The Homogenization of US Equity Trading

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Abstract

NASDAQ stocks once traded in quote-driven dealer markets while listed stocks traded in order-driven auctions on exchange floors stabilized by exchange specialists. Thesemarket structure differences caused higher volumes and transitory volatility for NASDAQ stocks. Following the adoption of certain SEC policies and the growth of electronic trading, all stocksnow trade in similar, albeit diverse,systems. This paper provides empirical evidence of the homogenization of US equity trading by showing that volumes and transitory volatility no longer differ by primary listing market. Secondary results indicate that specialists at listed exchanges have stopped providing measurable price stabilization services. The results have important public policy implications because they indicate that issuers no longer have meaningful control over how their stocks trade.

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1. Introduction

Regulatory interventions by the Securities and Exchange Commission into market structure over the last 25 years coupled with the introduction of electronic trading have essentially eliminated any meaningful differences between how NASDAQstocks trade from how NYSE and Amex-listed stocks trade. The order handing rules, unlisted trading privileges, Reg ATS, and Reg NMS all helped homogenize trading systems in the United States. The listing choice made by issuers once determined the character of the markets in which their stocks traded. Now, these decisions primarily only determine the exchange marketing image with which corporations identify their stocks.

This study provides evidence of the homogenization of trading in the United States. The empirical results show that two significant characteristics of market quality—trading volume and transitory volatility—have become indistinguishable, on average, between NASDAQstocks and those listed at the traditional listing exchanges. These results provide concrete evidence of a reality that is obvious to most practitioners: The market structures used for trading stocks are now essentially the same regardless of their primary listing markets.

The homogenization of trading should concern issuers ultimately their investors because they no longer have any input into how their stocks trade. Instead, decisions made by the SEC have effectively determined market structure for all US equities. Exchanges once competed to provide trading environments that would attract issuers. The present regulatory environment now focuses the competition among exchange service strictly on attracting order flow from investors instead of serving the needs of issuers, which, of course, are derived from the needs of their investors.

Investors can,and do, choose the market structures that appeal to them through their order routing decisions. But they lack the collective power, formerly exercised by the corporate managers of their investments, to choose market structures. Without this power, they cannot choose alternative market structures that might be collectively beneficial but which may be individually suboptimal.

For example, market structures that consolidate all trades to a single system that enforces universal time precedence might be optimal, but the present regulatory regime does not allow such market structures to emerge through competitive processes. No current mechanism can compel all traders to trade at one market or require all markets to enforce universal time precedence. Any trader who arrives late and wants to circumvent the time precedence rule at one market simply places an order in another market where the line is shorter.

Other examples of unavailable structures that might be desirable are call markets or shorter trading sessions. These structures concentrate liquidity and thereby facilitate trading when the market is open. But they cannot compete well against markets that provide longer trading sessions that appeal to some traders. Although the benefits that these other traders obtain can be of less value than the overall benefit of concentrating liquidity, no competitive mechanism can successfully reveal this information.

Still other examples of unavailable structures are those in which designated dealers are responsible for providing liquidity when no one else will. The NYSE specialist system died in part because specialists cannot meet their obligations to provide continuous liquidity when competing with other dealers who do not face similar obligations. The requirement to trade when no one else wants to trade generally leads to trading losses. Designated dealers can bear these losses if they can recoup them during normal trading, but they cannot do so when competing against other traders who can avoid trading when times get rough. Some commentators have argued that the capital raising process for small firms has been hurt because sponsoring dealers can no longer profit from supporting their markets when they have to compete with other dealers who do not face similar obligations.

The US markets are now more liquid than ever before.[1] The improved liquidity is largely due to the adoption of electronic trading and to the SEC's regulatory framework that has encouraged completion among exchanges for order flow from traders. These developments have been good for investors.

Whether these developments would have occurred earlier without the intervention of the SEC, or whether they would have never occurred had the SEC not intervened is interesting to speculate upon but essentially impossible to determine. Those opposed to regulatory intervention argue that the SEC's control over market structure protected incumbent trading systems for far too long. Those who welcomed the SEC's intervention argue that agency problems between investors and their brokers, and between investors and the managers of the corporations in which they are invested, prevented any meaningful changes in market structure.

Regardless of how well markets now function, they might function better if binding restrictions—such as the requirement to trade at a single venue or at limited times—could be placed upon all market participants. The SEC has interpreted its mandate to promote competition in a way that precludes granting monopolies to exchanges. To do so would obviously eliminate the day-to-day competition among exchange service providers that we presently have. However, as noted above, this framework also precludes market structures that

[1] See Angel, Harris, and Spatt (2011).

require coordinated action, and it does not allow corporations to make meaningful decisions on the behalf of their shareholders about the market structures in which their shares trade.

As an alternative to the current system, the government could allow corporations to make binding decisions over the market structures in which their stocks trade, if they so desire. To preserve competition among exchange services providers, these decisions should be contestable on a regular basis—perhaps every two to five years—so that if a corporation designated an exchange as the exclusive trading venue for its stock, that exchange could not exploit its unique position. The corporate managers, the board of directors, or a vote of the shareholders would make these decisions. This alternative system would allow investors, or their corporate agents, to choose the market structure that best serves them. When these decisions are made well, the costs of raising capital will drop and the economy will benefit.

The results presented in this paper do not indicate that we would be better off under this alternative regulatory framework. We will find the answer to this question only through market experimentation. However, these results show clearly that no experiment is now taking place, which is troubling for those who believe that in the absence of significant agency and externality problems, private entities, and not the government, should structure markets.

2. Empirical Methods

2.1 Overview

Volumes and bid/ask spreads are common measures of market quality that historically have differed substantially between the quote-driven NASDAQmarkets and the order-driven markets public exchange markets. For otherwise similar securities, quote-driven markets tend to have greater trading volumes and wider spreads than do order-driven markets.

Quote-driven markets report higher volumes because public buyers and sellersgenerally trade through the intermediation of dealers, which requires at least two trades to transfer shares from the seller to the buyer, and sometimes more if the trade ultimately involves multiple dealers. In contrast, in order-driven exchange markets, buyers and sellers often trade directly with each other so that only one trade prints.

