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The Cross-Section of Expected Trading Activity

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Abstract

The Cross-Section of Expected Trading Activity

This paper studies cross-sectional variations in trading activity for a comprehensive sample of NYSE/AMEX and Nasdaq stocks over a period of about 40 years. We test whether trading activity depends upon the degree of liquidity trading, the mass of informed traders, and the extent of uncertainty and dispersion of opinion about fundamental values. We hypothesize that liquidity (or noise) trading depends both on a stock's visibility and on portfolio rebalancing needs triggered by past price performance. We use firm size, age, price and the book-to-market ratio as proxies for a firm's visibility. The mass of informed agents is proxied by the number of analysts, while forecast dispersion and firm leverage proxy for differences of opinion. Earnings volatility and absolute earnings surprises proxy for uncertainty about fundamental values. Overall, the results provide support for theories of trading based on stock visibility, portfolio rebalancing needs, differences of opinion and uncertainty about fundamental values.

The literature on financial markets has traditionally focused on explaining asset prices, while trading activity has attracted only peripheral attention. Empirical investigations of well-known asset pricing models such as the CAPM have centered only on the determinants of expected returns. Yet trading activity is an inalienable feature of financial markets and, thus, warrants separate examination. Indeed, trading volumes are large in financial markets. For example, the NYSE website indicates that the annual share turnover rate in 2003 on the NYSE was about 99%, amounting to a total volume of about 350 billion shares. Assuming a per share value of $20 and a 50 basis point round-trip cost of transacting, this amounts to a transaction cost of $17.5 billion dollars that the investing public paid in 2003.

In addition to the generally high levels of volume, trading activity across individual stocks exhibits substantial variation. For instance, in 2001, the annual turnover of International Rectifier Corporation was more than eight times higher than that of IMC Global Incorporated, even though the market capitalizations of these two NYSE listed companies differed by less than 1%. The specific focus of this paper is to explain such cross-sectional variation in trading activity. Our study attains further significance because the literature has shown that trading activity is strongly related to the cross-section of expected returns and hence to the cost of equity capital.[1] Finally, if greater trading volume stimulates more information collection due to higher brokerage commissions as suggested by Brennan and Chordia (1993), then our results also have implications for stocks that are most likely to be informationally efficient due to increased scrutiny.

While there is a large literature on trading volume, this study is the first to comprehensively examine the cross-sectional determinants of trading activity. A number of empirical studies have documented a positive correlation between volume and absolute price changes (see Karpoff, 1987, Schwert, 1989, and Gallant, Rossi, and Tauchen, 1992). Amihud and Mendelson (1987, 1991) find that volume is higher at the market's open. Foster and Viswanathan (1993b) demonstrate a U-shaped intraday volume pattern and

[1] See Brennan, Chordia and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001).

also find that trading volume is lower on Mondays. Gallant, Rossi, and Tauchen (1992) investigate the relationship between price and volume using a semi-nonparametric method. In their time-series analysis, they find that daily trading volume is positively related to the magnitude of daily price changes and that high volume follows large price changes. Lakonishok and Maberly (1990) observe that volume from individuals is larger but institutional volume is smaller on Mondays. Ziebart (1990) documents a positive relation between volume and the absolute change in the mean forecast of analysts. Campbell, Grossman, and Wang (1993) and Llorente et al. (2002) analyze the dynamic relation between volume and returns in the cross-section. Lo and Wang (2000) regress median turnover for NYSE/AMEX stocks on a set of contemporaneous variables aggregated over five-year intervals. Building on these studies, we run predictive regressions for monthly turnover, for both NYSE/AMEX and Nasdaq stocks, using a broad set of lagged explanatory variables. We also examine another intuitive measure of trading activity - order flow.

Trading could arise naturally from the portfolio rebalancing needs of investors in response to changes in asset valuations. Apart from this motive, there are two schools of thought that develop theories for trading activity. In the first set of models, which are based on the rational expectations paradigm, trading occurs due to non-informational reasons as well as due to the profit motives of privately informed investors. These models generally examine trading among privately informed traders, uninformed traders, and liquidity or noise traders.[2] In these models, investors try to infer information from trading activity and market prices. Noise trading usually impedes this inference.

The second school of thought models trading as induced by differences of opinion; this line of research often de-emphasizes the role of information gleaned from market prices, and does not include noise traders. Examples of this literature include Harrison and Kreps (1978), Varian (1985, 1989), Harris and Raviv (1993), and Kandel and Pearson

[2]See Grossman and Stiglitz (1976, 1980), Hellwig (1980), Kyle (1985), Admati and Pfleiderer (1988), Grundy and McNichols (1989), Foster and Viswanathan (1990, 1993), Kim and Verrecchia (1991a, 1991b), and Wang (1994).

(1995). In Harris and Raviv (1993) and Kandel and Pearson (1995), investors share the same public information but interpret it differently, a scenario which results in trading activity.

We argue that trading activity depends on the amount of liquidity trading, the mass of informed agents, learning by investors about fundamental value or about the return generating process, as well as the dispersion of agents' information signals. Liquidity or noise trading is likely driven in part by portfolio rebalancing needs triggered by past returns. Following Merton (1987), we further propose that individual investors' liquidity needs are realized only in a subset of the most visible stocks. Proxies for visibility include size, firm age, the book-to-market ratio, and the price level. The number of analysts serves as a proxy for the mass of informed agents as suggested by Brennan and Subrahmanyam (1995). The extent of estimation uncertainty about fundamental values is proxied by systematic risk, earnings volatility, and earnings surprises. Finally, analyst forecast dispersion and firm leverage serve as proxies for the heterogeneity of opinion about a company.

While other studies have also examined the relation of volume with specific characteristics such as analyst following and firm size, our consideration of multiple characteristics within the same empirical framework allows us to examine the incremental impact of specific variables and takes a step towards building a comprehensive understanding of trading activity. The results show that higher positive and more negative returns substantially increase trading activity. In other words, the more extreme the returns (positive or negative) the higher is the trading activity. Overall, these results are consistent with portfolio rebalancing needs of investors and with positive feedback trading or the disposition effect as suggested by Hong and Stein (1999), Odean (1998) and Ströbl (2003). Analyst forecast dispersion is also positively related to trading activity suggesting that greater divergence of opinion leads to higher trading activity. Firm systematic risk as measured by beta, earnings surprise and earnings volatility are also important determinants of the cross-section of expected trading activity supporting the view that stocks with higher estimation uncertainty about fundamental values experience increased trading activity.

A variable with potentially strong explanatory power is the number of analysts. It may be argued, however, that stocks with more active trading are likely to attract more analysts instead of higher analyst coverage causing more active trading. We address this issue by examining a simultaneous equation system. Estimation of this system preserves our results on the determinants of trading activity other than analyst following. However, there is no evidence that, after controlling for our characteristics, the number of analysts following a stock itself influences trading activity. This suggests that analysts do not directly influence turnover by trading on private information, but act to facilitate the production of public information through their forecasts which are disseminated to the general public. This view of security analysis is consistent with that of Easley, O'Hara, and Paperman (1998).

We also focus on another intuitive measure of trading activity: annual order imbalances, as estimated in Chordia, Roll, and Subrahmanyam (2002). This measure is distinct from unsigned volume, because order imbalances capture net buying or selling pressure from traders who demand immediacy and thus are strongly related to price movements.[3] While signed imbalances simply capture net buying or selling pressure, the corresponding absolute values, by capturing extreme imbalances in either direction, are related to illiquidity since the cost of establishing and turning around a position is likely to be larger in stocks with higher absolute imbalances. We examine the predictors of both signed and absolute imbalances. Many of the variables that cause higher turnover are negatively related to absolute imbalances, thus, contributing to liquidity by reducing the cost of turning around a position. Further, trades in stocks with positively higher returns are more likely to be buyer-initiated in the following month. This points to the presence of feedback traders. The imbalance analysis thus sheds light on the source of the link between price movements and the trading behavior of traders as suggested by the models of De Long et al. (1990), Hirshleifer, Subrahmanyam and Titman (2004),

[3]Chordia and Subrahmanyam (2004) show that imbalances also have predictive power for future returns.

and Hong and Stein (1999).

The remaining sections of this paper are organized as follows. In Section 1, we explain our rationale for choosing explanatory variables. Section 2 describes the data and their adjustments. Section 3 discusses the empirical results and their implications. Section 4 provides some evidence on the determinants of order imbalances. Section 5 summarizes and concludes.

1 Selection of Variables

In this section, we discuss measures and candidate determinants of unsigned trading activity (turnover). We discuss signed trading activity (order imbalances) later in Section 4. For expositional convenience, till that time, we construe "trading activity" to signify unsigned measures. We first present economic arguments that guide our choice of the independent variables.

In our cross-sectional regressions, the dependent variable is turnover, a measure of unsigned trading activity. Lo and Wang (2000) argue that if all investors hold the same relative proportion of risky assets all the time (i.e., if two-fund separation holds), share turnover yields the sharpest empirical implications and hence is the most appropriate measure of trading activity. On account of the well-known double-counting issue related to Nasdaq volume (Atkins and Dyl, 1997), we separately examine NYSE/AMEX (interchangeably, the "exchange market") and Nasdaq (interchangeably, the "OTC market") stocks. The monthly turnover for each of the component stocks over the sample period is adjusted to account for trends and regularities; further details appear in Section 2.

The models of Hellwig (1980), Harris and Raviv (1993), and Kandel and Pearson (1995) suggest that trading volume is a function of liquidity trading, dispersion of opinion, and the mass of informed agents. There is an inextricable link between current price moves and current volume, which suggests the inclusion of current returns as an explanatory variable for current volume. However, in our empirical implementation, we do not include the contemporaneous return because our objective is to identify *predictors* of trading activity in the cross-section.[4] We hypothesize, however, that the volume of liquidity trading may be a function of *past* returns due to portfolio rebalancing needs triggered by past stock price performance. We further proxy for liquidity trading by attributes that measure a stock's visibility, which attracts individual investors (Merton, 1987). The mass of informed agents is proxied by analyst following as in Brennan and Subrahmanyam (1995).[5] We also use proxies for estimation uncertainty about a security's fundamental value or its return generating process. Estimation uncertainty could also lead to trading activity as agents update their beliefs and learn about fundamental values upon the revelation of new information. All of the specific variables are described more precisely in the next two subsections.

1.1 Proxies for the Extent of Liquidity Trading

We consider various aspects of a stock that may proxy for the volume of liquidity or noise trading in a stock. First, investors are likely to trade for portfolio rebalancing reasons, which gives rise to informationless liquidity trading. Second, following Goetzmann and Kumar (2002) and Merton (1987), we propose that agents focus only on a subset of the most visible stocks. This suggests that investor liquidity needs, which stimulate trading activity, tend to be realized mainly in the highly visible stocks.

We begin by proposing that liquidity trading triggered by portfolio rebalancing needs may imply that trading activity depends on past returns. Trading volume in response to past returns is also predicted by other theoretical models: viz. DeLong et al. (1990),

[4] We note that due to momentum in asset returns (Jegadeesh and Titman, 1993), past returns may be related to current returns, and thus may influence current trading volume.

[5] We could have used insider holdings to proxy for informed trading. However, data on insider holdings is not reliably available for a large sample period. Also, it is not clear that insider volume is a large enough fraction of total volume to yield any discernible relationships (Cornell and Sirri, 1992, Meulbroek, 1992, and Chakravarty and McConnell, 1999). One might also wonder why we do not include a direct liquidity measure in our empirical analysis of trading activity. There are two reasons for this. First, liquidity proxies such as spreads are not available for extended time-periods. Second, liquidity is an endogenous variable in microstructure models and, thus, a deterministic function of some of our independent variables.

Hong and Stein (1999), and Hirshleifer, Subrahmanyam, and Titman (1994, 2005). In order to check for asymmetric effects that could arise because of short-selling constraints and due to the disposition effect,[6] we define RET^+ as the monthly return of an individual stock if positive, and zero otherwise. Similarly, RET^- represents the monthly return if negative, and zero otherwise.

We use the book-to-market ratio, BTM, as one proxy for a stock's visibility. Low BTM stocks are growth stocks (for example, technology stocks) that are likely to be more visible. The book value of equity is obtained by adding deferred taxes to common equity as of the most recent fiscal year-end. Following Fama and French (1992), market value is measured as of the previous December.

To partially capture a stock's visibility, we also use a price-related variable, ALN(P), which is defined as log(ADJP) (i.e., the natural logarithm of ADJP)), where ADJP is the split- and stock dividend-adjusted price level.[7] Brennan and Hughes (1991) suggest that, because of the inverse relationship between brokerage commissions and price per share, brokers publicize the low priced stocks more. Moreover, Falkenstein (1996) shows that mutual funds are averse to holding low-price stocks. In addition, as suggested in the Lo and Wang (2001) model on the joint behavior of volume and return, the market value of a firm could affect trading activity. Thus, we include a firm size variable, ASIZE, which is defined as log(MV), where MV is month-end market capitalization.

How long a firm has been in business (firm age) could affect trading activity of the stock. For instance, young firms receive a lot of attention during the IPO process and this publicity could raise trading volumes. Since trading data are available only after a firm goes public, we measure the age of a firm, FAGE, as log(1+M), where M is the number of months since its listing on an exchange.

