ESSAYS ON EQUITY PRICES AND MARKET STRUCTURES

A Dissertation

by

JUAN WU

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2007

Major Subject: Finance

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Approved by:

Chair of Committee, Ekkehart Boehmer
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ABSTRACT

Essays on Equity Prices and Market Structures. (August 2007)

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In the first essay, we provide new evidence on the relationship between order flow and prices, an issue that is central to asset pricing and market microstructure. We examine proprietary data on a broad panel of NYSE-listed stocks that reveal daily order imbalances by institutions, individuals, and market makers. We can further differentiate regular institutional trades from institutional program trades. Our results indicate that order imbalances from different trader types play distinctly different roles in price formation. Institutions and individuals are contrarians with respect to previous-day returns but differ in the effect their order imbalances have on contemporaneous returns. Institutional imbalances are positively related to contemporaneous returns, and cross-sectional evidence suggests this relationship is likely to be the result of firm-specific information institutions have. Individuals, specialists, and other market makers appear to provide liquidity to these actively trading institutions. Our results also suggest a special role for institutional program trades. Institutions choose program trades when they have no firm-specific information and can afford to trade passively. As a result, program trades provide liquidity to the market. Finally, both institutional non-program and individual imbalances have predictive power for next-day returns. In the second essay, based on daily shorting flow data for a large sample of NYSE-listed stocks, we show that short sellers enhance the relative efficiency of transaction prices. We also provide new evidence on the recent suspension of the Uptick Rule for Regulation SHO Pilot stocks. Relative to matched control stocks, pilot stocks experience some improvement in price efficiency associated with increased shorting activity after the tick test was suspended. The third essay studies demutualization of stock exchanges. Using panel data on 132 major stock exchanges in 114 countries from 1990 to 2003, we examine the effect of demutualization on an exchange's performance in its primary product markets: trading and listings. We document some evidence that demutualization is associated with improved competitiveness in attracting trading volume. Results on listings following demutualization are weak.

To my parents

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CHAPTER I

INTRODUCTION

This dissertation consists of three essays on equity prices and market structures. The first essay is titled “Order Flow and Prices.” In this essay, we provide new evidence on the relationship between order flow and prices, an issue that is central to asset pricing and market microstructure. We examine proprietary data on a broad panel of NYSE-listed stocks that reveal daily order imbalances by institutions, individuals, and market makers. We can further differentiate regular institutional trades from institutional program trades. Our results indicate that order imbalances from different trader types play distinctly different roles in price formation. Institutions and individuals are contrarians with respect to previous-day returns, but differ in the effect their order imbalances have on contemporaneous returns. Institutional imbalances are positively related to contemporaneous returns, and cross-sectional evidence suggests this relationship is likely to be the result of firm-specific information institutions have. Individuals, specialists, and other market makers appear to provide liquidity to these actively trading institutions. Our results also suggest a special role for institutional program trades. Institutions choose program trades when they have no firm-specific information and can afford to trade passively. As a result, program trades provide liquidity to the market. Finally, both institutional non-program and individual imbalances (information which is not available to market participants) have predictive power for next-day returns.

This dissertation follows the style of *Journal of Finance.*

The second essay is titled “Short Selling and the Informational Efficiency of Prices.” One of the continuing controversies in financial economics concerns the effect of short selling on the informational efficiency of share prices. Based on daily shorting flow data for a large sample of NYSE-listed stocks, we show that short sellers enhance the relative efficiency of transaction prices. We also provide new evidence on the recent suspension of the Uptick Rule for Regulation SHO Pilot stocks. Relative to matched control stocks, pilot stocks experience some improvement in price efficiency associated with increased shorting activity after the tick test was suspended.

The third essay is titled “Demutualization and Stock Exchange Performance.” Demutualization of stock exchanges, a process of transforming member-owned not-for-profit cooperatives into shareholder-owned for-profit corporations, is one of the most recent trends in the exchange industry around the world. Using panel data on 132 major stock exchanges in 114 countries from 1990 to 2003, we examine the effect of demutualization on an exchange’s performance in its primary product markets: trading and listings. We document some evidence that demutualization is associated with improved competitiveness in attracting trading volume. Results on listings following demutualization are weak.

CHAPTER II

ORDER FLOW AND PRICES

A. Introduction

A central prediction of market microstructure theory is that order flow affects prices. This follows from inventory models, where market makers temporarily adjust prices in response to incoming orders (Garman, 1976; Amihud and Mendelson, 1980; Stoll, 1978; Ho and Stoll, 1981). It also follows from information-based models where some traders have information about future asset value, so their trades lead to permanent price adjustments (Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987). The prediction that order flow affects prices is robust to competition among informed traders (Holden and Subrahmanyam, 1992), endogenous order sizes (Back and Baruch, 2005), and the consideration of strategic uninformed traders (Admati and Pfleiderer, 1988; Spiegel and Subrahmanyam, 1992).