Bid/ask spreads generally are higher in quote-driven markets because dealers often compete for order flow through non-price mechanisms such as payment for order flow. In contrast, the time precedence rules enforced in order-driven markets provide strong incentives for traders to quote aggressively. Dealer spreads also tend to be larger because dealers must make continuous markets, which can be quite risky, especially if they often trade with informed traders or if markets are particularly volatile. Dealers who quote too aggressively tend to lose to informed traders. Finally, exchange spreads often are very small because public traders often quote aggressively to ensure that their orders fill quickly.

The bouncing of prices between bid and offer prices causes transitory volatility. This volatility is greater when bid/ask spreadsare large. Accordingly, dealer markets with wide spreads will tend to have more transitory volatility.

Exchange specialists charged with making continuous markets—as they were until recently at the NYSE and Amex,trade to attenuate transitory volatility on a transaction-by-transaction basis and also on a day-to-day basis. Transitory volatility thus is smaller on exchanges where bid/ask spreads tend to be smaller and where specialists provide price continuity.

Besides market structure, stock volumes and transitory volatility also depend on cross-sectional differences in firm size, fundamental volatility, price level, and industry. Since these variables vary systematically across NASDAQ and listed stocks (NASDAQ stocks tend to be smaller, more volatile, lower priced, and more technology focused than listed stocks), any effort to estimate the average difference between NASDAQ and listed volumes and transitory volatilities must control for these well-known cross-sectional determinants.

To this end, I estimate cross-sectional regressions to separately characterize for both marketshow volumes and transitory volatilitiesdepend on various cross-sectional determinants. I then use these estimates to predict the volumes and transitory volatilities that would have been observed for each stock had it traded in the other market structure. To provide summary measures useful for comparing volumes and transitory volatilities across the two markets, I compute weighted medians and means of the differences between actual and predicted values (the causaleffects) using weights obtained from an analysis of propensity scores. These methods help ensure that the two samples are effectively matched.

Repeating this analysis each year allows us to identify empirical evidence of the homogenization of market structures over time.

2.2 Models

I use regression models to identify how volumes and transitory volatilities depend on various firm characteristics. Numerous studies show that volumes and bid/ask spreads both depend strongly on firm size, price uncertainty, and stock price levels.[2]I use log market capitalization to measure firm size,an adjusted time-series return variance to measure price uncertainty, and inverse prices to identify effects related to the minimum price variation, which

[2]See for example, Benston and Hagerman (1974), Branch and Freed (1977), Harris (1994), Huang and Stoll (1996), and Chordia, Huh, and Subrahmanyam (2007).

will be proportional to inverse price. Since volumes also often depend on current returns (the volume leverage effect) I also include the average return in the volume regression.

Volumes and bid/ask spreads undoubtedly also depend on each other since traders are more likely to trade when the costs of trading are small, and the costs of trading tend to be small when many traders are trading. I specify reduced form models to avoid this endogeneity problem.

For the volume models,I use log dollar volume as the dependent variable. The log transformation helps stabilize the error variance. I use dollar volume instead of share volume to obtain a measure of risk transfer that is not as dependent on price levels as is share volume.

For the transitory volatility models, I use a difference in two variances as the dependent variable. In particular, I use twice the daily return variance minus the two-day return variance, measured with overlapping returns. This expression is exactly equal to half of the square of Roll's (1984) serial covariance spread estimator. If values follow a random walk, this difference in variancesestimates transitory return variance due to bid/ask bounce and perhaps also due to, or attenuated by,other liquidity effects. When closing prices are equally likely to be at the ask as at the bid, and no other transitory components affect prices, the expected value of this variance difference is equal to half of the square of the bid/ask spread, expressed as a fraction of price.[3]If

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[3]The following simple model shows why this difference in variances estimates transitory volatility due to bid/ask bounce. Assume that the closing price P is equal to value V plus a transitory component:

$$P_t = V_t + T_t$$

where T is a mean zero transitory price effect. Assume further that values follow a random walk $V_t = V_{t-1} + e_t$ so that

$$\Delta P_t = P_t - P_{t-1} = e_t + \Delta T_t$$

and

$$\Delta_2 P_t = P_t - P_{t-2} = e_t + e_{t-1} + \Delta_2 T_t$$

The variance of the one-period price change is specialists smooth prices so much that returns are positively autocorrelated, this transitory volatility measure will be negative.

The models for volumes and transitory volatility are

$$\log Volume_i = \alpha + \beta_1 \log MkCap_i + \beta_2 \log AdjRetVar_i + \beta_3 InvPrice_i + \beta_4 Ret_i + \varepsilon_i$$

$$TransVolity_i = \alpha + \beta_1 \log MkCap_i + \beta_2 AdjRetVar_i + \beta_3 InvPrice_i + \varepsilon_i$$

where$TransVolity_i = 2 \times Var\left(Return_{t,i}\right) - Var\left(Return_{t,i} + Return_{t-1,i}\right)$.

I measurereturn variance (*AdjRetVar*) by the variance of two-day returns. To remove transitory volatility from this variance, I subtract the one-day return variance from it. This adjusted variance should not reflect one-period transitory volatility which should affect both variances equally. I compute the two-day variance from overlapping returns to maximize its information content.

Note that the sum of *TransVolity* and *AdjRetVar*is the one-day return variance. Accordingly, these two variables partition the one-day return variance into two additive

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$$\mathrm{Var}(\Delta P_t) = \sigma_e^2 + \mathrm{Var}(\Delta T_t)$$

and the variance of the two-period price change is

$$\mathrm{Var}(\Delta_2 P_t) = 2\sigma_e^2 + \mathrm{Var}(\Delta_2 T_t)$$

so that

$$2\,\mathrm{Var}(\Delta P_t) - \mathrm{Var}(\Delta_2 P_t) = 2\,\mathrm{Var}(\Delta T_t) - \mathrm{Var}(\Delta_2 T_t)$$

The difference of variances thus estimates a difference in the variances of differences of the transitory component. If the transitory component is independently distributed, the two transitory variances are the same so that the difference in variances is just equal to the transitory variance. If bid/ask bounce accounts for all of the transitory component,

$$T_t = \frac{s}{2} Q_t$$

where s is the bid/ask spread and Q indicates with value 1 a closing price at the ask and with value -1 a closing price at the bid. If the indicator Q is independently distributed and if closing prices are equally likely to be at the bid as at the ask, the variance difference is equal to the one half of the square of the bid/ask spreads[2] because

$$\mathrm{Var}(\Delta_n T_t) = \frac{s^2}{4}\mathrm{Var}(Q_t - Q_{t-n}) = \frac{s^2}{4} 2 = \frac{s^2}{2}$$

for all $n > 0$.

components associated with transitory volatility and fundamental value volatility. The units of both variables are percentsquared.