[6]For example, Grinblatt and Keloharju (2001) document that past positive and negative returns differentially affect Finnish investors' buying and selling activity due to the disposition effect. See also Statman and Thorley (2003) and Nagel (2004) for behavioral approaches to the return-volume relation.

[7]To calculate ADJP from the CRSP database, the observed price (absolute value of the variable PRC) is divided by CFACPR (cumulative factor to adjust price).

1.2 Information Asymmetry, Differences of Opinion, and Learning

We use analyst coverage (ALANA) as a proxy for information-based trading. Brennan and Hughes (1991) and Brennan and Subrahmanyam (1995) discuss the link between analyst following and information production. In our regression specification, we use ALANA, which is defined as log(1+ANA), where ANA is the number of analysts who follow a company and report forecasts to the I/B/E/S database.

A firm with excessive debt is considered riskier to investors than a predominantly equity-financed firm due to a high probability of financial distress and default. Also, well-known agency arguments suggest that when a firm has less equity or is highly leveraged, managers (more precisely equity-holders) of the firm prefer to take on riskier and uncertain projects. We propose that with enhanced risk, differences of opinion could be larger for more highly levered firms, and these differences could in turn influence trading activity. Hence we include leverage (LEVRG) (the debt-to-asset ratio) as an explanatory variable. The ratio is obtained by dividing book debt by total assets, where book debt is the sum of current liabilities, long-term debt, and preferred stock.

We also employ analyst forecast dispersion as a direct measure of heterogeneous beliefs.[8] Diether, Malloy, and Scherbina (2002) provide evidence that stocks with higher forecast dispersion earn lower future returns than otherwise similar stocks. By employing forecast dispersion, we examine how differences of opinion in the market for information production affect cross-sectional trading activity. The monthly forecast dispersion, FDISP, is defined as the standard deviation of earnings per share (EPS) forecasts from multiple (two or more) analysts.[9]

[8] Another possible proxy for dispersion of opinion is the short interest in a stock, which is considered by Bessembinder, Chan, and Seguin (1996) as a determinant of aggregate market trading activity. Unfortunately, this variable is not available for the broad cross-section and the extended time period that we consider in this paper.

[9] By demonstrating a link between the extent of disagreement about a stock across newsletters and trading activity in the stock, Graham and Harvey (1996) provide suggestive evidence that dispersion of opinion is relevant for turnover.

To proxy for the extent to which estimation uncertainty about fundamental values plays a significant role in price formation, we consider measures of earnings surprises and earnings volatility. The notion is that if absolute earnings surprises are high then large rebalancing trades could be triggered as agents update their beliefs about fundamental values. Further, for volatile earnings streams, there is more scope for agents to make estimation errors, hence learning-induced volume could be greater. The earnings surprise (ESURP) variable is computed as the absolute value of the most recent quarterly earnings minus the earnings from four quarters ago, while earnings volatility (EVOLA) is defined as standard deviation of earnings of the most recent eight quarterly earnings.

Coles and Loewenstein (1988) and Coles, Loewenstein, and Suay (1995) argue that estimation risk is non-diversifiable and that low information securities or securities with high estimation uncertainty would tend to have high equilibrium betas.[10] Since we expect investors to make greater estimation errors in low information securities and since greater estimation uncertainty leads to greater error corrections and hence higher trading activity, we expect high betas to be positively related to turnover. Moreover, beta is more likely related to fundamental economic notions such as the cyclical nature of the firm's business, and is not likely to be jointly determined with turnover. We estimate beta by the following time-series regression:

$$R_i - R_f = \alpha_i + \beta_{i,m}[R_m - R_f] + \epsilon_i, \tag{1}$$

where R_i, R_f, and R_m are individual stock returns, risk-free interest rates, and CRSP value-weighted market index returns, respectively. To estimate individual betas (IBETA) from the above equation, we require that the firm have monthly returns for at least 48 months prior to the year in question. In order to reduce the measurement error problem, however, we use portfolio betas (PBETA) instead of individual betas (IBETA) as in Fama and French (1992). First, stocks are split into deciles by firm size, and then each of these 10 portfolios is again split into 10 portfolios after sorting by pre-ranking individual beta

[10]See also Klein and Bawa (1977), and Barry and Brown (1985). The broad intuition is that high estimation risk causes prices to be lower and covariances to be higher (if fundamental risk arises due to stochastic future cash flows). For other models of learning, see Wang (1994), Veronesi (1999), Brennan and Xia (2001), and Xia (2001).

(IBETA) estimated from equation (1). This results in 100 portfolios each year. Then we compute portfolio average returns for the next 12 months for 100 portfolios each year. Using the 100 time series of these average returns over the whole sample period, we estimate post-ranking betas for the 100 portfolios. Then we assign these post-ranking betas (Fama-French portfolio betas) to the component stocks of the relevant portfolios.

2 Data, Descriptive Statistics, and Adjustments

For this study, we use data at a monthly frequency over 39.5 years (474 months: from July 1963 to December 2002). In some cases where accounting variables and other data are available only on a yearly (or quarterly) basis, we keep those values constant for 12 months (or 3 months) in regressions.[11] Following Fama and French (1992) we assume a lag of six months before the annual accounting numbers are known to investors. We split the entire period into two subperiods [the first subperiod: 196307-198212 (234 months), and the second subperiod: 198301-200212 (240 months)] in order to compare the impact of the various structural changes in the U.S. stock market since the early 1980s. Two examples of those structural changes are the growth of the mutual fund industry and the introduction of futures contracts on indices.

The source of the number of analysts (ANA), ALANA, earnings surprise (ESURP), and earnings volatility (EVOLA) is the I/B/E/S database. If a firm has one or more missing value(s) in the number of analysts, the missing months are filled with the previous month's value. FDISP is computed using the raw forecast data, unadjusted for stock splits (provided by I/B/E/S on request), in order to correct rounding errors that may occur when the usual I/B/E/S database is used.[12] Given the limited availability of the ESURP, EVOLA, ALANA, and FDISP data for NYSE/AMEX stocks, we construct different regression specifications in Table 3 including some or all of these variables for

[11] The data series available only on a yearly basis are: LEVRG, PBETA, BTM, I1-I48, and ROA as well as LGBSEG to be used later in Subsection 3.2. Those available only on a quarterly basis are: ESURP and EVOLA.

[12] We are grateful to Anna Scherbina for generously providing the forecast dispersion data.

Subperiods 2a (with ESURP and/or EVOLA), 2b (with ALANA and/or FDISP), and 2c (with ESURP, EVOLA, ALANA, and/or FDISP), which are comparable with Subperiod 2 (198301-200212). For Nasdaq stocks, we do the same for Subperiods 2e, 2f, and 2g, which are comparable with Subperiod 2d (198301-200212). Henceforth, we will use the terminology "second subperiod" interchangeably to imply Subperiods 2, and/or 2a-2g.[13]

The graphs in Figure 1 present the trends in the three measures of trading activity by plotting the time-series of monthly cross-sectional averages for turnover (TURN), share volume (SHRVOL) in 100 thousand shares, and dollar volume (DVOL) in millions of U.S. dollars. As Figure 1(a) shows, the average turnover of NYSE/AMEX stocks exhibits an increasing (sometimes exponentially increasing) time trend. Monthly turnover began from only 1.54% in July 1963, reaching 9.25% in October 1987. Turnover dropped immediately after the 1987 crash but resumed the increasing trend again, eventually achieving a record high of 11.74% in July 2002. Monthly turnover in the OTC market, while not much different from that of NYSE/AMEX in January 1983 (NYSE/AMEX 5.96% vs. Nasdaq 5.42%), ends up with a level three times as high as that of the exchange market in February 2000 (NYSE/AMEX 8.69% vs. Nasdaq 27.07%). This high level of turnover in the Nasdaq market may partly be related to double counting as documented by Atkins and Dyl (1997). Reflecting the recent economic recession, turnover in the OTC market showed a sharp decline in 2001-2002 (10.88% in December 2002).

Table 1 reports the time-series average values of monthly means, medians, standard deviations (STD) and other descriptive statistics for our trading activity measures over the subperiods as well as the entire period. We include share volume (SHRVOL) and dollar volume (DVOL) in addition to turnover (TURN) for comparison purposes. The values of each statistic are first obtained cross-sectionally then averaged in the time-series.

Compared to those of Subperiod 1, the mean and median of the trading activity

[13] For estimation using the system instrumental variable (SIV) method in Table 4, the second subperiods are notated as Subperiods 2h (for NYSE/AMEX stocks) and 2i (for NASDAQ stocks). Since the order imbalance data are available from January 1988 to December 2002 only, in Table 5 the second subperiods are notated as Subperiods 2j (for trade number imbalances) and 2k (for dollar value imbalances).

measures and the price level for NYSE/AMEX stocks increased sharply in Subperiod 2. Specifically, the average monthly turnover is 4.45% for the entire period, but large differences emerge across the two subperiods. The mean turnover in Subperiod 2 (6.00%) is more than twice that of Subperiod 1 (2.85%). Figure 1 suggests that the mean turnover in the OTC market (8.42%) in Subperiod 2d (198301-200212) significantly exceeds that of the exchange market (6.00%) in the comparable Subperiod 2. The increase in trading activity over time can be attributed to lower trading costs due to increasing automation, as well as the explosion in online trading by individual investors.

Some of our time-series are inherently non-stationary. This creates the potential problem that the time-series average of the cross-sectional coefficients as in Fama and MacBeth (1973) may not converge to the population estimates. The obvious candidates for non-stationarity are price [log(ADJP)], firm size [log(MV)] and dollar order imbalances (DOIM-used in Section 4)]. Moreover, we are unable to reject the unit root null for a substantial fraction of stocks in the sample for the time series of turnover (TURN), and analyst coverage [log(1+ANA)]. In order to eliminate the non-stationarity, we adjust these data series in two steps along the lines of Gallant, Rossi, and Tauchen (1992). Calendar effects and trends are removed from the means and the variances of the above data series over the sample period for each of all the component stocks. As adjustment regressors, we use eleven dummy variables for months (January-November) of the year as well as the linear and quadratic time-trend variables (t, t^2).

In the first stage, we regress each of the series to be adjusted on the set of the adjustment regressors for each firm over the sample period as in the following mean equation:

$$\omega = x'\phi + \xi, \tag{2}$$

where ω represents one of the above series to be adjusted, and x is a vector of one and the adjustment regressors (11 monthly dummies, t, and t^2). In the second stage, we take the least squares residuals from the mean equation to construct the following variance equation:

$$\log(\xi^2) = x'\theta + \epsilon. \tag{3}$$

This regression standardizes the residuals from the above mean equation. Then we finally can obtain the adjusted series for each firm by the following linear transformation:

$$\omega_{adj} = \alpha + \lambda\{\widehat{\xi}/\exp(x'\theta/2)\}, \tag{4}$$

where α and λ are chosen so that the sample means and variances of ω and ω_{adj} are the same. This linear transformation makes sure that the units of adjusted and unadjusted series are equivalent, facilitating interpretation of our empirical results in the next sections. Our adjusted series (ω_{adj}) corresponding to the above unadjusted series [ω: TURN, log(MV), log(ADJP), log(1+ANA), and DOIM] will be notated as ATURN, ASIZE, ALN(P), ALANA, and ADOIM, respectively.[14] After the Gallant, Rossi, and Tauchen (1992) (GRT)-adjustments, the Dickey-Fuller unit-root tests show no evidence of a unit root in the vast majority of the component stocks over the sample period (in each case, the unit root hypothesis is rejected for more than 95% of the sample stocks; specific percentages are available on request).

Before moving on to detailed analyses, we examine the average correlation coefficients between our explanatory variables in Table 2. The lower and upper triangles present the correlations for NYSE/AMEX and Nasdaq stocks, respectively. Given that firm size is the product of price and the number of shares outstanding, its high correlation with price is not surprising. Also, size and the number of analysts show a strong linear relation with a correlation of 61% (53%) in the exchange market (Nasdaq market), suggesting that companies with large market capitalization are followed by more analysts. Earnings surprise has relatively high positive correlations with earnings volatility (50% in exchange market) and analyst forecast dispersion (also 50% in exchange market) suggesting that earnings surprises are larger in stocks that have higher earnings volatility and higher forecast dispersion. Given the high correlations between some of our variables as shown

[14]Considering that the firm age series (FAGE) is not stochastic, we do not apply our adjustment procedure to this variable.

in Table 2, multicollinearity might be an issue. Therefore, we report three different regression specifications for each (sub)period in Table 3 which involve including and omitting some highly correlated variables.

3 Cross-Sectional Regressions

Our method involves the following regression estimated at the monthly frequency:

$$Y_{i,t+1} = \gamma_{0t} + \sum_{j=1}^{L} \gamma_{1t} A_{i,j,t} + \epsilon_{i,t+1}, \tag{5}$$

where $Y_{i,t+1}$ represents our trading activity variable (ATURN), and $A_{i,j,t}$ denotes the explanatory characteristic j for stock i in month t.[15] In addition to the nonstationarity problem addressed by equations (2)-(4), another important question in the context of the above specification is how to infer the statistical significance of the explanatory variables. In Fama and MacBeth (1973), $Y_{i,t+1}$ is the monthly stock return, which is considered to be an *i.i.d.* process. This makes it justifiable to use simple Fama-MacBeth standard errors and their corresponding t-statistics. In our study, however, trading activity measure is persistent, and this causes serial dependence in the coefficients. In most cases where they are serially correlated, the Box-Jenkins approach suggests that an AR(1) process characterizes the coefficient series reasonably well. Therefore, in Appendix B we derive a formula for the standard errors, assuming that the estimated coefficient series follow a stationary AR(1) process. For comparison purposes, we present t-statistics obtained both from our AR(1) approach as well as from Newey and West (1987).