Empirical research is almost uniformly consistent with this basic prediction and generally supports both inventory and information effects. For example, Ho and Macris (1984) document that an options specialist adjusts prices in a way that is consistent with inventory models. Hasbrouck (1988, 1991a, 1991b) uses VAR models to disentangle (transient) inventory effects from (permanent) information effects. He demonstrates significant information effects on prices and some evidence consistent with inventory adjustments. More recent studies focus on daily net order flow, the difference between buy and sell volume, to explain contemporaneous and next-day returns. Chordia, Roll, and Subrahmanyam (2002) show that aggregate order imbalance is positively associated with market returns, and Chordia and Subrahmanyam (2004) obtain comparable results in the cross-section of stocks.[1]

While microstructure theory clearly distinguishes among different trader types according to their information and motives for trading, data limitations typically limit empirical tests to analysis that pools all traders. In this paper, we use a unique dataset derived from NYSE audit trail data that allows us to distinguish buys and sells from different trader types: individuals, institutions, non-NYSE market makers, and specialists. We further differentiate regular institutional trades, index arbitrage program trades, and other program trades.[2] These types are likely to differ in their trading motives and trading strategies and, in particular, in the quantity and quality of their private information. Therefore, we expect that the relationship between order flow, liquidity, and returns differs across these trader types, and our tests are designed to measure these differences. Understanding how trader type-specific order flow affects prices and liquidity has important implications for modeling the evolution of liquidity, trader behavior, and market design. Moreover, analyzing these differences allows us to refine inferences from empirical microstructure research that is based on aggregate data.

[1] A related literature focuses on the relation between trading volume and returns, see Baker and Stein (2004), Campbell, Grossman, and Wang (1993), Chordia, Roll, and Subrahmanyam (2001), Chordia, Huh, and Subrahmanyam (2004), and Llorente et al. (2002). Karpoff (1987) surveys earlier work.

[2] Program and index arbitrage program trades are institutional trades but we differentiate these from regular institutional trades. First, the NYSE defines program trades as simultaneous trades in 15 or more stocks worth at least $1 million. In contrast, the typical trade size on the NYSE is about $20,000. Second, trading motives differ. Index arbitrage program trading attempts to profit from the temporary discrepancies between derivative and cash markets, whereas regular program trading can be associated with other specific trading strategies. Third, regulatory treatment differs across these order types. Both types of program trade must be reported to the exchange, and NYSE Rule 80A suspends some type of index arbitrage program trades on volatile trading days.

Our analysis is closely related to Chordia and Subrahmanyam (2004) and Griffin, Harris, and Topaloglu (2003).[3] Chordia and Subrahmanyam develop a two-period trading model where a competitive discretionary liquidity trader can split orders between two periods. In addition, a nondiscretionary liquidity trader and a competitive informed trader, who receives a noisy signal before trading, submit orders in the second period. A competitive market maker picks up the imbalance resulting in each trading period. Chordia and Subrahmanyam show that it is optimal for the discretionary liquidity trader to split orders, so that order imbalances are positively autocorrelated over time. Moreover, because market makers can partially predict the second-period order imbalance, the model implies a positive relationship between returns and lagged imbalances. Using a sample of (on average) 1322 NYSE-listed stocks between 1988 and 1998, Chordia and Subrahmanyam estimate security-specific time series regressions and find evidence consistent with these predictions.[4]

Griffin, Harris, and Topaloglu observe the identity of brokerage firms in Nasdaq 100 stocks for each trade over 210 trading days from May 2000. They classify brokers according to their main clientele, and in this way obtain an approximate classification

[3] In a broader sense, our analysis is related to several other studies that address differences in order imbalances across trader types. Griffin, Harris, and Topaloglu (2005) study aggregate order imbalances of various types of Nasdaq traders around the “tech bubble.” Lee (1992) examines order imbalances around earnings announcements to see if institutional investors react differently from individual investors to the same earnings news using trade sizes as proxies for institutions and individuals. Several papers examine similar issues in other countries. Lee et al. (2004) examine marketable order imbalances from various investor categories on the Taiwan Stock Exchange. Grinblatt and Keloharju (2000) investigate the trading behavior of Finnish investors. Choe, Kho and Stulz (1999) analyze order imbalances to investigate if foreign investors contribute to the Korean stock market crisis in 1997.