Substantial evidence from the mixture of distributions literature suggests a linear or near linear relation between volumes and return variances.[4] Accordingly, I use the log of the adjusted return variance as an independent variable in the log volume regression.

Results from many theoretical and empirical bid/ask spread models suggest a linear or near linear relation between bid/ask spreads and the scale of price uncertainty.[5] As noted above, I use the time-series return standard deviation to proxy for price uncertainty. Since the transitory variance estimate measures bid/ask bounce, which is proportional to the square of the bid/ask spread, I usereturn variance as opposed to return standard deviation in the transitory volatility model.

For each year, I estimate these two models separately for the NASDAQ and exchange-listed stocks. For each stock and for each year, I measure volume by total dollar volume for the year, log market capitalization by the mean daily log daily market capitalization, return variance by the difference between the variances of two-day overlapping returns and one-day returns, inverse price as the mean daily inverse price, and average return as the mean daily return.

2.3 Data

Iobtained daily data for all actively traded common stocks primarily listed on NASDAQ, NYSE, or Amex from the CRSP US Daily Stock Database for the period January 1, 1993 to December 31, 2010.[6]Each year, I include only common stocks with at least 120 records

[4]See Karpoff (1987) and Harris (1986).
[5] See Benston and Hagerman (1994), Branch and Freed (1977), Glosten and Milgrom (1985), and Harris (1994).
[6]Data reporting and collection procedures for NASDAQ securities changed on June 15, 1992. We use only post-1992 data to avoid discontinuities associated with these changes.

indicating that the stock traded or was quoted at or above $1 in normal trading.[7]Each year, I exclude stocks that switchedlistings during that year (very few), stocks in two-digit SIC industries with fewer than 10 companies that otherwise met these criteria, and stocks for which the two-day return variance was less than 5% greater than the one-day return variance.[8]

The sample in 1993 includes 5,608 stocks. It grows monotonically to a maximum of 7,120 stocks in 1997 and then decreases monotonically to a minimum of 3,720 stocks in 2009. In 2010, 3,834 stocks appear in the sample. These counts reflect the IPO boom of the 1990s that was followed by bankruptcies and consolidations in the first decade of the 21stCentury. From the beginning of the sample through 2001, NASDAQ stocks accounted for approximately 65% of the sample. Following the bursting of the Internet bubble, their share in the sample quickly dropped to a stable 60%. NYSE-listed stocks outnumbered Amex-listed stocks by about 2.7:1 in 1993. This ratio rose to 6.3 to 1 by 2010 as common stock listings declined at the Amex.

When computing the two-day variances, I exclude all trading days for which the two-day return span more than five calendar days. For such events, I also exclude the corresponding one-day return. I analyze log returns rather than actual returns to stabilize variances and avoid biases associated with geometric cumulative returns that can be especially acute when substantial transitory volatility affects prices. Finally, I drop all observations for which fewer than five records of stock prices or bid/ask quotes appear in the previous 10 chronological days. This filter eliminates observations that span trading suspensions.

[7] We identified actively traded stocks by TrdStat = 'A' and common stocks by ShrCD = 10 or 11.
[8] The SIC and the variance filters respectively eliminated 1.4% and 1.3% of the stocks that otherwise would have appeared in the sample. The annual values of the SEC elimination ratio rose to a maximum of 2.3% in 2009 as the total number of traded stocks fell. The variance elimination ratio fell quickly from 4.15% in 1993 to 0.31% in 2010. Most of the drop occurred early in the sample. These stocks were small and infrequently traded.

2.4 Estimation

For each year and separately for the NASDAQ and listed stocks, I estimate the volume and transitory volatility regression models using OLS. The adjusted R^2s of the log volume regressions range between 85% and 92% for the NASDAQ stocks and between 87% and 92% for the listed stocks. For both markets, the most important dependent variable by far is log market capitalization, followed next by the adjusted return variance.

The adjusted R^2s of the transitory volatility regressions range between 13% and 42% for the NASDAQ stocks and between 7% and 56% for the listed stocks. For both markets, these goodness of fit statistics trended downwards across the years, undoubtedly due at least in part to the downward trend in bid/ask spreads over this period. The decrease also may be due to an increase in market efficiency as the markets matured.

For each stock, I then use the regression results to predict what volumes and bid/ask spreads that would have observed had it traded in the other market system. Finally, I summarize the differences—the causal effects—by computing weighted medians and means for each year. I choose the weights based on propensity scores described below. I report medians because they are more robust to extreme variation in the tails than are means. Both sets of results are very similar.

2.5 The Weighting Scheme

Volumes and bid/ask spreads may also vary by industry. Since industries are not equally represented among the NASDAQ and listed stocks, industrial differences can cause differences in volumes and bid/ask spreads across the two market structures even after accounting for the main cross-sectional determinants of volumes and bid/ask spreads.

Likewise, corporate decisions to list at NASDAQ or at a traditional listing exchange may depend on the same cross-sectional variables that determine volumes and bid/ask spreads. This selection problem will bias comparisons between the two market systems if volumes and bid/ask spreads have nonlinear relations to their cross-sectional determinants, as is undoubtedly the case.

To control for this selection bias and for the bias that can arise from unequal industrial representation, I generated a matched sample using the balanced propensity score approach introduced by Rosenbaum and Rubin (1983).[9] I computed annual propensity scores of listing on NASDAQ using the following logistic model:

$$Prob(Nasdaq_{i,t} = 1)$$
$$= f\big(\beta_1 \log MkVal_{i,t} + \beta_2 \log AdjRetVar_{i,t} + \beta_2 AdjRetVar_{i,t} + \beta_3 InvPrice_{i,t} + \beta_4 Ret_{i,t} + \beta_5 SIC_{i,t}\big)$$

where $Nasdaq$ is a dummy variable for trading on NASDAQ, SIC represented a set of class dummy variables for two-digit SIC industry groups, and *f* represents the logistic distribution function. The independent variables include all the independent variables that appear in the two regressions.

