmed that the overall trend is downward).[36] The evidence therefore indicates that the extent of "noise" induced by the trading process is smaller in later years.

To see if the relations proposed above hold at the individual firm level, in Panel C of Table 9, we present we present results from a cross-sectional regression where the dependent variables, in turn, are the change in average intraday volatility and the hourly/daily variance ratio across the two subperiods, and the explanatory variables are changes in turnover and institutional holdings. The right-hand variables are included separately in univariate regressions, and together in a multivariate regression. Based on the regressions where the variables are included separately, the results indicate that for either measure, stocks with the greatest increase in turnover and institutional holdings have experienced the greatest decrease in volatility and hourly/daily variance ratios. In the multivariate regressions for intraday volatility, the holdings variable subsumes the effect of turnover; however, both variables are significant for the hourly/daily variance ratio.[37] Thus, our analysis in this subsection, taken in totality, supports the notion that the dramatically increased trading activity in recent years has been accompanied by

[36]A split by holdings quintiles does not lead to substantial additional insight and therefore is not presented for brevity.
[37] Similar results are obtained when the change in the absolute daily first order return autocorrelation is used as the dependent variable; these are available upon request.

an increase in the degree of market quality and efficiency, both in the aggregate as well as at the individual firm level.

B. The Possible Impact of Hedge Funds: Changes in the Cross-Section of Expected Turnover and Expected Returns

Another potential reason for increased institutional trading activity has to do with the proliferation of hedge funds,[38] possibly stimulated by the exogenous decreases in trading costs described in the previous subsection. Academic research may also have stimulated hedge fund growth. Specifically, in the early 1990s academics (e.g., Fama and French, 1992, Jegadeesh and Titman, 1993) uncovered reliable predictors of returns in the cross-section that did not appear to be related to risk.[39] Fung and Hsieh (2000, 2002) suggest that these effects form the backbone of strategies used by many hedge funds. Thus, a potential explanation for the increased turnover is that institutions as a group, but mainly hedge funds, have employed rapid trading strategies more vigorously, as a result of prior academic research as well as secular declines in trading costs.

This hedge fund explanation would be bolstered if turnover has become more sensitive to typical quantitative strategy triggers.[40] Motivated by this observation, we cross-sectionally regress turnover for all NYSE-listed stocks on two explanatory variables as well as other controls. The first explanatory variable is the absolute value of the one-month lagged return, which approximates changes in book/market or short-term momentum. The second variable, intended to capture changes in long-term momentum, is the absolute value of the compounded return from month t-2 to month t-6, where t is the month in which turnover is measured.

[38] Federal Reserve estimates indicate that the total dollar value of assets under hedge fund management have increased from about $250 billion in mid-1998 to more than $1 trillion in recent years. For example, see http://www.federalreserve.gov/newsevents/testimony/warsh20070711a.htm and associated references therein.

[39] See, however, Conrad and Kaul (1998) and Jegadeesh and Titman (2002) for a debate on whether the profitability of these strategies is driven by rational time variation in expected returns.

[40] Consistent with the notion that hedge funds can short sell at lower cost than the typical investor, short interest on the NYSE has grown rapidly during our sample period (see Asquith, Pathak, and Ritter, 2005 or websites such as seekingalpha.com). This observation, however, does not directly indicate that hedge funds have contributed to upswings in turnover. Our analysis in this subsection is suggestive of the role of hedge funds in the trading activity trend.

As pointed out by Chordia, Huh, and Subrahmanyam (2007), past returns are the key determinants of trading activity, indicating that this regression is likely to be reasonably well specified. However, to be prudent, size, dispersion in analyst forecasts, and firm age are also included. Size (measured by market capitalization as of the end of the previous month) is an obvious candidate for explaining share turnover. Further, Chordia, Huh, and Subrahmanyam (2007) argue that analyst forecast dispersion and firm age represent uncertainty about a firm's future cash flows, which, in turn, contributes to speculative trading activity.[41] As in the previous section, analyst forecast dispersion represents the standard deviation of earnings per share (EPS) forecasts from two or more analysts, scaled by the stock price as of the end of the previous month. This variable is averaged annually, and the previous year's observation is used in the regression. Age is defined as the number of days since the date of first listing on CRSP, calculated as of the end of the previous year. The coefficients of these control variables are suppressed for brevity.[42]

Panel A of Table 10 provides summary statistics for the cross-sectional regression coefficients of monthly turnover on the two absolute return variables across the two subperiods. The mean coefficients for both return variables are greater in the latter subperiod than in the former, and the difference is statistically significant at the 5% level for both return variables. While the median coefficients are smaller than the means, a Wilcoxon rank sum test rejects the equality of the medians across the subperiods for both return coefficients, with p-values less than 0.05.[43] In Panel B, we fit the coefficients of the two absolute return variables to trends and find that the trend terms are strongly significant in either case.[44]

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[41] Note that while Table 7 does not show a considerable increase in aggregate dispersion, there is still a need to control for it in a cross-sectional regression to draw reliable inferences about the behavior of the return coefficients over our sample period.

[42] The qualitative features of our results are unaltered if the control variables are excluded, though the magnitudes of the return coefficients are higher without these variables.

[43] Both the average t-statistics from the cross-sectional regressions as well as the Newey and West (1987, 1994) t-statistics for the means are well in excess of five in both subperiods for the one-month and the two-to-six month absolute return variables.

[44] As a robustness check, we also perform panel regressions that use the random effects method of Fuller and Battese (1974). The dependent variable is turnover, and the explanatory variables are the same as those in Table 10.

The question naturally arises as to whether increased sensitivity of turnover to a key quantitative strategy trigger, namely, past returns, represents arbitrage activity that has reduced the cross-sectional predictability of equity returns. To address this, we regress monthly returns on the following predictive variables:[45]

1) SIZE: measured as the natural logarithm of the market value of the firm's equity in month t-2, where t is the current month
2) BM: the ratio of the book value of the firm's equity to its market value of equity at time t-2, where book value is calculated as in Fama and French (1992),
3) TURN: the logarithm of the firm's share turnover, measured as the trading volume divided by the total number of shares outstanding in month t-2,
4) RET6: the cumulative return on the stock over the six months ending at the beginning of the previous month.

The size, book/market, and momentum (RET6) variables are well-known cross-sectional return predictors. Turnover is also an important predictor and has been variously interpreted as capturing a liquidity premium (Datar, Naik, and Radcliffe, 1998) or investor optimism (Baker and Stein, 2004).[46] Our goal is to ascertain how the cross-sectional predictive power of these variables for equity returns has changed across the two subperiods.

We adjust returns for risk using the Fama and French (1993) factors following the method of Brennan, Chordia, and Subrahmanyam (1998). The risk-adjusted returns are then cross-sectionally regressed on the equity characteristics described above. The Fama-MacBeth

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Also, the return variables are interacted with an indicator variable that is unity in the 2001 to 2008 period, and zero otherwise. The sample is an unbalanced panel of all NYSE-listed firms that had data available on all of the explanatory variables each month. In this regression, turnover is strongly and positively related to the past return variables. Further, in accordance with the Table 9 coefficients, the interacted variables are both positive and significant. We also consider signed returns instead of absolute returns as the independent variables, in order to check if the increased sensitivity of turnover to past returns is asymmetric for negative and positive returns. The results indicate that more negative or more positive returns both imply increased turnover, and the variables interacted with the post 2000 dummy are all statistically significant, clearly implying a stronger relation between turnover and the return variables in recent years.