[4] Chordia, Roll and Subrahmanyam (2002) use a similar approach to study daily order imbalances aggregated across stocks. They document that aggregate imbalances are highly persistent and positively related to contemporaneous market returns. They also find that, in the aggregate, traders exhibit contrarian behavior on daily basis.

into institutional and retail for most of the trades. They document that institutional imbalances are persistent over several days. Moreover, institutions are more likely to buy after positive returns on the previous day and their imbalance has a positive contemporaneous relation to returns.

Our proprietary data set allows additional inferences that complement the results in Chordia and Subrahmanyam and Griffin, Harris, and Topaloglu. In contrast to Chordia and Subrahmanyam's analysis of order flow aggregated across all traders, we do not have to infer trade direction and, implicitly, market maker trades using the Lee and Ready (1991) algorithm. Rather, we directly observe buys and sells for each trader type and market-maker trades. Griffin, Harris, and Topaloglu's sample allows a distinction between institutional and retail trades, but it is limited to the 100 most liquid Nasdaq stocks over a short period. One important advantage of their data set is that it contains trade-by-trade information, which they exploit to look at the cause of institutional imbalances. They find results consistent with previous evidence that institutions are positive-feedback traders and using the intraday information helps to disentangle the direction of causality between returns and institutional trading decisions. In contrast, our panel is much larger both in the cross-section and over time and provides a finer trader-type classification that does not depend on classifying brokerage firms. Moreover, our NYSE data is not limited to the most liquid stocks. Finally, our objective is somewhat different. We also provide some results on the determinants of order imbalances, but our main focus is on their consequences for contemporaneous and future prices and on measures of market liquidity.

Our first finding is that, during our sample period, institutions trade as contrarians with respect to prior-day returns. This is consistent with aggregate evidence in Lipson and Puckett (2005) and Chordia, Roll, and Subrahmanyam (2002), but contrary to the Nasdaq evidence in Griffin, Harris, and Topaloglu (2003). We further show that, for the largest size quartile, institutions are momentum traders with respect to market movements on the previous day. We argue that the countervailing effects of idiosyncratic and market returns could explain the differences between our results and those in Griffin et al., whose sample is limited to large firms during a period of substantial negative returns.

Second, we find that institutional imbalances are positively related to contemporaneous returns, controlling for market movements and persistence in imbalances. This suggests that institutional trading is associated with positive price impacts, as predicted by theory, and is consistent with a prevalence of information-based trading. While our daily data limits inferences about information content, we show that the institutional price impact coefficient is positively related to cross-sectional proxies for information asymmetry. In particular, institutional imbalances have a greater effect on contemporaneous returns in stocks with larger effective spreads, controlling for firm size. This indicates that information is an important driver of the effect that institutional imbalances have on prices, but it is also consistent with an inventory effect: if market makers hold undesirable inventory levels, liquidity would be limited, causing high spreads and larger effects of trading on returns. To disentangle these two explanations, we decompose effective spreads into a temporary price impact (likely associated with inventory effects) and a permanent component (likely associated with information in order flow). We find that institutional order imbalances have a greater effect on returns when permanent price impacts are large, even when controlling for inventory effects. Therefore, traders' information appears to play a more prominent role than inventory effects in explaining how institutional trading affects prices. Finally, institutional order imbalances also have a greater price impact in stocks with higher R&D expenditures. Because the outcomes of R&D are very uncertain, firms with high R&D are more difficult to value, and subject to greater information asymmetry. Similar to the intraday proxies for information asymmetry, this also suggests that an important reason for the price impact of institutional trading is the traders' information.

Third, institutional imbalances have explanatory power for next-day returns. This also suggests that institutional trading is, at least in part, information based. We note that this predictive ability cannot be exploited to generate abnormal trading profits, because information on trader groups is confidential and not even disclosed ex post. No trader (including specialists) can observe the trader type and base his own trading on specific types' order flow.

About one quarter of institutional trading is in form of program trades, and we document that this order type plays a special role during our sample period. Institutions choose endogenously between a regular order and a program trade. Our priors are that program trades are unlikely to be motivated by firm-specific private information, and that their relationship to prices differs from the one we find for regular institutional imbalances. This is strongly supported by the evidence. While program-trade imbalances also tend to be contrarian, they have a negative relationship to contemporaneous returns. This suggests that institutions use program trades when they have little information and provide liquidity to other traders by trading passively.[5]

Consistent with Kaniel, Saar, and Titman (2007), we show that individuals also trade as contrarians. Kaniel et al. infer that individuals provide liquidity to institutions and we provide evidence consistent with this claim. Specifically, we show that individuals' order imbalances have a negative effect on contemporaneous returns, consistent with liquidity provision. While individuals, therefore, buy and sell at different times than institutions, their imbalances also have predictive power for next-day returns. But individuals provide only 5% of trading volume, so that they alone cannot satisfy the imbalances of informed institutional traders. More specifically, in our sample the dollar value of individuals' order imbalances accounts for less than one fifth of the opposite institutional imbalances. Our results suggest that the remaining imbalance is filled mainly by other institutional traders who use program trades (which account for about 20% of trading volume), and to some extent by specialists and other market makers.

