Asset Returns and the Listing Choice of Firms

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We propose a mechanism that relates asset returns to the firm's optimal listing choice. We use a theoretical model to show that a stock will be more liquid when it is listed on a market where ''similar'' securities are traded. We empirically examine the implications of our model using New York Stock Exchange (NYSE) and Nasdaq securities. We find that the return patterns of stocks that switch markets become more similar to the return patterns of securities listed on the new market prior to the switch. Stocks that are eligible to switch but stay put are more similar to securities listed on their market than to securities listed on the other market. Our results suggest that managers make listing decisions that enhance the liquidity of their firms' stocks. (*JEL* G12, G14, and G30)

Many firms have a choice to make about a primary market on which to list their stocks, e.g., they could qualify for listing on either the New York Stock Exchange (NYSE) or Nasdaq. Does it really matter where firms list? Why do firms in the same industry tend to cluster on the same market? Are observed listing choices consistent with rational decision making? These are the questions that we study in this article. Empirical evidence suggests that the listing decision can affect the liquidity of the stock or the firm's visibility.[1] As a result, prior literature has suggested several characteristics of markets that can bring about an optimal listing choice, such as market structure, listing requirements or fees, and regulatory oversight (including corporate governance rules).[2]

In this article we propose a new determinant of the listing decision. We abstract from the particular features of the alternative markets and

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[1] See Grammatikos and Papaioannou (1986), Sanger and McConnell (1986), Edelman and Baker (1990), Sanger and Peterson (1990), Cowan, Carter, Dark, and Singh (1992), Christie and Huang (1994), Kadlec and McConnell (1994), Aggarwal and Angel (1997), Baker, Powell, and Weaver (1999a, 1999b), Elyasiani, Hauser, and Lauterbach (2000), Kalay and Portniaguina (2001), and Bessembinder and Rath (2002).

[2] See, for example, Cowan, Carter, Dark, and Singh (1992), Wan (2001), Heidle and Huang (2002), Lipson (2002), and Foucault and Parlour (2004).

instead put forward a mechanism that relates the firm's asset returns to the optimal listing choice. The crucial element in our framework is not a difference in the structure or rules of the markets, but rather a difference in the return patterns of the securities that are traded on these markets.

We begin by developing a simple trading model where multiple securities are traded in one of two markets and there is information asymmetry among investors. We show that a stock is more liquid when it is listed on a market where "similar" securities (i.e., securities with which its value innovations are more correlated) are traded. The driving force behind the result is that market makers can extract information about the value of the stock from the order flows of other securities in the market. Naturally, this information is more relevant when assets are similar, and therefore trades have smaller price impacts (or lower adverse selection costs), reflecting greater confidence market makers have in the prices they set. If managers of firms care about the liquidity of their stocks, our model suggests that they should list their stocks on a market with similar securities.[3]

This insight can explain why managers of firms often cite their desire to be on a market with similar firms as a motive for choosing to list on a particular market. For example, the Chairman and CEO of Allied Capital commented on their move from Nasdaq to the NYSE, saying, "There aren't a lot of dividend-paying stocks on Nasdaq, and, as a dividend payer, we really think our stock is better suited to the NYSE." The CFO of CARBO Ceramics noted on the move of his firm from Nasdaq to the NYSE, "Although the Nasdaq National Market has been extremely helpful to us since our initial public offering in 1996, we believe that our move to the New York Stock Exchange is consistent with the NYSE listing of the majority of publicly-traded companies in the oilfield services industry."[4]

These quotes suggest that while managers of firms may not be thinking explicitly in terms of the comovement of their stocks' returns with those of other firms, they probably have an intuitive notion of what constitutes a "similar" firm. Therefore, our model provides the rationale for why firms in the same industry, presumably having more commonality in their return patterns, tend to list on the same market. Still, the quote about Allied Capital's move suggests that industry membership may not always be the determining criterion. A mature firm in a certain industry may have more in common with a mature firm in another industry than with a start-up in its own industry. When a firm matures and its return-generating process

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[3] Managers might care about the liquidity of their stocks for several reasons. For example, adverse selection and other impediments to liquidity could be priced (e.g., Amihud and Mendelson 1986 and Easley and O'Hara 2004). Liquidity could also be a determinant of the cost of raising external capital (Butler, Grullon, and Weston 2005).

[4] The quotes are taken from: (i) "Allied Capital Corp. Moves to Bid Board" by Robyn Kurdek in the Venture Capital Journal, June 1, 2001, and (ii) "CARBO Ceramics Announces Completion of Public Offering and Move to the NSE" on the PR Newswire, May 19, 2000.

changes to reflect more of the general conditions in the economy, it may be better off switching to a market with other mature firms. This seems to correspond to the path many firms take: listing for the first time on Nasdaq and then moving to the NYSE. Since not all Nasdaq firms that are eligible to list on the NYSE switch markets, one could look at the return pattern of a stock in relation to other securities listed on its market to see if staying put is indeed the optimal thing to do.

We therefore proceed empirically to examine the implications of our model using NYSE and Nasdaq securities over a three-year sample period (2000–2002). There is more than one way in which we can define similarity in the return patterns of securities, and each definition suggests a different empirical methodology. Our first definition draws on an interpretation of the value innovations in the model as private information about common factors in returns (see also Subrahmanyam 1991 and Caballe and Krishnan 1994). We therefore examine similarity in returns by looking at the loadings of securities on estimates of common factors from a principal component procedure. Alternatively, if private information is only relevant to a subset of stocks, our model suggests that better estimates of the sensitivities to the value innovations (which determine the optimal listing choice) can be obtained by eliminating the market component in returns. We therefore examine similarity measures constructed from correlations of market model residuals.

Our first test provides a check on the basic assumption of the model that the two markets differ in terms of the return patterns of the securities that are listed on them. We conduct a principal component analysis and find that Nasdaq securities load more heavily on the first principal component and that NYSE securities load more heavily on the second principal component, consistent with the assumption of our model. When testing the model's predictions, we look both at firms that switch markets and at firms that are eligible to switch but stay put. While managers of the switching firms make an "active" decision to move, managers of firms that are eligible to move (but choose not to do so) make "passive" decisions that impact the liquidity of their stocks.

We start by examining the managers' "passive" decisions. We create four groups: (i) Nasdaq National Market common domestic stocks that are eligible to list on the NYSE, (ii) all other Nasdaq National Market securities, (iii) NYSE common domestic stocks that are eligible to list on Nasdaq, and (iv) all other NYSE securities. If managers of firms seek to improve liquidity by their choice of a listing venue, our model suggests that stocks that are eligible to switch markets would have return patterns more similar to those of other securities in their own market and less similar to those of securities in the other market. We find that this is indeed the case, supporting the notion that the "passive" decisions managers make by remaining listed on their markets are optimal with respect to liquidity.

We then examine the "active" choices made by managers of firms that move from Nasdaq to the NYSE during our sample period.[5] We find evidence of a change in their return patterns two years prior to the move in the direction of being more similar to the return patterns of NYSE securities. These results support the conclusion that managers make listing decisions that enhance the liquidity of their firms' stocks. Looking at the return patterns of switching firms *before* they switch also demonstrates the robustness of our conclusions to the alternative hypothesis that the trading venue drives the similarity in return patterns (perhaps owing to correlated liquidity trading among securities that are listed on the same market).

Furthermore, we show using several price impact measures that the liquidity of the switching stocks improves upon moving to the NYSE. While consistent with an optimal listing decision, this result is hardly surprising because such liquidity gains were documented in prior studies. However, we also find that the degree of liquidity improvement is greater for stocks with more similar return patterns to those of NYSE securities, evidence consistent with the insights of our model.

Much of the prior literature analyzes the determinants of managers' optimal choice in the context of the two dominant markets in the U.S., the NYSE and the Nasdaq National Market.[6] Because there are differences in the market structure, rules, and listing requirements of these two markets, this research effort has focused on identifying the structural element or the rule that either makes one market superior to the other or explains the reasoning behind the decisions of some firms to list on Nasdaq and others on the NYSE.

For example, Heidle and Huang (2002) and Lipson (2002) observe that the NYSE is a centralized floor-auction market while the Nasdaq is a fragmented screen-based market with multiple dealers and alternative trading systems. If some investors have private information and they can better hide in a fragmented screen-based market, moving from Nasdaq to the NYSE would benefit investors by reducing the extent of adverse selection. Foucault and Parlour (2004) note that different markets may charge different listing fees, a situation that characterizes the NYSE and Nasdaq. They provide a model where firms self-select to the most appropriate market as a trade-off exists between listing fees and transaction

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[5] There was one firm, Aeroflex Incorporated, that voluntarily switched from NYSE to Nasdaq during our three-year sample period (see Kalay and Portniaguina 2001). We repeated all the tests with Aeroflex in the sample and our conclusions were unchanged. We chose to present the results without Aeroflex for two reasons. First, it simplifies the exposition. Second, it does not obscure the fact that the results are essentially driven by the 86 stocks that moved from Nasdaq to the NYSE rather than the single stock that moved in the opposite direction.

[6] The optimal listing decision we investigate concerns the firm's primary market. We do not study the decision of a manager to cross-list his firm's stock on additional markets abroad (see, for example, Pagano, Röell, and Zechner 2002 and references therein on the question of why firms list abroad).

costs.[7] Wan (2001) argues that the different market structures give rise to different volume figures on the NYSE and Nasdaq, and that SEC rules restricting the trading of insiders are therefore less binding on Nasdaq. His argument implies that incentives of insiders that are not shared by outside shareholders may affect the listing choice.[8] Cowan, Carter, Dark, and Singh (1992) suggest that NYSE rules discouraging unequal voting rights of multiple share classes may also influence the decision of managers on where to list.[9]

One contribution of our work is that it proposes a new determinant of the listing choice that does not rely on differences in the structure or rules of the markets. We also demonstrate how the listing venue can affect the liquidity of stocks through the learning process of market participants about private information in prices. We do not suggest that this is the only consideration that managers have when making a choice about listing on a market, and our approach does not state that this should be the only determinant. Still, our model provides a way to empirically evaluate whether managers care about liquidity and make listing decisions consistent with improving the liquidity of their stocks.

We test the model (both the assumption and the implications) using various methodologies and find that managers behave optimally in the sense of our model—as if they want to maximize the liquidity of their stocks.[10] When firms behave this way, the mechanism we propose as a determinant of the listing choice would perpetuate itself. In other words, when firms make active decisions to list on markets already populated by similar firms, the assumption of our model that the two markets differ in terms of the return patterns of the firms that are listed on them will continue to hold. As long as the assumption holds, the optimal listing choice will be to join the venue where similar firms are listed. Hence, this determinant of the listing choice seems robust to changes in the structure or rules of markets.