[45] The subscript *t-2* on the characteristics indicates that we lag them by at two months in order to avoid biases because of bid-ask effects and thin trading.

[46] Fama and French (1992, 1995) argue that size, book/market, and momentum are the critical cross-sectional predictors of stock returns. Brennan, Chordia, and Subrahmanyam (1998) demonstrate the statistical significance of turnover over and beyond these variables. We choose our four predictors based on these studies.

(1973) coefficients and the associated t-statistics for the two subperiods are presented in Table 11. Size and BM are not significant in either subperiod, consistent with the notion that the Fama-French factors capture these characteristics during our sample period. While turnover and momentum are significant in the first subperiod, their significance drops off completely in the second subperiod. The coefficient magnitudes for these variables also reduce by a factor of more than half. Coupled with other evidence that cross-sectional return anomalies have weakened in recent years (Henker, Martens, and Hunh, 2006; Chordia, Subrahmanyam, and Tong, 2009) and are now mainly confined to stocks where institutions are not well-represented (Nagel, 2005, Phalippou, 2008), the stronger connection between turnover and past returns seems consistent with institutional activity bringing about more efficient price formation.

Finally, it is worth mentioning that a technological factor leading to an increase in institutional turnover is likely the increasing prevalence of algorithmic trading by hedge funds and other institutions. Dramatic improvements in technology have allowed computer algorithms to speedily discern (possibly short-lived) profit opportunities and determine optimal order submission strategies, typically by dividing up a large order into smaller trades to reduce market impact. Such short-term algorithmic trading is often termed "high frequency trading" (HFT). [47] Algorithms also dynamically monitor liquidity across different trading venues and choose optimal price and quantity pairs along with order submission strategies (limit versus market orders) to efficiently execute orders.[48]

HFT algorithms are by nature proprietary, which precludes the precise identification of algorithmic trading in aggregate data. Nonetheless, our results on turnover patterns, including the decline in trade size, the increase in number of trades, the increased trading in stocks with higher institutional holdings, and the heightened sensitivity of turnover to past returns, are all consistent with HFT algorithms that have allowed institutions to trade more cheaply and more frequently. Indeed, Hendershott, Jones, and Menkveld (2008) show that algorithmic trades by

[47]See, for example, Brogaard (2010) or http://en.wikipedia.org/wiki/Algorithmic_trading.

[48] Algorithmic trading was non-existent in the early 1990s but is expected to represent about half of the trading volume by 2010. See "Ahead of the tape –Algorithmic Trading," Economist, March 10, 2007.

institutions play an important role in liquidity provision by *de facto* market making, thus contributing to the positive feedback between liquidity and trading activity. Our evidence indicates that this enhanced institutional activity is associated with increased efficiency of price formation.[49]

VI. Concluding Remarks

Share turnover has increased dramatically over the past several years. We explore the anatomy of this significant uptrend in aggregate trading activity and accompanying shifts in measures of market efficiency. The increase in trading is associated with more frequent smaller trades, which have progressively formed a larger fraction of trading volume over time. It appears that institutions, rather than retail investors, have played the dominant role in the volume trend, because share turnover has increased the most for stocks with the greatest level of institutional holdings. Institutions appear to breaking up orders into ever-smaller increments before trading.

The cross-sectional behavior of turnover around the exogenous decline in tick sizes suggest that a decline in trading costs plays a role in the dramatic increase in trading. Determinants of trading activity such as aggregate dispersion in analysts' forecasts and implied volatility show no dramatic shifts in a manner consistent with the increase in turnover. Variance ratio tests indicate that the increase in turnover is associated with greater information-based trading, particularly in stocks with greater levels of institutional holdings. Furthermore, intraday volatility has decreased and prices conform more closely to random walk in recent years, indicating that market efficiency has increased in response to the increased institutional trading. The cross-section of turnover has also changed, in that turnover has become more sensitive to past returns in recent years. Thus, at least part of the recent rise in turnover may be attributed to institutions such as hedge funds, which employ quantitative trading strategies. Evidence

[49] During the week of August 24-28, 2009, the three firms with the highest trading volumes on Nasdaq were all high frequency traders and they accounted for an average of 26.6% of the overall daily trading volume. The top twenty trading firms accounted for 62.7% of the Nasdaq daily trading volume and of this the high frequency traders accounted for 33.3% of the total daily trading volume (personal communication with Frank Hatheway, Chief Economist, Nasdaq). It is possible that similar trading patterns prevail on the NYSE as well.

indicates that such trading has been accompanied by decreased cross-sectional return predictability, providing further support to the general notion that the increased trading activity has increased the efficiency of price formation.

Our analysis sheds light on the policy debate surrounding securities transaction taxes (STTs) and market volatility. Specifically, lawmakers in both the US and the Europe have recently proposed taxing equity trading.[50] An oft-cited rationale for STTs (e.g., Summers and Summers, 1989; Stiglitz, 1989) is that they will curb high trading activity and, in turn, control price volatility. Our analysis indicates that the dramatically increased trading activity has been accompanied by an increase in market efficiency and *decreased* intraday volatility. Not only is our work at odds with the notion that high trading has increased intradaily price fluctuations, it also suggests any tax that reduces trading activity may in fact have an adverse impact on the quality of financial markets. Thus, our paper indicates that STTs should be pursued with an abundance of caution.

Our research raises a few questions, which are worthy of further analysis. First, the impact of the dramatic increase in trading activity on investor welfare is an open question. For example, which groups of traders have benefited the most from increased trading activity? Is it institutions trading for their accounts or retail investors that invest through institutions? While markets have generally become more liquid, are there more episodes of high and low liquidity in aggregate as institutions respond to similar algorithmic triggers? Has the speed of price discovery around informational events increased in conjunction with the increase in trading? These and other issues are left for future research.

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[50] See, for example, "Transaction Tax Still Has Traction, Lawmaker Says," (November 9, 2009) at http://blogs.wsj.com/washwire/2009/11/09/transaction-tax-still-has-traction-lawmaker-says/, or "EU to Push Levies on Banks, Financial-Transaction Tax at G-20" (June 17, 2010) at http://www.bloomberg.com/news/2010-06-17/eu-leaders-to-push-global-taxes-on-banks-financial-transactions-at-g-20.html

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Table 1
Turnover summary statistics and trend fits, 1993-2008

Panel A presents the monthly value-weighted average turnover for New York Stock Exchange stocks in two subperiods, 1993-2000 and 2001-2008. Stocks in the S&P 500 index and all other NYSE stocks are reported separately. Each month, a value-weighted average turnover is computed using the market capitalization at the end of the previous year. Time series means, medians and standard deviations are reported for the monthly value-weighted averages. The turnover data are obtained from CRSP. Panel B presents trend fits for the turnover series to orthogonal Legendre polynomials for the overall period 1993 to 2008.