The rest of this paper is organized as follows. We describe the data, sample selection, and variables in Section B. Section C contains the main empirical tests and Section D concludes.

B. Data and sample construction

We use proprietary data from the New York Stock Exchange that allows us to separately observe buy and sell transactions for different trader types. These data cover

[5] This seems consistent with observations by industry participants as well. In practice, sell-side brokers maintain separate trading desks for program trades that do not expect informed order flow to arrive.

all securities traded on the NYSE between January 2000 and April 2004 and are based on the NYSE's Consolidated Audit Trail Data (CAUD), which provide information on nearly all trades executed at the NYSE. CAUD are the result of matching trade reports to the underlying order data – for each trade, they show the executed portion of the underlying buy and sell orders. Each component is identified by an account-type variable that gives some information on trader identity. Providing the account type classification is mandatory for brokers (although it is not audited by the NYSE on a regular basis). Different regulatory requirements include obligations to indicate orders that are part of program trades, index arbitrage program trades, specialist trades, and orders from other market makers in the stock. Each of these categories is further divided into proprietary member trades, trades by retail customers, and agency trades.

The data set available for this study has aggregated buy and sell volume separately for each day and security for certain combinations of account types, using the number of trades, share volume, and dollar volume. We can distinguish the following six account-type categories: individuals, institutions, regular institutional program trades, institutional index arbitrage program trades, non-NYSE market maker proprietary trades, and specialists. NYSE account types have been used in a handful of other papers. For example, using the same data set Kaniel, Saar, and Titman (2007) investigate retail trading and Boehmer and Kelley (2006) look at the relationship between informational efficiency and institutional trading. Boehmer, Jones, and Zhang (2007) analyze differences in the informativeness of short selling across account types.

We match the NYSE data to security information from the Center for Research in Security Prices (CRSP) and obtain daily returns, market capitalization, and consolidated trading volume. Our sample includes only domestic, single-class common stocks. Once a security is delisted or its monthly average price falls below $1 or rises above $999, it is subsequently dropped from the sample. Next, we obtain all primary market prices and quotes from TAQ that satisfy certain criteria.[6] For each stock, we aggregate all trades during the same second that execute at the same price and retain only the last quote for every second if multiple quotes were issued. We require that the monthly average number of daily transactions for a stock be greater than 20. In addition, a stock has to have at least 100 trading days to be included in the empirical time-series analysis. This procedure leaves 1,300 different firms over the sample period. Unless noted otherwise, all tests involving daily returns are based on end-of-day quote midpoint returns computed from TAQ. We obtain qualitatively identical results using close-to-close returns from CRSP, but prefer the midpoint returns to abstract from bid-ask bounce in transaction-price returns.

B.1 Measuring order imbalances

Similar to Chordia, Roll, and Subrahmanyam (2002) and Chordia and Subrahmanyam (2004), we compute three measures of order imbalance for each trader group-stock-day observation: the number of buy transactions less the number of sell

[6] We use trades and quotes only during regular market hours. For trades, we require that TAQ's CORR field is equal to zero, and the COND field is either blank or equal to *, B, E, J, or K. We eliminate trades with non-positive prices or sizes. We also exclude a trade if its price is greater than 150% or less than 50% of the price of the previous trade. We include only quotes that have positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. We exclude quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price. We require that the difference between bid and ask be less than 25% of the quote midpoint.

transactions of a trader group scaled by the total number of trades, the number of shares bought less the number of shares sold by a trader group scaled by total share volume, and a trader group's dollar volume of buys minus sells scaled by total dollar volume. Scaling order imbalances by a stock's trading activity standardizes the imbalance measures across stocks. We use a volume-based normalization (rather than shares outstanding) for two reasons. First, we believe it is preferable to standardize a flow measure by a flow measure. Second, we wish to abstract from volume effects in order imbalances to better focus on the relative imbalances across different trader groups.