3.1 Basic Regression Results

Table 3, reports the average coefficients (in the first row for each variable) and the AR(1)-adjusted t-statistics (in the second row for each variable), computed as per equation (21) in Appendix B. We also provide the heteroskedasticity and autocorrelation-consistent

[15]Note that unlike the contemporaneous regressions in Lo and Wang (2000) and Tkac (1999), our explanatory variables are lagged one period.

(HAC) t-statistics (in the third row for each variable) computed as per Newey and West (1987).[16] In most cases the AR(1)-adjusted t-statistics are slightly more conservative than the Newey-West t-statistics, although the differences are generally small.

Along with the two types of t-statistics, we provide the average of adjusted R-squared (*Avg adj*-R^2) for each model specification, and the average number of companies used (*Avg Obs*) in the monthly regressions over the (sub)periods. *Avg adj*-R^2 is in the 6-19% range for the exchange market (Panel A). The explanatory power of the regressions increases substantially when including the earnings-related variables (ESURP, EVOLA) (e.g., see Subperiod 2 *vs.* Subperiod 2a) and especially analyst-related variables (ALANA, FDISP) (e.g., see Subperiod 2 *vs.* Subperiod 2b), suggesting that their marginal impacts on trading activity are strong. Also, the *Avg adj*-R^2's in the turnover regressions for Nasdaq stocks are higher than those for NYSE/AMEX stocks (see Subperiods 2, 2a-2c in Panel A *vs.* Subperiods 2d-2g in Panel B).

We now discuss the effects of individual variables on trading activity (ATURN). Most notable is that the hypothesis of a zero coefficient for RET^+ is strongly rejected at any conventional significance level over any (sub)period in any market. Table 3 indicates that when a monthly positive return is higher by 10% in any month, then the monthly turnover of this stock is expected to be about 0.88-1.52% higher for NYSE/AMEX stocks or 1.00-2.12% for Nasdaq stocks in the next month. These response magnitudes are high relative to the mean values of turnover documented in Table 1. Another way of presenting the economic significance is to note (based on the full sample NYSE/AMEX coefficient) that a persistently rising stock with extra returns of 1% per month over an year can be expected to have an extra annual turnover of 1.46%. The sensitivity of turnover to RET^+ is generally higher for Nasdaq stocks than that for NYSE/AMEX stocks. The effect of RET^- is also strong with the sensitivity being even higher in the second subperiod. Thus, more extreme the return (either positive or negative) in any month, higher is the turnover in the subsequent month. Given that both RET^+ and RET^- are statistically

[16] As suggested by Newey and West (1994), we use the lag-length L to equal the integer portion of $4\left(\frac{T}{100}\right)^{2/9}$, where T is the number of observations.

and economically significant, the disposition effect does not seem to be an important determinant of trading activity.

As mentioned earlier, trading activity may increase in response to past returns because of portfolio rebalancing needs of investors. Also consistent with the results is the notion of positive feedback trading (De Long et al. 1990, Hirshleifer, Subrahmanyam, and Titman, 2005, and Hong and Stein, 1999). We will shed more light on this issue when we discuss our order imbalance results in Section 4.

The impact of leverage on trading activity tends to be positive and statistically significant in the exchange market, with the effect being statistically insignificant in Subperiod 2. An interesting phenomenon is that the effect turns negative in the OTC market. This suggests that higher leverage leads to less active trading for younger, tech-oriented companies with uncertain cash flows, contrary to more seasoned exchange market firms. Possibly, the higher leverage in the younger companies in the OTC market is symptomatic of financial distress. Financial distress could result in lower trading activity, owing to a loss of interest in the stock on the part of analysts and/or individual investors.

Table 3 also documents the role of price in predicting turnover. Higher priced stocks experience higher trading activity, though this relationship becomes weaker when including size- or analyst-related variables. This positive impact of price on trading activity is consistent with its negative influence on transaction costs in the form of brokerage commissions, as documented in Brennan and Hughes (1991). Also, Falkenstein (1996) has documented that mutual funds are averse to holding low price stocks.

The regression results further suggest that in recent years (Subperiod 2), stocks with higher book-to-market ratio are expected to trade more actively in the exchange market. However, the coefficients of BTM become insignificant or negative in different subperiods when controlling for the effects of earnings- or analyst-related variables. Given that the sign often reverses with those variables also in the OTC market, it is hard to infer any unambiguous relationship. Overall, the impact of BTM on unsigned trading activity is not robust.

The effect of firm age on trading activity is consistently negative and statistically significant in both the exchange and the OTC markets. The coefficient estimate varies from -0.43 to -0.85 in the overall sample period for NYSE-AMEX stocks. (Note that all coefficients in the table except those for returns are multiplied by 100 and hence represent the impact of the relevant variable on percentage turnover.) The impact of age is weaker during Subperiod 1 (1963-1982) for NYSE-AMEX stocks. However, the impact is much stronger for Nasdaq stocks with coefficient estimates varying from -2.2 to -2.4 in Subperiod 2d. The latter coefficients suggest that a stock that has just started trading on Nasdaq can be expected to have a monthly turnover that is greater by about 7% relative to a stock that has been trading for two years. Our results suggest that relatively recently listed firms on the NYSE/AMEX and younger technology firms on the Nasdaq exhibit higher trading activity, possibly due to the publicity and attraction of broad media coverage during their going-public process.

Firm size is strongly related to higher turnover in any subperiod in any market. The only exception is in Subperiod 2b when price and the number of analysts are also included as explanatory variables. In general, larger firms experience higher trading activity. The effect of forecast dispersion, FDISP, is also unambiguously positive and significant in both markets, demonstrating that heterogeneous beliefs do induce more trading activity. From the perspective of economic significance, the time-series average of the cross-sectional deviation of FDISP for NYSE/AMEX stocks is 1.75. An increase in FDISP of this magnitude increases NYSE/AMEX monthly turnover by about 2.0-2.2% (based on the relevant coefficients for subperiod 2c), which is about one-fourth the standard deviation estimate of the NYSE/AMEX monthly turnover reported in Table 1.

Analyst following (ALANA) has a strong and positive impact on trading activity in both the NYSE-AMEX and Nasdaq stocks. The coefficient estimates for ALANA are significantly larger in the OTC market than in the exchange market. For instance, the coefficient estimates range from 1.06 to 1.79 in the exchange market and from 3.44 to 4.63 in the OTC market. One may explain the greater impact of ALANA in the OTC market by noting that the effect of analyst coverage may be greater for technology-oriented companies because with uncertain cash flows analyst forecasts provide greater information. Further, the distribution of analyst coverage in Nasdaq stocks may be more dispersed. The *Wall Street Journal* reports that, as of January 2003, 44% of approximately 3800 companies listed on the Nasdaq had no analyst coverage at all, and an additional 14% were covered by only one analyst.[17]

Our results also indicate that the parameters associated with uncertainty, namely, higher earnings volatility (EVOLA), and especially larger absolute earnings surprise (ESURP) in a month consistently evoke higher turnover in the following month. The effect of systematic risk (PBETA) is also consistently strong and significant, even after controlling for the effect of the earnings-related variables. With regard to magnitudes of these effects, for instance, in the Nasdaq market, the time-series means of the cross-sectional standard deviations of PBETA, ESURP, and EVOLA for subperiod 2g are 0.29, 0.56, and 0.50, respectively. An increase in PBETA in the amount of the estimated standard deviation of 0.29 increases monthly turnover by about 2.0% (based on the coefficients for the last subperiod for Nasdaq in Table 3). Similar increases in ESURP and EVOLA (of one estimated standard deviation) increase monthly turnover by 0.7% and 0.6%, respectively, which annualizes to the 7-8% range. These results are all consistent with the notion that stocks with greater estimation uncertainty about fundamental value or about the return generating process, as proxied by absolute earnings surprise, earnings volatility and systematic risk, exhibit higher trading activity.

One feature of the unreported coefficients on the industry dummies (I1-I47) is worth mentioning.[18] We find that the computer/high-tech sector as defined by Fama and French (1997) (SIC codes 3570-3579, 3680-3689, 3695, and 7373) is the most actively traded one on both the OTC and the exchange markets. The coefficient estimates are 50% and 25%

[17]See "Latest Call on Wall Street: Get a Real Job — Some Analysts Leave Industry In Search of 'New Adventures' As Down Market Takes Its Toll," *The Wall Street Journal*, February 28, 2003, by Kate Kelly (p. C1).

[18]The industry dummy definitions follow Appendix A of Fama and French (1997). Their last-listed dummy, financial firms (SIC codes 6200-6299 and 6700-6799), forms our base case.

higher than the next highest industry dummy coefficient for the NYSE/AMEX and the Nasdaq, respectively. This is presumably because the high-tech sector has inherently uncertain cash flows, thus leading to significant uncertainty about fundamental value and/or difference of opinion, and thus higher trading activity.

3.2 Endogeneity of Analyst Coverage

Endogeneity is a potential issue in our estimations. While the explanatory variables in equation (5) are lagged, persistence in their levels may still cause endogeneity problems. Within our context, the most compelling endogeneity argument stems from the notion that analysts may choose to follow stocks that have higher trading volumes, thus resulting in a reverse causality from trading activity to the number of analysts. Indeed, we do not expect past values of the other explanatory variables, namely, returns, leverage, beta, the book-to-market ratio, size, price levels, earnings volatility/surprises, and analyst dispersion to be causally determined by current trading activity. If analyst do indeed follow stocks with higher trading activity then simple OLS estimation will cause the coefficient estimates to be biased. To address this issue, each month we estimate a linear equation system for stock trading activity and analyst coverage using three-stage least-squares. In this system, because we are looking for evidence of endogeneity, we use contemporaneous values of turnover and analyst coverage, but continue to use lagged values of all other variables. Due to the data availability restrictions on analyst-related variables as well as a business and geographic segment (LGBSEG) series, the system estimation is performed only over the second subperiod [Subperiods 2h and 2i (240 months): 198301-200212] for both NYSE/AMEX and Nasdaq stocks.

The specification of the linear equation system is the following:

$$Y_{t+1} = \alpha_0 + \alpha_1 X_{t+1} + \sum_{j=2} \alpha_j Z_{1jt} + \varepsilon_{t+1}, \tag{6}$$

$$X_{t+1} = \beta_0 + \beta_1 Y_{t+1} + \sum_{k=2} \beta_k Z_{2kt} + \eta_{t+1}, \tag{7}$$

where Y_{t+1} represents ATURN and X_{t+1} represents ALANA. Z_1 includes preceding month's RET$^+$, RET$^-$, LEVRG, PBETA, BTM, ALN(P), FAGE, ESURP, EVOLA, FDISP, ASIZE, and industry dummies (I1-I47). Z_2 includes preceding month's ROA, PBETA, ALN(P), LGBSEG, and I1-I47. ROA is defined as return on assets and LGBSEG is defined as log(1+#GBSEG), where #GBSEG stands for the sum of the number of geographic segments and the number of business lines for a firm. We include ROA because we conjecture that analysts, driven by incentives to attract customer volume, may be attracted to more profitable stocks if investors face short-selling constraints in less-profitable stocks. We also consider LGBSEG in Equation (7) as Bhushan (1989) suggests that firms with more business and geographic segments may be followed by more analysts. Note that except for the two possible endogenous variables (ATURN and ALANA), the values of all other variables are calculated as of the preceding month.

Table 4 presents the results from Equation (6) in Panel A, while those from Equation (7) are reported in Panel B. The reported coefficient estimates for each explanatory variable are the time-series averages of coefficients obtained from the month-by-month system estimation using the three-stage least-squares method. As in Table 3, the AR(1)-adjusted t-statistics computed using equation (21) and the HAC t-statistics computed based on Newey and West (1987) standard errors. We use the same two approaches as earlier (i.e., the AR(1) and the Newey-West methods) to calculate t-statistics for the time-series of the system coefficients. To the best of our knowledge, Fama-MacBeth standard errors have not been used for systems of equations. However, the approach of using sample means of coefficient estimates applies to any time-series of coefficients. Indeed, Bartlett (1950) and Fuller (1996, p. 384) suggest a general method of averaging estimates obtained from subsamples to test hypotheses; in our case each individual estimate is a subsample of size unity.

Panel A of Table 4 shows that the coefficient of contemporaneous analyst following is not significant at the 5% level. The lagged RET$^+$ is significant and the point estimates are comparable to those in Table 3. RET$^-$, PBETA, FAGE, and ESURP continue to be significant. Panel B of Table 4 indicates that turnover is strongly related to the number of analysts following a stock, suggesting that analysts are indeed attracted to stocks with high trading activity. Higher ROA also attracts more analysts. Another discernible observation is that higher systematic risk of a firm discourages analysts from following the stock.