A: Summary Statistics (in % per month)

	S&P500 turnover	Non-S&P500 turnover
A: 1993-2000		
Mean	6.3	7.2
Median	6.2	6.8
Std. Dev.	1.3	1.5
B: 2001-2008		
Mean	12.4	16.2
Median	9.8	14.1
Std. Dev.	6.2	6.5

B: Trend Fits

	S&P 500 turnover		Non-S&P 500 turnover	
Variable	Coeff.	t-stat.	Coeff.	t-stat.
Linear	0.0682	23.21	0.0941	26.37
Quadratic	0.0457	11.96	0.0474	10.23
Cubic	0.0466	10.27	0.0329	5.98
Quartic	0.0464	8.97	0.0325	5.17
Adjusted R^2	0.8191		0.8185	

Table 2
The evolution of dollar trade size, number of transactions, and trade size

Panels A and B report, respectively, the average daily dollar trade size and average daily number of transactions on the NYSE in two subperiods, 1993-2000 and 2001-2008. The number of transactions and the average dollar trade size are calculated for each stock on each day and then value-weighted using the market capitalization at the end of the previous year. Panels C and D report the proportions of dollar trading volume represented by large and small trades, respectively, on the NYSE in the same subperiods. Large trades exceed \$10,000 and small trades are all others. Each trade on each day for each stock is classified as either large or small. Then the proportions of large and small trades are calculated for each stock each day and value-weighted across stocks using the market capitalization at the end of the previous year. Time series means, medians and standard deviations are reported for the daily value-weighted averages. Panel E reports non-linear time trends fit over 1993 to 2008 for the value-weighted average daily dollar trade size, daily number of transactions, and the percentage of trades less than \$10,000 on the NYSE. Trend fits are to orthogonal Legendre polynomials. The dollar value of each trade comes from the TAQ dataset.

	1993-2000	2001-2008	1993-2000	2001-2008
	A: Trade Size (\$thousands)		B: Number of Transactions	
Mean	82.9	36.4	1136.54	14779.35
Median	83.8	36.3	735.50	4250
Std. Dev.	9.7	20.7	882.17	22715.97
	C: Trades ≤ \$10,000 (%)		D: Trades > \$10,000 (%)	
Mean	4.46	18.18	95.54	81.82
Median	4.21	11.30	95.79	88.70
Std. Dev.	0.97	14.69	0.97	14.69

E: Time Trends

	Number of transactions		Trade Size		Percentage of trades ≤ \$10,000	
Variable	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Linear	0.1715	27.57	-0.0409	-86.16	0.1542	64.50
Quadratic	0.1940	24.17	-0.0272	-44.33	0.1641	53.16
Cubic	0.1861	19.58	0.0155	21.39	0.0947	25.93
Quartic	0.1558	14.46	0.0053	6.42	0.0630	15.20
Adjusted R^2	0.3292		0.7108		0.6683	

Table 3
Effective Spreads for Small (≤$10,000) and Large (>$10,000) Trades, and Depth

This table presents the time series means, medians and standard deviations of (i) the daily value-weighted average effective spreads for small (Panel A) and large (Panel B) trades and (ii) the value-weighted depth (Panel C) on the NYSE in the two subperiods 1993-2000 and 2001-2008. The effective spread is twice the absolute value of the difference between the transaction price and the mid-point of the bid-ask spread. Depth is the average of the numbers of shares available for trade at the inside ask and bid. Average effective spreads and depths are calculated for each stock on each day then value-weighted across stocks. The data for effective spreads and depths is obtained from TAQ.

	1993-2000	2001-2008
A: Effective Spread, Trade ≤ $10,000		
Mean	0.1022	0.0223
Median	0.1164	0.0184
Std. Dev.	0.0211	0.0092
B: Effective Spread, Trade > $10,000		
Mean	0.1069	0.0267
Median	0.1165	0.0220
Std. Dev.	0.0172	0.0106
C: Depth (shares)		
Mean	10353	2836
Median	11130	2797
Std. Dev.	3498	960.3

Table 4
Cross-sectional Regressions around Tick Size Changes

This table presents the coefficient estimates when the change in turnover is regressed on changes in the proportional quoted spread and in return volatility around the tick size events. The NYSE changed the tick size from \$0.125 to \$0.0625 (sixteenth shift) on June 24, 1997 and from \$0.0625 to \$0.01 (decimal shift) on January 29, 2001. The average daily turnover and the average daily proportional spread is computed for each stock over the one month period before and after the tick size changes. The monthly volatility is the standard deviation computed using daily returns. The dependent variable is the average change in turnover across the two months before and after the tick size change; and the explanatory variables are the average change in the proportional quoted spread (ΔRQSPR) and the change in the volatility of returns. Daily returns are obtained from CRSP while the turnover and spreads are obtained from the TAQ dataset.

Variable	Coefficient	t-statistic
Sixteenth Shift		
ΔRQSPR	-0.06524	-5.96
ΔVolatility	0.09254	19.88
Decimal Shift		
ΔRQSPR	-0.04164	-4.80
Δ Volatility	0.06004	15.79

Table 5
Turnover by Institutional Holding Quintiles

Stocks are divided into five groups by the level of institutional holdings (defined as the percentage of the total common stock held by institutions) in the immediately preceding quarter. Then, the total turnover, small trade turnover (estimated using trades that are less than or equal to $10,000) and large trade turnover (estimated using trades that are greater than $10,000) are computed for each stock each month. The value weighted average turnovers are then computed each month for each institutional holding quintile. In Panel A, these value-weighted averages are then averaged by institutional holding quintiles over the two sub-periods. Panel B fits the turnover difference between the largest and smallest holdings quintiles to trend variables. Trend fits are to orthogonal Legendre polynomials.

A: Summary Statistics (% per month)

	Institutional Holdings Group				
	Smallest	2	3	4	Largest
A: Total Turnover					
1993-2000	4.137	4.671	5.500	7.087	8.513
2001-2008	7.432	9.623	12.306	16.029	20.828
B: Small Trade Turnover, Trades ≤ $10,000					
1993-2000	0.435	0.217	0.187	0.205	0.216
2001-2008	1.875	2.342	3.111	4.433	6.263
C: Large Trade Turnover, Trades > $10,000					
1993-2000	3.702	4.454	5.314	6.883	8.297
2001-2008	5.557	7.281	9.194	11.596	14.566

B: Trend Fits for Difference in Turnover
between Largest and Smallest Institutional Holdings Group

	Total Turnover Difference		Small Trade Turnover Difference		Large Trade Turnover Difference	
Variable	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Linear	0.0881	13.86	0.0532	19.11	0.0351	7.83
Quadratic	0.0528	6.52	0.0567	15.91	-0.0034	-0.60
Cubic	0.0226	2.40	0.0425	10.22	-0.0194	-2.93
Quartic	0.0107	1.02	0.0232	4.99	-0.0117	-1.59
Adjusted R^2	0.5716		0.8077		0.2735	

Table 6
First order daily serial correlations in trade imbalances by institutional holdings

All stocks are divided into five groups by the level of institutional holdings (defined as the percentage of the total common stock held by institutions) in the immediately preceding quarter. For each stock each day, total imbalance is buy volume minus the sell volume, scaled by total volume; Small trade imbalance is the same but uses only trades less than or equal to \$10,000. Analogously, large trade imbalance uses only trades greater than \$10,000. The first order serial correlation of these imbalances is calculated for each stock during two subperiods. Finally, the value-weighted averages of the daily serial correlations are computed across institutional holding quintiles. The trading data are obtained from the TAQ dataset.