Following Dehejia and Wahba (2002), in each year, I sort all stocks by their propensity scores and then partitionthe distribution into 50 groups. Within each group, I then compute weights that balance the summed weights of the NASDAQstocks and of the listed stocks.For example, if one of the 50 groups has 40 listed stocks and 60 NASDAQ stocks, each listed stock receives a weight of 1 and each NASDAQ stock receives a weight of 40/60 = 2/3, so that the total weights on listed and NASDAQ stocks are equal within the group. This method ensures

[9] These methods also help control for selection biases that may result from misspecification errors in the regression model. Such errors may include misspecifications of functional forms or variable omissions.

that no stocks receive any weight if a group contains only stocks from one marketplace and that the total weight given to entire group is twice the count of the marketplace with the smaller number of stocks in the group.I then used these weights in all the analyses reported below.

3. Results

3.1 Causal Effects

The weighted mean weighted mean causal effects for the NASDAQ and listed stocks are statistically indistinguishable using equality of mean *t*-tests (results not reported). Accordingly, I pool the causal effects across both sets of stocks when reporting the results.

The causal effects are all expressed as “NASDAQ minus listed” so that positive causal effects indicate that dollar volumes or transitory volatilities are greater for NASDAQ stocks than for listed stocks.

Dollar volumes and transitory volatilities were once significantly higher for NASDAQ stocks than for listed stocks (Figures 1 and 2). These differences declined substantially between 1993 and 2010 so that these variables no longer display any essential difference across listing markets on average.

<Insert Figures 1 and 2 here>

To identify the statistical significance of these results, I computed a weighted average of variance-adjusted differences of the causality effects. In particular, I divided the estimate of the causal effect for each stock by the standard error of the prediction upon which it is based. Under the null hypothesis that the mean causal effect is zero, this ratio should be distributed with a zero mean and unit standard deviation. Weighted means of this ratio thus should be normally distributed with zero mean and variance given by $\sum_{i=0}^{N} w_i^2$ for large N (the number of stocks) if the weights are suitably distributed.[10]

In comparison to standard paired t-tests for unequal means, this method takes into account uncertainty in the prediction due to estimation errors in the regression coefficient estimates and due to the prediction itself (the regression error). In practice, it produces z-statistics only slightly lower (generally about 10%) than those produced by standard weighted t-tests because the standard errors of the regression coefficient estimates are small and because the regression mean squared errors used to produce the prediction error variances are very close to the causal effect variances. This evidence indicates that the regressions fit well and predict well for the balanced design created with the weighting scheme.

Using this test, the results in the earlier years are overwhelmingly significant at standard confidence levels because the differences are large and because the sample sizes are large.[11] The later results remain statistically significant due primarily to the large sample sizes, but they are no longer economically significant. The z-statistics for 2010 are 7.3 and 5.6, respectively, for the volume and transitory causality effects. Since these statistics do not consider contemporaneous cross-sectional correlations among the stocks, they undoubtedly are inflated.

3.2 Volumes and Variance Components

Over the sample period, dollar volumes increased substantially, as is well known(Figure 3). The weighted median daily NASDAQ dollar volume grew from $339 thousand in 1993 to $3.1 million in 2010, which corresponds to approximately 9-fold growth in volumes over the

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[10]In particular, the weights have to grow small for all observations as the number of observations increases.
[11] For example, in 1993, the z-statistics are 52 and 80, respectively, for the volume and transitory causality effects.

period. The growth in listed volumes is 20-fold. The causal effect results reported above suggest that the difference is due to the homogenization of trading.

<Insert Figure 3 here>

Weighted medians of the fundamental variance component,*AdjRetVar*,are very similar each year across both markets (Figure 4). These results indicate that the two samples are well matched. Not surprisingly, this volatility component rose very substantially when the Internet bubble burst and during the Financial Crisis.

<Insert Figure 4 here>

The weighted median transitory volatility component, *TransVolity*, decreased through time for the NASDAQ stocks (Figure 5). The decrease is likely associated with the substantial decrease in bid/ask spreads over the sample period that occurred following the introduction of the order handing rules in 1997, trading on sixteenths in 1997, and decimal trading in 2001.[12] In contrast, transitory volatilities are near zero for the listed stocks throughout most of the sample period, most probably due to narrower spreads in the listed stocks and the stabilization efforts of specialists.

<Insert Figure 5 here>

Transitory volatilities in the NASDAQ stocks rose when the Internet bubble burst and during the Financial Crisis. In the listed stocks, transitory volatility only rose significantly during the Financial Crisis even though fundamental volatilities rose to levels similar to the NASDAQ levels during both events. This difference may be due to stabilization by exchange specialists during the Internet bubble that was not provided later during the Financial Crisis, which occurred after the listed exchanges had already lost substantial market shares.

[12] The NYSE introduced decimal trading in the second half of 2000.

3.3 Robustness

I obtained essentially similar results whether I examined weighted median (reported) or weighted mean causal effects. I also obtain essentially similar results when I included squares and cross-products of the independent variables in the regression models in an attempt to identify the importance of nonlinear relations.

The method of identifying causaleffects allows the relation between the dependent variables and their other cross-sectional determinants to vary across markets. I also use weighted least squares to estimate a single regression model that includes a dummy variable to identify different intercepts for NASDAQ and listed stocks. This method also producessimilar results.

Finally, I also examined with more parsimonious models. I find essentially the same results when we use log market value as the only independent variable in the logit and regression models.

4. Conclusion

The results show that the well-known differences in average volumes and bid/ask spreads between NASDAQ and the listed exchange markets declined substantially over the last 20 years to the point that they are now no longer economically significant. These results provide empirical evidence of the homogenization of stock trading in the United States.

The results also suggest that specialist stabilization substantially reduced transitory volatility in the listed stocks until growing competition from other liquidity supplying traders make it impossible to continue providing these services. In particular, although fundamental price volatility increased substantially both the aftermath of the Internet bubble and during the Financial Crisis, transitory volatility only rose significantly during the later event.

The convergence of market structures is largely the result of competition among exchanges that the SEC promoted by allowing unlisted trading privileges and the proliferation of various alternative trading systems. Electronic trading technologies also have contributed to these trends. As a result, NASDAQ is no longer a dealer market, floor trading in NYSE and Amex stocks declined precipitously, and exchange specialists no long provide significant price stabilization services.