A surprising result is that while the effect of the number of business and geographic segments (LGBSEG) for NYSE/AMEX stocks is consistent with Bhushan (1989), its effect for Nasdaq stocks works in the opposite direction. Given that analyst coverage in the OTC market is much narrower and more dispersed, the marginal impact of LGBSEG on the number of analysts is negative after controlling for price, accounting profitability, and turnover. This may imply that analysts cannot obtain the economies of scope in the technology-heavy Nasdaq market and a complex firm with many geographic segments and lines of business attracts fewer analysts in this market.

In sum, estimating trading activity and the number of analysts following a stock as a system is justified. The overall finding is that analysts following does not cause trading activity but the reverse is true. Analysts are attracted to stocks that exhibit higher trading activity. Endogenizing the number of analysts, however, does not appear to alter the other major conclusions from the single-equation estimation. The results also suggest that turnover from informed agents is not caused primarily by security analysts; other outside agents appear to play this role. This finding supports the view of Easley, O'Hara and Paperman (1998), who argue that analysts facilitate the production of public information, as opposed to being the primary source of private information in financial markets.

4 Order Flows

On the one hand, turnover is the traditional measure of trading activity and is of interest because it stimulates liquidity as well as information collection. On the other hand, order imbalances are likely to exert a stronger effect on price movements, because they represent aggregate investor interest which is more likely to cause price pressures. In this section, we study the cross-section of signed and absolute order flows (or imbalances), as opposed to unsigned turnover.

A primary reason for considering order imbalances is that this exercise allows us to more closely examine the source of the relation between turnover and past returns. For example, if the relation is driven by positive feedback investing as in De Long et al. (1990), Hirshleifer, Subrahmanyam, and Titman (1994, 2005), and Hong and Stein (1999), then we would expect a positive relation between past returns and net buying pressure. We also consider cross-sectional regressions involving absolute values of order imbalances, in part because these could be related to illiquidity, in the sense that turning around a position is likely to be more difficult in stocks with higher absolute imbalances.

In our study of imbalances, we use the same set of explanatory characteristics as those used for volume in Table 3, because theoretical microstructure models suggest that the variables that affect volume are the same as those that affect order flows.[19] Also, Baker and Stein (2004) indicate that turnover and net buying pressure share common drivers under short-selling constraints. Further, if absolute imbalances are related to liquidity, then, because liquidity is strongly related to volume (Benston and Hagerman, 1974), the variables that influence the latter would also tend to influence the former.[20]

We obtain measures of imbalances by signing (virtually) all trades on the NYSE during the 1988-2002 period using the Lee and Ready (1991) algorithm; for details, see Chordia, Roll, and Subrahmanyam (2002). We define order imbalance (ADOIM) by

[19]In particular, under normality, expected volume equals the sum of the expected absolute order from the informed and liquidity traders and the expected absolute order flow that the market maker observes. Our theoretical arguments can be adapted in two ways to analyze order flow. First, a fraction of the informed agents can be designated as market makers who absorb the order flows of the other agents. Second, one can introduce a new class of utility-maximizing, but informationless market-making agents who absorb the demands of the informed and liquidity traders. In either of these cases, the variables that affect order flows are the same as those affecting volume. Details are available from the authors.

[20]With regard to endogeneity, while there is a compelling case that analysts would be attracted to high-volume stocks, it appears less compelling to argue that they should be attracted to stocks with high or low buying or selling pressures. However, we have ascertained in unreported analyses that within such a system, there is no evidence of a significant causality running from any of the imbalance measures to analyst following. Results are available from the authors.

GRT-adjusted DOIM, where DOIM is a measure of dollar-volume imbalances defined as the dollar values of buys less sells divided by the total value of buys plus sells. The corresponding absolute imbalance (LADOIM) is defined as the natural logarithm of one plus the absolute value of ADOIM. Note that order imbalances are measured in terms of trade initiators, i.e., agents that demand immediacy, who are likely to be market order traders. The other side of these market orders is taken by limit order traders, floor traders, and specialists.

In Table 5, we provide the results of monthly cross-sectional regressions over the 180 months (198801-200212) for the two categories of order imbalance measures: We first discuss the results with GRT-adjusted order imbalance as the dependent variable, and then consider results obtained using absolute imbalances. As in Table 3, the explanatory variables are all one-month preceding values.

RET^+ is positively related to dollar-value order imbalances (ADOIM), suggesting that trades in stocks with positively higher returns are more likely to be buyer-initiated in the following month. This points to the presence of feedback traders. Measures that proxy for differences in opinion including firm leverage (LEVRG) and analyst forecast dispersion (FDISP) are positively related to future order imbalances. These results are all consistent with short-selling constraints that preclude negative opinion from being reflected in trading activity as effectively as positive opinion, causing signed imbalances to be positively related to measures of opinion divergence. The same short selling constraint arguments suggest that more estimation uncertainty about fundamental values should lead to more buying activity. This is precisely what we see. Variables that proxy for uncertainty, including systematic risk (PBETA), absolute earnings surprises (ESURP) and earnings volatility (EVOLA) all lead to more buying. The impact of analyst following (ALANA) on order imbalances is positive and statistically significant suggesting, that the optimistic forecasts of analysts[21] are, on balance, likely to induce buying activity.

Turning to the results for absolute order imbalances (LADOIM), we see that many

[21] Womack (1996) has documented that analysts are generally optimistic in their forecasts.

of our explanatory variables are negatively related to absolute imbalances: for example, RET^{+}, RET^{-}, PBETA, EVOLA, ALANA, and ASIZE. Considering the fact in Section 3 that larger values in these variables induce higher turnover in stocks, it is reasonable to observe that they also improve liquidity in stocks by reducing the high net buying or selling pressure, which in turn means a decreased cost of turning around a position in such stocks. The only variable that is positively related to LADOIM is price. This is consistent with the findings of Falkenstein (1996) that investment companies prefer high-priced stocks; the trades of these agents may be manifested in more extreme imbalances.

Overall, the results on signed imbalances accord with the view that the return-volume relation is driven by feedback trading in the aggregate, which supports the theoretical models of DeLong et al. (1990), Hirshleifer, Subrahmanyam, and Titman (1994, 2005), and Hong and Stein (1999).

5 Summary and Conclusions

To enhance our understanding of financial market trading, we have investigated the behavior of the cross-section of expected trading activity by using a spectrum of plausible explanatory variables for a large sample of stocks across two different market structures (NYSE/AMEX and Nasdaq). Our main results can be summarized as follows. A secular upward trend has emerged in trading activity. We surmise that this trend can partly be explained by the growth of the mutual fund industry, lower trading costs, and computerized trading by institutional and individual investors. In addition to the increasing trend, we find large variations in trading activity across stocks. Theoretical arguments suggest that trading activity is driven by liquidity trading, the mass of informed agents, the estimation uncertainty and the potential for learning about fundamental values and the dispersion of opinion about a stock. Past returns proxy for the extent of liquidity or noise trading due to portfolio rebalancing needs. Further, based on Merton (1987), we postulate that liquidity needs are realized in the most visible stocks. We use size, firm age, price level, and the book-to-market ratio, as proxies for a firm's visibility. Analyst coverage forms a proxy for the extent of information asymmetry. The estimation uncertainty about fundamental value is proxied by earnings volatility, earnings surprises, and firm beta. Finally, differences of opinion is proxied by analyst forecast dispersion and leverage.

We find that an important indicator of a stock's turnover in any given month is its preceding price performance; and this result arises because stocks with good return performance in the past appear to attract more buying pressure in the future. Systematic risk, dispersion in analysts' forecasts, earnings surprises, earnings volatility, price, and firm size are also significant in predicting subsequent trading activity, while young firms are traded more actively on both markets. Finally, turnover is greater in the high-tech sector relative to other industry sectors. Our analysis of order imbalances indicates that higher positive returns strongly evoke greater buying activity, pointing to the actions of feedback traders. Higher systematic risk, leverage, forecast dispersion, and analyst coverage also lead to more buyer-initiated trades, possibly reflecting short-selling constraints and optimism of analyst forecasts. Many of the variables that induce higher turnover are also negatively related to absolute order imbalances. This result demonstrates that these variables play a role in improving liquidity by reducing the unbalanced, high buying or selling pressure.

In this study, we obtain a comprehensive set of stylized facts concerning cross-sectional predictors of trading activity by examining the effects of a broad set of economic variables, by comparing the features of different trading activity measures, and by using trading activity measures for two different markets (NYSE/AMEX and Nasdaq). The study is of interest both from an academic standpoint and from the perspective of intermediaries that earn revenues from volume-based brokerage commissions. Many issues still remain to be explored. From a theoretical viewpoint, it may be fruitful to construct a dynamic model which explicitly incorporates cross-sectional regularities identified in this study, especially the relationship of trading activity with past returns, earnings surprises and volatility, analyst coverage, systematic risk, and forecast dispersion.

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Appendix (Derivation and Discussion of the AR(1)-adjusted t-statistic)

In this appendix, we derive a formula for the t-statistic used in our analysis, assuming that the estimated coefficient series follow a stationary AR(1) process (an assumption that is discussed and justified following the presentation of our formula).

Let the average of the estimated coefficients for any particular firm characteristic be $\bar{\theta} \equiv \frac{\theta_1+\theta_2+...+\theta_T}{T}$, where θ_i's are a time series of the individual coefficients estimated in the cross-sectional regressions, and T is the sample size of the coefficients. The t-statistic, t, is defined as

$$t = \frac{\bar{\theta}}{\sqrt{Var(\bar{\theta})}} = \frac{\frac{\theta_1+\theta_2+...+\theta_T}{T}}{\sqrt{Var\left[\frac{\theta_1+\theta_2+...+\theta_T}{T}\right]}}. \tag{8}$$

Now consider the denominator of Equation (8). If the θ_i's follow an *i.i.d.* process, it is easy to show that the standard error of $\bar{\theta}$ is given by

$$SE_{indep} = \sqrt{Var\left[\frac{\theta_1+\theta_2+...+\theta_T}{T}\right]} = \frac{\sigma_\theta}{\sqrt{T}}, \tag{9}$$

where $\sigma_\theta^2 = Var(\theta)$. In this case, therefore, the usual Fama-MacBeth t-statistic, t_{indep}, is defined as

$$t_{indep} = \frac{\bar{\theta}}{\sqrt{Var(\bar{\theta})}} = \frac{\bar{\theta}}{\frac{\sigma_\theta}{\sqrt{T}}} = \frac{\sqrt{T}\bar{\theta}}{\sigma_\theta}. \tag{10}$$

However, when θ_i's are serially correlated, equations (9) and (10) no longer hold. For practical purposes, assume that θ_i's are identically distributed but follow a stationary AR(1) process (i.e., not independent), or

$$\theta_t = \kappa + \varphi\theta_{t-1} + \epsilon_t, |\varphi| < 1 \tag{11}$$

where ϵ_t is a white noise process. The expectation of θ_t is then $E(\theta_t) = \mu = \frac{\kappa}{1-\varphi}$. In addition, the pairwise autocovariances are defined by

$$\eta_s = Cov(\theta_t, \theta_{t+s}) = E[(\theta_t - \mu)(\theta_{t+s} - \mu)], s = ..., -2, -1, 0, 1, 2, ... \tag{12}$$

Or, Equation (12) can be rewritten as $\eta_{ij} = Cov(\theta_i, \theta_j) = E[(\theta_i - \mu)(\theta_j - \mu)]$, where *i, j=1, 2,...,T.* When *s = 0*, Equation (12) gives

$$\eta_0 = Var(\theta_t) = E[(\theta_t - \mu)]^2 = \sigma_\theta^2. \tag{13}$$

Given that $\theta_i's$ follow an AR(1) process by Equation (11) and their disturbances are homoskedastic, the autocorrelation coefficient of $\theta_i's$ at lag s is

$$\begin{aligned} \rho_s &= \frac{Cov(\theta_t, \theta_{t+s})}{\sqrt{Var(\theta_t)Var(\theta_{t+s})}} = \frac{\eta_s}{\eta_0} && (14) \\ &= \varphi^s, s = 0, 1, 2, ... \quad \text{(by equation (11))}. && (15) \end{aligned}$$

Using equations (13), (14), and (15), we can write the covariance matrix of $\theta_i's$, Ω, as follows:

$$\Omega = \begin{bmatrix} \eta_0 & \eta_1 & \eta_2 & ... & \eta_{T-1} \\ \eta_1 & \eta_0 & \eta_1 & ... & \eta_{T-2} \\ \eta_2 & \eta_1 & \eta_0 & ... & \eta_{T-3} \\ ... & ... & ... & ... & ... \\ \eta_{T-1} & \eta_{T-2} & \eta_{T-3} & ... & \eta_0 \end{bmatrix} = \eta_0 \begin{bmatrix} 1 & \rho_1 & \rho_2 & ... & \rho_{T-1} \\ \rho_1 & 1 & \rho_1 & ... & \rho_{T-2} \\ \rho_2 & \rho_1 & 1 & ... & \rho_{T-3} \\ ... & ... & ... & ... & ... \\ \rho_{T-1} & \rho_{T-2} & \rho_{T-3} & ... & 1 \end{bmatrix}$$

$$= \sigma_\theta^2 \begin{bmatrix} 1 & \varphi & \varphi^2 & ... & \varphi^{T-1} \\ \varphi & 1 & \varphi & ... & \varphi^{T-2} \\ \varphi^2 & \varphi & 1 & ... & \varphi^{T-2} \\ ... & ... & ... & ... & ... \\ \varphi^{T-1} & \varphi^{T-2} & \varphi^{T-3} & ... & 1 \end{bmatrix} \quad (16)$$

