Volatility, Returns and Liquidity: The Relation Between Online Trading and Stock Market Behavior

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Abstract

Using the level of Web traffic experienced by online brokers as a proxy for online equity trading, this paper examines the dynamic relations between online trading and aggregate measures of stock market behavior. We initially observe that online trading is positively related to market volatility. However, once we control for the total trading by small traders, online trading no longer contributes to market volatility. This result is inconsistent with the claim that the expansion of online trading increases stock market volatility. We find a significantly positive relation between online trading and contemporaneous market returns. This result is consistent with the presence of systematic noise as well as positive-feedback trading by online investors. Finally, we find that online trading is positively related to two measures of market liquidity, the bid-ask spread and the quoted depth. This joint result concerning liquidity likely benefits institutional investors who tend to place large orders, while increasing the cost of trading to individual investors who are likely to submit small orders.

Keywords: online trading; market volatility; liquidity; Web traffic

JEL Classifications: G12/G14

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I. Introduction

Online trading has exploded in recent years, due to the bull market of the late 1990s and developments in information technology, especially the Internet.[1] As recently as 1994, there was no online trading of stocks over the Internet. From 1995 to 2000, investors opened over 19 million online brokerage accounts (U.S. General Accounting Office (2000, 2001)). Salomon Smith and Barney (2002) estimates that at year-end 2001, total online brokerage assets exceeded one trillion dollars. Thus, this last decade has witnessed the birth and tremendous growth of a new way to trade equities.

In spite of its popularity, scholarly analysis of online trading is limited. Barber and Odean (2002) argue that online investors tend to become overconfident due to illusions of knowledge and control. They find that investors trade more frequently, more speculatively, but less profitably after they go online. Choi, Laibson and Metrick (2002) analyze the impact of a web-based trading channel on trader behavior in two large corporate 401(k) plans. They find that the trading frequency for their sample firms with Web access is double that of firms lacking a Web channel.

Our study builds upon this initial literature by explicitly examining the relation between online trading and more aggregate components of market behavior such as volatility, returns, and liquidity. These issues are of interest not only to academics, but also to market participants, policy makers, and market regulators. The media and some academics have suggested that online

[1] The multiple benefits of online trading such as lower commissions, quicker execution, and easier access to research information has further enhanced its popularity among investors.

trading destabilizes financial markets by inducing excessive trading, greater risk taking, and higher volatility in the stock market.[2] Shiller (2000), for instance, contends that the expansion of online trading will increase the level of stock market volatility. Moreover, some critics contend that online trading played an important role in both the growth and ultimate burst of the recent bubble in technology stocks. For example, Thaler (1999) appears to believe that online and day traders are at least partially responsible for the Internet bubble, as evidenced from the following quote: “I hope someday soon a scholar will acquire a data set of online and day traders. Until such data become available, we will never fully understand what I think will become known as the Great Internet Stock Bubble”. Further, policy makers and market regulators are concerned with the impact of online trading on good order and discipline in the financial marketplace. For instance, then SEC Chairman Arthur Levitt (1999a, 1999b, 1999c) issued a series of cautionary policy statements in 1999 concerning online and day trading.

This study makes two contributions to the literature on investor and market behavior, especially as they are influenced by the emergence of online trading. Using a new database, we construct an innovative proxy for online trading. Specifically, we use Web traffic for six leading online brokers as a proxy for aggregate online trading. Such a proxy is especially appropriate for investigating the aggregate relations between online investors and critical dimensions of stock market behavior. The sample firms over which we construct our proxy represent an 80% share of the online trading market while their Web traffic is based on the sampling of 50,000 internet users.

This is the first study that empirically examines the dynamic relations that exist between online trading and aggregate market volatility, returns, and liquidity. Earlier studies focus on the trading behavior of individual investors and use disaggregated data. By focusing on aggregate

[2] See, for example, Choi, Laibson, and Metrick (2002) and the references in their footnote 1.

market relationships in the U.S., this study complements previous research and provides a more complete view of the effects of online trading on the equity market.

We begin by examining the relation between online trading and market volatility. Many studies document a positive relation between price volatility and trading volume in the financial markets. This relation is robust to various data frequencies and financial markets (see Karpoff (1987) for a review). Consequently, one might expect a positive relation between online trading and market volatility.

Online trading and price volatility might also be positively related due to overconfidence. Odean (1998) develops a model in which investors are overconfident. Odean shows that both trading volume and price volatility increases as investor overconfidence increases. Gervais and Odean (2001) develop a dynamic model in which overconfidence is determined endogenously and changes dynamically. They show that trading volume and price volatility are both positively related to the degree of self-attribution bias, which is the underlying cause for overconfidence in their model. In practice, the degree of overconfidence is not observed. If one is willing to consider the level of online trading as a proxy for the degree of online traders' overconfidence, one might argue based on Odean (1998) and Gervais and Odean (2001) that online trading should be positively related to price volatility.

Next we examine the relation between online trading and stock market returns. Individual investors are routinely viewed as unsophisticated, uninformed, and as noise traders in the literature (see, for example, Nofsinger and Sias (1999), Kumar and Lee (2002), Barber, Odean, and Zhu (2003), and Griffin, Harris and Topaloglu (2003)). Shleifer and Summers (1990) and Shleifer and Vishny (1997) argue that demand by noise traders could cause asset prices to deviate from their fundamental values because of limits to arbitrage. Kumar and Lee (2002) and

Barber, Odean and Zhu (2003) study the behavior of individual investors and find that trading by individual investors is systematic. As a result, they argue that noise trading has the potential to affect asset prices. If online traders are noise traders, it is useful to examine the extent to which online trading can influence market prices.

Lastly, we examine the relation between online trading and market liquidity. If online traders tend to be uninformed, then an increase in online trading should reduce bid-ask spreads by lowering the probability of informed trading (see, for example, Copeland and Galai (1983), Glosten and Milgrom (1985), and Easley and O'Hara (1987)). However, if online trading tends to be systematic, then an increase in online trading might widen bid-ask spreads by creating or exacerbating the market-maker's inventory problems (see, for example, Demsetz (1968), Ho and Stoll (1981), and Stoll (1979)). Therefore, it remains an important empirical question as to how an increase in online trading would affect market liquidity.

The remainder of the paper proceeds as follows. Section II discusses the related literature. Section III presents our new proxy for online trading and describes the sample we use in our analysis. In Section IV we discuss the results from our preliminary data analysis. Section V investigates the relation between online trading and stock market volatility. In Section VI, we test for the possibility of online trading influencing price formation by examining the relation between online trading and contemporaneous market returns. Section VII contains the results from our examination of the relation between online trading and market liquidity. We conclude with a brief summary and interpretation in Section VIII.

II. Related Literature

Several studies examine the trading behavior of online investors. Barber and Odean

(2002) argue that online investors tend to become overconfident due to illusions of knowledge and control. They analyze the trading activities of 1,607 investors of a large discount broker that switched from phone-based trading to online trading. They find that investors trade more frequently, more speculatively, but less profitably after they go online. Glaser and Weber (2003) report results from a survey of internet traders and find that those who identify themselves as more overconfident trade more often. Choi, Laibson and Metrick (2002) analyze the impact of a web-based trading channel on trader behavior and performance in two large corporate 401(k) plans. They find that the trading frequency for their sample firms with Web access is double that of firms lacking a Web channel. Jackson (2002) examines cross sectional differences between internet and traditional investors and concludes that internet investors are more sensitive to both recent returns and volatility in those returns.

Our analysis of the relation between online trading and market volatility is related to a large literature on the volume-volatility relation and two theoretical papers on overconfidence. Numerous studies document a positive relation between price volatility and trading volume in financial markets. For example, Karpoff (1987) summarizes the results of nineteen empirical studies and reports that eighteen out of nineteen studies find a positive correlation between absolute price change and trading volume. Many recent studies of volume-volatility relations either use a (two-stage) regression model or a generalized autoregressive conditional heteroskedasticity (GARCH) model. For example, Schwert (1990), Bessembinder and Seguin (1993), Jones, Kaul, and Lipson (1994), and Chan and Fong (2000) adopt the regression approach while Lamoureux and Lastrapes (1990) use the GARCH model.

Odean (1998) develops a model in which uninformed traders, informed traders, and market makers are all overconfident. Specifically, these traders overestimate the precision of their signals. Odean shows that both trading volume and price volatility increase as the investor's overconfidence increases. This result holds whether the investor is informed or uninformed. Gervais and Odean (2001) develop a dynamic model in which overconfidence is determined endogenously through a self-attribution bias. In their model, a trader's level of overconfidence changes dynamically with his success and failures. They show that expected trading volume and price volatility are both positively related to the extent of the self-attribution bias. In practice, the degree of overconfidence is not observed. But since online traders tend to become overconfident, one might argue based on Odean (1998), Gervais and Odean (2001), and Barber and Odean (2002) that their trading, reflective of their overconfidence, should be positively related to price volatility.