These changes generally have greatly lowered transaction costs, but they have come at a cost. Corporations can no longer exercise any meaningful influence on how their stocks trade. Instead, traders choose the market structures that most appeal to them. While the competition for their orders decreased transaction costs, it also greatly increased the fragmentation of trading.

The only process that now consolidates trading is the tendency for liquidity to attract liquidity. This process works well when traders have similar needs and when agency problems that traders have with the brokers that route their orders do not corrupt the search for best price.

Traders whose needs are not best served by dominant market systems seek alternative systems that serve them better, which fragments markets. However, when making routing decisions, they consider only the personal benefits that they obtain and not also the increased costs that they impose on other traders by making it harder from them to trade. Regulatory consolidation of order flow could address this externality problem, but at the cost of limiting competition among exchanges.

Agency problems also fragment markets by allowing brokers to send market orders to internalizing dealers and limit orders to trading systems that pay liquidity rebates. In principle, customers seeking brokers who execute best, or regulators demanding best execution of brokers,should limit these problems, but the information necessary to effectively buy or regulate best execution is expensive. Regulatory consolidation of order flow would eliminate these agency problems, but again at the cost of limiting competition among exchanges.

Regulatory consolidation of order flow presently is unimaginable because it eliminates competition among exchange service providers. Given the diversity of traders, obtaining any consensus about what market structure should be chosen would be impossible.

However, order flow consolidation can be consistent with competition among exchange service providers if the agents responsible for the consolidation were responsible to the traders. In particular, if corporations could specify the market structures for their stocks, the competition for listings would again become meaningful.

To facilitate this competition, the government could act to allow corporations to limit the markets at which their securities can trade, if they so wish. To ensure that agency problems between corporate managers and their shareholders do not overly affect these decisions, shareholders should have the opportunity to periodically vote on the market structures in which their shares trade. By creating the possibility of contestable monopolies in the provision of exchange services, the government can ensure that competition continues to restrain costs and promote high quality and services while at the same time providing a means to obtain benefits from consolidated market structures that presently are not possible under the currently regulatory framework.

References

Anderson T.G.,1996, Return Volatility and Trading Volume: An Information Flow Interpretation of Stochastic Volatility. *Journal of Finance*51 ,169-204.

Angel, James, Lawrence Harris, and Chester Spatt (2011), Equity Trading in the 21st Century, forthcoming, *Quarterly Review of Finance*, v1 (1).

Benston, George J. and Robert L. Hagerman, 1974, Determinants of bid-asked spreads in the over-the-counter market, *Journal of Financial Economics* 1, 353-364.

Branch, Ben and Walter Freed, 1977, Bid-asked spreads on the AMEX and the big board, *Journal of Finance* 32, 159-163.

Campbell, John Y., Sandord J. Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 107, 905-939.

Chordia, Tarun, Sahn-Wook Huh, and AvanidharSubrahmanyam, The Cross-Section of Expected Trading Activity, *Review of Financial Studies*. (May 2007) 20(3): 709-740.

Dehejia, R., and S. Wahba, (2002), Propensity Score-Matching Methods for Nonexperimental Causal Studies, *Review of Economics and Statistics* 84:1, 151-61.

Glosten, Lawrence R. and Paul R. Milgrom, 1985, Bid, Ask and Transaction Prices in a Specialist Market with Heterogenously Informed Traders, *Journal of Financial Economics*, 14, 71-100.

Fama, Eugene and Ken French, Permanent and Temporary Components of Stock Prices,*Journal of Political Economy* 96 (April 1988), 246-273.

Harris, Lawrence, Cross-security Tests of the Mixture of Distributions Hypothesis, *Journal of Financial and Quantitative Analysis* v. 21 no. 1, March 1986, p. 39-46.

Harris, Lawrence, 1994, Minimum Price Variations, Discrete Bid/Ask Spreads and Quotation Sizes, *Review of Financial Studies* v. 7, no. 1, 149-178.

Harris, Lawrence, (1994), Minimum Price Variations, Discrete Bid-Ask Spreads, and Quotation Sizes, *The Review of Financial Studies* 7:1, 149-78.

Huang, Roger D., Stoll, H., 1996, Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE, *Journal of Financial Economics* 41(3), 313-357.

Karpoff, Jonathan M., The Relation between Price Changes and Trading Volume: A Survey, *Journal of Financial and Quantitative Analysis* (1987), 22: 109-126.

Lo Andrew.W, Wang Jiang.2003.'Trading Volume' chapter in *Advances in Economics and Econometrics*

Pagano, M., 1989, Trading volume and asset liquidity, *Quarterly Journal of Economics* 104,255-276.

Roll, Richard, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, *Journal of Finance* 39 no. 4 (September 1984) 1127-39.

Rosenbaum, P., and D. Rubin, (1983), The Central Role of the Propensity Score in Observational Studies for Causal Effects, *Biometrika*70:1, 41-55.

Rubin, D., (1976a), Matching Methods that are Equal Percent Bias Reducing: Some examples, *Biometrics* 32, 109-20.

Rubin, D., (1976b), Multivariate Matching Methods that are Equal Percent Bias Reducing: Maximums on Bias Reduction for Fixed Sample Sizes, *Biometrics* 32, 121-32.

Securities and Exchange Commission (SEC), (1998), Regulation of Exchanges and Alternative Trading Systems, Release No. 34-39884, File No. S7-12-98

Securities and Exchange Commission (SEC), (2005), Regulation NMS, Release No. 34-51808, File No. S7-10-04