	All Stocks	Institutional Holdings Group				
		Smallest	2	3	4	Largest
A: Total Trade Imbalance						
1993-2000	0.102	0.103	0.101	0.103	0.101	0.099
2001-2008	0.198	0.171	0.191	0.200	0.212	0.227
B: Trade Imbalance in Small Trades (≤ \$10,000)						
1993-2000	0.183	0.132	0.168	0.213	0.222	0.176
2001-2008	0.223	0.189	0.221	0.224	0.239	0.252
C: Trade Imbalance in Large Trades (> \$10,000)						
1993-2000	0.089	0.076	0.084	0.092	0.096	0.097
2001-2008	0.160	0.117	0.155	0.167	0.180	0.192

Table 7
Regressions for Aggregate Turnover, 1993-2008

The upper panels present summary statistics for potential determinants of NYSE turnover across the two subperiods 1993-2000 and 2001-2008. The proposed determinants are (i) the value-weighted analyst forecast dispersion, (ii) the implied volatility of S&P 500 index, measured by VIX, and (iii) the monthly aggregated money flows into equity funds. The forecast dispersion is defined as the monthly standard deviation of earnings per share (EPS) forecasts from two or more analysts, divided by the previous month's price and scaled up by 100. This is value-weighted using the market capitalization as of the end of the previous year. The lower panels report regressions whose dependent variable is the monthly value-weighted NYSE turnover from 1993 to 2008. The explanatory variables consist of linear through quartic trend fits to orthogonal Legendre polynomials and, in the second regression, the potential determinants whose summary statistics are given in the upper panels. The coefficient for equity fund flows is scaled upwards by 10^6.

	1993-2000	2001-2008
Analysts' Forecast Dispersion		
Mean	0.246	0.275
Median	0.246	0.267
Std. Dev.	0.055	0.073
Implied Volatility (VIX)		
Mean	20.52	23.00
Median	19.43	22.18
Std. Dev.	6.92	11.24
Equity Fund Flows ($millions/month)		
Mean	11655	3984
Median	12447	6448
Std. Dev.	11673	16701

	With trend variables only		With trend variables and other potential determinants	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
Linear	0.0650	31.06	0.0600	26.11
Quadratic	0.0398	14.79	0.0455	13.41
Cubic	0.0386	12.22	0.0263	7.25
Quartic	0.0328	9.20	0.0125	2.65
Analysts' Forecast Dispersion			0.0615	0.29
Equity Fund Flows			-0.1281	-1.29
VIX			0.0012	4.76
Adjusted R-squared	0.8830		0.9027	

Table 8
Variance Ratios Computed using Open-to-Close and Close-to-Open Returns

The panels below present basic summary statistics for per hour open/close to close/open variance ratios for NYSE stocks during the sub-periods 1993-2000 and 2001-2008. The ratios are computed monthly from value-weighted open-to-close and close-to-open returns. Then means, medians and standard deviation are computed across months within each subperiod. Panel A includes all firms. Panel B presents five groups sorted by the level of institutional holdings (defined as the percentage of the total common stock held by institutions) in the immediately preceding quarter. Panel C provides coefficient estimates from a regression that fits a non-linear time trend to the difference in the open-to-close to close-to-open variance ratio between high and low institutional holdings quintile portfolios.

A: All Firms

	1993-2000	2001-2008
Mean	9.917	12.46
Median	8.301	10.99
Std. Dev.	6.432	7.563

B: By Institutional Holding Quintiles

	Smallest		2		3		4		Largest	
Sub-period	1993-2000	2001-2008	1993-2000	2001-2008	1993-2000	2001-2008	1993-2000	2001-2008	1993-2000	2001-2008
Mean	13.10	12.07	9.923	11.26	9.088	11.90	9.061	14.35	11.60	15.68
Median	11.54	10.29	8.742	9.816	7.813	10.36	7.481	11.92	9.211	13.22
Std. Dev.	9.345	8.736	6.765	7.179	6.441	7.463	7.133	9.682	8.726	10.84

C: Trend Fit for Difference in the Open-to-Close to Close-to-Open Variance Ratio
Between the Largest and Smallest Institutional Holdings Groups

	Open/Close to Close/Open Variance Ratio Difference (Largest-Smallest)	
Variable	Coefficient	t-statistic
Linear	4.901	3.79
Quadratic	-2.270	-1.37
Adjusted R^2	0.0795	

Table 9
Intraday Volatility and Hourly/Daily Variance Ratios, 1993-2008

The panels below present basic summary statistics for intraday volatility computed at five minute intervals (grossed up to daily volatility) and hourly/daily variance ratios for NYSE stocks during the sub-periods 1993-2000 and 2001-2008. The ratios are computed monthly and then means, medians and standard deviation are computed across months within each subperiod in Panel A. Panel B presents trend fits of the time series to orthogonal Legendre polynomials. In Panel C, we present results from a cross-sectional regression where the dependent variables, in turn, are the change in the intraday volatility and the hourly/daily variance ratio, and the explanatory variables are changes in turnover and institutional holdings across the two sub-periods.

A: Summary Statistics

	1993-2000	2001-2008
Intraday Volatility		
Mean	0.0419	0.0252
Median	0.0429	0.0205
Std. Dev.	0.0063	0.0114
Hourly/DailyVariance Ratios		
Mean	1.302	1.180
Median	1.300	1.179
Std. Dev.	0.0995	0.0914

B: Trend Fit

	Intraday Volatility		Hourly/Daily Variance Ratios	
Variable	Coeff.	t-stat.	Coeff.	t-stat.
Linear	-0.0141	-12.32	-0.1207	-6.86
Quadratic	0.0037	2.49	0.0772	3.38
Adjusted R^2	0.4496		0.2274	

C: Cross-Sectional Regressions

	Intraday Volatility						Hourly/Daily Variance Ratios					
Variable	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Turnover	-0.051	-4.61			0.003	0.26	-0.456	-5.47			-0.235	-2.71
Inst. Hldgs.			-0.089	-15.67	-0.089	-14.87			-0.406	-9.10	-0.364	-7.70
Adjusted R^2	0.0135		0.1423		0.1417		0.0192		0.0526		0.0566	

Table 10
Cross-Sectional Regressions of Turnover on Past Absolute Returns and Controls

This table presents coefficients of the past month's absolute return (LARET) and the absolute value of the compounded return over the past two to six months (LARET26) in the cross-sectional regression of monthly turnover of NYSE stocks on these variables. The sample period is 1993 to 2008. Size, dispersion in analyst forecasts, and firm age are also included as controls. Size is measured by market capitalization as of the end of the previous month. Analyst forecast dispersion represents the standard deviation of earnings per share (EPS) forecasts from two or more analysts, scaled by the stock price as of the end of the previous month. This variable is averaged annually, and the previous year's observation is used in the regression. Age is defined as the number of days since the date of first listing on CRSP, calculated as of the end of the previous year. The coefficients of these control variables are suppressed for brevity. In Panel A, summary statistics for the monthly return coefficients are computed separately across the subperiods 1993-2000 and 2001-2008. Panel B fits the coefficients to trend variables. Trend fits are to orthogonal Legendre polynomials.

A: Summary Statistics

	Past One-Month Return Coefficient (LARET)		Past Two-to Six-Month Return Coefficient (LARET26)	
	1993-2000	2001-2008	1993-2000	2001-2008
Mean	2.032	4.477	0.899	1.766
Median	1.868	3.960	0.894	1.604
Std. Dev.	0.942	2.668	0.347	1.154

B: Trend Fits

	Past One-Month Return Coefficient (LARET)		Past Two-to Six-Month Return Coefficient (LARET26)	
Variable	Coeff.	t-stat.	Coeff.	t-stat.
Linear	2.426	8.87	0.9830	7.64
Quadratic	1.973	5.64	0.9593	5.86
Adjusted R^2	0.3703		0.3304	

Table 11
Fama-MacBeth Regression Coefficients

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates and the associated *t*-statistics. Following the methods of Brennan, Chordia and Subrahmanyam (1998) the dependent variable is the excess return risk-adjusted using the Fama-French (1993) factors. SIZE represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURN represents the logarithm of turnover. These variables are lagged by two months. RET6 is the cumulative return over the second through the sixth month prior to the current month.