Another contribution of our approach is to propose a relation that goes from asset return patterns to the decisions of managers through an information-asymmetry-driven market microstructure trading model. Dow and Gorton (1997) and Subrahmanyam and Titman (1999, 2001) recently presented models where a manager can learn useful information

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[7] See also Macey and O'Hara (2002) on the economics of stock exchange listing fees and listing requirements.

[8] See also the models of Huddart, Hughes, and Brunnermeier (1999) and Chemmanur and Fulghieri (2006) that demonstrate how insiders' listing decisions can be affected by public disclosure requirements.

[9] See also Aggarwal and Angel (1997), Bessembinder (2000), Corwin and Harris (2001), and Jain and Kim (2006).

[10] We use the word "optimal" to describe liquidity-enhancing decisions by managers because better liquidity is the benefit to an optimal listing choice in our theoretical framework. There can be costs associated with listing on a particular market that are outside the scope of our model. Such costs would require a manager to perform a cost-benefit analysis to arrive at an optimal listing choice.

from his firm's stock price. Our analysis suggests that certain managerial decisions would benefit from examining the firm's return pattern alongside the return patterns of other securities in the market. And while we find support for the liquidity-enhancing listing choices of NYSE and Nasdaq firms, the nature of our approach provides an intuition that is more general than the specifics of these two markets.

The rest of the article proceeds as follows. We present the theoretical model and derive the implications for the relation between the listing choice and liquidity in Section 1. Section 2 is devoted to the empirical work, and Section 3 states our conclusions.

1. Theory

In this section we develop a simple model that relates the listing choice to liquidity. We first describe the market prior to the listing of a new asset. We consider an economy with one risk-free asset and two risky assets (asset 1 and asset 2). Without loss of generality, we set the return on the risk-free asset to zero. Each risky asset is traded in a separate market organized as in Kyle (1985), where prices are set by competitive and risk-neutral market makers.[11] After each round of trading, there is a public release of information and the competitive market makers agree that the values of risky assets 1 and 2 have changed by the value innovations $\tilde{s}_1 + \tilde{\theta}_1$ and $\tilde{s}_2 + \tilde{\theta}_2$, respectively. We further assume that $\tilde{s}_1$ and $\tilde{s}_2$ are standard normal random variables, independent of each other and independent of $\tilde{\theta}_1$ and $\tilde{\theta}_2$. The random variables $\tilde{\theta}_1$ and $\tilde{\theta}_2$ have zero means and can be correlated with each other.

We view each asset in the model as representing a group of similar assets traded on a single market. To simplify the exposition, we assume that assets listed on one market have a value innovation that does not exist in the values of assets listed on the other market. Similar results can be obtained if value innovations for assets in both markets are weighted averages of both $\tilde{s}_1$ and $\tilde{s}_2$, but the weight on $\tilde{s}_1$ is greater in one market and the weight on $\tilde{s}_2$ is greater in the other market. The primitive of our approach therefore is that similar assets (those with a common value innovation) are listed on the same market. We then investigate the implication of this assumption to the choice of a firm that considers where to list or whether to move from one market to another when the distribution of its value innovations changes.

The economy is populated by liquidity traders, informed traders, and two groups of market makers. We assume that the aggregate demand of the liquidity traders for each asset is a standard normal random variable

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[11] See also Baruch, Karolyi, and Lemmon (2006), who investigate international cross-listings in a multimarket model in the spirit of Kyle (1985).

that is independent of all other innovations in the market. There are two risk-neutral informed traders. The first one observes the realization of $\tilde{s}_1$, which is an unbiased signal of the value innovation of asset 1, and the second informed trader observes the realization of $\tilde{s}_2$. As in Kyle (1985), anonymity of the traders implies that market makers observe only aggregate net orders.

Since we posit two markets that are identical with respect to their structures and rules, we need to introduce some sort of segmentation in order to have a meaningful distinction between them. We assume that market makers observe only the aggregate order flow that arrives in their own market before setting clearing prices. This is not the first theoretical article to use such a friction. Chowdhry and Nanda (1991), for example, model a single asset that is traded on different exchanges and assume that market makers in a given exchange observe only the order flow that arrives to their exchange (this is the feature that distinguishes one market from another in their model).[12] Empirical work by Benveniste, Marcus, and Wilhelm (1992) and Coval and Shumway (2001) suggests that traders in one market indeed have access to valuable information that is not shared by traders in another market.[13] It is important to note, though, that the segmentation we consider exists only at the time the order flow arrives in the market. After a trade has taken place, market makers in one market can observe prices set in the other market. Since we assume public release of information after each round of trading, the model allows for economy-wide reporting of last-trade prices.

We now introduce another risky asset, asset 3, that could potentially be listed on either market. To have the most general case, the innovation of asset 3 is given by a linear combination of $\tilde{s}_1$ and $\tilde{s}_2$: $a\tilde{s}_1 + b\tilde{s}_2 + \tilde{\theta}_3$. The scalars a and b are the sensitivities of asset 3's value to the innovations $\tilde{s}_1$ and $\tilde{s}_2$. The magnitudes of a and b determine whether asset 3 is more similar to asset 1 or asset 2. The random variable $\tilde{\theta}_3$ has zero mean and is independent of $\tilde{s}_1$ and $\tilde{s}_2$ but possibly correlated with $\tilde{\theta}_1$ and $\tilde{\theta}_2$. The liquidity demand for this asset is a standard normal random variable, independent of all other random variables.[14] Say asset 3 is listed on

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[12] This assumption is also used in Foucault and Gehrig (2006) and Baruch, Karolyi, and Lemmon (2006).

[13] Our empirical work in Section 2 uses NYSE and Nasdaq as the two markets. If, as in Benveniste, Marcus, and Wilhelm (1992), human interaction on the NYSE floor conveys information, Nasdaq market makers have no access to information that NYSE specialists observe. Linkages such as the Intermarket Trading System (ITS) do not alleviate this informational friction because only the orders a market wishes to pass on to another market travel through ITS, as opposed to the entire order flow. Also, conversations with practitioners suggest that many trading desks on Wall Street are organized such that traders in listed stocks sit together and traders in over-the-counter stocks sit together, facilitating better information sharing on stocks that are traded on the same market.

[14] In Section 2.3 we discuss an extension of the model that relaxes the independence assumption by allowing liquidity trading in one asset to be correlated with liquidity trading in another asset that is listed on the same market. We show that this does not change the main implication of the model.

2245

market 1, where asset 1 is traded. Then, market makers price asset 3 on the basis not only of its own aggregate demand but also of the demand they observe for the other asset listed on the same market. Similarly, if asset 3 is listed on market 2, market makers can observe the aggregate demands for both assets 2 and 3 when setting the price of asset 3.

Segmentation of markets and risk-neutrality of the informed traders imply that the trading strategies and price rules in one market are unaffected by the trading activity taking place in the other market. We can therefore study the outcome of each market separately, and we focus on the market where asset 3 is listed.

Consider first the case in which asset 3 is listed on market 1. We can write the value of the assets traded in market 1 using matrix notation as

$$\tilde{V} = \mu + F\tilde{S} + \tilde{\Theta},$$

where $\tilde{V} = (\tilde{v}_1, \tilde{v}_3)$, $\mu \in R^2$ is the value of the assets prior to the innovation, F is a matrix of scalars given by

$$F = \begin{pmatrix} 1 & 0 \\ a & b \end{pmatrix}, \tag{1}$$

$\tilde{S} = (\tilde{s}_1, \tilde{s}_2)$ is the vector of value-relevant signals of the informed traders, and $\tilde{\Theta} = (\tilde{\theta}_1, \tilde{\theta}_3)$. Let $\tilde{Z} \in R^2$ be the orders submitted by the liquidity traders to market 1. Let $X_1 \in R^2$ and $X_2 \in R^2$ be the orders submitted by the first and second informed traders, respectively. Note that each informed trader can submit orders for both assets 1 and 3. Let $\tilde{P} \in R^2$ be the clearing prices of the two assets, $X = X_1 + X_2$ be the aggregate demand of the informed traders, and $Y = X + Z$ be the net order flow submitted to the market.

An *equilibrium* is a price rule $P : R^2 \rightarrow R^2$ and strategies $X_1, X_2 \in R^2$ such that: (i) given the strategies, the price rule satisfies the condition $\tilde{P} = E[\tilde{V}|\tilde{Y}]$, and (ii) given the price rule, the ith informed trader $(i = \{1, 2\})$ maximizes the expected profits $E[(\tilde{V} - \tilde{P})X_i|s_i]$.

Theorem 1. *There exists a linear equilibrium in which (i) the price rule is given by $P(\tilde{Y}) = \mu + \Lambda\tilde{Y}$, where Λ is a 2×2 matrix of scalars, and (ii) aggregate informed trading can be written as $X = \beta S$, where β is a 2×2 matrix of scalars. The matrices Λ and β are the solutions to the system of Equation (2) below satisfying the second-order condition that $-(\Lambda^T + \Lambda)$ is a negative semidefinite matrix:*[15]

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[15] Superscript T denotes the transpose operation and I denotes the identity matrix.

$$\beta = (\Lambda + \Lambda^T)^{-1} F \qquad (2)$$
$$\Lambda = F\beta^T (I + \beta\beta^T)^{-1}$$

Proof of the theorem can be found in Appendix A. In equilibrium, the diagonal entries of the matrix Λ are the price impacts of market orders in asset 1 and asset 3. Let $\lambda_3(1)$ be the price impact of market orders in asset 3 when it is listed on market 1 (i.e., the second row, second column entry of the matrix Λ). Similar to λ in the single-asset Kyle (1985) model, $\lambda_3(1)$ measures the liquidity of asset 3. Indeed, an uninformed trader who demands z of asset 3 expects to pay $z^2\lambda_3(1)$ for immediacy. The off-diagonal entries represent price changes in one asset induced by observing order flow in the other asset. These affect the informational efficiency of the asset's price, but like other cases where the price of an asset changes owing to public information, these price movements are not manifestations of the illiquidity of a stock. Liquidity is measured by how much the order flow in an asset moves its own price (the diagonal entries).

It follows from the proof provided in Appendix A (see Equation (A3)) that

$$\lambda_3(1) = \frac{a^2 + |b|\,(1 + |b|)}{2\sqrt{a^2 + (1 + |b|)^2}}.$$

In order to compare liquidity when an asset is listed on one market versus the other, we need to find the price impact of market orders when asset 3 is listed on market 2. It is straightforward to show that a similar linear equilibrium exists in this case as well, where the price impact of market orders in asset 3 is given by[16]

$$\lambda_3(2) = \frac{b^2 + |a|\,(1 + |a|)}{2\sqrt{b^2 + (1 + |a|)^2}}.$$

To determine whether liquidity is better when asset 3 is listed on market 1 or on market 2, we calculate the difference

$$\lambda_3(1)^2 - \lambda_3(2)^2 = \frac{b^4 - a^4 + 2(|b|^3 - |a|^3) + b^2 - a^2}{4\left(a^2 + (1 + |b|)^2\right)\left(b^2 + (1 + |a|)^2\right)}. \qquad (3)$$

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[16] The proof is analogous to the one of Theorem 1 and is therefore omitted for brevity.