Systematic trading by individual investors is one of the necessary conditions "for the biases and sentiment of individual investors to have a cumulative effect on asset prices" (Barber, Odean, and Zhu (2003)).[3] Kumar and Lee (2002) and Barber, Odean, and Zhu (2003) both document that the aggregate trading of individual investors is systematic. Barber, Odean, and Zhu show that the trading of individual investors is highly correlated and argue that this coordinated trading is likely driven by the disposition effect, the representativeness heuristic, and limited attention. Kumar and Lee find that the buy-sell imbalance in individual investor trades contains a systematic component. Moreover, this systematic component has incremental explanatory power for small-cap returns.

Our analysis of the relation between online trading and market liquidity builds on several recent studies that examine commonality in liquidity and market liquidity. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2000), and Huberman and Halka (2001)

[3] The other necessary condition is the existence of limits of arbitrage.

document commonality in the liquidity of individual stocks. This result emphasizes the importance of studying the behavior of market liquidity. In particular, there is now evidence that systematic liquidity variation is a priced factor (Pastor and Stambaugh (2003)). Chordia, Roll, and Subrahmanyam (2001, 2002) study how market liquidity varies over time. They find that recent market returns, market volatility, macroeconomic variables, and trading imbalances are important determinants of market liquidity. This paper contributes to this burgeoning literature by focusing on the relation between aggregate online trading and market liquidity.

III. Data and Variables

A. New Proxy for Online Trading

Aggregate online trading data more frequent than monthly for the U.S. are not readily available to academic researchers. Consequently, in this study we make use of a new data source that contains Web traffic data for a number of online brokers. More specifically, we use the total Web traffic from six leading online brokers' websites as a proxy for aggregate online trading. The six online brokers we use in our proxy construction are Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. Because the online brokerage industry is highly concentrated, our sample of six online brokers is sufficient to allow meaningful analysis. Indeed, McMillan (1999, 2000) notes that the six online brokers of our sample are the industry's six largest online brokers and represent a combined market share of 80%.

We believe that the level of Web traffic observed for an online broker is an effective proxy for the online trading actually experienced by a broker for several reasons. First, a portion of the Web traffic is directly related to online trading because investors must log-on to their brokers' websites to execute online trades. The remaining Web traffic is likely to be positively correlated with online trading because of two behavioral factors. Researchers in psychology such as Festinger (1957) find that people prefer cognitive consonance between their actions. Hence, investors who visit a broker's website are more likely to trade either immediately or in the future. Web traffic and actual trading are conceptually consonant activities which will result in a positive correlation between them, thus allowing one to proxy for the other. Researchers in the area of marketing note the existence of a "mere exposure" effect in individual attitudes towards a product (e.g., Krugman (1977), Batra and Ray (1986), Stuart, Shimp, and Engle (1987), and Janiszewski and Warlop (1993)). According to this effect, consumer attitudes towards a product can change without cognition since mere exposure to the product has the ability to make an individual's attitude more favorable. Thus, as investors visit a broker's website, they become increasingly aware of available financial products and are ultimately more likely to place a trade.

Finally, we examine the correlations between online brokers' Web traffic and actual aggregate trading levels by small traders. We find that correlations between Web traffic and small trades, defined as 500 shares or fewer, are significantly positive. The correlation exceeds 0.40 when calculated with variable levels and is over 0.60 when using changes in the variables.[4] These consistently strong correlations between Web traffic and actual trading levels provide empirical support for our argument that the Web traffic of online brokers can proxy for online trading.

B. Data and Sample

Our sample period extends from December 8, 1999 to July 28, 2002. This constitutes a total sample period of 138 weeks and corresponds to the period for which we have Web traffic

[4] Using changes in variables mitigates a concern that this high correlation simply reflects a common underlying trend or other commonalities.

data. We obtain weekly Web traffic data for six leading online brokers for this period from Media Metrix. Media Metrix is a leading internet rating firm that provides third-party audience data used by clients to make business decisions. Media Metrix uses a random recruitment method to form a representative sample, or panel, of internet users. The panel consists of 50,000 individuals in the United States. Media Metrix provides a number of different metrics for internet usage. In this study, we focus on one particular measure, the "average daily number of unique visitors." This measure represents the average number of different individuals that visit a specific website per day during the course of the reporting week.[5]

To complete our empirical analysis, we collect equity return and price data from several different sources. We obtain S&P 500 index data from CRSP. We collect NASDAQ composite index data from the NASDAQ website.[6] To construct market trading and liquidity variables, we obtain intra-daily trade and quote data for all common stocks from the NYSE Trade and Quote (TAQ) database.

C. Variable Construction

In this section we describe the construction of the variables that we use in our analysis. Since the Web traffic data are weekly, our subsequent analysis is weekly. Again, we use the aggregate weekly Web traffic from the six leading online brokers' websites as a proxy for aggregate online trading. Because two of these brokers, Fidelity and Schwab, offer a wide range of financial products, it might be that much of their Web traffic is unrelated to equity trading,

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[5] Media Metrix data are used by a number of studies in finance and accounting including Lazer, Lev, and Livnat (2001), and Trueman, Wong, and Zhang (2000).

[6] We also examine the Russell 2000 index and the AMEX Internet index and find qualitatively similar results to that of S&P 500 index and Nasdaq index. Hence, we do not separately report these findings.

Hence, we calculate an alternative measure that aggregates Web traffic across the remaining four more focused online brokers.

We construct weekly S&P 500 index returns (RETSPX) and weekly NASDAQ composite index returns (RETNASD) by aggregating their respective daily returns. We use the high-low return, which is defined as the difference between the highest and the lowest logarithm of price during a day, as a proxy for market volatility. This range-based volatility proxy is widely used among academics and practitioners.[7]

We follow Chordia, Roll and Subramanyam (2001, 2002) to construct market-wide liquidity and trading activity measures. We apply a number of data screens that exclude specific trades or quotes to ensure that erroneous data are not included in the analysis. Online investors are individual investors and tend to engage in small trades. To determine if online investors have an incremental effect on the stock market, we must control for the aggregate trading activity of individual investors. Following many studies in the literature including Lee (1992), Lee and Radhakrishna (2000), Hvidkjaer (2003), and Malmendier and Shanthikumar (2003), we use trade size to distinguish between individual and institutional trades. We classify trades of 500 shares or fewer as individual trades.[8] To maintain this study's focus, we place the details concerning the construction of market liquidity and trading activity variables in the Appendix.

IV. Preliminary Data Analysis

A. Web traffic and Return Variables

In Table 1 we present summary statistics for a variety of Web traffic and return variables. We observe in Panel A that the daily average number of unique visitors to the six online brokers'

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[7] See Alizadeh, Brandt, and Diebold (2002) and references therein.

[8] Using an alternative cutoff such as 1000 shares for small trades does not affect any of our results.

websites is 924,950. This measure is our proxy for aggregate online trading, and for ease of exposition is referred to as online trading or aggregate online trading throughout this study. Both online trading (OL) and its logarithm (LOGOL) are persistent time-series with first order autocorrelations of 0.85 and 0.84 respectively.

Over our sample period of December 1999 to July 2002, we observe the effect of the collapse of the Internet bubble and the subsequent weak economy on equity values. We calculate a mean weekly return of -0.38% to the S&P 500 index. The weekly returns to the Nasdaq composite index are even lower, with a mean of -0.74%.

As noted above, both OL and LOGOL are quite persistent. To test whether these two variables are stationary, we conduct a unit root test. Panel B contains our results. Overall, we cannot reject the hypothesis that OL and LOGOL contain unit roots, whether we allow for a linear trend or not. This result suggests that OL and LOGOL might be non-stationary. It is well-known that using non-stationary variables in regressions can generate spurious results (see, for example, Ferson, Sarkissian, and Simin (2003)). Consequently, in our subsequent regression analysis, we use the first difference of either online trading (ΔOL) or the logarithm of online trading (ΔLOGOL). Panel C contains a summary description of the Web traffic for each of the six online brokers, Ameritrade, Datek, E*Trade, Fidelity, Schwab, and TD Waterhouse.

B. Market Liquidity and Trading Activity Variables

In Table 2 we examine the characteristics of those variables which capture market liquidity and trading activity. In Panel A, we present a series of univariate summary statistics. We examine two measures of bid-ask spreads, the quoted spread and the effective spread, in both absolute and percentage terms. Another important dimension of liquidity is captured by the quoted depth. We also examine several market trading activity variables, including share volume, number of trades, and order imbalance.