	1993-2000		2001-2008	
	mean	*t*-stat.	mean	*t*-stat.
RET6	1.0668	3.27	0.4513	1.15
SIZE	0.0465	0.87	-0.0356	-0.59
BM	0.0062	0.07	0.0671	0.73
TURN	-0.2168	-2.44	-0.0365	-0.36

Figure 1. Average Turnover, S&P 500 Stocks and Other Stocks, 1993-2008. This figure plots the monthly value-weighted average turnover for New York Stock Exchange stocks from 1993 to 2009. Stocks in the S&P 500 index and others are shown separately. Each month, the value-weighted average turnover is computed using the market capitalization at the end of the previous year. The turnover data are obtained from CRSP.

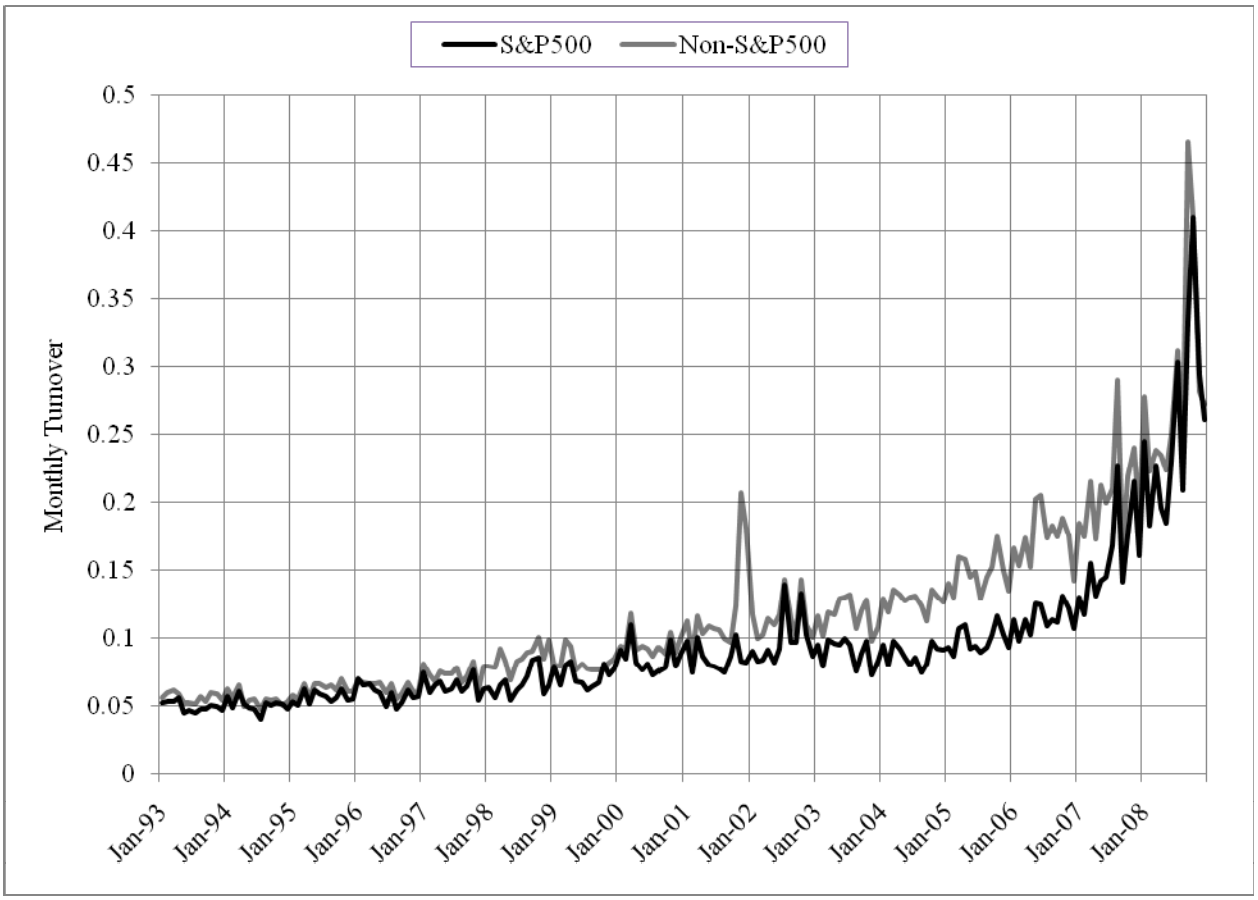
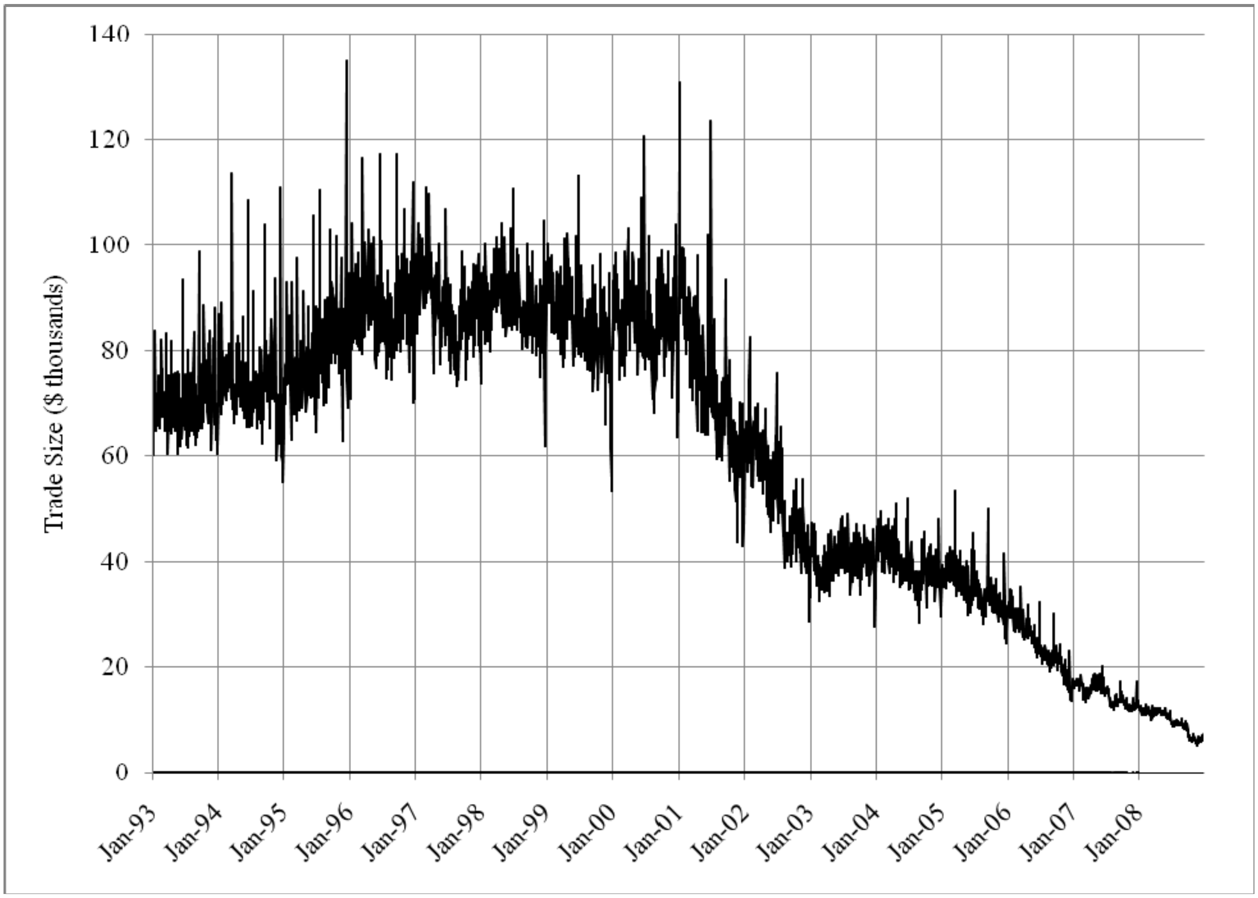