The following proposition follows immediately:

Proposition 1. *If $|a| > |b|$ then liquidity is better when asset 3 is listed on market* 1*, and if $|b| > |a|$ then liquidity is better when asset 3 is listed on market* 2*.*

Proposition 1 states that if the magnitude of the sensitivity of asset 3 to $\tilde{s}_1$ (the value-relevant private information of the first informed trader) is greater than the magnitude of its sensitivity to $\tilde{s}_2$, then liquidity will be better if the asset is listed on market 1. Conversely, if the magnitude of the sensitivity of asset 3 to $\tilde{s}_1$ is smaller than its sensitivity to $\tilde{s}_2$, then liquidity will be better if the asset is listed on market 2.

What is the intuition behind this result? The key can be found in the off-diagonal terms of the matrix Λ that are specified in the proof of Theorem 1. They represent the market makers' inference from order flow of one asset that is relevant to the price of the other asset. In the model, if we assume that θ_1 and θ_3 are uncorrelated, a is the comovement of the value innovations of asset 1 and asset 3. Heuristically, the greater the magnitude of a, the more that market makers can learn about the value innovation in asset 3 by observing the order flow in asset 1.[17] As such, they do not need to change their beliefs (and hence the price) to the same extent in response to the order flow in asset 3, and therefore the price impact of market orders in asset 3, $\lambda_3(1)$, is smaller. In other words, the liquidity of asset 3 when listed on market 1 will be better than its liquidity when listed on market 2 if asset 3 comoves more with asset 1 than with asset 2. In a similar fashion, when asset 3 comoves more with asset 2 than with asset 1, or when $|b| > |a|$, liquidity will be better if asset 3 is listed on market 2.[18]

It is interesting to note that the liquidity of the existing asset in the market on which asset 3 lists also improves. For example, if asset 3 lists on market 1, the ability of market makers who trade asset 1 to learn about the private signal $\tilde{s}_1$ increases because they can observe the order flow in asset 3. Therefore, the new listing provides a positive externality to the market. We can further show that when $|a| > |b|$, the improvement to

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[17] See also Strobl (2001), who investigates the allocation of multiple stocks to specialists on the NYSE in a noisy rational expectations framework.

[18] One could claim that this logic should also apply to allocation of stocks to specialists on the floor of the NYSE. In other words, that liquidity would be enhanced if stocks with correlated value innovations are traded by the same specialist. Unfortunately, the limitations of any single person with respect to information processing or interactions with brokers and computer screens prevent specialists from trading stocks that are very similar (like two large technology stocks). The reason is that when there is news about a firm or an industry, the number of orders that arrive for one active stock makes the specialist (and the specialist's clerk) unable to handle trading in any other security. Having another actively traded security that is influenced by the same news event at the same time would prevent the specialist from maintaining an orderly market in either security.

the liquidity of asset 1 when asset 3 lists on market 1 is greater than the improvement to the liquidity of asset 2 when asset 3 lists on market 2 (and vice versa if $|b| > |a|$).[19] This result is rather intuitive because the efficiency with which market makers learn about private information depends on the strength of the commonality in the value innovations of the existing and the new assets.

Since the improvement in liquidity increases in the degree of similarity between the assets (i.e., with the correlation between their value innovations), a natural question to ask is what happens in the limit. More specifically, we would like to know whether the equilibrium breaks down when the two assets are perfectly correlated.[20] We can show that there is an equilibrium with two perfectly correlated assets.[21] It is interesting to contrast this case with the model in Bhattacharya, Reny, and Spiegel (1995) (henceforth, BRS). They feature a multiasset framework with a single informed investor and a continuum of risk-averse, uninformed investors. In their model, there is a market breakdown when the value innovations of the assets are too correlated. An important feature of the BRS framework is the lack of pure noise trading. Noise is created by the unknown hedging needs of the risk-averse informed trader. The introduction of a new asset with correlated value innovations generates correlation in hedging-motivated trade in their model. When value innovations are too highly correlated, so is the correlation induced by hedging needs and therefore there is not enough noise to prevent a market breakdown.

While the Kyle framework we use can survive perfect correlation in value innovations, the equilibrium breaks down when liquidity trading is perfectly correlated across assets (and this is independent of the correlation in value innovations). In Section 2.3 we discuss a more general version of our model with correlated liquidity trading. If the correlation in liquidity trading goes to one, all elements of the price impact matrix Λ explode.

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[19] To prove this claim we verified that whenever $|a| > |b|$,

$$\frac{(1 + |b|)}{2\sqrt{a^2 + (1 + |b|)^2}} - \frac{(1 + |a|)}{2\sqrt{b^2 + (1 + |a|)^2}} < 0$$

where the first term is the price impact of asset 1 when asset 3 lists on market 1 and the second term is the price impact of asset 2 when asset 3 lists on market 2.

[20] An example could be a derivative and an underlying asset that are listed on the same market.

[21] This holds in the general case where liquidity demands for the two assets can be different. We can find an equilibrium even in the case of identical assets: both assets would have the same price in equilibrium, and the price would be a linear function of the sum of order flows in the two assets. Existence of this equilibrium requires a separate proof because the proof of Theorem 1 uses invertibility of the price impact matrix Λ that does not hold in this case.

Thus, like BRS, we also get a market breakdown when there is not enough noise in the market.[22]

2. Empirical Evidence

Proposition 1 suggests that firms should list on markets where similar securities are listed. We use this implication of our model to study the listing choices of firms on the two main U.S. markets: NYSE and Nasdaq.

The sample and data sources are discussed in Section 2.1. The tests in Section 2.2 have two goals. First, we examine whether the basic assumption of the model—that the two markets differ in terms of the return patterns of the securities listed on them—holds. Second, we study the "passive" decisions of firms that are eligible to move to the other market but do not. Our model implies that eligible stocks should not move if their returns are more correlated with securities listed on their own market than with the securities on the other market.

In Section 2.3 we present tests of the "active" decisions of managers using a sample of firms that switch markets. Our model suggests that a firm should switch if its return pattern has changed to more closely resemble the return patterns of stocks on the other market. We also discuss in this section the robustness of our conclusions to return behavior induced by correlated liquidity trading among stocks that are listed on the same market. Finally, we examine whether differences in liquidity improvement upon switching are related to the extent of similarity between the return patterns of the switching firms and those of securities listed on the new market.

2.1 Sample, data, and definitions of return similarity
Our sample period is 2000–2002 (three years). In order to investigate the "passive" listing choices of managers in Section 2.2 we need to identify the firms that actually have a choice: those that are listed on one market and satisfy the listing requirements of the other market. Therefore, we want to identify Nasdaq common domestic stocks that were eligible to list on the NYSE on the first day of the sample period, as well as NYSE common domestic stocks that were eligible to list on Nasdaq on that date.

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[22] One could also ask what happens if we let the three assets trade in one market as opposed to the two-market setup of the model. We can show that there exists an equilibrium (though it requires a proof different from the one we use for Theorem 1 because the price impact matrix cannot be inverted). We find that the assets' liquidity is better when they are all listed on a single market. For example, if we set $a = 1$ and $b = 1$ in our two-market model, then the price impact of order flow in asset 3 when it is listed on market 1 (together with asset 1) is 0.67. If all three assets are listed on a single market, the price impact of order flow in asset 3 is reduced to 0.58. The reason is that market makers are able to learn potentially useful information for the pricing of each asset from the order flows of all assets. The better liquidity we find in the single market provides a rationale for consolidation among exchanges. Still, it is not clear that one market is always optimal. One should weigh the enhanced liquidity benefit against a reduction in competition across exchanges that could weaken the incentives to innovate and cause fees to increase.

We use information in the CRSP and COMPUSTAT databases to evaluate each common domestic stock and see if it satisfies the initial listing requirements of the other market. Most criteria specified by the NYSE and Nasdaq can be mapped rather well to the information in these two databases. Appendix B contains the variables we use from CRSP and COMPUSTAT for different listing requirements. Some slippage, however, is inevitable as the NYSE and Nasdaq evaluate information provided by the firms themselves, which is not necessarily identical to what we observe in the databases. Therefore, despite our best efforts, the procedure we use to determine eligibility may introduce some noise into the analysis.

Our procedure identifies 1155 NYSE common domestic stocks that were eligible to list on Nasdaq on January 1, 2000. We will refer to them throughout the analysis as the NYSE1 group. Similarly, our procedure yields a list of 408 Nasdaq National Market common domestic stocks that were eligible to list on the NYSE at the beginning of our sample period, henceforth NNM1. Panel A of Table 1 presents summary statistics for the securities in both groups using information from the CRSP database.

For the tests of the "active" listing decision of managers in Section 2.3 our sample consists of all common domestic stocks that voluntarily switched from the Nasdaq National Market to the NYSE during our sample period. There were 86 such moves in the years 2000–2002. While the NYSE revised Rule 500 in 1999 to make it easier for firms to voluntarily delist, only one firm (Aeroflex) chose to move from the NYSE to Nasdaq during our sample period.[23] When we include Aeroflex in our tests, the results are unchanged. However, to simplify the exposition and not to obscure the fact that the results are driven by switches in one direction, we present in the article the results of the tests on the sample of firms that moved from Nasdaq to the NYSE.[24] Panel B of Table 1 provides summary statistics on the switching sample.

Moving from the theoretical model to the empirical tests requires us to define carefully what we mean by "similarity" of firms. In the model, similarity was formalized by a common source of variation in the value innovations of the assets. In the empirical work, we would like to capture this similarity by looking at the daily return patterns of securities. Still,

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[23] There can be several reasons for the fact that many firms switch from Nasdaq to the NYSE but not vice versa. As we mention in the introduction, maturing firms may choose to switch to a market with other firms in the same stage of their development. Since Nasdaq attracts younger firms due to its less stringent listing standards, this "graduation" hypothesis would create movement from Nasdaq to the NYSE. Since firms do not normally get smaller and less profitable by choice, not many would be going in the other direction unless they were involuntarily delisted from the NYSE. Another reason for the lack of movement in the other direction could be that the Nasdaq Composite Index lost much more ground than the NYSE Composite Index during our sample period (following the collapse of the technology sector), possibly creating an image problem for the Nasdaq market that dissuaded firms from switching. Finally, perhaps it takes time for firms to digest the possibilities opened by the revision of NYSE Rule 500, and we would therefore see more firms switching from the NYSE to Nasdaq in the future.