Our goal is to derive the standard error of $\bar{\theta}$ when the $\theta_i's$ follow an AR(1) process. Note here that

$$\begin{aligned} Var\left[\frac{\theta_1 + \theta_2 + ... + \theta_T}{T}\right] &= \frac{1}{T^2} Var(\theta_1 + \theta_2 + ... + \theta_T) \\ &= \frac{1}{T^2} Cov[\theta_1 + \theta_2 + ... + \theta_T, \theta_1 + \theta_2 + ... + \theta_T] \\ &= \frac{1}{T^2} \sum_{i=1}^{T} \sum_{j=1}^{T} \eta_{ij} \\ &= \frac{1}{T^2} \begin{bmatrix} \eta_{11} + \eta_{21} + \eta_{31} + ... + \eta_{T1} + \\ \eta_{12} + \eta_{22} + \eta_{32} + ... + \eta_{T2} + \\ \eta_{13} + \eta_{23} + \eta_{33} + ... + \eta_{T3} + \\ ... \\ \eta_{1T} + \eta_{2T} + \eta_{3T} + ... + \eta_{TT} \end{bmatrix} \\ &= \frac{1}{T^2} \begin{bmatrix} \eta_0 + \eta_1 + \eta_2 + ... + \eta_{T-1} + \\ \eta_1 + \eta_0 + \eta_1 + ... + \eta_{T-2} + \\ \eta_2 + \eta_1 + \eta_0 + ... + \eta_{T-3} + \\ ... \\ \eta_{T-1} + \eta_{T-2} + \eta_{T-3} + ... + \eta_0 \end{bmatrix} && (17) \end{aligned}$$

By using Equation (16), we can show that Equation (17) becomes

$$Var\left[\frac{\theta_1+\theta_2+...+\theta_T}{T}\right]=\frac{\sigma_\theta^2}{T^2}\left[\begin{array}{c}1+\varphi+\varphi^2+...+\varphi^{T-1}+\\ \varphi+1+\varphi+...+\varphi^{T-2}+\\ \varphi^2+\varphi+1+...+\varphi^{T-3}+\\ ...\\ \varphi^{T-1}+\varphi^{T-2}+\varphi^{T-3}+...+1\end{array}\right]$$

$$=\frac{\sigma_\theta^2}{T^2}\left[T+2\left\{\begin{array}{c}(T-1)\varphi+(T-2)\varphi^2+(T-3)\varphi^3+\\ ...+3\varphi^{T-3}+2\varphi^{T-2}+\varphi^{T-1}\end{array}\right\}\right]. \tag{18}$$

We observe from Equation (18) that $Var\left[\frac{\theta_1+\theta_2+...+\theta_T}{T}\right]$ is obtained by summing the elements of the covariance matrix, Ω, in Equation (16) and then dividing the sum by T^2. In the next step, we simplify equation (18). Let the expression in $\{.\}$ of Equation (18) be S. Then, using some series algebra, S can be solved out as[22]

$$\begin{aligned} S &= \frac{1}{1-\varphi}\left\{\varphi T-\frac{\varphi(1-\varphi^T)}{1-\varphi}\right\} \\ &= \frac{\varphi T}{1-\varphi}-\frac{\varphi(1-\varphi^T)}{(1-\varphi)^2}. \end{aligned} \tag{19}$$

Substituting Equation (19) into (18), we have

$$Var\left[\frac{\theta_1+\theta_2+...+\theta_T}{T}\right]=\frac{\sigma_\theta^2}{T^2}\left[T+2\left\{\frac{\varphi T}{1-\varphi}-\frac{\varphi(1-\varphi^T)}{(1-\varphi)^2}\right\}\right]$$

$$=\sigma_\theta^2\left[\frac{1}{T}+\frac{2\varphi}{(1-\varphi)T}-\frac{2\varphi(1-\varphi^T)}{(1-\varphi)^2T^2}\right].$$

Thus, the standard error of $\bar{\theta}$ is given by

$$SE_{dep}=\sqrt{Var(\bar{\theta})}=\sqrt{Var\left[\frac{\theta_1+\theta_2+...+\theta_T}{T}\right]}$$

$$=\sigma_\theta\sqrt{\frac{1}{T}+\frac{2\varphi}{(1-\varphi)T}-\frac{2\varphi(1-\varphi^T)}{(1-\varphi)^2T^2}}. \tag{20}$$

Finally, from Equation (8) our formula of the AR(1)-adjusted t-statistic when θ_i's are identically distributed but follow an AR(1) process is obtained as follows:

$$t_{dep} = \frac{\bar{\theta}}{\sqrt{Var(\bar{\theta})}}=\frac{\frac{\theta_1+\theta_2+...+\theta_T}{T}}{\sqrt{Var\left[\frac{\theta_1+\theta_2+...+\theta_T}{T}\right]}}$$

[22]To solve out S, multiply the expression for S by φ and subtract the resulting expression from the original one.

$$= \frac{\bar{\theta}}{\sigma_\theta \sqrt{\frac{1}{T} + \frac{2\varphi}{(1-\varphi)T} - \frac{2\varphi(1-\varphi^T)}{(1-\varphi)^2 T^2}}}. \tag{21}$$

Notice that if θ_i's follow an *i.i.d.* process (i.e., if $\varphi = 0$), then equations (20) and (21) are reduced to equations (9) and (10), respectively. We use Equation (20) as the primary basis to adjust the standard errors in our analysis of the effects of the explanatory variables on trading activity.

We can verify that if $\varphi > 0$ ($\varphi < 0$), SE_{dep} given by Equation (20) is greater (smaller) than SE_{indep} in Equation (9). This in turn implies that the appropriate t-statistic should be smaller (larger) when the coefficients are serially positively (negatively) correlated than when they are independent. To elaborate on this further, Table A1 provides a feel for the magnitudes of the estimated autocorrelations and their consequent impacts on the t-statistics for the four regression specifications reported in Table 3. In addition to the AR(1)-adjusted t-statistics, we also provide as a second check the heteroskedasticity and autocorrelation-consistent (HAC) t-statistics computed based on Newey and West (1987). As shown in Table A1, our AR(1)-adjusted t-statistics are generally more conservative than the HAC t-statistics.

To examine whether our AR(1) assumption is warranted, in unreported analyses (which are available upon request), we perform ARMA tests using the Box-Jenkins approach for each coefficient series in every model presented in Table 3. The test results indicate that in some cases a white noise process is a better fit and, occasionally, that higher-order autoregressive processes seem more appropriate. However, an AR(1) scheme is the best choice in the vast majority of the cases, and this is the procedure we adopt in the paper.

Table 1. Descriptive Statistics for the Three Measures of Monthly Trading Activity as well as Prices and eturns

This table reports descriptive statistics for monthly turnover ratio *(TURN)*, share volume (*SHRVOL*: in 1,000 shares), dollar volume (*DVOL*: in $1,000), price (*PRC*), and stock return (*RETURN*) during the 474 months (39.5 years: 196307-200212) for NYSE/AMEX stocks and the 240 months (20 years: 198301-200212) for NASDAQ stocks. The values of each statistic are first calculated cross-sectionally month by month and then the time-series averages of those values for each (sub)period are reported here. The average numbers of component stocks available each month in Panel A (NYSE/AMEX stocks) are 1647.2, 1470.8 and 1819.1 for Entire Period (196307-200212), Subperiod 1 (196307-198212), and Subperiod 2 (198301-200212), respectively. Those in Panel B (NASDAQ stocks) are 1722.1 for Subperiod 2d (198301-200212). The coefficient of variation (CV) is obtained by (STD/Mean)*100 each year.

			Panel A: NYSE/AMEX			
	Mean	Median	STD	CV	Skewness	Kurtosis
	Entire Period (196307-200212)					
TURN	0.0445	0.0302	0.0670	148.57	8.77	178.59
SHRVOL	2463.49	535.82	6143.76	199.59	5.60	56.09
DVOL	91395.78	9494.71	286612.56	277.13	8.51	127.52
PRC	32.52	21.07	304.13	636.43	18.53	695.96
RETURN	0.0119	0.0046	0.1105	-96.43	1.71	21.34
	Subperiod 1 (196307-198212)					
TURN	0.0285	0.0178	0.0481	157.94	8.24	151.33
SHRVOL	260.99	95.84	465.87	172.08	4.93	43.59
DVOL	8520.36	1952.04	21733.14	253.77	8.04	112.12
PRC	26.95	22.25	25.37	92.97	5.64	78.64
RETURN	0.0123	0.0042	0.0959	-24.46	1.27	8.47
	Subperiod 2 (198301-200212)					
TURN	0.0600	0.0423	0.0854	139.44	9.29	205.16
SHRVOL	4610.93	964.80	11679.69	226.41	6.26	68.27
DVOL	172199.31	16848.81	544870.00	299.92	8.97	142.53
PRC	37.96	19.91	575.92	1166.31	31.10	1297.85
RETURN	0.0114	0.0050	0.1247	-166.61	2.15	33.88
			Panel B: NASDAQ			
	Mean	Median	STD	CV	Skewness	Kurtosis
	Subperiod 2d (198301-200212)					
TURN	0.0842	0.0422	0.1540	183.25	9.78	209.54
SHRVOL	2890.66	317.54	15716.87	414.86	13.14	241.60
DVOL	85506.29	2107.34	677262.91	643.04	16.71	368.55
PRC	14.58	8.95	33.03	214.98	13.41	381.76
RETURN	0.0146	-0.0008	0.1814	-357.71	3.36	53.32

Table 2. Correlations between Explanatory Variables

The lower triangle shows the average correlations between the regressors for NYSE/AMEX stocks over the 474 months (39.5 years: 196307-200212), and the upper triangle shows those for NASDAQ stocks over the 240 months (20 years: 198301-200212). The correlation coefficients are first calculated month by month and then the time-series averages of those values over the 2 periods are reported here. The definitions of the regressors are as follows: *RET+ (RET-)*: monthly return of individual stocks if positive (negative), and 0 otherwise; *LEVRG*: book debt divided by total asset; *PBETA*: portfolio beta estimated by the method of Fama and French (1992) (First, stocks are split into deciles by firm size, and then each of the 10 portfolios is again split into 10 portfolios by pre-ranking individual beta in order to form 100 portfolios for each year. Then we compute portfolio average returns for the next 12 months for each portfolio for each year. Using the 100 time series of these average returns over the whole sample period, we estimate post-ranking betas for the 100 portfolios. Then we assign the post-ranking betas to the component stocks of the relevant portfolios.); *BTM*: book value divided by the average of the month-end market values; *ALN(P)*: Gallant, Rossi, and Tauchen (1992) (GRT)-adjusted value of log(*ADJP*), where *ADJP* is split- and stock dividend-adjusted price; *FAGE*: firm age defined as log(1+M), where M is the number of months since its listing in an exchange; *ASIZE*: GRT-adjusted value of log(*MV*), where *MV* is month-end market value; *ESURP*: earnings surprise defined as the absolute value of the current earnings minus the earnings from four quarters ago; *EVOLA*: earnings volatility defined as standard deviation of earnings of the most recent eight quarters; *ALANA*: GRT-adjusted value of log(1+*ANA*), where *ANA* is the monthly number of analysts who follow a firm and report forecasts to the I/B/E/S database; *FDISP*: forecast dispersion defined as standard deviation of EPS forecasts reported by analysts in the I/B/E/S database. The monthly average numbers of component stocks are 1647.2 for NYSE/AMEX stocks (lower triangle) over the 474 months (196307-200212) and 1722.1 for NASDAQ stocks (upper triangle) over the 240 months (198301-200212). *ESURP, EVOLA, ANA, ALANA*, and *FDISP* are available in common over 198301-200212 (the monthly average component stocks for these variables are 853.6 for NYSE/AMEX stocks and 482.8 for NASDAQ stocks over this period).