We construct the market-wide liquidity and trading activity variables from an average of 4,870 stocks. This is less than the number of stocks covered by the CRSP and TAQ database because of our screening criteria described in the Appendix. The average quoted spread over our sample period is 9.20 cents while the average percentage quoted spread is 0.91%. The average effective spread is 7.36 cents and the average percentage effective spread is 0.73%. The finding that the effective spreads are smaller than the quoted spreads is expected because effective spreads incorporate the possibility that trades might occur inside the bid-ask prices. The average quoted depth is 1,562 shares. The average weekly trading volume is 12.39 billion shares for all sized trades and 2.28 billion shares for small-sized trades. On average, there are 14.32 million trades per week, and 10.38 million of them are small trades. Small trades represent 72.5% of the total number of trades, but only 18.4% of share volume. The average order imbalance for small trades is positive whether we measure it by share volume or by the number of trades. This result suggests that small investors are net buyers over our sample period, which is characterized by a generally declining stock market.

The NYSE and NASDAQ have evolved different market microstructures to trade stocks (see, Harris (2003) for a comprehensive review). The NYSE is an order-driven market, based on a centralized public limit order book, which is handled by a single specialist. The NASDAQ is primarily a quote-driven market, based on multiple dealers who compete for order flow. These differences have important implications for interpreting the quoted depth and trading volume of these exchanges. In particular, the NASDAQ trading volume is likely to be inflated relative to that reported for the NYSE, and the NASDAQ quoted depth likely understates the true depth of the market. These differences raise issues regarding the appropriateness of aggregating across NYSE and NASDAQ stocks. To mitigate such concerns, we construct several market liquidity and trading activity variables separately using NYSE and NASDAQ stocks. The results from these calculations are contained in Panel B.

The average percentage quoted spread is 1.11% for NASDAQ stocks and only 0.40% for NYSE stocks. Similarly, the average percentage effective spread is 0.92% for NASDAQ and only 0.26% for NYSE. One should be cautious, however, about concluding that trading costs on the NYSE are lower than those of NASDAQ, because we do not control for stock characteristics that are related to trading costs. One of the reasons why the average spread is higher on the NASDAQ is that most of the NASDAQ stocks are those of small firms.

As expected, we find that NYSE stocks have greater quoted depth. The average NYSE depth is 3,086 shares. This compares to 1,562 shares for stocks of all exchanges (Panel A). Small trades appear to be concentrated on NASDAQ issues. For example, each week there are on average 8.11 million small trades on the NASDAQ, but only 2.23 million small trades occur on the NYSE.

Figure 1 plots our market-wide liquidity variables over the sample period. Panel A plots the absolute quoted spread, percentage quoted spread, absolute effective spread, and percentage effective spread. Not surprisingly, all four measures of bid-ask spreads move closely with each other. Furthermore, there is a downward trend in all four measures, indicating that bid-ask spreads generally decline over our sample period.

Panel B in Figure 1 plots the quoted depth across all exchanges as well as separately for the NYSE. Consistent with existing evidence on decimalization (Bessembinder (2003)), we find that the quoted depth decreases substantially after decimalization in January 2001. In our subsequent analysis of the quoted depth, we remove the week that NYSE decimalization becomes effective as well as the following week from our sample period for two reasons. We eliminate the week of decimalization because decimalization represents a structural change rather than a response to market conditions or trading information. Our use of first differences in constructing measures of the dependent variable requires we also eliminate the week following decimalization.

C. Correlations between Online Trading and Market Trading

In Table 3 we present the results from a correlation analysis between our proxy for online trading and various measures of market trading activity. Because Fidelity and Schwab offer an extensive set of services other than stock trading, we include an additional variable, OL4, which measures aggregate Web traffic for the other four online brokers in our sample. We use both the share volume and the number of trades as our measures of market trading activity.

In Panel A we observe that the correlation between Web traffic for the six brokers, OL, and that for the focused brokers, OL4, is 0.98. This high correlation suggests that Fidelity and Schwab's diversified menu of financial products does not contaminate the use of their Web traffic when constructing our proxy for online trading. We find that for both OL and OL4, the correlations with our two measures of actual trading by small traders are significantly positive and in excess of 0.40. These results are consistent with our use of Web traffic as a proxy for online trading.

Because we can not reject the existence of a unit root for OL, we examine in Panel B the correlations between weekly changes in Web traffic and corresponding changes in trading volume. We again note the high correlations (>0.60). This result suggests that the positive correlation between Web traffic and actual trading volume is not driven by common trends or other commonalities.

D. Determinants of Online Trading

To determine what factors affect online trading, we develop and then test a simple linear model. Lamoureux and Lastrapes (1990) and Gallant, Rossi, and Tauchen (1992) are among many researchers who find that trading volume is persistent. Hence, we conjecture that online trading will likewise demonstrate persistence and anticipate that it will be positively related to its lagged values. We include lagged stock returns, RET_{t-1}, in our regression because Statman and Thorley (2003) find that high trading volume is associated with high stock returns in previous weeks. They interpret this result as evidence in favor of the overconfidence and disposition effects. Statman and Thorley contend that in rising markets investors tend to attribute success to their own abilities more than they should. As a result, they become overconfident and trade more actively. Alternatively, when the market declines, investors tend to hold their losers due to loss aversion and consequently trade less actively. We expect that online trading will be lower during weeks which include holidays. We include a dummy variable, *Holiday*, that assumes a value of 1 if a national holiday falls within the week of interest and is 0 otherwise.[9] Note that our data frequency is weekly. Therefore, markets are still open on some days even during a holiday week. In summary, we specify our model of online trading as follows:

$$OL_t = \alpha + \beta\, OL_{t-1} + \gamma\, OL_{t-2} + \theta\, RET_{t-1} + \psi\, Holiday + \varepsilon_t \tag{1}$$

In Table 4 we provide our regression estimates, using both the level of online trading (Panel A) and its logarithmic transformation (Panel B). The results in Table 4 illustrate the

[9] Our set of national holidays is: New Year's Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, and Christmas.

importance of temporal variables in determining the level of online trading. We observe that online trading is highly auto-correlated and that the past two weeks' level of trading is an important determinant of next week's trading. Further, we note that the holiday variable is negatively related to the level of trading, consistent with reduced trading around holidays.

We examine the impact of lagged aggregate market returns by including as regressors the returns to the S&P 500 index as well as the NASDAQ composite index. The impact of lagged aggregate market returns is consistently negative, but statistically insignificant for both measures of market performance. These results do not support the presence of overconfidence and disposition effects in online trading. The nature of previous returns appears not to influence the trading levels of online investors. Because the results are qualitatively identical for OL and its logarithmic transformation, we elect to report findings for only OL in our subsequent analyses.

V. Online Trading and Market Volatility

The media and academics suggest that online trading destabilizes financial markets by inducing excessive trading and higher volatility in the stock market. For example, Shiller (2000) suggests that the expansion of online trading will increase stock market volatility. The findings of Odean (1998) and Gervais and Odean (2001) regarding investor overconfidence also suggest that online trading might positively impact market volatility. Consequently, we examine in this section how online trading influences the stock market's volatility. We employ two different models in our analysis. The first is a regression model while the second is the standard GARCH model.

A. Regression Model

In the first approach, we proxy volatility with high-low returns and then employ a regression model to examine the impact of online trading on market volatility. We use the high-low return as our dependent variable since it better captures intraday volatility than absolute return when the difference between the open and closing prices is small. Specifically, we estimate the following regression model:

$$SPXHL_t = \alpha + \beta\,\Delta OL_t + \gamma\,SPXHL_{t-1} + \delta\,\Delta NTS_t + \psi\,\Delta VOLS_t + \varepsilon_t \qquad (2a)$$

$$NASDHL_t = \alpha + \beta\,\Delta OL_t + \gamma\,NASDHL_{t-1} + \delta\,\Delta NTS_t + \psi\,\Delta VOLS_t + \varepsilon_t \qquad (2b)$$

The dependent variables are the high-low returns of the S&P 500 index in equation (2a) and the Nasdaq composite index in equation (2b). The independent variables include the change in online trading, lagged high-low returns, the change in total share volume of small trades, and the change in the number of small trades. We showed earlier that we cannot reject the existence of a unit root for online trading. Therefore, we use first differences in our analysis. We include as regressors changes in the total share volume of small trades (*VOLS*), and the total number of small trades (*NTS*) to examine whether online trading impacts market volatility differently from that of other individual investors' trading.

In Table 5 we present the results for both S&P 500 volatility (Panel A) and NASDAQ volatility (Panel B). Consistent with the existing literature (e.g., Bollerslev, Engle and Nelson (1994)), we find stock volatilities to be persistent. More importantly, changes in online trading are positively and significantly related to stock index volatility, whether we examine the S&P 500 or NASDAQ volatility. This is as expected. Many studies report a positive relation between trading volume and volatility. To the extent that online trading represents a portion of the total trading volume, it should be positively related to volatility.