[24] See Kalay and Portniaguina (2001) for a discussion of Aeroflex's move from the NYSE to Nasdaq.

there is more than one way in which the model can be used to motivate empirical definitions of such similarity, and we are using two separate definitions in our tests.

For the first definition of return similarity we interpret the private information in the model as information about common factors in returns. "Pure" Nasdaq stocks may be more sensitive to a certain common factor, say $\tilde{s}_1$, while "pure" NYSE stocks may be more sensitive to another common factor, $\tilde{s}_2$. According to this interpretation, the value innovation components modeled by θ_1, θ_2, and θ_3 represent unsystematic risk and are therefore uncorrelated with each other. Our model predicts that Nasdaq stocks that are eligible to list on the NYSE stay on Nasdaq if they are more sensitive to $\tilde{s}_1$ than to $\tilde{s}_2$, i.e., if $|a| > |b|$ (see Proposition 1). Similarly, NYSE stocks that are eligible to list on Nasdaq remain on the NYSE because their returns are more sensitive to $\tilde{s}_2$, like the other NYSE securities, than to $\tilde{s}_1$ ($|b| > |a|$). If managers of switching firms behave

Table 1
Summary statistics

Panel A: Sample for tests in Section 2.2

		AvgCap (in million $)	AvgPrc (in $)	AvgTurn (in %)	AvgVol (in $1000)	AvgRet (in %)
NNM1	Mean	5473.3	27.31	1.184	75415.8	0.020
	Median	785.3	22.51	0.878	6932.2	0.037
	Obs.	408	408	408	408	408
NYSE1	Mean	8015.9	90.34	0.500	33784.0	0.028
	Median	1409.8	25.20	0.406	6843.6	0.034
	Obs.	1155	1155	1155	1155	1155

Panel B: Switching sample for tests in Section 2.3

		AvgCap (in million $)	AvgPrc (in $)	AvgTurn (in %)	AvgVol (in $1000)	AvgRet (in %)
	Mean	2118.5	25.26	0.919	19078.9	0.043
	Median	952.5	23.65	0.606	7215.8	0.051
	Obs.	86	86	86	86	86

This table presents summary statistics for the samples used in the empirical work. The following variables are calculated for each security using data in CRSP: AvgCap is the average daily market capitalization (the number of shares outstanding multiplied by the daily closing price), AvgPrc is the average daily closing price, AvgTurn is the average daily turnover (the number of shares traded divided by the number of shares outstanding), AvgVol is the average daily dollar volume, and AvgRet is the average daily returns computed from closing prices. Panel A looks at the sample of securities that we use for the analysis in Section 2.2. We focus our analysis on two groups: (i) NNM1 are Nasdaq National Market common domestic stocks that were eligible to list on the NYSE on the first day of 2000 (408 stocks), and (ii) NYSE1 are NYSE common domestic stocks that were eligible to list on Nasdaq on the first day of 2000 (1155 stocks). The summary statistics are computed over the three-year sample period (2000–2002). Panel B presents the sample of switching firms that we use for the analysis in Section 2.3. The sample includes all firms with common domestic stocks that voluntarily switched from the Nasdaq National Market to the NYSE over the sample period (86 stocks). The summary statistics for each firm are computed over the year in which it switched listings.

optimally in the sense of enhancing liquidity, we should see prior to their move that they become more sensitive to $\tilde{s}_2$. The empirical methodology we use to examine this definition of return similarity is principal component analysis, where we look at the loadings of NYSE and Nasdaq securities on the principal components that constitute estimates of common sources of return variation.

Our second definition of return similarity interprets a private signal in the model as information that can be relevant to certain firms but not necessarily to the entire market. Since θ_i in the model could be correlated across securities, it can represent the stock-specific sensitivity to the market portfolio multiplied by the excess return on the market. Therefore, θ_i assumes the role of the common element in returns, while the independent signals, $\tilde{s}_1$ and $\tilde{s}_2$, induce some comovement in the returns of certain stocks even if they are not common to the entire economy.[25] Under this interpretation, we would obtain a cleaner picture of return variation due to $\tilde{s}_1$ and $\tilde{s}_2$ by removing the influence of the market portfolio and constructing empirical estimates of $|a|$ and $|b|$ from the absolute values of correlations of return residuals. These estimates could then be used to look at the implications of Proposition 1.

2.2 Similarity in return patterns: NYSE and Nasdaq stocks

In this section we look at the return patterns of NYSE and Nasdaq securities. First, we would like to see if the assumption of our model that the two markets differ in terms of the return patterns of the firms that are listed on them indeed holds. We also investigate in this section the "passive" decisions of firms to remain listed on a given market. If indeed these are optimal in the sense of our model (i.e., they enhance liquidity), then we should observe that stocks that are eligible to move to the other market but do not switch are more similar to securities listed on their market than to securities listed on the other market.

To carry out the tests, we create two additional groups of securities. NYSE2 consists of all securities that were continuously listed on the NYSE during the sample period and are not included in NYSE1. Similarly, NNM2 consists of all securities that were continuously listed on the Nasdaq National Market during our sample period and are not part of NNM1.[26]

We examine the first definition of return similarity using a principal component analysis. Because there are 752 days in the sample period and

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[25] This does not change if one adds uncorrelated sources of noise, ϵ_1 and ϵ_2, to the values of securities 1 and 2, respectively.

[26] NYSE2 and NNM2 include noncommon stocks (ADRs, REITs, etc.). We include them because market makers in our model can potentially learn useful information from all other securities that are listed on the same market. We see no reason to restrict the market makers' information set in the empirical work. We focus on common domestic stocks for NYSE1 and NNM1 in order to make the determination of eligibility to list on the other market less complex (and therefore to reduce potential misclassifications).

several thousand securities, we form 15 portfolios from the securities in each group (for a total of 60 portfolios).[27] Since each group contains a different number of securities, N, we randomly assign approximately $N/15$ securities to each portfolio. For example, the 1155 stocks in the NYSE1 group are divided into 15 portfolios containing 77 stocks each.[28] Portfolio returns are computed as averages of the daily returns on the stocks in the portfolio. We then perform a principal component analysis of daily portfolio returns in the three-year sample period, retain the first two principal components, and use an orthogonal rotation.[29] The procedure provides estimates of the loadings on the two principal components. These loadings can be interpreted as the bivariate correlations between the portfolios' returns and the principal components.

Panel A of Table 2 shows the means and standard deviations of the rotated factor loadings for the two markets and the four groups: NNM1, NNM2, NYSE1, and NYSE2. NYSE securities seem to load more heavily on the first principal component (0.797) than do Nasdaq securities (0.474). In contrast, Nasdaq securities load more heavily on the second principal component than do NYSE securities. A t-test demonstrates that the mean loading of NYSE securities is different from that of Nasdaq securities (p-value < 0.0001). Furthermore, the mean loading on the first component of the NNM1 group (Nasdaq common domestic stocks that are eligible to move to the NYSE) is closer to the mean of all other Nasdaq securities (NNM2) than to that of either of the NYSE groups. The same can be said of the common domestic stocks in NYSE1: their mean loading on the first principal component (0.868) looks more like that of other NYSE securities (0.726) than those of NNM1 (0.558) or NNM2 (0.389). A similar pattern is observed in the loadings on the second principal component (e.g., NYSE1 is closer in magnitude to NYSE2 than to NNM1 or NNM2).

The results of the principal component analysis are important in two respects. First, if we take the principal components to represent estimates of common factors, Nasdaq stocks are more sensitive to one factor ($\tilde{s}_1$) and NYSE stocks are more sensitive to another factor ($\tilde{s}_2$). This finding is consistent with the assumption that we use as the primitive of our

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[27] We aggregate securities into portfolios because the principal component analysis cannot identify loadings when the number of observations (days) is smaller than the number of variables (securities).

[28] We repeated the analysis with an equal number of securities in each of the 60 portfolios by randomly drawing without replacement 25 securities from each group to form each portfolio. The number of stocks was chosen such that even the smallest group (NNM1) would enable us to form 15 different portfolios with 25 stocks each. The results of this analysis were similar to the results presented below and are therefore not reported.

[29] We apply the commonly used VARIMAX rotation (see, for example, Kaiser 1958 and Hatcher 1994). To assist us in making the decision on how many principal components to retain, we used the tests proposed by Conway and Reinganum (1988) and Connor and Korajczyk (1993). The tests suggested retaining two principal components, which explain over 69% of the variance, both in the analysis here and in the analysis performed in Section 2.3.

2254

Table 2
Principal component analysis

Dependent variable	1st Principal component		2nd Principal component	
	Mean	Standard deviation	Mean	Standard deviation
NNM	0.474	0.095	0.768	0.104
NNM1	0.558	0.050	0.672	0.050
NNM2	0.389	0.029	0.863	0.014
NYSE	0.797	0.078	0.442	0.067
NYSE1	0.868	0.021	0.388	0.043
NYSE2	0.726	0.037	0.496	0.034

This table presents the principal component analysis of daily returns over the sample period (2000–2002). We use all securities that were traded on the Nasdaq National Market or the NYSE during the sample period. We separate the universe of securities into four groups: (i) NNM1 are Nasdaq National Market common domestic stocks that were eligible to list on the NYSE on the first day of 2000 (408 securities), (ii) NNM2 are all other Nasdaq National Market securities, (iii) NYSE1 are NYSE common domestic stocks that were eligible to list on Nasdaq on the first day of 2000 (1155 securities), and (iv) NYSE2 are all other NYSE securities. In order to carry out the principal component analysis we construct 15 equally weighted portfolios from each group (for a total of 60 portfolios). Let N be the number of securities in a group. Each portfolio contains $N/15$ securities. We retain the first two principal components of portfolio returns and use the orthogonal VARIMAX rotation to compute the loadings on the principal components. The table presents the means and the standard deviations of the estimated portfolio loadings for the four groups.

approach: that there are two groups of firms with different return patterns and each group is listed on a different market. Second, since our test looks separately at common domestic stocks that are eligible to move to the other market, we can say something about the optimality of managers' "passive" decision to remain listed on a market. We find that common domestic stocks that have the option to switch but opt not to do so have loadings that are more similar to those of other securities in the same market than to loadings of securities listed on the other market. The evidence is consistent with managers who are making optimal (passive) listing decisions by not moving to the other market.

We also carry out a test of the "passive" decisions using the second definition of similarity in return patterns that was discussed in Section 2.1. To remove the effect of common variability in returns and focus on $\tilde{s}_1$ and $\tilde{s}_2$, we run a market model for each security using daily returns over the sample period and the value-weighted portfolio of NYSE, AMEX, and Nasdaq stocks (from CRSP) as a proxy for the market portfolio. We then take the residuals from the market model (to eliminate the common variation in returns represented by θ_i) and normalize them to have unit variance.