Average Correlations: NYSE/AMEX (Lower Triangle) and NASDAQ (Upper Triangle)

	RET+	RET-	LEVRG	PBETA	BTM	ALN(P)	FAGE	ASIZE	ESURP	EVOLA	ALANA	FDISP
RET+	1	0.259	0.024	0.049	-0.007	0.027	-0.047	-0.002	0.025	0.017	-0.013	0.022
RET-	0.305	1	-0.089	-0.114	0.015	0.168	0.088	0.169	-0.045	-0.035	-0.005	-0.066
LEVRG	0.013	-0.067	1	0.021	0.006	-0.088	-0.041	-0.154	0.054	0.091	-0.086	0.141
PBETA	0.067	-0.109	-0.012	1	-0.051	-0.050	-0.179	0.072	0.017	0.005	0.108	0.022
BTM	-0.002	0.006	-0.012	-0.044	1	0.034	0.054	-0.058	0.020	0.033	-0.136	-0.009
ALN(P)	0.017	0.126	-0.012	-0.088	-0.018	1	0.012	0.582	0.018	0.039	0.070	-0.011
FAGE	-0.052	0.080	-0.038	-0.173	-0.026	0.077	1	0.029	0.029	0.047	0.016	0.025
ASIZE	-0.043	0.170	-0.060	-0.116	-0.089	0.472	0.272	1	0.035	0.053	0.529	-0.028
ESURP	0.013	-0.026	0.041	-0.002	0.030	0.078	0.074	0.050	1	0.353	0.054	0.338
EVOLA	0.009	-0.016	0.058	-0.011	0.043	0.107	0.125	0.073	0.498	1	0.054	0.322
ALANA	-0.043	0.046	-0.011	-0.142	-0.102	0.127	0.260	0.606	0.042	0.073	1	0.031
FDISP	0.014	-0.046	0.088	0.018	0.053	0.084	0.085	0.031	0.495	0.506	0.054	1

Table 3. Results of Monthly Cross-sectional Regressions: Turnover for NYSE/AMEX and NASDAQ Stocks

This table reports the Fama and MacBeth (1973)-type cross-sectional regressions for monthly stock trading activity of NYSE/AMEX- and NASDAQ-listed stocks. In Panel A, the dependent variable (*ATURN)* is Gallant, Rossi, and Tauchen (1992) (GRT)-adjusted value of the monthly turnover ratio *(TURN)* for NYSE/AMEX stocks over the 474 months (39.5 years: 196307-200212) and its subperiods, while in Panel B, it is the same for NASDAQ stocks over the 240 months (20 years: 198301-200212). The explanatory variables are all one-month preceding values (no contemporaneous regressors are used). The definitions of the regressors are as follows: *RET+ (RET-)*: monthly return of individual stocks if positive (negative), and 0 otherwise; *LEVRG*: book debt divided by total asset; *PBETA*: portfolio beta estimated by the method of Fama and French (1992) (First, stocks are split into deciles by firm size, and then each of the 10 portfolios is again split into 10 portfolios by pre-ranking individual beta in order to form 100 portfolios for each year. Then we compute portfolio average returns for the next 12 months for each portfolio for each year. Using the 100 time series of these average returns over the whole sample period, we estimate post-ranking betas for the 100 portfolios. Then we assign the post-ranking betas to the component stocks of the relevant portfolios.); *BTM*: book value divided by the average of the month-end market values; *ALN(P)*: GRT-adjusted value of log(*ADJP*), where *ADJP* is split- and stock dividend-adjusted price; *FAGE*: firm age defined as log(1+M), where M is the number of months since its listing in an exchange; *ASIZE*: GRT-adjusted value of log(*MV*), where *MV* is month-end market value; *ESURP*: earnings surprise defined as the absolute value of the current earnings minus the earnings from four quarters ago; *EVOLA*: earnings volatility defined as standard deviation of earnings of the most recent eight quarters; *ALANA*: GRT-adjusted value of log(1+*ANA*), where *ANA* is the monthly number of analysts who follow a firm and report forecasts to the I/B/E/S database; *FDISP*: forecast dispersion defined as standard deviation of EPS forecasts reported by analysts in the I/B/E/S database; *I1-I48*: 48 industry classification dummy variables of Fama and French (I1-I47 are included in the regressions, but not reported in the table). The average numbers of component stocks available each month in Panel A (NYSE/AMEX stocks) are 1647.2, 1470.8 and 1819.1 for Entire Period (196307-200212), Subperiod 1 (196307-198212), and Subperiod 2 (198301-200212), respectively. Those in Panel B (NASDAQ stocks) are 1722.1 for Subperiod 2d (198301-200212). *ESURP, EVOLA, ALANA*, and *FDISP* are available in common over 198301-200212, resulting in the comparable regression specifications by including some or all of these additional variables for *Subperiods 2a-2g*. When all of these variables are included in the regressions, the monthly average numbers of component stocks used are 853.6 for NYSE/AMEX stocks (Subperiod 2c) and 482.8 for NASDAQ stocks (Subperiod 2g). Three regression specifications are reported for each (sub)period. The values in the first row for each explanatory variable are the time-series averages of coefficients obtained from the month-by-month cross-sectional regressions. The average coefficients are multiplied by 100, except for those of *RET+, RET-* , and the intercept. The values italicized in the second row of each variable are *AR(1)-adjusted* t-statistics computed by equation (21):

$$t_{dep} = \frac{\overline{\theta}}{\sigma_\theta \sqrt{\frac{1}{T} + \frac{2\varphi}{(1-\varphi)T} - \frac{2\varphi(1-\varphi^T)}{(1-\varphi)^2 T^2}}},$$

where $\overline{\theta}$ and σ_θ are the mean and standard deviation of the estimated coefficients, respectively, T is the sample size of the coefficients, and φ is the 1st-order serial correlation of the oefficients. The values italicized in the third row of each variable are *heteroskedasticity and autocorrelation-consistent (HAC)* t-statistics computed based on Newey and West (1987). *Avg adj-* R^2 is the average of adjusted R-squared. *Avg Obs* is the monthly average number of companies used in the regressions over the (sub)periods. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

Panel A: NYSE/AMEX Stocks, Dependent Variable = ATURN

Explanatory Variables	Entire Period (196307-200212)			Subperiod 1 (196307-198212)			Subperiod 2 (198301-200212)			Subperiod 2a (198301-200212)		
	1	2	3	1	2	3	1	2	3	4	5	6
RET+	0.122**	0.116**	0.123**	0.152**	0.146**	0.152**	0.093**	0.080**	0.094**	0.106**	0.098**	0.106**
	(10.27)	*(9.74)*	*(10.27)*	*(6.69)*	*(6.41)*	*(6.69)*	*(14.01)*	*(12.92)*	*(13.73)*	*(13.90)*	*(12.27)*	*(14.03)*
	(9.40)	*(8.93)*	*(9.38)*	*(6.20)*	*(5.96)*	*(6.20)*	*(13.30)*	*(12.29)*	*(13.03)*	*(13.15)*	*(11.64)*	*(13.26)*
RET-	-0.116**	-0.101**	-0.111**	-0.085**	-0.069**	-0.085**	-0.146**	-0.131**	-0.136**	-0.169**	-0.147**	-0.169**
	(-7.01)	*(-5.88)*	*(-6.74)*	*(-10.62)*	*(-8.11)*	*(-10.66)*	*(-4.67)*	*(-4.06)*	*(-4.34)*	*(-4.84)*	*(-4.11)*	*(-4.86)*
	(-7.18)	*(-5.99)*	*(-6.96)*	*(-9.16)*	*(-7.11)*	*(-9.22)*	*(-4.90)*	*(-4.24)*	*(-4.58)*	*(-5.02)*	*(-4.24)*	*(-5.05)*
LEVRG	0.781**	0.501**	0.784**	1.271**	0.985**	1.315**	0.304	0.029	0.265	0.688*	0.212	0.700**
	(3.81)	*(2.69)*	*(3.77)*	*(4.61)*	*(3.21)*	*(4.77)*	*(1.13)*	*(0.17)*	*(0.97)*	*(1.86)*	*(0.72)*	*(1.87)*
	(4.37)	*(2.96)*	*(4.34)*	*(5.36)*	*(3.85)*	*(5.55)*	*(1.40)*	*(0.18)*	*(1.22)*	*(2.55)*	*(0.90)*	*(2.61)*
PBETA	2.713**	2.753**	2.632**	2.106**	2.189**	2.093**	3.304**	3.303**	3.158**	3.234**	3.249**	3.240**
	(10.35)	*(10.33)*	*(10.43)*	*(7.64)*	*(7.88)*	*(7.57)*	*(8.26)*	*(7.97)*	*(8.20)*	*(18.97)*	*(18.53)*	*(18.86)*
	(12.61)	*(12.75)*	*(12.59)*	*(10.15)*	*(10.53)*	*(10.07)*	*(10.29)*	*(10.13)*	*(10.10)*	*(20.59)*	*(20.59)*	*(20.54)*
BTM	0.022	0.010	0.025*	-0.032*	-0.055*	-0.030*	0.074**	0.073**	0.078**	0.368	0.192	0.355
	(1.84)	*0.52*	*(2.06)*	*(-2.45)*	*(-2.02)*	*(-2.40)*	*(5.03)*	*(4.68)*	*(4.95)*	*(1.36)*	*(0.70)*	*(1.31)*
	(1.95)	*0.65*	*(2.17)*	*(-2.37)*	*(-2.51)*	*(-2.28)*	*(6.24)*	*(5.91)*	*(6.27)*	*(1.39)*	*(0.72)*	*(1.34)*
ALN(P)	0.464**	0.618**		0.087	0.276**		0.831**	0.952**		0.317*	0.751**	0.318*
	(2.29)	*(4.17)*		*1.18*	*(3.27)*		*(2.34)*	*(4.07)*		*(1.57)*	*(4.43)*	*(1.60)*
	(3.99)	*(7.31)*		*1.57*	*(4.66)*		*(4.37)*	*(7.57)*		*(2.32)*	*(6.86)*	*(2.35)*
FAGE	-0.687**	-0.426**	-0.851**	-0.269**	0.020	-0.280**	-1.095**	-0.860**	-1.408**	-1.291**	-0.795**	-1.282**
	(-4.85)	*(-2.54)*	*(-4.56)*	*(-3.70)*	*0.31*	*(-3.88)*	*(-5.04)*	*(-3.04)*	*(-5.29)*	*(-5.08)*	*(-2.60)*	*(-5.08)*
	(-7.02)	*(-3.68)*	*(-7.36)*	*(-4.88)*	*0.39*	*(-5.12)*	*(-7.41)*	*(-4.66)*	*(-8.39)*	*(-9.09)*	*(-4.41)*	*(-9.09)*
ESURP										0.153**	0.145**	
										(4.79)	*(4.03)*	
										(5.34)	*(4.50)*	
EVOLA										0.146**		0.189**
										(3.23)		*(3.69)*
										(3.38)		*(4.21)*
ALANA												
FDISP												
ASIZE	0.283**		0.441**	0.341**		0.370**	0.226**		0.510**	0.533**		0.533**
	(4.43)		*(15.04)*	*(9.81)*		*(10.78)*	*(1.83)*		*(11.76)*	*(8.07)*		*(8.06)*
	(5.54)		*(15.62)*	*(10.68)*		*(11.83)*	*(2.59)*		*(12.78)*	*(9.24)*		*(9.20)*
Constant	0.020**	0.018**	0.031**	0.006	0.005	0.007	0.033**	0.031**	0.055**	0.029**	0.029*	0.029**
	(2.59)	*(2.27)*	*(3.37)*	*(1.17)*	*(0.83)*	*(1.32)*	*(2.44)*	*(2.21)*	*(3.58)*	*(2.19)*	*(2.06)*	*(2.20)*
	(3.34)	*(2.96)*	*(4.58)*	*(1.52)*	*(1.11)*	*(1.69)*	*(3.43)*	*(3.11)*	*(5.14)*	*(2.67)*	*(2.52)*	*(2.67)*
Avg adj-R^2	0.077	0.065	0.073	0.089	0.075	0.087	0.065	0.055	0.060	0.099	0.080	0.098
Avg Obs		1647.2			1470.8			1819.1			1534.8	

(Panel A continued)

Panel A: NYSE/AMEX Stocks, Dependent Variable = ATURN						
Explanatory	Subperiod 2b (198301-200212)			Subperiod 2c (198301-200212)		
Variables	7	8	9	10	11	12
RET+	0.134**	0.134**	0.132**	0.145**	0.145**	0.147**
	(15.73)	*(15.66)*	*(15.27)*	*(18.49)*	*(18.35)*	*(18.96)*
	(15.50)	*(15.48)*	*(15.08)*	*(18.55)*	*(18.36)*	*(18.97)*
RET-	-0.174**	-0.177**	-0.181**	-0.202**	-0.195**	-0.206**
	(-19.53)	*(-18.42)*	*(-19.36)*	*(-21.88)*	*(-19.33)*	*(-22.19)*
	(-18.41)	*(-17.00)*	*(-18.54)*	*(-19.44)*	*(-17.23)*	*(-19.85)*
LEVRG	0.886**	0.896**	0.926**	0.640*	0.522	0.752*
	(1.86)	*(2.03)*	*(2.08)*	*(1.55)*	*(1.31)*	*(1.78)*
	(2.59)	*(2.77)*	*(2.83)*	*(2.15)*	*(1.79)*	*(2.47)*
PBETA	2.965**	3.049**	3.097**	3.759**	3.639**	3.807**
	(8.09)	*(8.65)*	*(7.84)*	*(24.44)*	*(24.00)*	*(24.63)*
	(9.73)	*(10.38)*	*(9.62)*	*(25.78)*	*(25.25)*	*(25.88)*
BTM	0.190**	0.200**	0.189**	-0.015	-0.125*	0.000
	(1.92)	*(1.90)*	*(1.96)*	*(-0.23)*	*(-1.96)*	*(0.00)*
	(2.96)	*(3.00)*	*(3.01)*	*(-0.22)*	*(-1.98)*	*(0.00)*
ALN(P)	0.927**	0.511**	0.623**	0.173	0.316**	0.183
	(2.36)	*(2.98)*	*(1.79)*	*(0.92)*	*(2.75)*	*(0.97)*
	(4.00)	*(4.72)*	*(2.99)*	*(1.31)*	*(3.78)*	*(1.39)*
FAGE	-1.945**	-2.005**	-1.658**	-1.839**	-1.729**	-1.801**
	(-7.81)	*(-6.86)*	*(-7.21)*	*(-7.60)*	*(-5.84)*	*(-7.48)*
	(-11.24)	*(-10.28)*	*(-10.14)*	*(-12.53)*	*(-10.68)*	*(-12.36)*
ESURP				0.184**	0.177**	
				(5.62)	*(4.92)*	
				(6.16)	*(5.38)*	
EVOLA				0.022		0.206**
				(0.42)		*(4.77)*
				(0.47)		*(5.39)*
ALANA	1.792**	1.318**		1.063**	1.356**	1.087**
	(5.93)	*(11.24)*		*(10.08)*	*(19.27)*	*(10.71)*
	(8.90)	*(13.67)*		*(12.65)*	*(21.17)*	*(13.21)*
FDISP	0.715**	0.771**	0.895**	1.247**	1.050**	
	(2.26)	*(2.41)*	*(2.72)*	*(4.08)*	*(5.44)*	
	(2.58)	*(2.79)*	*(3.16)*	*(5.41)*	*(6.16)*	
ASIZE	-0.419*		0.102	0.236**		0.231**
	(-1.52)		*(0.52*	*(2.21)*		*(2.17)*
	(-2.36)		*(0.77)*	*(3.08)*		*(3.01)*
Constant	0.080**	0.071**	0.074**	0.056**	0.058**	0.054**
	(4.62)	*(4.68)*	*(4.28)*	*(3.23)*	*(3.46)*	*(3.11)*
	(6.24)	*(6.23)*	*(5.81)*	*(5.46)*	*(5.67)*	*(5.27)*
Avg adj-R^2	0.161	0.154	0.155	0.193	0.185	0.190
Avg Obs		921.0			853.6	