Our measures of order imbalances are similar to those used in Griffin, Harris, and Topaloglu (2003), but differ in important ways from the TAQ-based measures used in Chordia, Roll, and Subrahmanyam (2002) and Chordia and Subrahmanyam (2004). TAQ provides information on executed trades, so by construction there is precisely one share bought for every share sold. Therefore, a direct measure of imbalances between demand and supply is not available – shares bought always equal shares sold. Researchers get around this issue by defining order imbalances in terms of order aggressiveness. TAQ does not provide information on trade direction – it has to be inferred from approximate algorithms such as Lee and Ready (1991). Based on this algorithm, a trade executed at a price higher (lower) than the prevailing quote midpoint is classified as a buyer- (seller-) initiated. If the transaction price equals the quote midpoint, it is classified as buyer- (seller-) initiated if the transaction price is above (below) the previous transaction price. This procedure seeks to identify the active side of the trade, that is, the side that is less patient and therefore pays the spread. In practice, the active side is likely to be a trader using a marketable order; the passive side could be a limit-order trader or a market maker. Order imbalances based on only the initiating side then provide a measure of the relative impatience of buyers and sellers. This makes economic sense, because one can imagine a latent pool of liquidity that becomes available when the premium offered by an impatient trader becomes sufficiently large. An impatient trader can access this latent liquidity by offering better prices than currently available.

Defining imbalances in terms of trader aggressiveness has two disadvantages. First, the Lee and Ready (1991) algorithm is known to be somewhat inaccurate. Lee and Radhakrishna (2000) show that 40% of NYSE trades cannot be classified at all, and 7% of the remaining trades are not classified correctly. Second, we need to assume that all traders who intend to achieve a certain portfolio position use marketable orders. While this assumption is relatively innocuous on a trade-by-trade basis, it becomes problematic when traders have longer-term horizons and use different order types to achieve their trading targets. Evidence suggests that traders do indeed use complex strategies to achieve trading objectives. In an experimental study, Bloomfield, O'Hara and Saar (2005) find that traders switch among order types based on the value of their information. Anand, Chakravarty, and Martell (2005) document similar order switching behavior among informed traders based on TORQ data (November 1990- January 1991), complementing Bloomfield et al's experimental results. Kaniel and Liu (2005) show that informed traders may prefer to use limit orders depending on the horizon of their information. Order switching affects inferences from TAQ-based imbalances. To illustrate this point, suppose a portfolio manager sets a trading target for the day of

100,000 IBM shares and no other active traders are in the market. To achieve this position, his strategy need not be limited to marketable orders. For example, he might initially try to obtain the position at low cost by placing passive limit orders, which may attract some sellers. But if execution rates are low, he may resort to marketable orders towards the end of the trading day. Another example is the prevalence of VWAP trading, where traders aim at achieving an average execution price that equals the volume-weighted price (VWAP) over the same period. In both cases, the true order imbalance is 100,000 shares, but the TAQ-based imbalance could be very different, depending on the fraction of trades using marketable orders. As these simple examples illustrate, TAQ-based imbalances may not capture true imbalances when traders use complex strategies.

In this paper, we use a different approach that is not sensitive to order choice or to misclassification associated with trade-signing algorithms. While our data is also trade-based, so aggregate demand equals aggregate supply, this is not true within individual trader types. For each trading day and each security, we observe imbalances that reflect the entire buying and selling activity for each trader type, including the specialist. For example, suppose retail buyers purchase N shares from institutions; in this case, the aggregate imbalance is zero, but we would observe a retail imbalance of N and an institutional imbalance of $-N$. Consistent with the evidence in Kaniel and Liu (2005), our approach implicitly assumes that market and limit orders can both affect price.

B.2. Characteristics of order imbalances

We summarize the trading activity and order imbalances for our sample in Table 2.1. For each trader type, we compute cross-sectional averages of time-series means. Panel A shows that institutions account for the bulk of the trading: regular institutional share volume averages 56% of total volume, and program/index arbitrage program trading account for 19% and 1.6%, respectively. Retail traders account for 5% of volume, other market makers for 0.7%, and specialists for about 18%. These averages are similar in terms of dollar trading volume. Compared to the percentages of trades, we see that institutional trades tend to be larger than the average, while program trades are somewhat smaller. Consistent with Madhavan and Sofianos (1998), we note that specialists do not always take the opposite side of externally initiated trades, which would imply a participation rate of 50%. This implies that a substantial fraction of trading is among market participants.

Table 2.1
Summary Statistics

We present cross-sectional averages of time-series means for 1300 NYSE common stocks from January 2000 to April 2004. Panel A shows the fraction of trading volume of each trader type. Panel B presents the level of order imbalances by trader types. Panel C presents each trader type's imbalances scaled by a stock's trading activity.