Note that in the model, the comovement of the value innovations of asset 1 and asset 3 in market 1 after eliminating θ_1 and θ_3 is simply a. Similarly, the comovement of asset 2 and asset 3 in market 2 after

eliminating θ_2 and θ_3 is equal to b. Proposition 1 states that the difference between the absolute values of a and b determines the optimal choice of a manager between the two markets. Our market model procedure is meant to eliminate θ_i from the returns of all securities. Therefore, to estimate $|a|$, we compute for each stock in NYSE1 and NNM1 the correlation between its normalized residual and the normalized residuals of all securities in the NNM2 group. We denote the average of the absolute values of these correlations as $|\overline{a}_i|$. To estimate $|b|$, we compute for each stock in NYSE1 and NNM1 the correlation between its normalized residual and the normalized residuals of all securities in the NYSE2 group. We denote the average of the absolute values of these correlations as $|\overline{b}_i|$.

If Nasdaq common domestic stocks that are eligible to move to the NYSE optimally stay on Nasdaq, it should be that the average absolute value of their correlations with other Nasdaq securities (NNM2) is greater than the average absolute value of their correlations with the other NYSE securities (NYSE2). On the other hand, for eligible NYSE common domestic stocks we would predict that their estimates of $|\overline{b}_i|$ (the magnitude of comovement with NYSE2 securities) will be greater than their estimates of $|\overline{a}_i|$ (the magnitude of comovement with NNM2 securities). Therefore, we test whether $|\overline{a}_i| - |\overline{b}_i| > 0$ for NNM1 stocks and $|\overline{b}_i| - |\overline{a}_i| > 0$ for NYSE1 stocks.

Panel A of Table 3 provides the means and medians of $|\overline{a}_i|$, $|\overline{b}_i|$, and $|\overline{a}_i| - |\overline{b}_i|$ for the 408 NNM1 stocks. The t-test indicates that the mean of $|\overline{a}_i| - |\overline{b}_i|$ is positive and highly statistically significant (p-value < 0.0001). Similarly, a Wilcoxon signed-rank test shows that the median is positive and statistically significant. Panel B of Table 3 provides the results for the 1155 NYSE1 common domestic stocks. The mean and median of the differences $|\overline{b}_i| - |\overline{a}_i|$ are positive and highly statistically different from zero. Hence, all our findings in this section point to the conclusion that managers of firms choose to list their companies on the market where similar firms are listed, consistent with liquidity maximization. We qualify this conclusion, though, because so far we have only tested the "passive" choices of managers—where we infer the choice from the fact that no action was taken to move the stock to a different market. Next we examine the "active" decisions of managers to switch markets.

2.3 Tests using switching firms

In this section, we test the implications of our model using firms that switched from Nasdaq to the NYSE during the three-year sample period (2000–2002). Our model suggests that a stock's return pattern affects its liquidity via the interaction with other securities that are listed on the same market. If the return patterns of the stocks that switch changed to be less similar to those of other securities in the old market and more similar to

the return patterns of securities in the new market, the decision to switch markets could be motivated by the desire to improve liquidity.

The use of switching firms has another advantage in that it helps empirically to disentangle the implications of our model from an alternative explanation: that correlated liquidity trading is the driving force behind the return patterns we documented in Section 2.2. More specifically, say each market has its own class of liquidity (or noise) traders who trade the assets listed on their market but not assets listed on the other market. An example of such a trader is someone buying or selling index funds. As some indexes are market specific (e.g., the Nasdaq 100 Index), it is conceivable that cash flows into and out of such index funds, or creation and redemption of Exchange Traded Funds that follow market-specific indexes (e.g., the QQQ), may cause the prices of assets listed on the same market to move together.

We first look at what happens if correlated liquidity trading among assets that are listed on the same market is introduced into the model of

Table 3
**Correlation analysis of market model residuals**

Panel A: Nasdaq common domestic stocks eligible to switch (NNM1)

	$|\overline{a}_i|$	$|\overline{b}_i|$	$|\overline{a}_i| - |\overline{b}_i|$	*p*-value	Obs.
Mean	0.0458	0.0415	0.0042	< 0.0001	408
Median	0.0426	0.0408	0.0020	< 0.0001	408

Panel B: NYSE common domestic stocks eligible to switch (NYSE1)

	$|\overline{a}_i|$	$|\overline{b}_i|$	$|\overline{b}_i| - |\overline{a}_i|$	*p*-value	Obs.
Mean	0.0441	0.0451	0.0023	< 0.0001	1,155
Median	0.0416	0.0443	0.0031	< 0.0001	1,155

This table presents the analysis of correlation measures estimated from market model residuals. We use all securities that were traded on the Nasdaq National Market or the NYSE during the sample period (2000–2002). We separate the universe of securities into four groups: (i) NNM1 are Nasdaq National Market common domestic stocks that were eligible to list on the NYSE on the first day of 2000 (408 securities), (ii) NNM2 are all other Nasdaq National Market securities, (iii) NYSE1 are NYSE common domestic stocks that were eligible to list on Nasdaq on the first day of 2000 (1155 securities), and (iv) NYSE2 are all other NYSE securities. We run a market model for each security using daily returns over the sample period and the CRSP Value-Weighted Portfolio as a proxy for the market portfolio. We then take the residuals from the market models of all securities, normalize them to have unit variance, and compute for each stock in either NNM1 or NYSE1 the correlation between its normalized residual and the normalized residuals of all NNM2 securities. We denote the average of the absolute value of these correlations as $|\overline{a}_i|$. We also compute for each eligible stock in either NNM1 or NYSE1 the correlation between its normalized residual and the normalized residuals of all NYSE2 securities. We denote the average of the absolute value of these correlations as $|\overline{b}_i|$. Panel A presents the means and medians of $|\overline{a}_i|$, $|\overline{b}_i|$, and $|\overline{a}_i| - |\overline{b}_i|$ for the NNM1 group. The last column shows the *p*-values (against a two-sided alternative) of a *t*-test and a Wilcoxon signed-rank test for zero mean and median differences ($|\overline{a}_i|$-$|\overline{b}_i|$). Panel B presents the means and medians of $|\overline{a}_i|$, $|\overline{b}_i|$, and the difference between them for the NYSE2 group. The last column shows the *p*-values (against a two-sided alternative) of a *t*-test and a Wilcoxon signed-rank test for zero mean and median differences ($|\overline{b}_i| - |\overline{a}_i|$).

2257
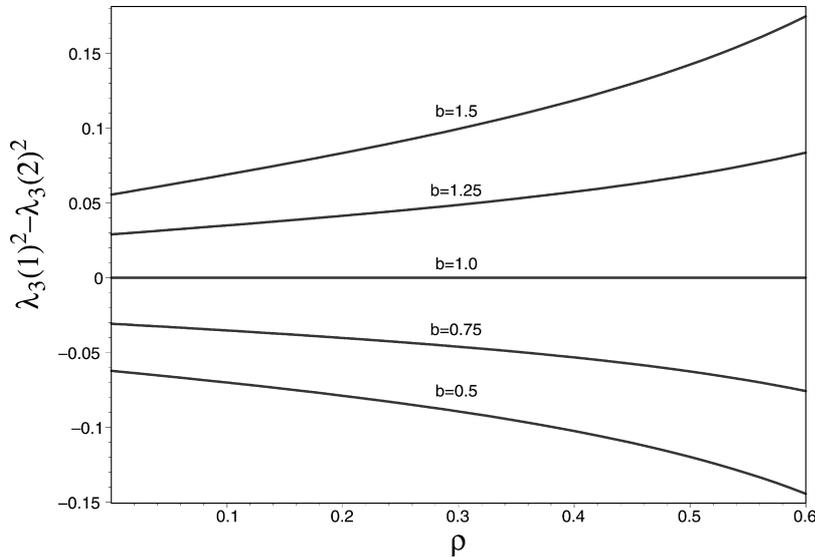
Figure 1
Differences across markets in the price impact of asset 3 with correlated liquidity trading
This figure presents the difference between the squared price impact of asset 3 when it is listed on market 1, $\lambda_3(1)^2$, and the squared price impact of asset 3 when it is listed on market 2, $\lambda_3(2)^2$, as a function of the correlation in the liquidity demand of the two assets in a market, ρ. When this difference is negative (positive), liquidity is better on market 1 (market 2). We fix the value of the sensitivity of asset 3 to s_1 ($a = 1$), and graph the difference in price impacts as a function of ρ for 5 values of the sensitivity of asset 3 to s_2: $b = 0.5, 0.75, 1.0, 1.25,$ and 1.5.

Section 1. Let ρ denote that correlation. Figure 1 shows how the difference $\lambda_3(1)^2 - \lambda_3(2)^2$ from Proposition 1 changes with ρ.[30] To maintain a two-dimensional figure, we fix $a = 1$ and draw 5 lines: two for $|a| > |b|$, two for $|a| < |b|$, and one for $|a| = |b|$. We see that the two curves for which $|a| > |b|$ are in the negative domain, implying better liquidity on market 1, and the difference $\lambda_3(1)^2 - \lambda_3(2)^2$ becomes more negative as ρ increases. The opposite happens when $|a| < |b|$: the two curves are in the positive domain, implying that liquidity is better on market 2, and the difference is monotonically increasing with ρ. Therefore, the main implication of our model (Proposition 1) still holds when correlated liquidity trading is considered.

From an empirical point of view, there are clear distinctions between our model and the correlated liquidity trading explanation. The model uses return patterns as a primitive and suggests that these determine optimal listing choices that reinforce the situation where firms listed on the same market have more similar return patterns. On the other hand, the alternative explanation takes the act of listing as a primitive and claims

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[30] The solution to the model with correlated liquidity trading is available from the authors upon request.

that listing on a market brings about correlated liquidity trading and thus induces similarity in the return patterns of the newly listed firm and other firms traded on the same market.[31] To examine the robustness of our conclusions to this alternative explanation, we use the switching firms to see whether changes in return patterns occur *before* a firm is listed on a market, and whether the listing decision is consistent with moving to a market populated by more similar firms.

There are a couple of issues that should be mentioned up front with respect to this exercise. First, there may be other reasons besides liquidity to switch markets (e.g., a preferred regulator). Switches that are motivated by other considerations would introduce noise into the tests and make it more difficult for us to find an effect. Second, there are really no guidelines for how long prior to a switch we should analyze the data to detect the changes in return patterns. It is reasonable to look at the year prior to the move, as the decision to move was probably made at that point, but the decision could have been made following a period in which the return pattern changed to be more like that of firms listed on the other market before managers decided to switch.[32] Therefore, the choice of a period to analyze prior to a switch is arbitrary in nature. With these reservations in mind, we proceed to use the methodologies from Section 2.2 to examine the return patterns of the stocks in the switching sample.