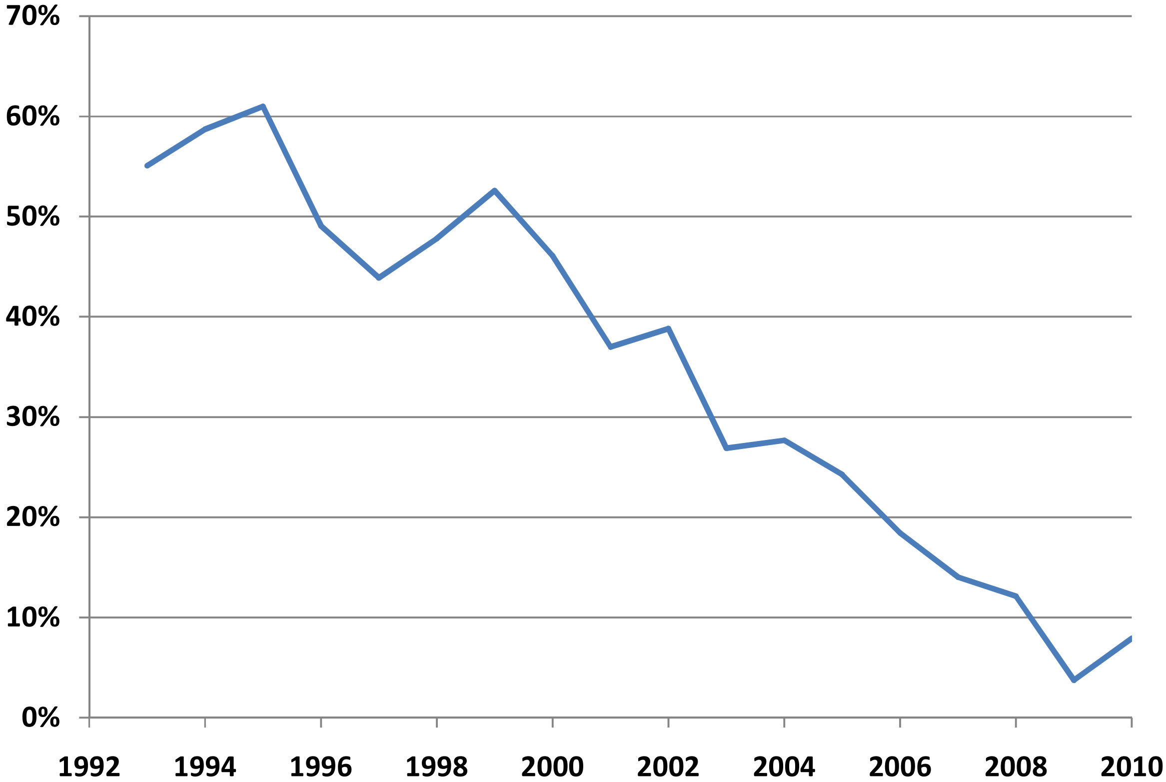

Figure 1

Effect on Dollar Volumes of NASDAQ Listing versus NYSE or Amex Listing

The figure plots the weighted median difference between actual and predicted log dollar volumesfor a large subset of all stocks that were primarily listed on NYSE or Amex or traded on NASDAQ. For a NASDAQ stock, the predicted log dollar volume is the prediction of its volume had it traded on the NYSE or Amex. Likewise, for a listed stock, the prediction is of its volume had it traded on NASDAQ. The predictions are obtained from OLS regressions of log dollar volume on log market capitalization, log return variance, inverse price, and average return, estimated each year separately for the NASDAQ and listed stocks. The sample in each year includes all common stocks that had more than 120 trades with a price at or above a dollar and which were in a two-digit SIC industry with 10 or more stocks. The weights are chosen each year to equalize the summed weights of NASDAQ stocks and of listed stocks within each of 50 buckets formed by sorting all stocks by propensity scores obtained from a logit analysis of the probability that a stock is a NASDAQ stock based on its characteristics. The numbers of observations per year range from 3,720 to 7,120 stocks.