Means	Institutions	Regular program trades (institutional)	Index arbitrage program trades (institutional)	Individuals	Specialists	Other market makers
Panel A: Relative trading volume of each trader type						
% of transactions	45.3%	27.0%	3.5%	5.3%	18.0%	0.9%
% of share volume	56.0%	18.8%	1.6%	5.0%	17.9%	0.7%
% of dollar volume	56.0%	18.8%	1.6%	5.0%	17.9%	0.7%
Panel B: Level of order imbalances by trader types						
Order imbalances in number of transactions	-12	9	4	-5	-5	-1
Order imbalances in shares	3,032	5,007	1,034	-4,696	-311	-538
Order imbalances in dollar volume	150,686	190,623	43,317	-205,093	-10,543	-40,025
Panel C: Scaled order imbalances by trader types						
Scaled order imbalances in transactions / number of trades	-1.3%	1.0%	0.4%	-1.5%	-0.2%	-0.2%
Scaled order imbalances in shares / share volume	0.7%	0.8%	0.1%	-1.5%	0.1%	-0.2%
Scaled order imbalances in dollars / dollar volume	0.7%	0.8%	0.1%	-1.5%	0.1%	-0.2%

Panel B of Table 2.1 reports mean levels of order imbalances for each trader type. Institutions are net buyers over the sample period, whether using regular or program trades (the negative imbalance in terms of transactions indicates that institutional buys tend to be larger than institutional sells). The three remaining groups are net sellers. Panel C of Table 2.1 presents mean order imbalance scaled by the corresponding measure of total trading volume of a stock. Again, we observe that institutions are net buyers in terms of share and dollar volume, regardless of order type. One difference to the levels in Panel B is that specialists are net buyers based on scaled order imbalances. This could be due to relatively high buying activity from specialists for less actively traded stocks. If the public tries to sell these less liquid stocks, specialists are more likely to step in to provide liquidity by buying from an outside trader. Consistent with a policy that seeks to minimize inventory, we note that specialists' average imbalance is small relative to those of other traders.

B.3 Cross correlations of order imbalances among trader groups

Table 2.2 shows imbalance correlations across trader groups. We compute the time-series correlation for each stock and then average across stocks. The three different imbalance measures generally provide comparable results, and we make a couple of interesting observations. First, with the exception of index arbitrage trades, specialists' imbalances are negatively correlated with those of each other group. This is what we would expect if their trading is mainly passive, that is, specialists engage in market making activity and provide liquidity when orders arrive.

Table 2.2
Cross Correlations Across Trader Types

We report cross-sectional averages of time-series correlations. The sample includes 1300 NYSE common stocks from January 2000 to April 2004.

	Institutions	Regular program trades (institutional)	Index arbitrage program trades (institutional)	Individuals	Specialists	Other market makers	Closing quote-midpoint return
Panel A: Order imbalances measured in transactions standardized by the total number of transactions							
Institutions	1.00	-0.20	-0.12	-0.08	-0.27	-0.02	-0.02
Regular program trades		1.00	0.13	-0.11	-0.43	-0.05	-0.03
Index arbitrage program trades			1.00	-0.06	-0.21	-0.05	0.11
Individuals				1.00	-0.10	0.19	-0.05
Specialists					1.00	-0.04	-0.17
Other market makers						1.00	-0.10
Return							1.00
Panel B: Order imbalances measures in shares standardized by total share volume.							
Institutions	1.00	-0.24	-0.08	-0.13	-0.21	-0.05	0.01
Regular program trades		1.00	0.07	-0.06	-0.05	-0.03	-0.02
Index arbitrage program trades			1.00	-0.03	0.00	-0.02	0.09
Individuals				1.00	-0.04	0.10	-0.06
Specialists					1.00	0.02	-0.25
Other market makers						1.00	-0.08
Return							1.00
Panel C: Order imbalances measures in dollars standardized by total dollar volume.							
Institutions	1.00	-0.24	-0.08	-0.13	-0.21	-0.05	0.01
Regular program trades		1.00	0.07	-0.06	-0.05	-0.03	-0.02
Index arbitrage program trades			1.00	-0.03	0.01	-0.02	0.08
Individuals				1.00	-0.04	0.10	-0.06
Specialists					1.00	0.02	-0.25
Other market makers						1.00	-0.08
Return							1.00

Second, institutions trade in the opposite direction as individuals do. This is consistent with Kaniel, Saar, and Titman’s (2007) interpretation that individuals provide liquidity to institutions, although the simple correlations do not reveal whether institutions or retail are the more active side. Third, institutions appear to use regular trades and program trades as substitutes. This suggests that program trades serve a specific purpose – we will return to this issue later on.