Once we introduce the total volume of small trades into our model, however, online trading is no longer significantly related to volatility. The positive relation between online trading and volatility is completely subsumed by the aggregate trading volume of small trades, whether we use share volume or the number of trades.[10] This result suggests that online trading does not have a positive impact on market volatility above and beyond the well-documented trading volume effect. If online trading provides an incremental positive impact on market volatility, we would expect the coefficient of online trading to be significantly positive. It appears that online trading does not contribute to excessive volatility in the stock market.

B. GARCH Model

In the second approach, we employ the standard GARCH model to examine the impact of online trading on market volatility. Specifically, we consider a GARCH (1,1) framework.

$$r_t = a + b\, r_{t-1} + u_t \;\; where \quad u_t = \sigma_t \varepsilon_t \quad \varepsilon_t \sim \mathrm{N}(0,1)$$
$$\sigma_t^2 = \omega + \alpha\, u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma\, \Delta OL + \delta\, \Delta VOLS + \eta\, \Delta NTS \qquad (3)$$

Table 6 contains the estimation results. Panel A presents the results for the S&P 500 index while Panel B presents the results for the NASDAQ composite index. In each panel, we estimate three models. In Model 1, we include online trading in the variance equation. Model 2 adds the total volume of small trades to the variance equation while model 3 includes the number of small trades in the variance equation.

[10] We report earlier that online trading is positively correlated with total trading volume of small trades, whether it is measured in shares or number of trades. Therefore, it is possible that our results are affected by multicollinearity. We do not believe, however, that this is a serious issue in our analysis because the coefficients on total trading by small traders are statistically significant. Nonetheless, we conducted a robustness check by orthogonalizing online trading against total trading volume of small trades. Our results are not affected when we use this alternative method. These results are not reported, but are available on request. We also use the orthogonalization method for our examination of market liquidity and market returns. Again, we find qualitatively similar results.

Our results are very similar to those obtained by using the regression approach (as reported in Table 5). When used alone, online trading has a significant positive relation with market volatility. However, when the volume of small-sized trades or the number of small-sized trades is included in the variance specification, the significance of online trading vanishes. Consistent with previous GARCH analyses of high frequency data, we find that the ARCH and GARCH parameters are positive and their sum is close to one. This indicates that volatility is persistent.

Overall, we conclude from this analysis that online trading is positively related to market volatility. However, after controlling for total trading volume of small traders, online trading is no longer significantly related to market volatility. The impact of online trading on market volatility is dominated by the total trading volume of small traders. These results show that online trading does not have an incremental impact on market volatility.

VI. Online Trading and Contemporaneous Market Returns

Individual investors are frequently viewed as noise traders in the literature (Kumar and Lee (2002), Barber, Odean, and Zhu (2003), and Griffin, Harris and Topaloglu (2003)). The traditional view is that noise traders do not affect equilibrium asset prices because arbitrageurs can arbitrage away any deviations from the fundamental values. More recently, studies such as Shleifer and Summers (1990) and Shleifer and Vishny (1997) allow for the possibility that demand by noise traders might cause asset prices to deviate from their fundamental values for extensive periods of time because of limits to arbitrage. Barber, Odean and Zhu (2003) contend that trading by individual investors is surprisingly systematic due to the presence of limited attention, the representativeness heuristic, and a disposition effect.[11] Because the trading activity of individual investors is highly correlated, they argue that noise trading has the potential to affect asset prices. Therefore, it is useful to determine the extent to which online trading can influence market prices.

We begin by examining the relation between online trading and the contemporaneous order flow of small trades. Panels A and B of Table 7 contain the results from a regression analysis of the aggregate order flow of small trades on aggregate online trading. We find that online trading has a significant and positive relation with order imbalance, whether it is measured in the number of shares or in the number of trades. Our result is robust to the inclusion of control variables such as lagged order imbalance, the total share volume of small trades, the total number of small trades, and lagged market returns. This result is consistent with the view that higher levels of online trading are associated with greater net buying and consequently a more bullish sentiment among online investors.

Having established the relation between online trading and investor sentiment, we now examine the relation between online trading and contemporaneous market returns. We estimate the following regression model:

$$RETSPX_t = \alpha + \beta\, \Delta OL_t + \gamma\, RETSPX_{t-1} + \delta\, \Delta NTS_t + \psi\, \Delta VOLS_t + \varepsilon_t \tag{4}$$

Panel C presents the regression results. We find a significantly positive relation between online trading and contemporaneous market returns. Controlling for total trading volume does not alter this result. This result also holds when we use the NASDAQ Composite index (Panel

[11] Barber and Odean (2002) contend that investors manage the costs associated with evaluating the thousands of stocks available for purchase by focusing on those that have gained their attention. This phenomenon is more characteristic of stock buying than selling. The representativeness heuristic (Tversky and Kahnemann (1974)) asserts that individuals expect small samples and short intervals of time-series data to be representative of the underlying population or data. The disposition effect (Shefrin and Statman (1985)) is an application of prospect theory to investments, and is the tendency of an individual to hold losers and to sell winners.

D). There are two possible explanations for this result. One possibility is that online trading moves prices. This would be consistent with the systematic noise argument of Kumar and Lee (2002) and Barber, Odean, and Zhu (2003). The other possibility is that online traders engage in intra-week positive feedback trading. That is, online investors trade more actively after the market rises. Unfortunately, we are unable to distinguish between these two possibilities with the weekly data that is available.

Overall, we find strong evidence that online trading is positively related to contemporaneous market returns. While this result might be consistent with the view that online trading moves prices, it is also consistent with the hypothesis that online investors simply engage in intra-week positive feedback trading.

VII. Online Trading and Market Liquidity

In this section we examine the relation between online trading and two critical dimensions of market liquidity: the bid-ask spread and quoted depth.[12]

A. Bid-ask Spreads

Online trading is likely to impact bid-ask spreads for two reasons. First, assuming that online traders are noise traders, an increase in online trading decreases the probability that the market maker trades with informed traders, thereby reducing the spread's adverse selection component. Second, if online trading is systematic, then an increase in online trading also increases the order imbalance. An increase in order imbalance, even absent any information content, is likely to cause an increase in the spread because it creates or exacerbates the market-maker's inventory problem. Thus, we have two conflicting predictions regarding the effect of

[12] A third critical dimension of liquidity is the depth on the limit order book. Unfortunately, the limit order data are not publicly available.

online trading on the bid-ask spread. Our subsequent empirical analysis will determine which effect dominates by estimating the following regression model:

$$\Delta Spreads_t = \alpha + \beta\,\Delta OL_t + \gamma\,\Delta VOLS_t\,(or\,\Delta NTS_t) + \theta\,RETSPX_t + \varepsilon_t \tag{5}$$

where *Spreads* are quoted or effective spreads expressed in either absolute or percentage terms. Since we cannot reject the existence of a unit root in OL, we perform our regression analysis using changes in the variables of interest. Specifically, we regress the changes in spreads against the change in online trading and other control variables. To examine whether online trading effects market liquidity differently from that of other individual investors' trading, we include as regressors the changes in total share volume of small trades (*VOLS*) and the total number of small trades (*NTS*). Chordia, Roll, and Subrahmanyam (2001) find that the market liquidity improves in up markets and worsens in down markets. Therefore, we also control for the return to the S&P 500 index (*RETSPX*). In estimating the above model we eliminate those observations falling within the week of and the week following decimalization because of its impact on market spreads and depth. Note that since our dependent variables are *changes* (not levels) of spreads, it is sufficient to drop just two weeks of data.

Table 8 presents the estimation results for regression equation (5). Panel A contains the results for absolute spreads while Panel B uses percentage spreads. In both panels, we find that changes in online trading are significantly and positively related to changes in spreads, whether we consider quoted or effective spreads. This result appears to be consistent with the contention that greater online trading leads to increased order imbalance, which causes wider spreads because of inventory concerns. It might also suggest that any order imbalance effect resulting from online trading dominates the reduction in the adverse selection component of the bid-ask spread attributable to the noise trading of online investors. This positive relation between online trading and bid-ask spreads holds while controlling for the return to the S&P 500, the total share volume of small-sized trades, and the total number of small-sized trades.

As we discuss in Section IV.B, the NYSE and NASDAQ have different market microstructures. Therefore, it is useful to examine the relation between online trading and the bid-ask spreads of NYSE and NASDAQ stocks separately. To accomplish such an analysis we separately estimate the mean quoted (effective) spread for NYSE and NASDAQ stocks.

Table 9 presents the results of our analysis of the relation between online trading and spreads by individual exchange. Overall, Table 9 contains findings very similar to those in Table 8. The coefficients for online trading are significantly positive for all measures of spread and across both exchanges. These results indicate that high volumes of online trading are associated with poor liquidity as reflected in large bid-ask spreads. Again, we find a significantly negative relation between changes in spreads and contemporaneous stock returns. Overall, controlling for NASDAQ or NYSE trading volume separately does not alter our basic conclusion that online trading is positively related to the bid-ask spread.