Figure 2. Average Dollar Trade Size and Average Daily Number of Transactions, 1993-2008. This figure shows the value-weighted average daily dollar trade size (Panel A) and value-weighted average daily number of transactions (Panel B) on the NYSE, 1993 to 2008. The number of transactions and the average dollar trade size are calculated for each stock on each day and then value weighted across stocks using market capitalization at the end of the previous year. Data for the number of transactions and dollar trade size are obtained each day from the TAQ dataset.

Panel A: Average Dollar Trade Size, 1993-2008



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Panel B: Average Daily Number of Transactions, 1993-2008

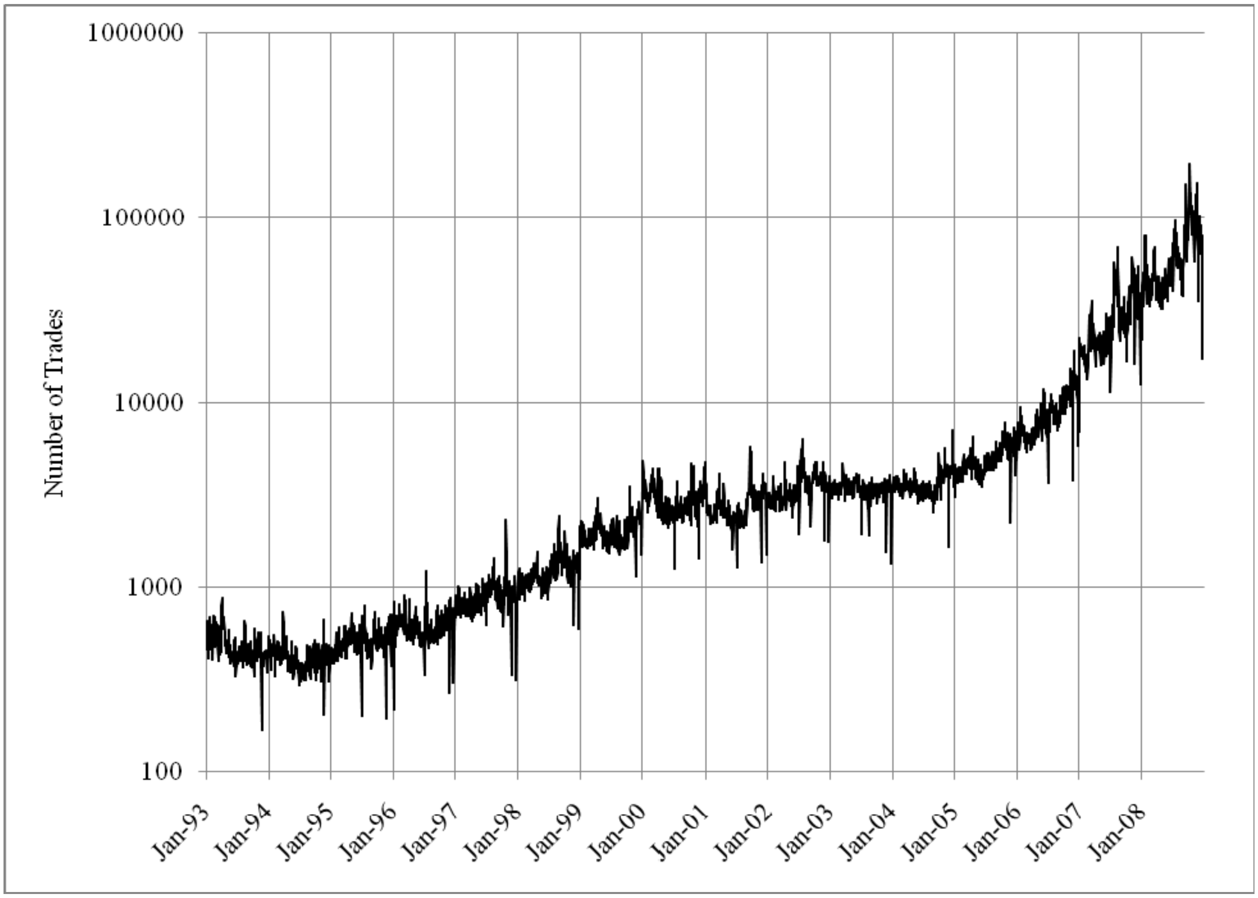
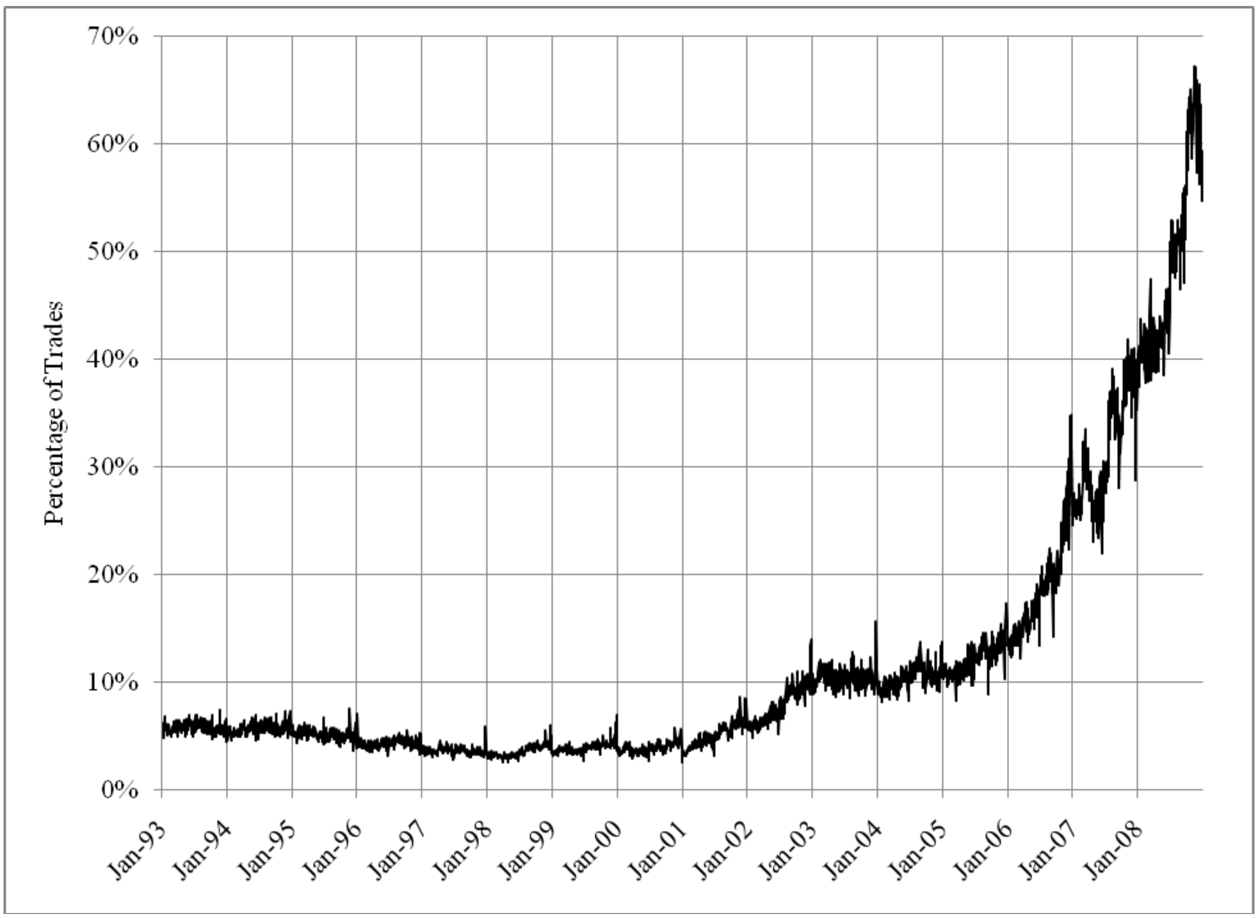