Panel B: NASDAQ Stocks, Dependent Variable = ATURN												
Explanatory	Subperiod 2d (198301-200212)			Subperiod 2e (198301-200212)			Subperiod 2f (198301-200212)			Subperiod 2g (198301-200212)		
Variables	13	14	15	16	17	18	19	20	21	22	23	24
RET+	0.107**	0.100**	0.109**	0.138**	0.127**	0.139**	0.212**	0.212**	0.206**	0.208**	0.207**	0.211**
	(12.23)	*(11.39)*	*(12.16)*	*(14.02)*	*(12.82)*	*(14.06)*	*(15.15)*	*(15.10)*	*(14.71)*	*(17.45)*	*(17.48)*	*(17.60)*
	(10.31)	*(9.62)*	*(10.27)*	*(12.11)*	*(11.04)*	*(12.17)*	*(15.05)*	*(14.85)*	*(14.63)*	*(16.13)*	*(16.07)*	*(16.30)*
RET-	-0.114**	-0.091**	-0.111**	-0.160**	-0.124**	-0.161**	-0.249**	-0.237**	-0.260**	-0.269**	-0.257**	-0.275**
	(-11.27)	*(-8.84)*	*(-11.03)*	*(-15.86)*	*(-11.25)*	*(-15.51)*	*(-13.27)*	*(-12.65)*	*(-13.70)*	*(-18.80)*	*(-17.65)*	*(-19.53)*
	(-10.06)	*(-8.03)*	*(-9.77)*	*(-13.58)*	*(-9.99)*	*(-13.48)*	*(-11.85)*	*(-11.30)*	*(-12.18)*	*(-16.42)*	*(-15.52)*	*(-16.86)*
LEVRG	-1.014**	-1.742**	-1.026**	-1.760**	-3.315**	-1.689**	-1.002	-1.254	-1.197	-2.281**	-2.588**	-2.062**
	(-2.29)	*(-3.95)*	*(-2.32)*	*(-7.76)*	*(-12.39)*	*(-7.52)*	*(-1.08)*	*(-1.36)*	*(-1.43)*	*(-5.16)*	*(-5.81)*	*(-5.01)*
	(-2.78)	*(-4.84)*	*(-2.82)*	*(-8.44)*	*(-13.41)*	*(-8.09)*	*(-1.34)*	*(-1.68)*	*(-1.73)*	*(-5.32)*	*(-5.96)*	*(-5.09)*
PBETA	5.506**	6.544**	5.369**	5.879**	6.748**	5.895**	6.836**	6.728**	7.487**	6.812**	6.750**	6.895**
	(16.11)	*(16.65)*	*(15.30)*	*(21.32)*	*(24.36)*	*(21.35)*	*(6.52)*	*(6.34)*	*(7.32)*	*(16.39)*	*(16.36)*	*(16.46)*
	(18.81)	*(19.93)*	*(17.85)*	*(22.53)*	*(25.62)*	*(22.62)*	*(8.74)*	*(8.54)*	*(9.75)*	*(17.57)*	*(17.65)*	*(17.63)*
BTM	0.074**	0.068**	0.075**	-0.504**	-1.237**	-0.496**	0.259**	0.243**	0.238**	-1.231**	-1.496**	-1.175**
	(3.46)	*(3.30)*	*(3.49)*	*(-3.56)*	*(-8.10)*	*(-3.59)*	*(2.56)*	*(2.47)*	*(2.29)*	*(-7.36)*	*(-8.36)*	*(-6.98)*
	(4.77)	*(4.48)*	*(4.83)*	*(-4.25)*	*(-9.74)*	*(-4.25)*	*(2.82)*	*(2.70)*	*(2.59)*	*(-7.16)*	*(-8.20)*	*(-6.86)*
ALN(P)	0.450**	1.520**		0.088	1.519**	0.099	-0.415	0.257	-1.019**	0.093	0.845**	0.118
	(2.43)	*(7.19)*		*(0.46)*	*(5.34)*	*(0.51)*	*(-1.60)*	*(0.90)*	*(-4.12)*	*(0.52)*	*(2.81)*	*(0.64)*
	(3.15)	*(10.78)*		*(0.57)*	*(8.81)*	*(0.64)*	*(-1.71)*	*(1.01)*	*(-4.47)*	*(0.67)*	*(4.51)*	*(0.84)*
FAGE	-2.349**	-2.195**	-2.371**	-2.971**	-2.810**	-2.971**	-2.611**	-2.492**	-2.444**	-2.992**	-2.822**	-2.920**
	(-4.96)	*(-4.73)*	*(-4.68)*	*(-9.74)*	*(-9.37)*	*(-9.74)*	*(-2.85)*	*(-2.66)*	*(-2.86)*	*(-5.16)*	*(-4.49)*	*(-4.54)*
	(-7.96)	*(-7.47)*	*(-7.69)*	*(-12.94)*	*(-12.02)*	*(-12.94)*	*(-4.57)*	*(-4.32)*	*(-4.44)*	*(-6.15)*	*(-5.52)*	*(-5.74)*
ESURP				0.691**	0.871**				5.713**	1.311**	1.583**	
				(4.36)	*(5.05)*				*(5.07)*	*(5.07)*	*(5.97)*	
				(5.48)	*(6.50)*				*(5.11)*	*(5.71)*	*(6.75)*	
EVOLA				0.367**		0.545**				1.128**		1.466**
				(3.39)		*(4.65)*				*(4.55)*		*(5.12)*
				(3.68)		*(5.21)*				*(5.14)*		*(6.22)*
ALANA							3.444**	4.463**		3.459**	4.629**	3.496**
							(10.96)	*(10.86)*		*(9.01)*	*(7.78)*	*(8.93)*
							(12.61)	*(14.28*		*(12.01)*	*(12.88)*	*(11.94)*
FDISP							5.281**	4.965**		1.174*	1.291*	
							(4.69)	*(4.43)*		*(1.88)*	*(2.20)*	
							(4.73)	*(4.47)*		*(2.04)*	*(2.37)*	
ASIZE	1.282**		1.467**	1.667**		1.671**	0.889**		1.824**	0.978**		0.977**
	(4.68)		*(5.49)*	*(6.60)*		*(6.62)*	*(8.57)*		*(11.19)*	*(5.22)*		*(5.32)*
	(7.98)		*(10.67)*	*(10.66)*		*(10.67)*	*(9.25)*		*(14.21)*	*(7.35)*		*(7.42)*
Constant	0.041*	0.061**	0.044*	0.089**	0.124**	0.089**	0.008	0.021	0.016	0.054*	0.066**	0.050*
	(1.44)	*(2.28)*	*(1.43)*	*(5.13)*	*(8.18)*	*(5.14)*	*(0.16)*	*(0.44)*	*(0.33)*	*(2.32)*	*(2.62)*	*(2.00)*
	(2.41)	*(3.77)*	*(2.44)*	*(6.55)*	*(9.95)*	*(6.55)*	*(0.25)*	*(0.66)*	*(0.50)*	*(2.56)*	*(2.95)*	*(2.30)*
Avg adj-R^2	0.099	0.087	0.096	0.131	0.104	0.130	0.231	0.228	0.222	0.226	0.219	0.223
Avg Obs		1722.1			1246.3			556.3			482.8	

Table 4. Results of System Estimation

This table reports the results from the Fama and MacBeth (1973)-type regressions using a three-stage least-squares (3SLS) estimation for ATURN and ALANA. The specification of the linear equation system is the following:

Equation 1: $$ATURN_{t+1} = \alpha_0 + \alpha_1 ALANA_{t+1} + \sum_{j=2} \alpha_j Z_{1jt} + \varepsilon_{t+1}$$

Equation 2: $$ALANA_{t+1} = \beta_0 + \beta_1 ATURN_{t+1} + \sum_{k=2} \beta_k Z_{2kt} + \eta_{t+1},$$

where t = 198301-200212 (240 months) for both NYSE/AMEX-listed and NASDAQ-listed firms. Z_1 includes RET^+, RET^-, LEVRG, PBETA, BTM, ALN(P), FAGE, ESURP, EVOLA, FDISP, ASIZE, and industry dummies (I1-I47). Z_2 includes ROA, PBETA, ALN(P), LGBSEG, and I1-I47. ROA is return on assets. LGBSEG is defined as log(1+#GBSEG), where #GBSEG stands for the sum of the number of geographic segments and the number of business lines for a firm. The definitions of other variables are the same as in Table 3. The values in the first row for each explanatory variable are the time-series averages of coefficients obtained from the month-by-month 3SLS regressions. The average coefficients in Panel A are multiplied by 100, except for those of *RET+, RET-* , and the intercept. The values italicized in the second row of each variable are *AR(1)-adjusted* t-statistics computed by equation (21):

$$t_{dep} = \frac{\overline{\theta}}{\sigma_\theta \sqrt{\frac{1}{T} + \frac{2\varphi}{(1-\varphi)T} - \frac{2\varphi(1-\varphi^T)}{(1-\varphi)^2 T^2}}},$$

where $\overline{\theta}$ and σ_θ are the mean and standard deviation of the estimated coefficients, respectively, T is the sample size of the coefficients, and φ is the 1st-order serial correlation of the coefficients. The values italicized in the third row of each variable are *heteroskedasticity and autocorrelation-consistent (HAC)* t-statistics computed based on Newey and West (1987). The statistics associated with the industry dummies (I1-I47) are not reported. *Avg Obs* is the average number of observations used in the regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

	Panel A: Dep Var = ATURN			
	NYSE/AMEX		NASDAQ	
Explanatory Variables	Subperiod 2h (198301-200012)		Subperiod 2i (198301-200012)	
ALANA	-2.159		-3.537	
	-1.07		*-0.61*	
	-1.16		*-0.56*	
RET+	0.105	**	0.145	**
	5.24		*3.42*	
	6.15		*4.15*	
RET-	-0.229	**	-0.197	**
	-3.62		*-2.91*	
	-3.67		*-3.01*	
LEVRG	1.214		3.607	
	1.48		*1.02*	
	1.54		*1.04*	
PBETA	7.474	*	8.532	**
	2.71		*2.69*	
	2.92		*2.97*	
BTM	0.837		1.533	
	0.84		*0.87*	
	0.92		*0.88*	
ALN(P)	-2.655		-2.684	
	-1.52		*-1.13*	
	-1.66		*-1.07*	
FAGE	-1.853	**	-1.910	**
	-2.94		*-3.14*	
	-2.99		*-3.01*	
ESURP	1.132	*	3.165	*
	2.59		*2.31*	
	2.69		*2.39*	
EVOLA	0.314		2.389	*
	0.77		*2.51*	
	0.82		*2.38*	
FDISP	0.875	*	1.450	
	1.93		*1.64*	
	2.15		*1.75*	
ASIZE	4.795		4.883	
	1.38		*1.61*	
	1.50		*1.50*	
Constant	-0.117		-0.047	
	-1.61		*-0.91*	
	-1.74		*-0.94*	
Avg Obs	811.3		477.1	

	Panel B: Dep Var = ALANA			
	NYSE/AMEX		NASDAQ	
Explanatory Variables	Subperiod 2h (198301-200012)		Subperiod 2i (198301-200012)	
ATURN	8.169	**	5.424	**
	3.62		*7.77*	
	5.57		*9.71*	
ROA	0.629	**	0.591	**
	6.78		*1.92*	
	7.85		*3.67*	
PBETA	-0.615	**	-0.271	**
	-9.54		*-2.92*	
	-11.10		*-3.96*	
ALN(P)	0.068	**	0.011	
	6.06		*0.79*	
	8.37		*1.04*	
LGBSEG	0.270	**	-0.212	**
	11.44		*-3.46*	
	13.72		*-5.89*	
Constant	2.001	**	1.744	**
	42.18		*16.34*	
	44.32		*23.99*	
Avg Obs	811.3		477.1	