Our first test is based on the principal components methodology. The 86 firms that switched from Nasdaq to the NYSE did so at different points in time during the sample period. Ideally we should look at the time periods (say, 1 or 2 years) defined individually for each firm going back from its switch date. We are able to do that using our second definition of return similarity, which involves measures constructed from correlations of market model residuals. However, for the first definition of return similarity, which involves a principal component analysis, we need to have the same time interval for all stocks. Therefore, we use calendar time to define the periods we investigate. In other words, for the firms that switch in the year 2000 we look at the similarity of return patterns in calendar years 1999 (year $t-1$) and 1998 (year $t-2$). Similarly, for the firms that switch in the year 2001 we look at return patterns in calendar years 2000 and 1999, and for the firms that switch in 2002 we look at return patterns in 2001 and 2000.

The first step in our principal component methodology is to generate from the CRSP database a universe of all securities that were traded continuously each year (1998, 1999, 2000, and 2001) on either the NYSE

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[31] See also Chan, Hameed, and Lau (2003).

[32] One could also argue that managers may be able to foresee that their firms would become more similar to NYSE firms before the return pattern changes, and so the move would come in anticipation of this process. Of course, the implication of this interpretation is similar to that of the alternative explanation, so our tests would not be able to separate the two.

or the Nasdaq National Market (excluding the 86 stocks in our switching sample). To explain our procedure we will focus on the 21 stocks that switched in 2000. For these stocks, year $t - 1$ is 1999. As in Section 2.2, we form 30 portfolios from the securities in each market in 1999 (for a total of 60 portfolios) by randomly assigning approximately $N/30$ securities to each portfolio. We also form a switching portfolio by computing the equal-weighted returns in 1999 of the stocks that moved from Nasdaq to the NYSE in 2000. Using these 61 portfolios we then perform a principal component analysis of daily portfolio returns in 1999 and retain the loadings on the first two principal components.

We want to look at the "distance" of the switching portfolio's loading from the loadings of the NYSE and NNM portfolios, and how this distance changes over time. We therefore compute 30 distances of the switching portfolio's loading from NYSE stocks by taking the absolute value of the difference between the loading (say, on the first principal component) of the switching portfolio and the loadings on the same principal component of the 30 NYSE portfolios. Similarly, we compute 30 distances of the switching portfolio's loading from the loadings of the NNM portfolios. We repeat this process of randomly assigning securities into portfolios and performing a principal component analysis 100 times. This procedure is repeated for the same switching stocks using daily returns in 1998 to get their loadings in year $t - 2$. We then look at the 27 common domestic stocks that switched in 2001 and perform the same procedure to get the loadings in year $t - 1$ (2000) and year $t - 2$ (1999), and similarly for the 38 common domestic stocks that switched in 2002.

Panel A of Table 4 shows the mean, median, and standard deviation of the distances from the NYSE and NNM stocks across the 9000 observations (30 distances from each market times 100 random assignments times three years in the sample period) for the first principal component. The mean distance of the switching portfolio's loading from the loadings of the NYSE portfolios in year $t - 2$ is 0.2274, which is larger than the mean distance of the switching sample from the NNM portfolios, 0.1735. The statistical tests we perform are all highly significant, indicating that the distance of the switching sample from NYSE stocks is indeed larger than the distance of the switching sample from NNM stocks.[33] We repeat the same procedure for the year $t - 1$, and the results in Panel A of Table 4 indicate a pronounced shift. The average distance of the switching sample from NYSE stocks is smaller than its average distance from NNM stocks, and all statistical tests indicate that indeed the NYSE distance is significantly smaller.

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[33] We report several statistical tests of this hypothesis. First, we perform a t-test and a Wilcoxon signed-rank test using all 9000 observations. Second, we perform a separate test on each random draw (30 observations), average the magnitude of the t-statistic or the Z-statistic over the 300 random draws, and report the p-value associated with this average magnitude.

Table 4
Switching sample: principal component analysis
Panel A: analysis of loadings on 1st principal component

Distances	Year $t-2$		Year $t-1$	
	|NYSE-switching|	|NNM-switching|	|NYSE-switching|	|NNM-switching|
Mean	0.2274	0.1735	0.1894	0.2459
Median	0.1975	0.1224	0.1883	0.2688
Standard deviation	0.0903	0.1174	0.0920	0.0664
p-value of t-test (9000 Obs.)	< 0.0001		< 0.0001	
p-value of W-test (9000 Obs.)	< 0.0001		< 0.0001	
Avg. of 300 t-stat. (30 Obs.)	7.57		−6.10	
p-value of average t-stat.	< 0.0001		< 0.0001	
Avg. of 300 W-stat. (30 Obs.)	2.24		−2.14	
p-value of average W-stat.	0.0249		0.0323	

Table 4
(continued)

Panel B: Analysis of loadings on 2nd principal component

Distances	Year $t-2$		Year $t-1$	
	|NYSE-switching|	|NNM-switching|	|NYSE-switching|	|NNM-switching|
Mean	0.1615	0.1805	0.1045	0.2915
Median	0.1989	0.1940	0.0993	0.2854
Standard deviation	0.1023	0.0669	0.0703	0.0510
p-value of t-test (9000 Obs.)	< 0.0001		< 0.0001	
p-value of W-test (9000 Obs.)	< 0.0001		< 0.0001	
Avg. of 300 t-stat. (30 Obs.)	−7.75		−21.99	
p-value of average t-stat.	< 0.0001		< 0.0001	
Avg. of 300 W-stat. (30 Obs.)	−1.32		−6.56	
p-value of average W-stat.	0.1863		< 0.0001	

This table presents the principal component analysis of the switching sample. The 86-stock switching sample includes all firms with common domestic stocks that voluntarily switched from the Nasdaq National Market to the NYSE during our sample period (2000–2002). Since the principal component analysis necessitates looking at the same time period for all switches, we form a portfolio from the stocks that switch in each of the years (2000, 2001, and 2002) and look at how patterns of returns of the switching stocks differ from the return patterns of NNM and NYSE stocks in the two years prior to the calendar year in which the stocks switched. For example, we would compare the return patterns of the 21 stocks that switched in 2000 to return patterns of NNM and NYSE stocks in year $t-2$ (1998) and year $t-1$ (1999). In each of these calendar years we construct 30 random portfolios from each market (NNM and NYSE). Let N be the number of securities in a market. Each portfolio contains $N/30$ securities. We carry out a principal component analysis of 61 portfolios (30 from each market and one for the switching sample). We retain the first two principal components of portfolio returns and use the orthogonal VARIMAX rotation to compute the loadings on the principal components. We compute 30 distances of the switching portfolio loading from NYSE (NNM) stocks by taking the absolute value of the difference between the loading of the switching portfolio and the loadings on the same principal component of the 30 NYSE (NNM) portfolios. For each year, we repeat 100 times this procedure of randomly assigning securities into portfolios and performing the principal component analysis. This procedure is performed separately for the stocks that switched in each of the three years in the sample period. Panel A presents the mean, median, and standard deviation of the switching sample's distances from the NYSE and NNM securities across the 9000 observations (30 distances for each market times 100 random assignments times 3 years in the sample period) for the first principal component. We report several statistical tests of the hypothesis that the distance of the switching sample from NYSE securities is different from the distance of the switching sample from NNM securities. In the first set of t-tests and Wilcoxon signed-rank tests we use all 9,000 observations. In the second set we perform the tests separately on each random draw (30 observations), and then average the magnitude of the t-statistic or the Z-statistic over the 300 random draws (100 random draws for each portfolio of switching stocks in each year during the sample period) and report the p-value associated with this average magnitude. The p-values are against a two-sided alternative. Panel B presents the results for the second principal component.

Panel B of Table 4 shows that the directional change from year $t - 2$ to year $t - 1$ is the same for the second principal component as it is for the first principal component: the distance from NYSE stocks decreases and that from Nasdaq stocks increases. We tested the mean and median change from year $t - 2$ to year $t - 1$ of the NYSE and NNM distances, and the tests were highly statistically significant for both the first and second principal components. It appears that indeed the return patterns of the stocks in the switching sample become more similar to those of NYSE securities in the two years prior to joining the NYSE.[34]

Our next test is based on the second methodology of Section 2.2 (the market model residuals). We define three nonoverlapping one-year periods for each stock in the sample relative to the date it moved to the NYSE: from the switch date to one year prior to that date (period $t - 1$), from one year prior to the date to two years prior to the date (period $t - 2$), and from two years prior to the date to three years prior to the date (period $t - 3$). For each of the one-year periods prior to the switch and for each stock in the switching sample we compute $|\overline{a}_i|$ and $|\overline{b}_i|$. To do that, we run for each security on the NYSE and Nasdaq a daily market model in each calendar year (1997 through 2002) and save the normalized residuals. The measure $|\overline{a}_i|$ ($|\overline{b}_i|$) for stock i in the switching sample is defined as the average of the absolute values of the correlations of its normalized market model residuals with the normalized residuals of all Nasdaq (NYSE) securities (similar to what we did in Section 2.2).[35] Note that these correlations are computed over periods that are unique to stock i in that they are determined relative to its switch date.

Table 5 provides the cross-sectional means and medians of $|\overline{b}_i| - |\overline{a}_i|$ for the 86 stocks in our switching sample in each of the one-year periods, as well as p-values from a t-test and a Wilcoxon signed-rank test against the hypothesis of a zero difference. In period $t - 3$, the mean magnitude of the difference is 0.0025, and it increases to 0.0041 in period $t - 2$ and 0.0042 in period $t - 1$. The same pattern is observed with the median difference. The increase in the mean and median differences from period $t - 3$ to period $t - 2$ is statistically significant with a t-test (Wilcoxon test) p-value of 0.014 (0.015). The statistical tests in the table show that the means and medians of $|\overline{b}_i| - |\overline{a}_i|$ are significantly different from zero in all periods.

To summarize, both methodologies provide evidence that the return patterns of stocks that switch from Nasdaq to the NYSE become more similar to the return patterns of securities listed on the NYSE *prior* to

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[34] Note that we do not need to utilize a separate control sample in order to establish this result because our methodology uses all securities listed on each market as a control, and our tests compare differences between our sample and these controls.

[35] If there are fewer than 3 months of daily returns common to a sample switching stock and a Nasdaq or NYSE security in any given one-year period, we do not include the correlation between them in the computation of $|\overline{a}_i|$ or $|\overline{b}_i|$.

switching. In fact, this change is documented up to 2 years before moving to the NYSE and hence is likely to have been underway when the decision to switch was made. These findings have two implications for our discussion. First, they document a change in return patterns prior to a decision to switch listings, which is consistent with our model where return patterns affect the listing decision. Second, they show a shift to having return patterns more similar to NYSE stocks prior to the sample stocks' actually moving to list on the NYSE. This supports the conclusion that managers switch markets to enhance the liquidity of their stocks. The results of this section are therefore consistent with our findings in Section 2.2 that managers of firms choose to list their firms on the market where similar firms are listed. Our model would suggest that these choices are optimal with respect to their stocks' liquidity.