B. Quoted Depth

Online trading might affect quoted depth through its effects on trading volume. As trading volume increases, the market maker faces less inventory risk and thus will be willing to quote greater depth. However, if online trading is systematic, an increase in online trading would exacerbate the inventory problem faced by the market maker, who can be expected to respond by changing the quoted depth. Specifically, facing large inventory imbalance on one side of the market, market makers likely respond with lower depth on the same side of the quote, but with greater depth on the opposite side of the quote. Thus, an order imbalance will likely yield canceling effects on the quoted depth. Overall, we predict a weak positive relation between online trading and quoted depth.

In Table 10 we examine the relation between online trading and another dimension of liquidity, quoted depth. We analyze quoted depth with the following regression model:

$$\Delta Depth_t = \alpha + \beta \, \Delta OL_t + \gamma \, \Delta VOLS_t \, (or \, \Delta NTS_t) + \theta \, RET_t + \varepsilon_t \qquad (6)$$

The above model is similar to the quoted depth regression of Chordia, Roll, and Subrahmanyam (2001). We measure quoted depth for the combined sample of NYSE/AMEX/NASDAQ stocks as well as for the NYSE stocks separately. Again, because of the impact of decimalization on market depth, we exclude those observations falling within the week of and the week following decimalization. Regardless of the depth measure, we observe that the coefficients for online trading are significantly positive across all model specifications. Thus, it appears that an increase in online trading is associated with an increase in market depth.

The combined results of Tables 8, 9 and 10 provide mixed evidence concerning the nature of online trading's influence on market liquidity. We observe that online trading is associated with greater quoted depth. Simultaneously, however, we find that online trading tends to be positively related to bid-ask spreads, thus reducing market liquidity. The combined effect of wider spreads and greater depth hurts individual investors who tend to submit small orders, but likely benefits institutional investors who are more likely to submit large orders.

VIII. Conclusions

Many in the media as well as academia argue that online trading contributes to excessive trading, increased stock market volatility, and the perverse machinations of the Internet bubble of late 1990s and early 2000. Using a new database of the Web traffic of the six largest online brokers allows us to gain new insights regarding the effects of online trading on aggregate market. Specifically, we examine the dynamic relations between online trading and the volatility, return, and liquidity of the U.S. equity market.

During our examination of the relation between online trading and volatility, we initially find that online trading is positively related to stock market volatility. However, once we control for the aggregate volume of small trades, online trading ceases to be a significant explanatory factor for market volatility. Rather, it is the trading activity of all small traders that influences market volatility. This suggests that the claim that online trading generates excess market volatility might be over-stated.

We also analyze whether online trading might be able to impact market prices. We find that online trading is significantly and positively related to contemporaneous market returns. Such a result is consistent with Barber, Odean and Zhu (2003) and Kumar and Lee (2002) in that the systematic noise of individual investors impacts equity prices. It might also be the result of intra-week positive feedback trading. The coarseness of our weekly Web traffic data, however, does not permit a facile distinction between these two possible explanations.

Finally, we find that online trading has a mixed relation with market liquidity. Higher online trading appears to be related to wider bid-ask spreads, whether they are measured as quoted or effective spreads. Simultaneously however, we find that online trading is positively related to the quoted depth. This combined result of wider spreads and greater depth likely benefits institutional investors who tend to place large orders, while increasing the cost of trading to individual investors who are likely to submit small orders. We conclude from our analysis that online trading is related to the volatility, returns, and liquidity of the stock market, but these relations are more subtle than that generally portrayed in the popular media.

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Table 1
Summary Statistics of Web traffic and Return Variables

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. OL is the average daily number of unique visitors to six leading online brokers' websites. These six online brokers are: Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. LOGOL is the logarithm of OL. RETSPX is the weekly return of the S&P 500 index. RETNASD is the weekly return of the NASDAQ composite index. ρ_1 is the first order autocorrelation coefficient. Web traffic data are from Media Metrix, while return data are obtained from CRSP and the NASDAQ website.

Panel A: Aggregate Web traffic and Returns

	Mean	Median	Standard Deviation	Minimum	Maximum	ρ_1
Aggregate Web traffic of Online Brokers (thousands) – OL	924.95	958.00	284.20	400.00	1611.00	0.85
Log Aggregate Web traffic of Online Brokers – LOGOL	6.78	6.86	0.34	5.99	7.38	0.84
S&P 500 Index Return (percent) – RETSPX	-0.38	-0.45	3.03	-12.33	7.49	-0.16
Nasdaq Composite Index Return (percent) – RETNASD	-0.74	-0.77	5.97	-29.18	17.38	-0.08

Panel B: Unit Root Tests

	Augmented Dickey-Fuller Unit Root Test Statistic	1% Critical Value	5% Critical Value
OL	-1.31	-3.48	-2.88
OL (with trend)	-2.56	-4.03	-3.44
LOGOL	-1.59	-3.48	-2.88
LOGOL (with trend)	-2.59	-4.03	-3.44

Panel C: Disaggregate Web traffic (thousands)

	Mean	Median	Standard Deviation	Minimum	Maximum	ρ_1
Ameritrade	112.30	112.00	35.83	25.00	199.00	0.65
Datek	118.13	118.00	35.54	27.00	207.00	0.63
Etrade	281.93	285.50	57.22	112.00	417.00	0.50
Fidelity	221.91	232.00	72.66	76.00	422.00	0.79
Schwab	154.54	154.50	40.11	64.00	267.00	0.66
TD Waterhouse	116.73	91.00	58.51	39.00	287.00	0.83

Table 2
Summary Statistics of Market Liquidity and Trading Activity Variables

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. NUM is number of stocks in the sample from which we calculate market-wide liquidity and trading activity variables. QA is the average daily equally-weighted quoted spread. QP is the average daily equally-weighted percentage quoted spread. EA is the average daily equally-weighted effective spread. EP is the average daily equally-weighted percentage effective spread. DEPTH is the average daily equally-weighted depth. DEPTHY is the average daily equally-weighted depth of NYSE stocks. VOL is the total trading volume. VOLS is the total trading volume of small-sized trades. NT is the number of trades. NTS is the number of small-sized trades. OIS is the order imbalance of small-sized trades in share volume. OINUMS is the order imbalance of small-sized trades in the number of trades. QPQ (QPY) is the average daily equally-weighted percentage quoted spreads of NASDAQ (NYSE) stocks. EPQ (EPY) is the average daily equally-weighted percentage effective spreads of NASDAQ (NYSE) stocks. VOLSQ (VOLSY) is the total trading volume of small-sized trades on the NASDAQ (NYSE). NTSQ (NTSY) is the total number of small-sized trades in NASDAQ (NYSE.). ρ_1 is first order autocorrelation coefficient. Transactions data are drawn from the NYSE Trade and Quote (TAQ) database. Small trades are defined as trades of 500 shares or less. Web traffic data are obtained from Media Metrix.

Panel A: Univariate Summary Statistics – All Exchanges

	Mean	Median	Standard Deviation	Minimum	Maximum	ρ_1
Number of Stocks (thousands) – NUM	4.87	4.66	0.62	3.90	6.00	0.98
Quoted Spread (cent) – QA	9.20	8.84	2.16	6.38	13.84	0.98
% Quoted Spread (percent) – QP	0.91	0.97	0.19	0.62	1.35	0.97
Effective Spread (cent) – EA	7.36	6.94	1.75	5.25	11.39	0.98
% Effective Spread (percent) – EP	0.73	0.76	0.15	0.51	1.10	0.96
Depth (hundred shares) –DEPTH	15.62	12.34	5.72	9.14	26.60	0.97
Aggregate Share Volume (billion shares) – VOL	12.39	12.60	2.31	2.44	18.47	0.24
Aggregate Share Volume of Small Trades (billion shares) – VOLS	2.28	2.31	0.39	0.46	3.28	0.28
Number of Trades (millions) – NT	14.32	14.52	2.50	2.85	21.21	0.29
Number of Small Trades (millions) – NTS	10.38	10.51	1.84	2.10	15.42	0.31
Order imbalance of Small Trades (billion shares) – OIS	0.10	0.10	0.06	-0.10	0.23	0.32
Order imbalance of Small Trades (millions) – OINUMS	0.39	0.39	0.28	-0.47	1.00	0.23