Table 5. Results of Monthly Cross-Sectional Regressions: Order Imbalances for NYSE Stocks

This table reports the result of the Fama and MacBeth (1973)-type cross-sectional regressions for signed trading activity measures (order imbalances) from January 1988 to November 2002 (179 months). Dependent variables are the 2 measures of GRT-adjusted imbalances: 1) *ADOIM*: GRT-adjusted *DOIM*, where *DOIM* is defined as [(the dollar value of buyer-initiated trades - the dollar value of seller-initiated trades)/(the dollar value of buyer-initiated trades + the dollar value of seller-initiated trades)], and 2) *LADOIM*: log(1+|*ADOIM*|). The explanatory variables are all one-month preceding values (no contemporaneous regressors are used). The definitions of the explanatory variables are the same as in Table 3. The values in the first row for each explanatory variable are the time-series averages of coefficients obtained from the month-by-month cross-sectional regressions. The average coefficients are multiplied by 100, except for those of *RET+, RET-* , and the intercept. The values italicized in the second row of each variable are *AR(1)-adjusted* t-statistics. The values italicized in the third row of each variable are *heteroskedasticity and autocorrelation-consistent (HAC)* t-statistics computed based on Newey and West (1987). The statistics associated with the industry dummies *(I1-I47)* are not reported. *Avg adj-*R^2 is the average of adjusted R-squared. *Avg Obs* is the average number of companies used each month in the regressions. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

Explanatory Variables	Order Imbalances over Subperiod 2j (198801-200211)	
	ADOIM	LADOIM
RET+	0.068**	-0.031**
	(4.62)	*(-2.98)*
	(4.54)	*(-3.02)*
RET-	0.001	0.047**
	(0.04)	*(5.74)*
	(0.05)	*(4.99)*
LEVRG	1.142**	0.306
	(3.43)	*(1.42)*
	(3.44)	*(1.37)*
PBETA	0.928**	-1.308**
	(3.00)	*(-6.04)*
	(2.66)	*(-5.50)*
BTM	-0.159	0.106
	(-0.69)	*(0.98)*
	(-0.66)	*(0.92)*
ALN(P)	-1.150**	0.875**
	(-11.54)	*(14.09)*
	(-10.70)	*(13.60)*
FAGE	0.114	-0.515**
	(0.94)	*(-5.82)*
	(0.87)	*(-4.86)*
ESURP	0.294**	-0.023
	(3.26)	*(-0.40)*
	(3.70)	*(-0.36)*
EVOLA	0.275**	-0.153**
	(3.79)	*(-3.30)*
	(3.58)	*(-3.30)*
ALANA	1.378**	-0.785**
	(8.70)	*(-8.18)*
	(8.03)	*(-7.41)*
FDISP	2.281**	0.262
	(4.71)	*(1.28)*
	(5.21)	*(1.24)*
ASIZE	1.420**	-1.364**
	(12.41)	*(-16.61)*
	(12.55)	*(-16.42)*
Constant	-0.096**	1.275**
	(-9.30)	*(134.45)*
	(-8.60)	*(129.14)*
Avg adj-R2	0.041	0.046
Avg Obs	753.8	

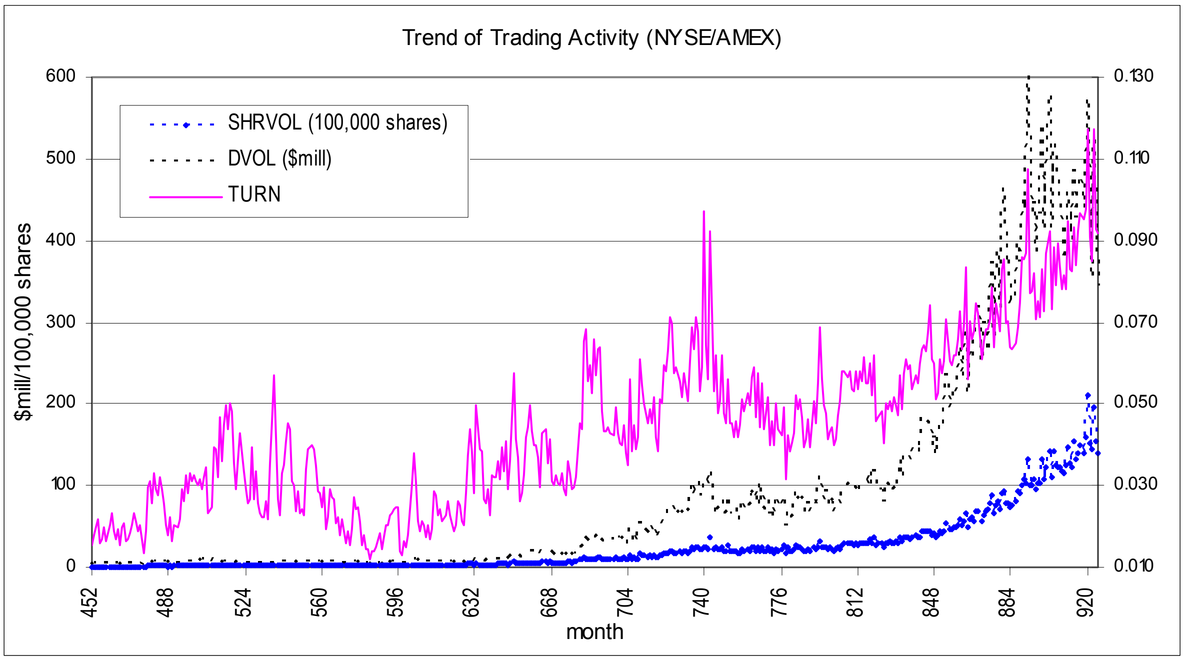
Table A1. Comparison of t-Statistics

This table presents how the 3 different types of t-statistics compare each other in 4 cases of the total 24 specifications reported in Table 3 (Panel P: For Model 1 in Entire Period of Panel A, Table 3; Panel Q: For Model 11 in Subperiod 2c of Panel A, Table 3; Panel R: For Model 19 in Subperiod 2f of Panel B, Table 3; Panel S: For Model 22 in Subperiod 2g of Panel B, Table 3). *Mean Coeff* is the average of the estimated coefficients in the monthly cross-sectional regressions. The average coefficients are multiplied by 100, except for those of *RET+, RET-* , and *Constant*. *Autocorr* is the 1st-order serial correlation (φ) of the estimated coefficients. *t-FM* is the usual t-statistic based on Fama and MacBeth (1973), *t-AR(1)* is that based on AR(1)-adjustment by equation (21), and *t-HAC* is the *heteroskedasticity and autocorrelation-consistent (HAC)* t-statistic computed based on Newey and West (1987).

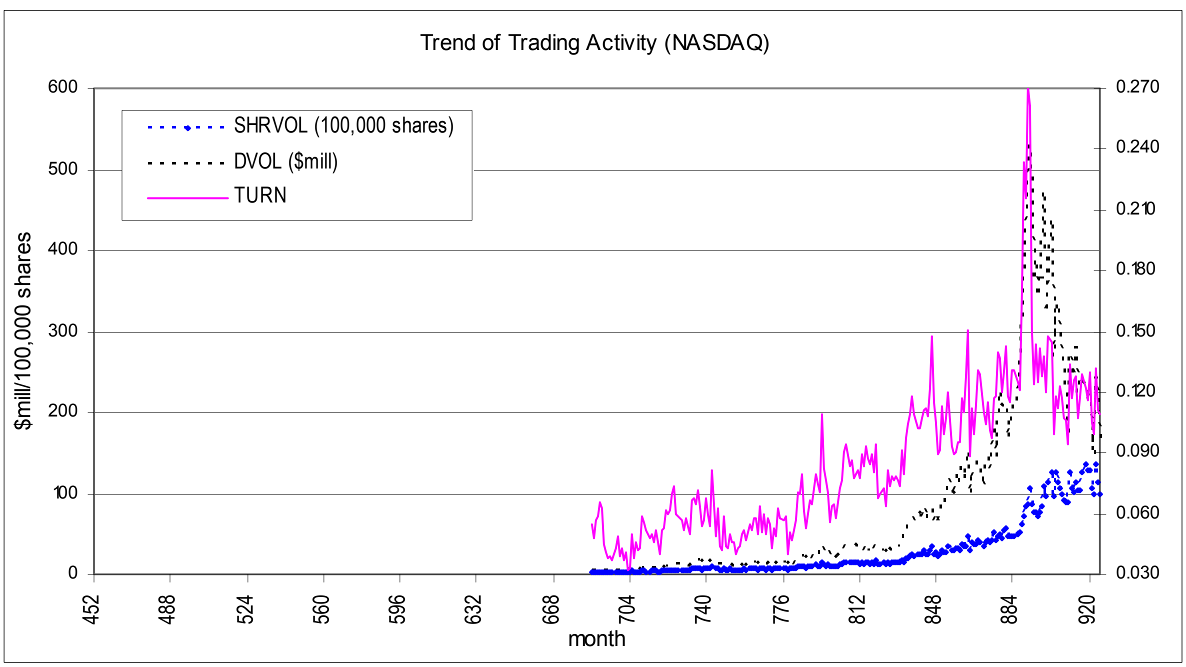
Dep Var and Market	Items	RET+	RET-	LEVRG	PBETA	BTM	ALN(P)	FAGE	ESURP	EVOLA	ALANA	FDISP	ASIZE	Constant
Panel P: For Model 1 in Entire Period of Panel A, Table 3														
ATURN	Mean Coeff	0.122	-0.116	0.781	2.713	0.022	0.464	-0.687					0.283	0.020
NYSE/AMEX	Autocorr	0.026	0.132	0.662	0.702	0.635	0.880	0.825					0.752	0.771
	t-FM	10.54	-8.01	8.43	24.68	3.89	8.99	-15.59					11.73	7.17
	t-AR(1)	10.27	-7.01	3.81	10.35	1.84	2.29	-4.85					4.43	2.59
	t-HAC	9.40	-7.18	4.37	12.61	1.95	3.99	-7.02					5.54	3.34
Panel Q: For Model 11 in Subperiod 2c of Panel A, Table 3														
ATURN	Mean Coeff	0.145	-0.195	0.522	3.639	-0.125	0.316	-1.729	0.177		1.356	1.050		0.058
NYSE/AMEX	Autocorr	0.142	0.234	0.750	0.474	0.333	0.752	0.875	0.311		0.576	0.472		0.840
	t-FM	21.17	-24.51	3.44	40.06	-2.76	7.26	-22.22	6.77		37.03	9.06		11.62
	t-AR(1)	18.35	-19.33	1.31	24.00	-1.96	2.75	-5.84	4.92		19.27	5.44		3.46
	t-HAC	18.36	-17.23	1.79	25.25	-1.98	3.78	-10.68	5.38		21.17	6.16		5.67
Panel R: For Model 19 in Subperiod 2f of Panel B, Table 3														
ATURN	Mean Coeff	0.212	-0.249	-1.002	6.836	0.259	-0.415	-2.611			3.444	5.281	0.889	0.008
NASDAQ	Autocorr	0.052	0.069	0.669	0.727	0.532	0.487	0.834			0.617	0.411	0.518	0.808
	t-FM	15.96	-14.23	-2.42	16.30	4.62	-2.71	-9.34			22.44	7.23	15.17	0.49
	t-AR(1)	15.15	-13.27	-1.08	6.52	2.56	-1.60	-2.85			10.96	4.69	8.57	0.16
	t-HAC	15.05	-11.85	-1.34	8.74	2.82	-1.71	-4.57			12.61	4.73	9.25	0.25
Panel S: For Model 22 in Subperiod 2g of Panel B, Table 3														
ATURN	Mean Coeff	0.208	-0.269	-2.281	6.812	-1.231	0.093	-2.992	1.311	1.128	3.459	1.174	0.978	0.054
NASDAQ	Autocorr	0.122	0.010	0.451	0.542	0.402	0.713	0.665	0.525	0.608	0.747	0.453	0.755	0.571
	t-FM	19.72	-18.98	-8.38	30.00	-11.26	1.26	-11.44	9.06	9.19	23.48	3.06	13.84	4.42
	t-AR(1)	17.45	-18.80	-5.16	16.39	-7.36	0.52	-5.16	5.07	4.55	9.01	1.88	5.22	2.32
	t-HAC	16.13	-16.42	-5.32	17.57	-7.16	0.67	-6.15	5.71	5.14	12.01	2.04	7.35	2.56

Figure 1. Trends in Trading Activity

The following graphs show the trends of our 3 measures of monthly trading activity: turnover *(TURN)*, share volume *(SHRVOL)*, and dollar volume *(DVOL)* over the 474 months (39.5 years: 196307-200212). The series are the monthly cross-sectional averages of the three activity measures over the period. The average numbers of component stocks used each month are 1647.2 for NYSE/AMEX (196307-200212) stocks and 1722.1 for NASDAQ (198301-200212) stocks. The starting month number (452) indicates July 1963, while the ending month number (925) indicates December 2002. Figure 2(a) is for the stocks on the NYSE/AMEX, and Figure 2(b) for those on the NASDAQ [available from January 1983 (month number 686) to December 2002 (month number 925)]. Share volume (in 100 thousand shares) and dollar volume (in $million) are measured on the left-hand scale, while turnover is measured on the right-hand scale.



(a)



(b)