Figure 3. Percentage of Total Dollar Volume Due to Large and Small trades, 1993-2008. This figure presents the percent of dollar trading volume represented by large and small trades on the NYSE. Large trades are defined as exceeding $10,000 and small trades are all others. Each trade on each day for each stock is classified as either large or small. Then the proportion of large and small trades is calculated for each stock each day. The value-weighted average proportion of large and small trades is calculated each day. The dollar value of each trade comes from the TAQ dataset.

Panel A: Percentage of Trades Less or Equal to $10,000



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Panel B: Percentage of Trades Greater Than $10,000

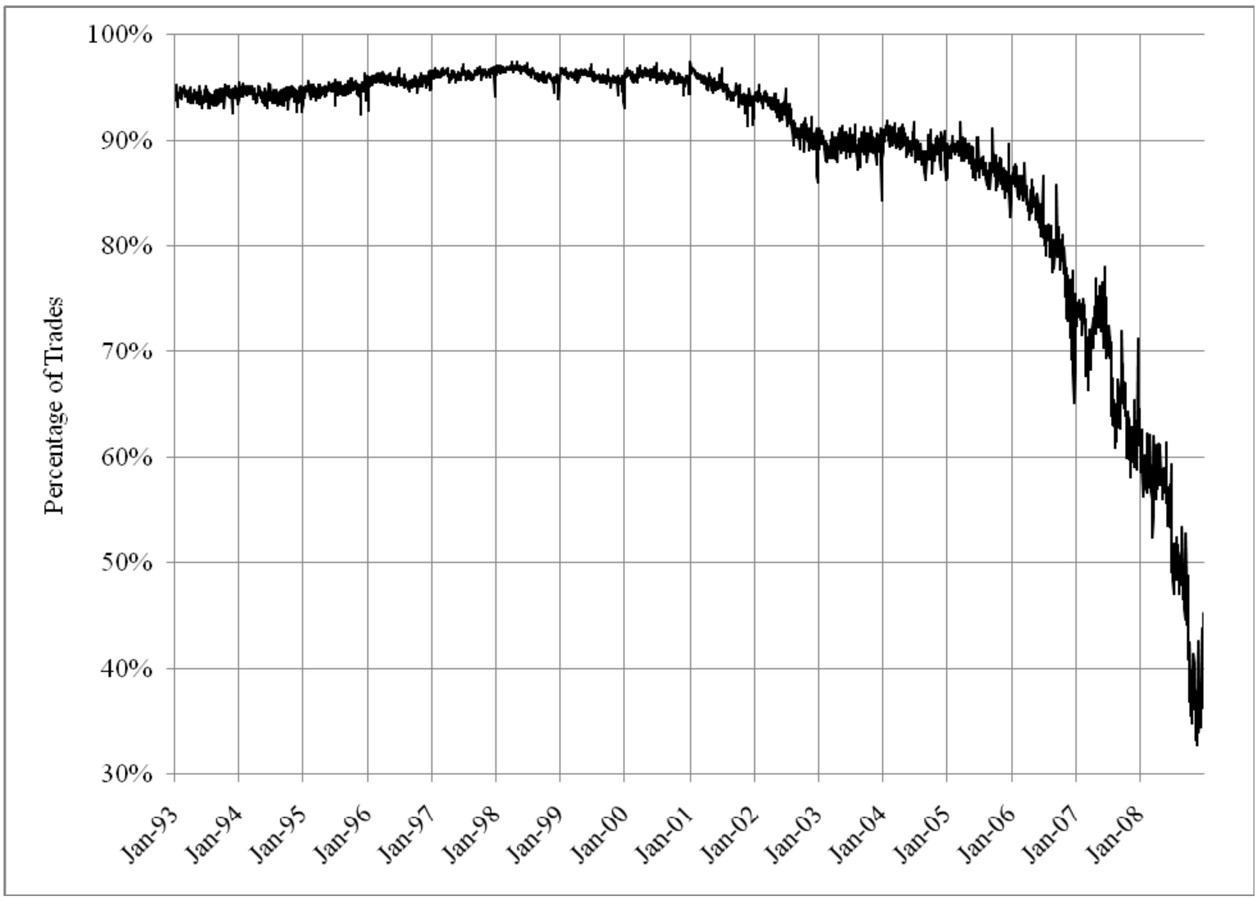
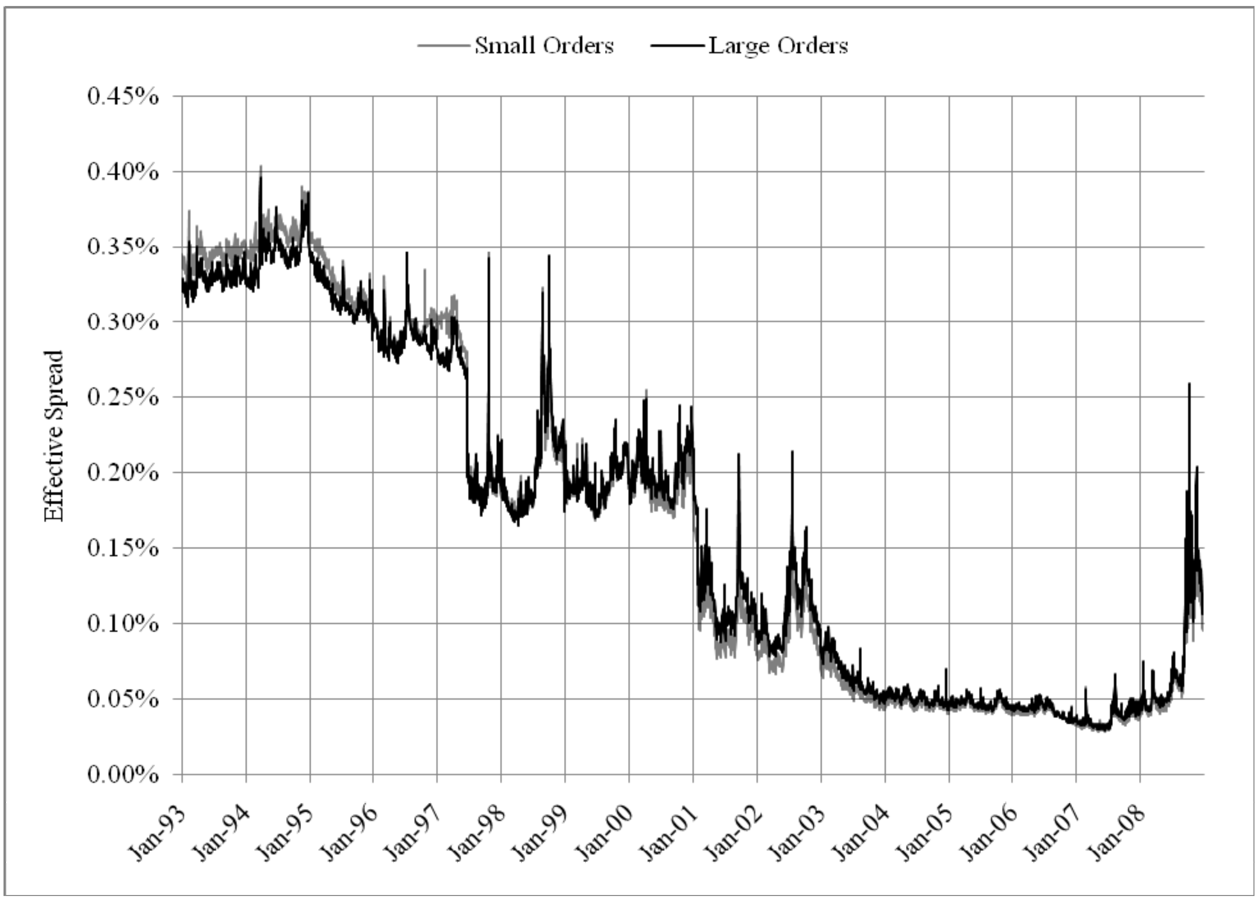