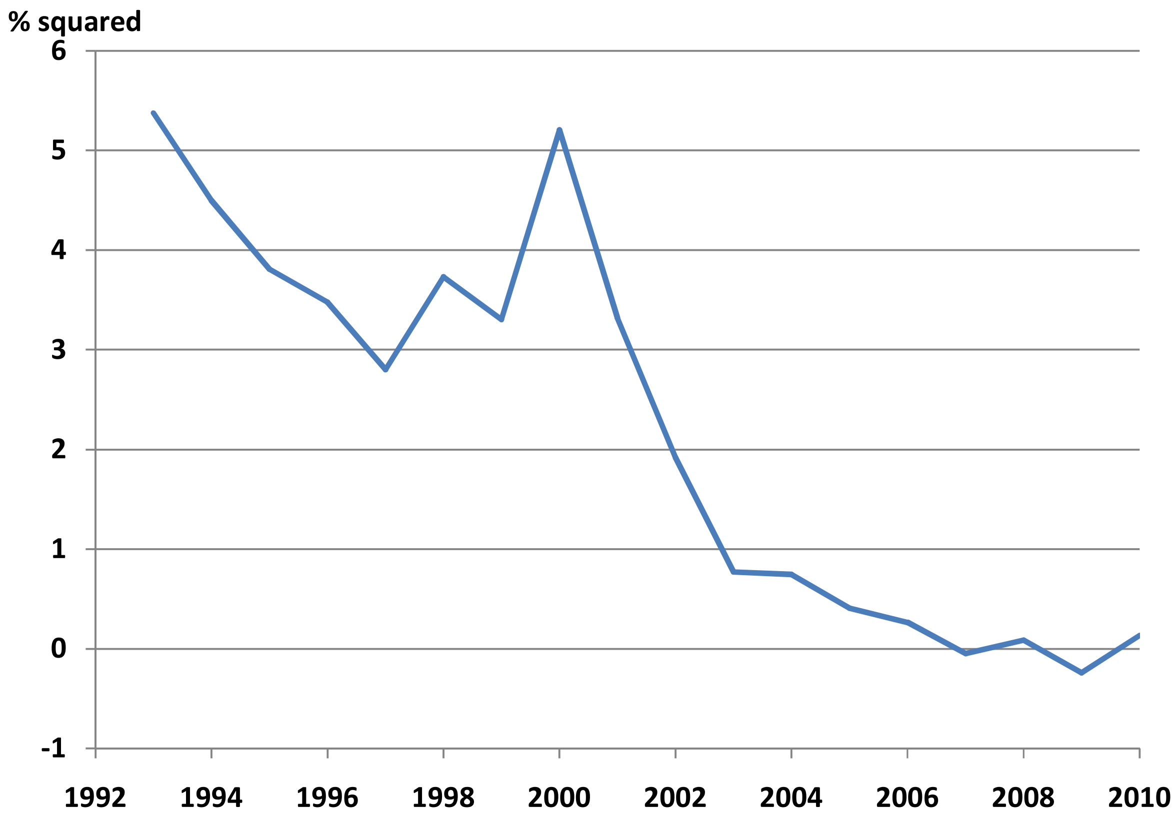

Figure 2

Effect on Transitory Volatility of NASDAQ Listing versus NYSE or AMEX Listing

This figure plots the weighted median difference between actual and predicted transitory volatilities for a large subset of all stocks that were primarily listed on NYSE or Amex or traded on NASDAQ. Transitory volatility is measured by twice the one-day return variance minus the corresponding two-day overlapping return variance. The expected value of this difference is equal to half of the square of the bid/ask spread if no other processes contribute to or attenuate transitory volatility. For a NASDAQ stock, the predicted transitory volatility is the prediction of its value had it traded on the NYSE or AMEX. Likewise, for a listed stock, the prediction is of its value had it traded on NASDAQ. The predictions are obtained from OLS regressions of transitory volatility on log market capitalization, return variance, inverse price, and average return, estimated each year separately for the NASDAQ and listed stocks. The sample in each year includes all common stocks that had more than 120 trades with a price at or above a dollar and which were in a two-digit SIC industry with 10 or more stocks. The weights are chosen each year to equalize the summed weights of NASDAQ stocks and of listed stocks within each of 50 buckets formed by sorting all stocks by propensity scores obtained from a logit analysis of the probability that a stock is a NASDAQ stock based on its characteristics. The numbers of observations per year range from 3,720 to 7,120 stocks.

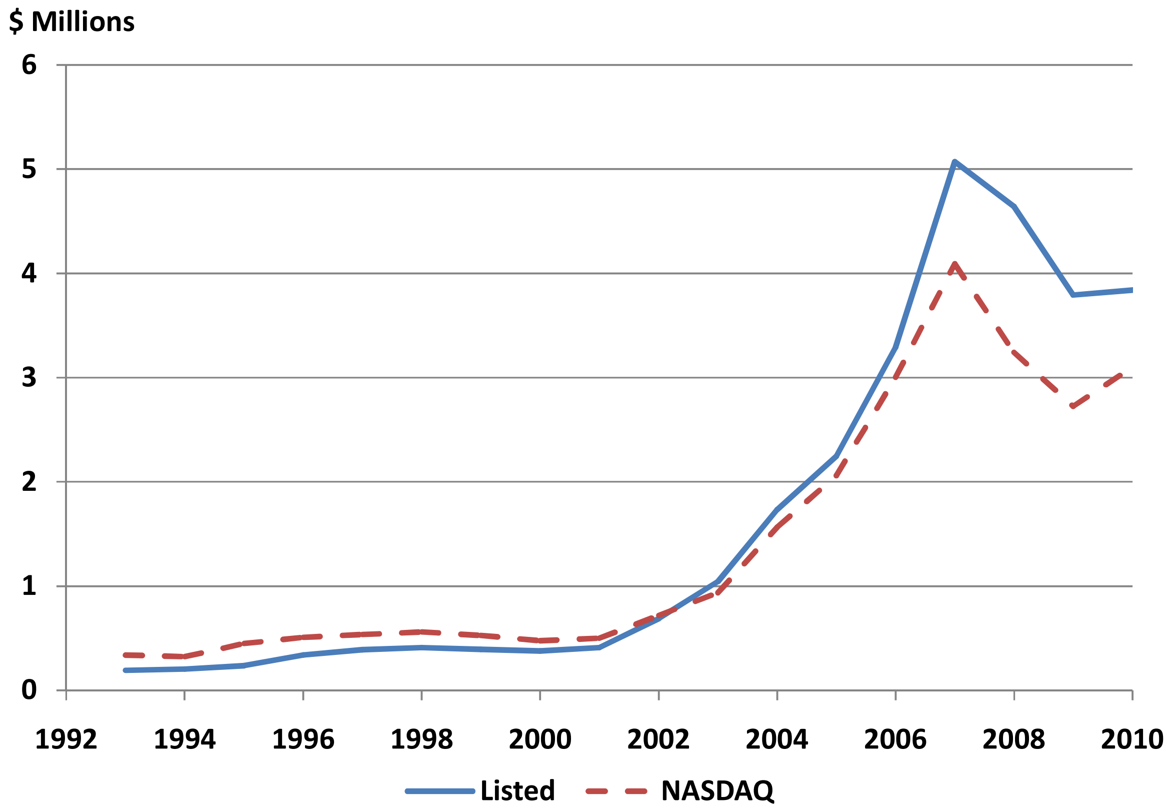

Figure 3

Median Daily Dollar Trading Volumes

This figure plots weighted median dollar volumesfor a large subset of all stocks that were primarily listed on NYSE or Amex or traded on NASDAQ. The sample in each year includes all common stocks that had more than 120 trades with a price at or above a dollar and which were in a two-digit SIC industry with 10 or more stocks. The weights are chosen each year to equalize the summed weights of NASDAQ stocks and of listed stocks within each of 50 buckets formed by sorting all stocks by propensity scores obtained from a logit analysis of the probability that a stock is a NASDAQ stock based on its characteristics. The numbers of observations per year range from 3,720 to 7,120 stocks.