The table also shows the correlation between imbalances and contemporaneous returns. Consistently across different measures, specialist imbalances are strongly and negatively correlated with returns. This is again an expected consequence of market making – as other traders buy, for example, they drive up price and specialists sell in the course of liquidity provision. Again consistent with Kaniel, Saar, and Titman's interpretation, individuals also seem to provide liquidity in that their imbalances are negatively correlated with returns. Most interesting are the three institutional types. Focusing on one of the volume measures in Panel B or C, regular institutional trades and index arbitrage trades are moving with the market. In contrast, program trades are moving against the market. This suggests that institutions use regular orders when they are trading actively. Index arbitrage trades attempt to exploit potentially short-lived price discrepancies between derivative and cash markets; therefore, they are also active trades that move price in the direction of trading. In contrast, institutions appear to use program trades primarily when they are trading passively and therefore program trades seem to provide liquidity. Of course, the correlation evidence presented here is only suggestive and we address each of these issues more rigorously below.

B.4. Persistence of order imbalances

Chordia and Subrahmanyam (2004) report that TAQ-based order imbalances are highly persistent on a daily basis. They suggest that this is because traders split order to minimize price impact. Order splitting is typically attributed to large traders, such as institutions (Keim and Madhavan, 1995; Chan and Lakonishok, 1995). Table 2.3 shows evidence consistent with this claim: regular institutional trades and program trades are highly persistent. Individual trades, however, show even stronger persistence, consistent with the Nasdaq evidence in Griffin, Harris, and Topaloglu (2003). We measure the weakest persistence for index arbitrage trades; this makes sense if these traders' motives are short-lived. Specialists are the only trader type with negatively autocorrelated (volume-based) imbalances. This is consistent with inventory management – when specialists accumulate a long inventory position, for example, they are more likely to sell on the subsequent day.

Table 2.3
Persistence of Order Imbalances

We report cross-sectional averages of time-series autocorrelations. The sample includes 1300 NYSE common stocks from January 2000 to April 2004.

	Institutions	Regular program trades	Index arbitrage program trades	Individuals	Specialists	Other market makers
Panel A: Order imbalances measured in transactions standardized by the total number of transactions						
lag1	0.26	0.32	0.09	0.45	0.17	0.21
lag2	0.15	0.20	0.07	0.37	0.10	0.17
lag3	0.11	0.15	0.08	0.33	0.08	0.15
lag4	0.08	0.12	0.06	0.31	0.07	0.14
lag5	0.06	0.08	0.01	0.29	0.04	0.13
Panel B: Order imbalances measured in shares standardized by total share volume.						
lag1	0.21	0.29	0.04	0.27	-0.14	0.14
lag2	0.12	0.18	0.04	0.20	-0.03	0.11
lag3	0.09	0.13	0.05	0.18	-0.01	0.09
lag4	0.07	0.11	0.02	0.16	0.00	0.09
lag5	0.05	0.08	0.01	0.14	0.00	0.08
Panel C: Order imbalances measured in dollars standardized by total dollar volume.						
lag1	0.21	0.29	0.04	0.27	-0.14	0.14
lag2	0.12	0.18	0.04	0.20	-0.03	0.11
lag3	0.09	0.13	0.05	0.18	-0.01	0.09
lag4	0.07	0.11	0.02	0.16	0.00	0.09
lag5	0.05	0.08	0.01	0.14	0.00	0.08

C. The relationship between order imbalances and returns

Microstructure theory suggests that informed traders impact stock prices (Kyle, 1985; Glosten and Milgrom, 1985). We also know from previous analysis that different market participants are differentially informed and have different trading motives, and therefore their orders are likely to have a different relationship to price changes. While several studies examine institutional influence on returns (see, for example, Keim and Madhavan, 1995; Chan and Lakonishok, 1995; Griffin, Harris, and Topaloglu, 2003), fewer studies examine the influence of retail trading (see Jones and Lipson, 2004; Kaniel, Saar, and Titman, 2007), and relatively little is known about how program trading and specialist activity are related to returns (Hendershott and Seasholes, 2006). In this section, we analyze the dynamic relationship between imbalances and returns for the different trader types in three different ways. First, we test how past price changes affect imbalances. These tests allow inferences on the determinants of order imbalances. Second, we estimate the price impact of imbalances. Using regressions of returns on contemporaneous imbalances, we make inferences about which traders demand and which traders supply liquidity. Purchases on positive-return days are likely to demand liquidity, while purchases on negative-return days are likely to supply liquidity (and vice versa for sales). Third, we estimate simple predictive regressions that relate returns to imbalances on the previous day. These tests allow inferences on the information of traders in the different groups.