Table 2 - Continued

Panel B: Univariate Summary Statistics – NASDAQ or NYSE only	Mean	Median	Standard Deviation	Minimum	Maximum	ρ_1
NASDAQ % Quoted Spread (percent) – QPQ	1.11	1.17	0.20	0.80	1.62	0.95
NYSE % Quoted Spread (percent) – QPY	0.40	0.37	0.13	0.20	0.59	0.99
NASDAQ % Effective Spread (percent) – EPQ	0.92	0.94	0.17	0.67	1.38	0.94
NYSE % Effective Spread (percent) – EPY	0.26	0.24	0.08	0.15	0.38	0.98
NYSE Depth (hundred shares) – DEPTHY	30.86	19.02	17.29	12.40	63.86	0.97
NASDAQ Share Volume of Small Trades (billion shares) – VOLSQ	1.74	1.77	0.33	0.33	2.49	0.38
NYSE Share Volume of Small Trades (billion shares) – VOLSY	0.52	0.50	0.15	0.13	1.07	0.71
NASDAQ Number of Small Trades (millions) – NTSQ	8.11	8.18	1.56	1.53	11.64	0.39
NYSE Number of Small Trades (millions) – NTSY	2.23	2.13	0.67	0.56	4.62	0.73

Table 3
Correlations Among Online Trading and Market Trading Activity Variables

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. OL is the average daily number of unique visitors to six leading online brokers' websites. These six online brokers are: Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. OL4 is the average daily number of unique visitors to Ameritrade, Datek, E*trade, and TD Waterhouse's websites. VOLS is the total trading volume of small-sized trades. NTS is the number of small-sized trades. Web traffic data are from Media Metrix. Transactions data are drawn from the NYSE Trade and Quote (TAQ) database. Small trades are defined as trades of 500 shares or less. Δ denotes the first difference. *, ** and *** represent statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively.

Panel A: Correlation of Levels

	OL	OL4	NTS	VOLS
OL	1.00			
OL4	0.98***	1.00		
NT	0.44***	0.44***	1.00	
VOLS	0.44***	0.44***	0.99***	1.00

Panel B: Correlation of Changes

	ΔOL	ΔOL4	ΔNTS	ΔVOLS
ΔOL	1.00			
ΔOL4	0.92***	1.00		
ΔNT	0.64***	0.61***	1.00	
ΔVOLS	0.65***	0.62***	0.99***	1.00

Table 4
Determinants of Online Trading

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. Returns are provided in percent. C represents the regression intercept and is multiplied by 100 to facilitate reporting. OL is the average daily number of unique visitors (thousands) to six leading online brokers' websites. These six online brokers are: Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. LOGOL is the logarithm of OL. RETSPX is the weekly return to the S&P 500 index. RETNASD is the weekly return to the NASDAQ composite index. HOLIDAY is an indicator variable that is 1 if New Year's Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, or Christmas falls in that week. Web traffic data are drawn from Media Metrix. Return data are obtained from CRSP and the NASDAQ website. The dependent variable is OL in Panel A and LOGOL in Panel B. In each regression, the first row provides the OLS coefficient estimates. The second row (in parentheses) contains the Newey-West standard errors. *, ** and *** represent statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively.

Panel A: Determinants of OL

C × 100	OL(-1)	OL(-2)	HOLIDAY	RETSPX(-1)	RETNASD(-1)	R^2
1.27***	0.87***					0.76
(0.37)	(0.04)					
1.37***	0.86***		-49.48			0.76
(0.40)	(0.04)		(42.51)			
1.04***	0.59***	0.31***	-56.01			0.78
(0.36)	(0.07)	(0.06)	(36.13)			
1.03***	0.59***	0.31***	-55.55	-0.98		0.78
(0.36)	(0.07)	(0.06)	(35.87)	(3.49)		
1.02***	0.60***	0.30***	-53.87		-1.28	0.78
(0.36)	(0.07)	(0.06)	(35.48)		(1.86)	

Panel B: Determinants of LOGOL

C	LOGOL(-1)	LOGOL(-2)	HOLIDAY	RETSPX(-1)	RETNASD(-1)	R^2
0.97***	0.86***					0.75
(0.24)	(0.04)					
1.02***	0.85***		-0.05			0.75
(0.25)	(0.04)		(0.05)			
0.69***	0.55***	0.35***	-0.06*			0.78
(0.24)	(0.07)	(0.06)	(0.04)			
0.69***	0.55***	0.35***	-0.06*	-0.72×10^{-3}		0.78
(0.24)	(0.07)	(0.06)	(0.04)	(3.81×10^{-3})		
0.69***	0.56***	0.34***	-0.06*		-1.74×10^{-3}	0.78
(0.24)	(0.07)	(0.06)	(0.04)		(2.39×10^{-3})	

Table 5
Online Trading and Market Volatility – High-low Returns

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. Returns are in percent. OL is the average daily number of unique visitors (thousands) to six leading online brokers' websites. These six online brokers are: Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. SPXHL is the daily average high-low return of the S&P 500 index. NASDHL is the daily average high-low return to the NASDAQ composite index. VOLS is the total trading volume of small-sized trades in billions of shares. NTS is the total number of small-sized trades. Web traffic data are drawn from Media Metrix. Return data are obtained from the CRSP, NYSE and NASDAQ websites. Transactions data are obtained from the NYSE Trade and Quote (TAQ) database. Small trades are defined as trades of 500 shares or less. In each regression, the first row provides the OLS coefficient estimates. The second row (in parentheses) provides the Newey-West standard errors. *, ** and *** represent statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. Δ denotes the first difference.

Panel A: S&P 500 Index

Dependent Variable	Independent Variables				R^2
	$\Delta OL \times 10^3$	SPXHL(-1)	ΔVOLS	$\Delta NTS \times 10^{-1}$	
SPXHL	0.98**	0.60***			0.36
	(0.42)	(0.13)			
SPXHL	-0.04	0.63***	0.46***		0.42
	(0.50)	(0.13)	(0.14)		
SPXHL	-0.01	0.64***		0.10***	0.42
	(0.49)	(0.13)		(0.03)	

Panel B: Nasdaq Composite Index

Dependent Variable	Independent Variables				R^2
	$\Delta OL \times 10^3$	NASDAQHL (-1)	ΔVOLSQ	ΔNTSQ	
NASDHL	2.16***	0.67***			0.47
	(0.82)	(0.08)			
NASDHL	0.41	0.69***	1.07***		0.52
	(0.79)	(0.08)	(0.32)		
NASDHL	0.44	0.69***		0.23***	0.52
	(0.78)	(0.08)		(0.07)	

Table 6
Online Trading and Market Volatility – GARCH (1,1)

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. Returns are in percent. OL is the average daily number of unique visitors (thousands) to six leading online brokers' websites in thousands. These six online brokers are: Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. RETSPX is the weekly return to the S&P 500 index. RETNASD is the weekly return to the NASDAQ composite index. VOLS is the total trading volume of small-sized trades in billions of shares. NTS is the total number of small-sized trades. Web traffic data are drawn from Media Metrix. Return data are obtained from the CRSP, NYSE and NASDAQ websites. Transactions data are obtained from the NYSE Trade and Quote (TAQ) database. Small trades are defined as trades of 500 shares or less. The numbers in parentheses are maximum likelihood standard errors. *, ** and *** represent statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. Δ denotes the first difference.

$$r_t = a + b\, r_{t-1} + u_t \;\; u_t = \sigma_t \varepsilon_t \quad where \quad \varepsilon_t \sim \mathrm{N}(0,1)$$

$$\sigma_t^2 = \omega + \alpha\, u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma\, \Delta OL + \delta\, \Delta VOLS + \eta\, \Delta NTS$$

Panel A: RETSPX

	Model 1	Model 2	Model 3
a	-0.53 (0.25)**	-0.19 (0.28)	-0.21 (0.25)
b	-0.13 (0.08)	-0.12 (0.07)*	-0.15 (0.08)*
ω	2.44 (1.50)*	3.27 (3.28)	3.46 (3.43)
α	0.04 (0.06)	0.01 (0.05)	0.02 (0.03)
β	0.66 (0.17)***	0.60 (0.39)	0.56 (0.40)
$\gamma \times 10^3$	2.27 (0.70)***	0.29 (1.05)	0.30 (1.05)
$\delta \times 10^2$		5.47 (2.43)**	
$\eta \times 10^2$			1.22 (0.50)**
Log Likelihood	292.35	294.56	295.00
Schwarz Criterion	-4.05	-4.05	-4.06

Panel B: RETNASD

	Model 1	Model 2	Model 3
a	-1.05 (0.48)**	-0.51 (0.54)	-0.64 (0.48)
b	-0.13 (0.08)*	-0.09 (0.10)	-0.09 (0.08)
ω	3.78 (3.75)	11.98 (18.28)	11.30 (18.32)
α	0.04 (0.03)	0.04 (0.09)	0.05 (0.12)
β	0.84 (0.09)***	0.63 (0.49)	0.64 (0.53)
$\gamma \times 10^2$	0.91 (0.37)**	0.22 (0.53)	0.19 (0.53)
$\delta \times 10$		2.07 (1.02)**	
$\eta \times 10$			4.57 (2.00)**
Log Likelihood	196.33	196.43	196.43
Schwarz Criterion	-2.65	-2.62	-2.62

Table 7
Online Trading, Order Flows, and Contemporaneous Market Returns

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. Return data are in percent. RETSPX is the weekly return to the S&P 500 index. RETNASD is the weekly return to the NASDAQ composite index. VOLS is the total trading volume of small-sized trades in billions of shares. NTS is the total number of small-sized trades. OIS is the total order imbalance of small-sized trades in billions of shares. OINUMS is the total order imbalance of small-sized trades measured by the number of trades. RETSPX is the weekly return to the S&P 500 index. RETNASD is the weekly return of the NASDAQ composite index. OL is the average daily number of unique visitors (thousands) to six leading online brokers' websites. These six online brokers are Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. Transactions data are obtained from the NYSE Trade and Quote (TAQ) database. Small trades are defined as trades of 500 shares or less. Web traffic data are drawn from Media Metrix. In each regression, the first row gives the OLS coefficient estimates. The second row (in parentheses) contains the Newey-West standard errors. *, ** and *** represent statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively.