2.3.1 Robustness tests. We performed additional tests to examine the robustness of our conclusions. The first robustness test was to look at the similarity of the switching stocks to NYSE and Nasdaq securities after the switch. In the previous section we examined the return patterns of the switching stocks before the switch because only prior to the move itself did our model have implications different from those of the correlated

Table 5
Switching sample: correlation analysis of market model residuals

	Period $t - 3$	Period $t - 2$	Period $t - 1$
Mean	0.0025	0.0041	0.0042
Median	0.0010	0.0020	0.0031
p-value (t-test)	0.0007	0.0000	0.0000
p-value (Wilcoxon test)	0.0047	0.0000	0.0000

This table presents the analysis of correlation measures estimated from market model residuals for the switching sample. The 86-stock switching sample includes all firms with common domestic stocks that voluntarily switched from the Nasdaq National Market to the NYSE during our sample period (2000–2002). We use CRSP to identify all securities traded on the NYSE and the Nasdaq National Market from 1997 through 2002. We run for each security a daily market model in each calendar year, and normalize the residuals to have unit variance. We define three nonoverlapping one-year periods for each stock in the switching sample relative to the date it moved to the NYSE: from the switch date to one year prior to that date (period $t - 1$), from one year prior to the date to two years prior to the date (period $t - 2$), and from two years prior to the date to three years prior to the date (period $t - 3$). For each of the one-year periods prior to the switch and for each stock in the switching sample we compute the correlation between the stock's normalized residual and the normalized residuals of all Nasdaq securities. We denote the average of the absolute value of these correlations as $|\overline{a}_i|$. We also compute for each stock in the switching sample in each one-year period the correlation between its normalized residual and the normalized residuals of all NYSE securities. We denote the average of the absolute value of these correlations as $|\overline{b}_i|$. We present the mean and median of $|\overline{b}_i| - |\overline{a}_i|$ for the 86 stocks in our switching sample in each of the one-year periods, as well as p-values from a t-test and a Wilcoxon signed-rank test against the two-sided hypothesis of a zero difference.

liquidity trading explanation. However, one could claim that we should also look at return patterns after the move because finding that the switching stocks become less similar to NYSE securities and more similar to Nasdaq securities would be inconsistent with our conclusions.

Therefore, we carried out analysis of return patterns in periods $t + 1$ and $t + 2$ using the same methodologies: the principal component analysis and the correlations of market-model residuals.[36] We found that the mean distance of the switching stocks' loading (on either principal component) from the loadings of NYSE securities was significantly smaller than their mean distance from the loadings of Nasdaq securities in both $t + 1$ and $t + 2$. If at all, the loadings on the second principal component showed that the switching stocks became even more similar to NYSE securities and less similar to Nasdaq securities in $t + 2$. The analysis using the correlations of market-model residuals showed that the similarity in return patterns stabilized after the move and the magnitude of $|\overline{b}_i| - |\overline{a}_i|$ in years $t + 1$ and $t + 2$ did not change. Hence, we could not find evidence in return patterns after the switch that would contradict our conclusions.

The second robustness test that we performed looked at a different prediction of our model. Theorem 1 shows that the equilibrium price of asset 3 is a function of both the order flow of asset 3 and the order flow of the other asset that is listed on the same market. It can be shown that if $|a| > |b|$, then the sensitivity of asset 3 to the order flow of asset 1 (when asset 3 is listed on market 1) is greater than the sensitivity of asset 3 to the order flow of asset 2 (when asset 3 is listed on market 2). This implication is reversed when $|b| > |a|$. Greater sensitivity to the order flow of the other asset in the market (represented by the off-diagonal entries of the matrix Λ in Equation (A3)) means that market makers are able to learn more information that is relevant for the pricing of asset 3 from the order flow of the other asset in the market. We looked at whether it is possible to empirically detect a change in that sensitivity when stocks switch markets.[37]

There are a couple of issues that should be pointed out with respect to such an investigation. First, market makers in our model can learn from the order flow only after a stock is listed on their market. Hence, we should see the most change between $t - 1$ and $t + 1$, which is also when correlated liquidity trading could cause the stock's return to be more sensitive to order flow of other securities that are listed on the same market. Unlike our tests with return patterns, this robustness test does not differentiate our model's implications from the correlated liquidity trading explanation.

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[36] For the principal component analysis, the periods were defined in terms of calendar time (i.e., $t + 1$ is the year following the calendar year in which the move from Nasdaq to the NYSE took place). For the correlations of market-model residuals, $t + 1$ was defined as the one-year period starting immediately after the switch date.

[37] We thank the referee for suggesting this robustness test.

Second, the volume figures reported by Nasdaq and the NYSE are not necessarily comparable owing to the more active presence of dealers on Nasdaq (see, for example, Atkins and Dyl 1997). It is therefore not obvious that coefficients from regressions of returns on order flow can be compared across the two markets, even if we attempt to normalize the order flow relative to the total volume of trading in each market.

With these reservations in mind, we carried out the following experiment. We used the TAQ database to obtain trade and quote information for all securities traded on the NYSE and the Nasdaq National Market from 1998 through 2004. We signed all trades using the Lee and Ready (1991) algorithm, and aggregated the dollar volume of all buys and sells (with positive sign for buys and negative sign for sells) to get a net dollar imbalance number for each security on each day. We then computed the equal-weighted dollar imbalance of all NYSE securities (excluding our sample switching stocks) to get a daily measure of the signed order flow of NYSE securities. We created a similar signed order flow measure for Nasdaq securities. Then, we ran for each stock in the switching sample and for each 1-year period ($t-2$, $t-1$, $t+1$, and $t+2$) one regression of daily returns on NYSE signed order flow and another regression of daily returns on Nasdaq signed order flow.[38] We computed for each stock in each 1-year period the difference between the coefficient on NYSE's order flow and the one on Nasdaq's order flow.

The mean difference of the coefficients in period $t-2$ ($t-1$) was -0.0122 (-0.0137). There was a pronounced change after the switch: -0.0064 in $t+1$ and -0.0026 in $t+2$. This change indicates that the coefficient on NYSE's order flow increased and the one on Nasdaq's order flow decreased after the stocks moved from Nasdaq to the NYSE.[39] In order to account for possible differences in the volume figures between Nasdaq and the NYSE, we created another order flow variable by dividing the dollar imbalance measure of a market every day by the average dollar volume of the securities listed on that market (from the CRSP database). We ran the same regressions and the mean difference of the coefficients showed an even more pronounced increase from 0.0275 in period $t-1$ to 0.1687 in period $t+1$, indicating that the stocks became more (less) sensitive to order flow in the new (old) market in a manner consistent with the prediction of our model.

2.3.2 Changes in liquidity of switching stocks. While our approach relates return patterns to liquidity, the main body of empirical work in this article

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[38] The periods were defined individually for each switching stock relative to its switch date.

[39] The pricing equation that comes from our model has the stock's own order flow in addition to the market's order flow. We therefore ran another specification where we added the stock's own order flow as another regressor. The results were nearly identical and showed exactly the same change around the switch date.

involves looking at returns rather than at liquidity measures. The reason for this is that the optimal listing decision of managers should be based on similarity in return patterns and hence studying their choices necessitates looking at return patterns. Nonetheless, the end result of an optimal listing decision is better liquidity and so a natural question to ask is whether managers of firms that switch do in fact improve the liquidity of their stocks.

Our finding that the return patterns of firms switching to the NYSE move in the direction of being more similar to the return patterns of securities already listed on the NYSE suggests that the managers' switching decision should result in a liquidity gain. There is ample evidence in the literature that liquidity improves when stocks move from Nasdaq to the NYSE (e.g., Christie and Huang 1994; Kadlec and McConnell 1994; Barclay 1997; Barclay, Kandel, and Marx 1998; Elyasiani, Hauser, and Lauterbach 2000; and Bessembinder and Rath 2002). Therefore, finding an improvement in liquidity for our sample of switching stocks would not be surprising and hence could hardly be considered a test of the model. However, there is a way in which we can potentially use liquidity measures to examine the implications of our model. Since the degree of liquidity improvement should be greater the more similar the switching stock is to NYSE securities, we could partition the sample along the similarity dimension and look at differences in the degree of liquidity improvement.

We therefore use the TAQ database to compute four standard liquidity measures for each of the switching stocks over two time intervals: 100 days prior to the switch (pre-switch period) and 100 days after the switch (post-switch period). The four measures we compute are the average quoted spread, the average relative quoted spread (quoted spread divided by the midquote), the average effective spread (average of the distances from each trade's price to the midquote prevailing at the time of the trade), and the average relative effective spread (effective spread divided by the midquote). The first two rows of Table 6 show that the four price impact measures decrease significantly for the switching stocks from before to after the move to the NYSE. This evidence of improved liquidity is consistent with our findings on the optimal listing choice and also with prior studies that looked at liquidity changes when Nasdaq stocks move to the NYSE.

Next, we sort the sample by a measure of the similarity of the return pattern of the switching stock to the return patterns of NYSE securities, $|\bar{b}_i|$. We then divide the sample into quartiles and look at changes in the liquidity measures separately for the top quartile (relatively more similar to the return patterns of NYSE securities) and the bottom quartile (relatively less similar to the return patterns of NYSE securities). The numbers in Table 6 demonstrate that the improvement in liquidity is greater for stocks in the top quartile. The last line of the table provides a t-test for the difference in means between the top and bottom quartiles. We observe

2267

a statistically significant difference between the two quartiles for all four liquidity measures. These results provide further evidence consistent with our approach whereby similarity in return patterns for stocks listed on the same market affects their liquidity.

3. Conclusion

In this article we provide an explanation for the listing choice of firms based on asset returns. To make this point very clear, our model features two markets with the same structure and price-setting rule. As a primitive of the problem we assume that securities listed on the two markets differ with respect to their return patterns. There are many ways in which such a situation can arise. For example, it may be caused by listing requirements: one market sets listing requirements that are met only by very large firms, while another market tries to attract small start-ups. Examples of markets that cater to different firms exist around the world and reflect a multitude of business models and marketing decisions. The end result is that more related firms tend to be traded on the same market.