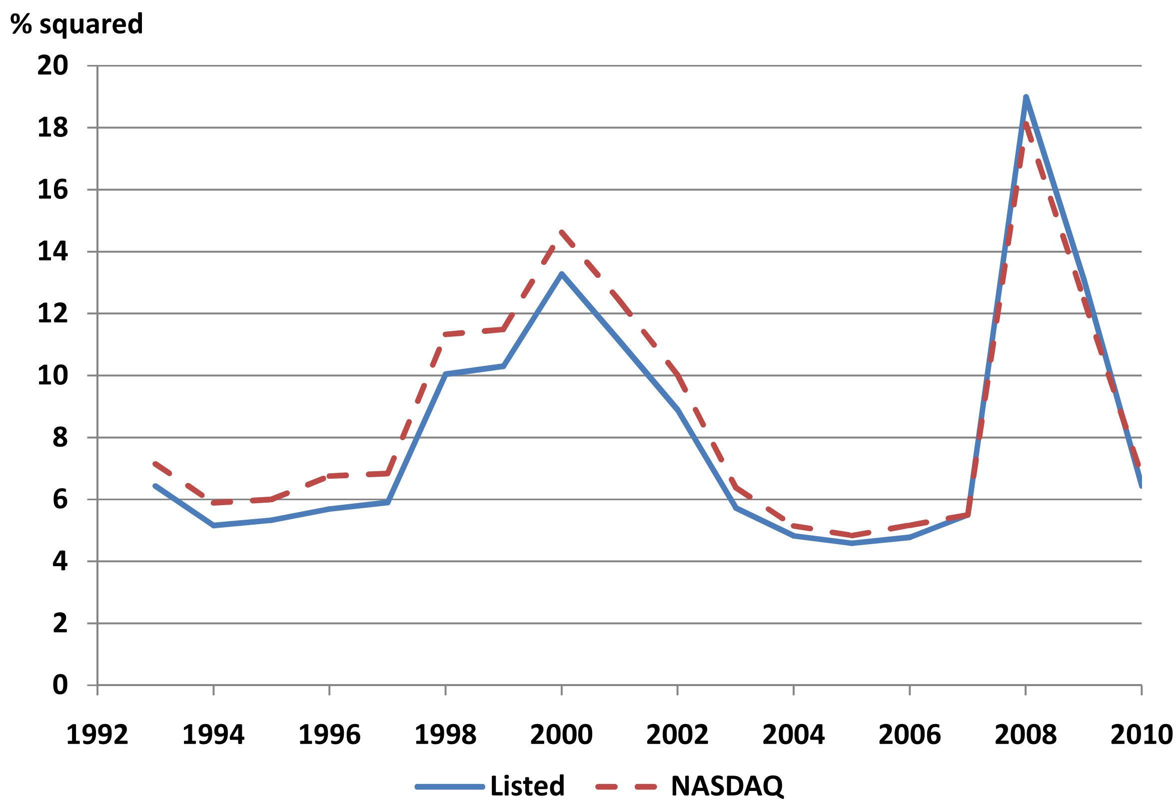

Figure4

Median Daily Fundamental Return Volatilities

This figure plots the weighted median fundamental volatility component of one-day return variances (*AdjRetVar*) for a large subset of all stocks that were primarily listed on NYSE or Amex or traded on NASDAQ. The component is equal to the two-day overlapping return variance minus the one-day return variance. The sample in each year includes all common stocks that had more than 120 trades with a price at or above a dollar and which were in a two-digit SIC industry with 10 or more stocks. The weights are chosen each year to equalize the summed weights of NASDAQ stocks and of listed stocks within each of 50 buckets formed by sorting all stocks by propensity scores obtained from a logit analysis of the probability that a stock is a NASDAQ stock based on its characteristics. The numbers of observations per year range from 3,720 to 7,120 stocks.

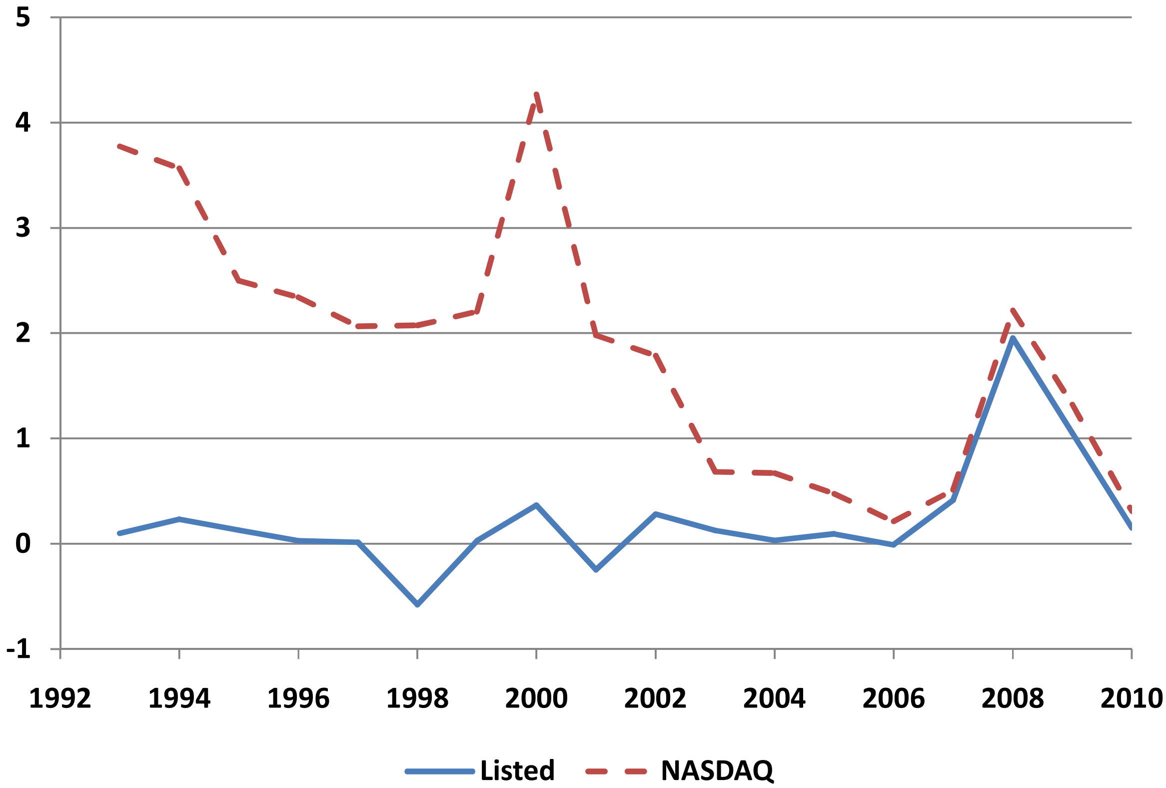

Figure 5

Median Daily Transitory Return Volatilities

This figure plots the weighted median transitory volatility component of one-day return variances (*TransVolity*) for a large subset of all stocks that were primarily listed on NYSE or Amex or traded on NASDAQ. The component is equal to twice the one-day return variance minus the two-day overlapping return variance. The sample in each year includes all common stocks that had more than 120 trades with a price at or above a dollar and which were in a two-digit SIC industry with 10 or more stocks. The weights are chosen each year to equalize the summed weights of NASDAQ stocks and of listed stocks within each of 50 buckets formed by sorting all stocks by propensity scores obtained from a logit analysis of the probability that a stock is a NASDAQ stock based on its characteristics. The numbers of observations per year range from 3,720 to 7,120 stocks.