Panel A: Dependent Variable is Aggregate Order Imbalance (number of shares)

OIS(-1)	OL $\times 10^{-5}$	VOLS $\times 10^{-2}$	RETSPX (-1)	R^2
0.25***	6.64***			0.19
(0.07)	(1.70)			
0.26***	4.45***	3.50***		0.23
(0.07)	(1.87)	(1.33)		
0.30***	6.31***		-0.19×10^{-3}	0.20
(0.07)	(1.78)		(0.13×10^{-3})	

Panel B: Dependent Variable is Aggregate Order Imbalance (number of trades)

OINUMS(-1)	OL $\times 10^{-3}$	NTS $\times 10^{-2}$	RETSPX (-1)	R^2
0.17**	0.30***			0.14
(0.07)	(0.08)			
0.18**	0.22**	2.62**		0.16
(0.07)	(0.09)	(1.32)		
0.21*	0.29***		-0.73×10^{-3}	0.14
(0.08)	(0.08)		(0.60×10^{-3})	

Panel C: Dependent Variable is Weekly Return to the S&P 500 index

RETSPX(-1)	ΔOL $\times 10^{3}$	ΔVOLS	ΔNTS	R^2
-0.14	3.45**			0.05
(0.09)	(1.59)			
-0.12	7.93***	-2.47***		0.13
(0.08)	(1.79)	(0.63)		
-0.12	7.83***		-0.54***	0.13
(0.08)	(1.75)		(0.14)	

Panel D: Dependent Variable is Weekly Return to the NASDAQ Composite Index

RETNASD(-1)	ΔOL $\times 10^{2}$	ΔVOLS	ΔNTS	R^2
-0.04	1.07***			0.06
(0.06)	(0.32)			
-0.02	1.73***	-3.59***		0.11
(0.05)	(0.42)	(1.35)		
-0.02	1.74***		-0.82***	0.11
(0.05)	(0.41)		(0.29)	

Table 8
Online Trading and Market Liquidity – Spreads

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. QA is the average daily equally-weighted quoted spread in cents. QP is the average daily equally-weighted percentage quoted spread. EA is the average daily equally-weighted effective spread in cents. EP is the average daily equally-weighted percentage effective spread. VOLS is the total trading volume of small-sized trades in billions of shares. NTS is the total number of small-sized trades. RETSPX is the weekly return to the S&P 500 index. OL is the average daily number of unique visitors to six leading online brokers' websites in thousands. These six online brokers are: Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. Transactions data are drawn from the NYSE Trade and Quote (TAQ) database. Small trades are defined as trades of 500 shares or less. Web traffic data are obtained from Media Metrix. In each regression, the first row provides the OLS coefficient estimates. The second row (in parentheses) contains the Newey-West standard errors. *, ** and *** represent statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. Δ denotes the first difference.

Panel A: Absolute Spreads

Dependent Variable	Independent Variables				R^2
	$\Delta OL \times 10^{-4}$	$RETSPX \times 10^{-2}$	$\Delta VOLS \times 10^{-3}$	$\Delta NTS \times 10^{-5}$	
ΔQA	6.15*	-4.46**			0.18
	(3.42)	(1.95)			
ΔQA	9.25**	-5.05**	-1.44		0.20
	(4.14)	(1.94)	(1.03)		
ΔQA	9.09**	-5.04**		-3.06	0.20
	(4.14)	(1.95)		(2.23)	
ΔEA	7.14**	-4.36**			0.24
	(2.78)	(1.68)			
ΔEA	8.15**	-4.56***	-0.47		0.24
	(3.53)	(1.69)	(0.78)		
ΔEA	8.05**	-4.54***		-0.94	0.24
	(3.52)	(1.70)		(1.69)	

Panel B: Percentage Spreads

Dependent Variable	Independent Variables				R^2
	$\Delta OL \times 10^{-5}$	$RETSPX \times 10^{-2}$	$\Delta VOLS \times 10^{-2}$	$\Delta NTS \times 10^{-3}$	
ΔQP	6.56*	-0.58**			0.17
	(4.12)	(0.24)			
ΔQP	10.30**	-0.65***	-1.74		0.19
	(4.98)	(0.23)	(1.17)		
ΔQP	10.10**	-0.65***		-3.72	0.19
	(5.01)	(0.23)		(2.54)	
ΔEP	7.64**	-0.55***			0.24
	(3.27)	(0.20)			
ΔEP	8.84**	-0.58***	-0.56		0.24
	(4.19)	(0.20)	(0.87)		
ΔEP	8.74**	-0.57***		-1.15	0.24
	(4.19)	(0.20)		(1.90)	

Table 9
Online Trading and Market Liquidity – NASDAQ and NYSE Spreads

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. QPQ is the average daily equally-weighted percentage quoted spread of NASDAQ stocks. QPY is the average daily equally-weighted percentage quoted spread of NYSE stocks. EPQ is the average daily equally-weighted percentage effective spread of NASDAQ stocks EPY is the average daily equally-weighted percentage effective spread of NYSE stocks. VOLSQ is the total trading volume of small-sized trades on the NASDAQ. VOLSY is the total trading volume of small-sized trades on the NYSE. NTSQ is the total number of small-sized trades on the NASDAQ. NTSY is the total number of small-sized trades on the NYSE. RETSPX is the weekly return to the S&P 500 index. RETNASD is the weekly return to the NASDAQ composite index. OL is the average daily number of unique visitors (thousands) to six leading online brokers' websites. These six online brokers are: Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. Transactions data are drawn from the NYSE Trade and Quote (TAQ) database. Small trades are defined as trades of 500 shares or less. Web traffic data are obtained from Media Metrix. In each regression, the first row provides the OLS coefficient estimates. The second row (in parentheses) contains the Newey-West standard errors. *, ** and *** represent statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. Δ denotes the first difference.

Panel A: NASDAQ Spreads

Dependent Variable	Independent Variables				R^2
	ΔOL $\times 10^{-4}$	RETNASD $\times 10^{-2}$	ΔVOLSQ $\times 10^{-3}$	ΔNTSQ $\times 10^{-3}$	
ΔQPQ	1.01*	-0.49***			0.21
	(0.61)	(0.15)			
ΔQPQ	1.62**	-0.53***	-0.36		0.23
	(0.71)	(0.15)	(0.22)		
ΔQPQ	1.62**	-0.54***		-7.85*	0.23
	(0.72)	(0.15)		(4.52)	
ΔEPQ	1.23**	-0.46***			0.28
	(0.50)	(0.12)			
ΔEPQ	1.40**	-0.47***	-0.10		0.28
	(0.59)	(0.12)	(0.15)		
ΔEPQ	1.40**	-0.47***		-2.27	0.28
	(0.60)	(0.12)		(3.19)	

Panel B: NYSE Spreads

Dependent Variable	Independent Variables				R^2
	ΔOL $\times 10^{-5}$	RETSPX $\times 10^{-2}$	ΔVOLSY $\times 10^{-2}$	ΔNTSY $\times 10^{-3}$	
ΔQPY	0.31*	-0.25***			0.23
	(0.18)	(0.09)			
ΔQPY	0.26*	-0.24***	0.09		0.23
	(0.14)	(0.07)	(0.23)		
ΔQPY	0.26*	-0.24***		2.26	0.23
	(0.14)	(0.07)		(5.46)	
ΔEPY	0.24**	-0.17***			0.24
	(0.12)	(0.06)			
ΔEPY	0.20**	-0.16***	0.10		0.24
	(0.10)	(0.05)	(0.14)		
ΔEPY	0.20**	-0.16***		2.29	0.24
	(0.10)	(0.05)		(3.47)	