Figure 4. Effective Spreads for Small and Large Orders and Market Depth, 1993-2008. This figure presents the daily value-weighted average effective spreads for small and large trades (Panel A) and value-weighted mean depth (Panel B) on the NYSE in the period 1993 to 2008. Large trades exceed $10,000 and small trades are all others. Each trade on each day for each stock is classified as either large or small. The effective spread is twice the absolute value of the difference between the transaction price and the mid-point of the bid-ask spread. Depth is the average of the number of shares available for trade at the inside ask and bid, and is averaged for each stock on each day. The value-weighted average over stocks is obtained for both effective spreads and depth for each day over the time period. The data for effective spreads and depths are obtained from TAQ.

Panel A: Effective Spreads for Small (≤$10,000) and Large (>$10,000) Trades



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Panel B: Market Depth, 1993-2008

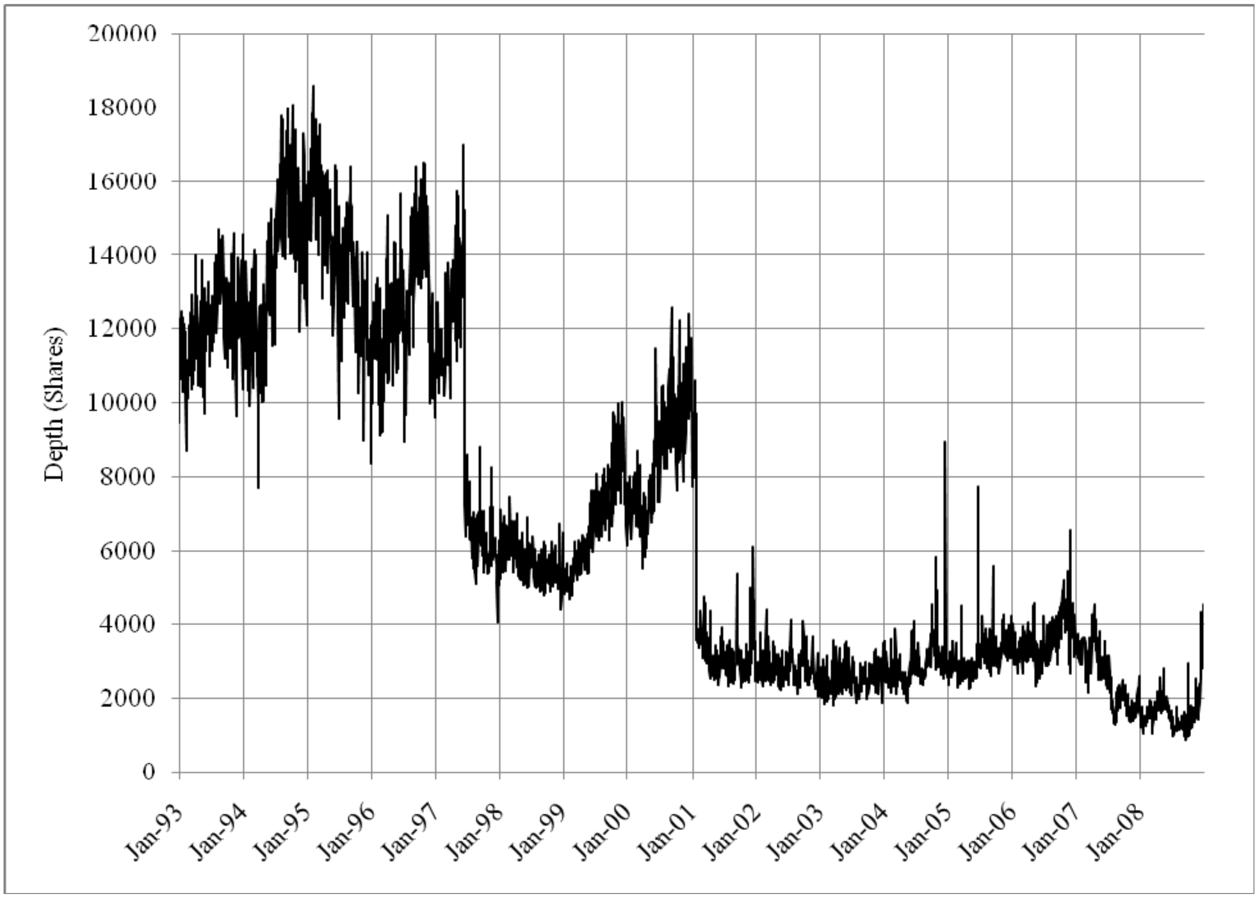

Figure 5. Value-Weighted Average Turnover across Institutional Holdings Quintiles, 1993-2008, . All stocks are divided into five groups by the level of institutional holdings (defined as the percentage of the total common stock held by institutions) in the immediately preceding quarter. Then, the total share turnover is computed for each stock each month. The value weighted average turnovers (using market capitalizations as of the end of the previous year) are then computed each month for each institutional holding quintile. The trading data are obtained from the TAQ dataset.