We would like to emphasize that our approach can coexist with other potential influences on the listing decision that have been discussed in

Table 6
Switching sample: analysis of changes in liquidity measures

		Quoted spread (cents)	Relative quoted spread (%)	Effective spread (cents)	Relative effective spread (%)
Entire sample	Mean change	−7.91	−0.23	−6.97	−0.22
t-test (Mean change$\neq$0)	p-value	0.0003	0.0035	< 0.0001	0.0001
Higher $|\overline{b}_i|$ quartile	Mean change	−8.03	−0.28	−8.39	−0.34
Lower $|\overline{b}_i|$ quartile	Mean change	−3.06	−0.04	−2.54	−0.06
t-test (higher $\neq$ lower)	p-value	0.0007	0.0170	0.0066	0.0227

This table presents the analysis of changes in liquidity measures for the switching sample. The 86-stock switching sample includes all firms with common domestic stocks that voluntarily switched from the Nasdaq National Market to the NYSE during our sample period (2000–2002). We use the TAQ database to compute four measures of liquidity for each of the switching stocks over two time intervals: 100 days prior to the switch (pre-switch period) and 100 days after the switch (post-switch period). The four measures we compute are the average quoted spread, the average relative quoted spread (quoted spread divided by the midquote), the average effective spread (average of the distances from each trade's price to the midquote prevailing at the time of the trade), and the average relative effective spread (effective spread divided by the midquote). The first two rows present the mean change (post-switch minus pre-switch) in the four liquidity measures for all sample stocks as well as p-values from a t-test against a two-sided hypothesis of a zero change. We then sort all stocks according to the degree of similarity between each stock's return pattern and the return patterns of NYSE securities in the year prior to the switch. We use for that the $|\overline{b}_i|$ measure described in Section 2.3 (the average of the absolute values of the correlations between a stock's normalized return residual and the normalized return residuals of all NYSE securities). We then divide the sample into quartiles and look at changes in the liquidity measures separately for the top quartile (relatively more similar to the return patterns of NYSE securities) and the bottom quartile (relatively less similar to the return patterns of NYSE securities). We present the mean change in the liquidity measures for the top and bottom quartiles with p-values from a t-test of equality of means between the top and bottom quartiles.

the literature (e.g., listing requirements, market structure, or corporate governance regulation). What makes our approach unique is that it does not require such differences across markets in order to have an optimal listing decision. What we do is to identify a specific mechanism that creates an optimal listing choice when stocks with different return patterns are listed on different markets. In fact, that mechanism will tend to perpetuate itself (firms will continue to list on the market where similar firms are listed) and therefore can create path-dependence even if the reason for the initial clustering of similar firms on a market no longer exists.

Our model suggests that by making optimal listing decisions, managers can help reduce the adverse selection costs incurred by investors who trade their firms' stocks. Indeed, managers often cite liquidity as a factor in choosing a market.[40] Firms listed on the Deutsche Börse even pay Designated Sponsors to act as market makers for the firms' stocks in order to enhance their liquidity. A primary reason for managers to care about liquidity is if they maximize shareholder wealth and liquidity is priced. However, even if liquidity is not priced directly (i.e., it does not affect the firm's cost of capital), there may be other reasons for a manager to care about liquidity. For example, liquid stocks may attract a larger investor base, which would make it easier for the firm to issue more equity and negotiate a lower underwriting fee (see Butler, Grullon, and Weston 2005). Irrespective of the specific rationale that makes managers care about liquidity, our empirical results suggest they do.

We test our model on the two dominant markets in the U.S.: NYSE and Nasdaq. We first consider whether the basic assumption of our model—that there are two groups of firms with different return patterns each listed on a different market—holds for the NYSE and Nasdaq. We show that Nasdaq securities load more heavily on one principal component of returns while NYSE securities load more heavily on another principal component, consistent with the assumption of the model. We also show that the loadings of Nasdaq common domestic stocks that are eligible to list on the NYSE look more similar to those of other Nasdaq securities than to those of NYSE securities; NYSE common domestic stocks that are eligible to list on Nasdaq look more like other NYSE securities than Nasdaq securities. We then use correlations of market model residuals to define similarity of return patterns in a different manner, and reach the same conclusions. The results of these tests suggest that the "passive" choice made by managers of eligible firms not to switch markets is optimal. By that we mean that the return patterns of eligible stocks that remain

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[40] See, for example, the surveys by Baker and Pettit (1982), Freedman and Rosenbaum (1987), and Baker and Johnson (1990).

2269

listed on their market despite the ability to switch are such that staying put is indeed the liquidity-maximizing thing to do.

We then turn to tests of managers' "active" choices by looking at firms that switch markets. We find that the return patterns of stocks in the sample change *before* the actual change in listings (and possibly before the decision on the change in listings was made), and that the change makes them more similar to stocks listed on the new market. These results are consistent both with our model, where return patterns affect listing decisions, and with our conclusion that managers act to enhance liquidity by their choice of where to list their stocks. Furthermore, we document that the liquidity of the stocks improves upon moving to the new market, and that the greatest improvement in liquidity is experienced by the stocks most similar to those traded on the new market.

Probably the main insight that comes from the empirical work is that managers seem to make listing decisions as if they care about liquidity. We are able to test that by looking mostly at nonliquidity variables (return patterns) because our model provides a relation going from patterns in value innovations to liquidity (or the price impact of market orders). The model provides yet another insight that may aid markets and regulators in making decisions about listing policies. A new listing generates a positive externality for the firms already listed on a market: the liquidity of the existing asset in the model improves when the new asset lists because market makers can learn private information about the value innovation that is common to both assets. Managers who decide on the listing venue for their firms may not take that effect into account when making their choices. Hence, deciding on a listing venue using a different criterion (not liquidity maximization) could be socially suboptimal in that it may prevent the improvement in liquidity that the other stocks would experience if the decision were made on the basis of return patterns. Already-listed firms (or exchange officials) may therefore have an incentive to lure new firms that they consider "similar" so that everyone benefits from that positive externality. Attracting groups of similar firms may also be a way for competing markets to impose switching costs on listed firms (since switching would result in worsened liquidity).

Our work demonstrates how corporate decision making can be influenced by the return pattern of the firm's stock and its relation to return patterns of other securities in the market. The connection we form between asset pricing and corporate finance goes through market microstructure and shows how the investigation of imperfections in the trading environment of assets may hold some clues to the relation between asset returns and decision making within the firm.

2270

Appendix A:

Proof of Theorem 1. Without loss of generality, assume that the value of the assets prior to the innovation is zero ($\mu = 0$). Conjecture that the price rule is linear. Then, the ith informed trader problem is

$$\max_{X_i \in R^2} E[(V - \Lambda Y)X_i|s_i].$$

Because (i) $cov(\tilde{s}_1, \tilde{s}_2) = 0$, ($ii$) $\tilde{S}$ has zero mean, and (iii) the other informed trader follows a linear strategy, we have

$$E[(V - \Lambda Y)X_i|s_i] = E[(E[V|s_i] - \Lambda X_i)X_i|s_i].$$

The first-order condition implies

$$X_i = (\Lambda + \Lambda^T)^{-1} E[\tilde{V}|s_i].$$

Thus, the strategy of the ith trader is also linear. Also

$$X = X_1 + X_2 = (\Lambda + \Lambda^T)^{-1} E[\tilde{V}|s_1] + (\Lambda + \Lambda^T)^{-1} E[\tilde{V}|s_2] = (\Lambda + \Lambda^T)^{-1} FS.$$

We therefore have $\beta = (\Lambda + \Lambda^T)^{-1} F$ in the first equation of (2). From the theory of linear filtering (see, for example, Theorem 1.1.1 in Bensoussan (1992)) it follows that the matrix Λ is given by the second Equation in (2).

To solve the system, we guess (and verify later) that Λ is symmetric. From the first equation in (2), we have

$$\beta = 0.5\Lambda^{-1}F. \tag{A1}$$

Multiply the second equation from the left by Λ^{-1}, and insert β to get

$$I = 2\beta\beta^T(I + \beta\beta^T)^{-1}.$$

Multiply both sides from the right by $(I + \beta\beta^T)$ to get

$$I + \beta\beta^T = 2\beta\beta^T.$$

Subtract $\beta\beta^T$ from both sides:

$$I = \beta\beta^T.$$

Insert the above in (A1) to get

$$\frac{1}{4}FF^T = \Lambda\Lambda. \tag{A2}$$

The matrix equation in (A2) has more than one solution. The linear equilibrium is the one in which $-\Lambda$ is negative semi-definite. This solution is given below.[41]

$$\Lambda = \begin{pmatrix} \frac{(1+|b|)}{2\sqrt{a^2+(1+|b|)^2}} & \frac{a}{2\sqrt{a^2+(1+|b|)^2}} \\ \frac{a}{2\sqrt{a^2+(1+|b|)^2}} & \frac{a^2+|b|(1+|b|)}{2\sqrt{a^2+(1+|b|)^2}} \end{pmatrix} \tag{A3}$$

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[41] In particular, we verify that Λ is indeed symmetric, and that Λ is positive semi-definite: $\Lambda_{11} > 0$, $\Lambda_{22} > 0$ and $\Lambda_{11}\Lambda_{22} - \Lambda_{12}\Lambda_{21} = \frac{1}{4}|b| > 0$.

Appendix B:

The listing requirements of the New York Stock Exchange and the Nasdaq National Market can be found on their respective Web sites. We use data in CRSP and COMPUSTAT to identify Nasdaq National Market common domestic stocks that were eligible to list on the NYSE on January 1, 2000, and NYSE common domestic stocks that were eligible to list on Nasdaq on that date. Below we provide the specific data items from CRSP and COMPUSTAT that we use for the listing criteria of each market.

Database Definitions for Nasdaq National Market Listing Requirements

- Net Tangible Assets:[42] COMPUSTAT (Data 6 − Data 181 − Data 204)
- Market Capitalization: CRSP (|prc|∗curshr, 90 consecutive days ending December 31, 1999)
- Total Revenue: COMPUSTAT (Data 12)
- Total Assets: COMPUSTAT (Data 6)
- Income from Continuing Operations before Income Taxes: COMPUSTAT (Data 170)
- Public Float (shares): CRSP (curshr, on December 31, 1999)
- Market Value of Public Float: CRSP (|prc|∗curshr, on December 31, 1999)
- Shareholders: COMPUSTAT (Data 100)
- Minimum Bid Price: CRSP (|prc|, 90 consecutive days ending December 31, 1999)

Database Definitions for New York Stock Exchange Listing Requirements

- Shareholders: COMPUSTAT (Data 100)
- Average Monthly Trading Volume: CRSP (vol, average in 1999)
- Public Shares: CRSP (curshr, on December 31, 1999)
- Market Value of Public Shares: CRSP (|prc|∗curshr, on December 31, 1999)
- Pre-tax Earnings: COMPUSTAT (Data 170 − Data 49 + Data 55)
- Market Capitalization: CRSP (|prc|∗curshr, average in 1999)
- Total Revenue: COMPUSTAT (Data 12)
- Operating Cash Flow: COMPUSTAT (Data 308 − Data 307 − Data 304 − Data 303 − Data 302)

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[42] On June 29, 2001, Nasdaq replaced the Net Tangible Assets requirement with a Stockholders' Equity requirement.

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