Table 10
Online Trading and Market Liquidity – Quoted Depth

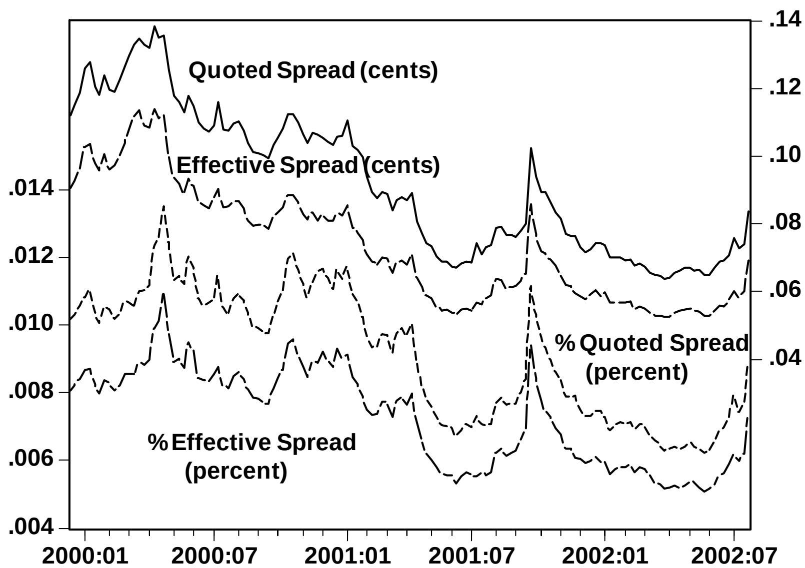
The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. All variables are calculated weekly. The week including January 31, 2001 is excluded because of decimalization. DEPTH is the average daily equally-weighted depth in hundreds of shares. DEPTHY is the average daily equally-weighted depth in hundreds of shares of NYSE stocks only. VOLS is the total trading volume of small-sized trades in billions of shares. NTS is the total number of small-sized trades. RETSPX is the weekly return to the S&P 500 index. OL is the average daily number of unique visitors (thousands) to six leading online brokers' websites. These six online brokers are: Ameritrade, Datek, E*trade, Fidelity, Schwab, and TD Waterhouse. OL is our proxy for online trading. Transactions data are drawn from the NYSE Trade and Quote (TAQ) database. Small trades are defined as trades of 500 shares or less. Web traffic data are obtained from Media Metrix. In each regression, the first row provides the OLS coefficient estimates. The second row (in parentheses) contains the Newey-West standard errors. *, ** and *** represent statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. Δ denotes the first difference.

Dependent	Independent Variables				R^2
Variable	ΔOL ×10^2	RETSPX ×10^2	ΔVOLS	ΔNTS	
ΔDEPTH	0.15***	-1.77			0.11
	(0.05)	(2.09)			
ΔDEPTH	0.10*	-0.78	0.24		0.12
	(0.06)	(2.40)	(0.22)		
ΔDEPTH	0.11*	-0.95		0.04	0.11
	(0.06)	(2.40)		(0.05)	
ΔDEPTHY	0.45***	-8.04			0.12
	(0.14)	(5.84)			
ΔDEPTHY	0.25*	-4.14	0.94*		0.14
	(0.16)	(6.76)	(0.57)		
ΔDEPTHY	0.27*	-4.45		0.19	0.14
	(0.16)	(6.76)		(0.12)	

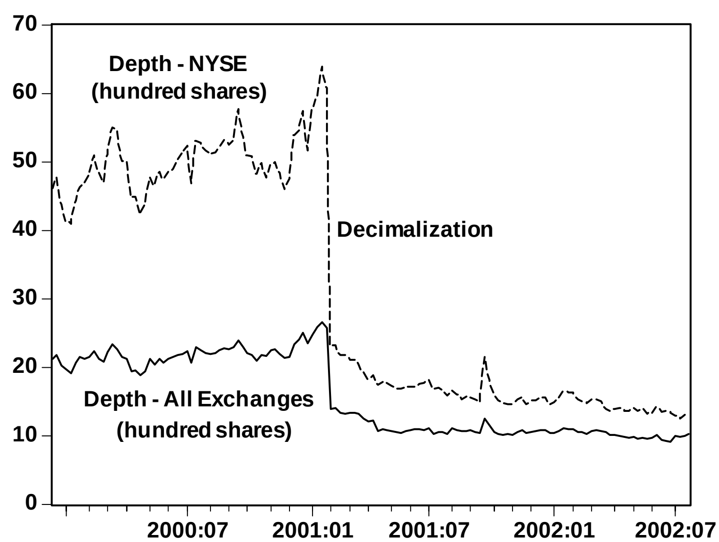
Figure 1: Market Liquidity.

The sample period extends from December 8, 1999 to July 28, 2002, representing a total of 138 weeks. QA is the average daily equally-weighted quoted spread. QP is the average daily equally-weighted percentage quoted spread. EA is the average daily equally-weighted effective spread. EP is the average daily equally-weighted percentage effective spread. DEPTH is the average daily equally-weighted quoted depth. DEPTHY is the average daily equally-weighted quoted depth of NYSE stocks. Transactions data are obtained from the NYSE Trade and Quote (TAQ) database.

Panel A: Spreads



Panel B: Quoted Depth



Appendix: Construction of Market Liquidity and Trading Activity Variables

This appendix details how we construct market liquidity and market trading activity measures. We follow the procedure by Chordia, Roll and Subramanyam (2001, 2002). We start with the TAQ database and exclude a stock from the sample based on the following criteria:

- We exclude a stock if we cannot find a match in the CRSP database.
- We exclude a stock if its share code in the CRSP database is not 10 or 11. That is, we only use common stocks.
- We exclude a stock if it is not listed on NYSE, NASDAQ or AMEX.
- We exclude a stock if its closing price or closing quote midpoint is greater than $999 or less than $2.
- We exclude a stock if there is a trading halt for that day.

We include or exclude a trade or a quote based on the following criteria:

- A quote or a trade is discarded if it is indicated as an error or correction.
- A quote or a trade is discarded if it is before the open or after the closing time.
- A quote or a trade is discarded if the price is negative.
- A quote is discarded if it is not originated from the market that the stock is listed in.
- A quote is discarded if the depth is negative.
- A quote is discarded if bid price is greater than the ask price.
- A quote is discarded if bid-ask spread is greater than $4.
- A quote is discarded if percentage bid-ask spread is greater than 15%.
- A trade is discarded if it changes from previous trade price by more than 25%.

Each trade except the first trade of NYSE and AMEX stocks for each trading day is signed as either buyer-initiated or seller-initiated according to the Lee and Ready (1991) algorithm. Specifically, a trade is classified as buyer (seller) initiated if it is above (below) the midpoint of the prevailing quote. The prevailing quote must be at least five seconds old. If the trade occurs at the midpoint of the quote, the tick test is used. In this case, a trade is classified as buyer (seller) initiated if the trade price is higher (lower) than the previous transaction price. Although it is not perfect, the Lee and Ready algorithm is quite effective as shown by Lee and Radhakrishna (2000).

Online traders are individual investors that tend to engage in small trades. To investigate if online investors have any incremental impact on the stock market, we need to control for the trades of all individual investors. We classify trades of 500 shares or fewer as small-sized trades. Many studies have used trade size to distinguish between individual and institutional trades (see, for example, Lee (1992).) In addition, Lee and Radhakrishna (2000) demonstrate the usefulness of using small trades/large trades in separating trades initiated by individual investors from those initiated by institutional investors.

We construct order imbalance as the buyer-initiated share volume less the seller-initiated share volume. We also construct order imbalance in terms of number of trades. For the liquidity variables (spreads and depth), we first aggregate over all stocks for each trading day and then we average across all days in a week. For the trading activity variables (volume, trades, and order imbalance), we simply aggregate over all the stocks and all trading days in a week. More specifically, we construct the following market-wide liquidity and trading activity variables:

- QA: equally-weighted absolute quoted spread
- QP: equally-weighted percentage quoted spread
- QPQ: equally-weighted percentage quoted spread of NASDAQ stocks
- QPY: equally-weighted percentage quoted spread of NYSE stocks
- EA: equally-weighted absolute effective spread

- EP: equally-weighted percentage effective spread
- EPQ: equally-weighted percentage effective spread of NASDAQ stocks
- EPY: equally-weighted percentage effective spread of NYSE stocks
- DEPTH: equally-weighted quoted depth
- DEPTHY: equally-weighted quoted depth of NYSE stocks
- VOL: trading volume in shares
- NT: number of trades
- VOLS: share volume of small-sized trades
- NTS: number of small-sized trades
- VOLSQ: share volume of small-sized trades in NASDAQ
- NTSQ: number of small-sized trades in NASDAQ
- VOLSY: share volume of small-sized trades in NYSE
- NTSY: number of small-sized trades in NYSE
- OIS: order imbalance of small-sized trades in shares
- OINUMS: order imbalance of small-sized trades in number of trades