Following Chordia and Subrahmanyam (2004), we estimate time-series regressions for each stock and conduct inferences on the cross-section of estimated coefficients. Extending Chordia and Subrahmanyam's analysis, we estimate separate models for each trader type. The Fama-MacBeth approach alleviates problems with autocorrelated errors in the time-series regressions, but cross-sectional correlation could affect the standard errors we use to construct test statistics. Although the cross-sectional correlations in most regression specifications turn out to be quite small, we correct all test statistics for cross-sectional correlation using the procedure described in Chordia and Subrahmanyam (2004).

From here on, we report only results based on dollar-volume imbalances, which we believe best capture the essence of the argument based on Kyle (1985) and Glosten and Milgrom (1985) that order imbalances are related to returns. We have repeated all regressions using scaled imbalances defined in terms of transactions and share volume. Our results do not qualitatively change across measures and we note differences where applicable.

C.1. Determinants of order imbalances

To determine how order imbalances on day *t* depend on past returns, we estimate the following time-series regression for each trader type:

$$OIB_{it} = \alpha_i + \sum_{k=1}^{5} \beta_{ik} R^*_{i,t-k} + \sum_{k=1}^{5} \gamma_{ik} R_{m,t-k} + \sum_{k=1}^{5} \delta_{ik} OIB_{i,t-k} + \varepsilon_{it} \quad (2.1)$$

where *OIB* is the scaled trader-type specific dollar imbalance, R_m is the equally-weighted close-to-close midpoint return across all sample stocks, and R^*_i is the residual from a time-series regression of R_i, the close-to-close midpoint returns for stock *i*, on R_m.[7] We employ close-to-close midpoint returns to mitigate the effect of bid-ask bounce on returns, although we obtain qualitatively identical results using returns based on closing prices from CRSP. Decomposing returns into market and idiosyncratic returns allows us to separately assess each component's effect on order imbalances.

[7] Unfortunately, we have little theoretical guidance on how to best scale order imbalances. Throughout our analysis, we use contemporaneous volume, but certain time-series patterns in volume could conceivably affect inferences from these tests. To address this issue, we follow Kaniel et al. (2007) and divide current order imbalances by the average annual volume. Repeating our tests using this modified measure leaves our results qualitatively unchanged and therefore these tests are not tabulated.

We first estimate a restricted variant of Equation (2.1) that replaces the R_i^* and R_m by the respective weekly returns preceding day *t*. Panel A of Table 2.4 presents cross-sectional mean coefficients for the restricted model and Panel B presents the unrestricted model. Consistent with Table 2.3, both regressions show that specialists' order imbalances tend to be negatively autocorrelated and those of all other trader types are positively autocorrelated.

We show that institutions trade as contrarians relative to past returns. In fact, comparing the magnitude of coefficients, institutions show the strongest contrarian response among all trader types when using regular trades. Contrarian behavior with respect to security-specific past returns is less pronounced when institutions use program trades, and it is not visible when they engage in index arbitrage. Our results contrast to Griffin, Harris, and Topaloglu's (2003) findings, who argue that institutions are trend chasers on a daily basis. But our results are consistent with Lipson and Puckett (2005), who study pension fund order imbalances on volatile days and find that pension funds are contrarian traders. They are also consistent with the evidence presented in Chordia, Roll and Subrahmanyam (2002), who find that aggregate trade-based order imbalances are contrarian. In Panel B, we show that the contrarian behavior is primarily driven by returns on the previous two days.

Table 2.4
Determinants of Order Imbalances

For each security, we regress dollar order imbalance scaled by total dollar volume, OIB (t), on a stock's lagged residual returns (the residual from regressing stock returns on contemporaneous market returns), lagged market return, Rm (t-k), and trader-type specific lagged order imbalances, OIB (t-k). Security-specific returns are computed based on closing-price midpoint, and market returns are computed as the equally-weighted average of these returns across all sample stocks. We report cross-sectional averages of the time-series regression coefficients. The sample includes 1300 NYSE common stocks from January 2000 to April 2004. Panel A uses cumulative returns over the previous week, while Panel B uses daily returns over the previous week. Panel C uses the same model as Panel A, but provides separate average coefficients for each size quartile (using the time-series mean market value of equity for each firm). T-stats are corrected for cross-sectional correlations (Chordia and Subrahmanyam, 2004).

	Institutions		Regular program trades		Index arbitrage program trades		Individuals		Specialists		Other market makers	
	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t
Panel A: Order imbalances and previous-week cumulative returns												
Intercept	0.0048	8.38	0.0050	14.57	0.0007	9.82	-0.0076	-16.23	0.0005	2.28	-0.0008	-9.92
Residual Ret (t-5, t-1)	-0.1584	-14.25	-0.0947	-15.01	-0.0012	-0.69	-0.0822	-23.91	0.1589	22.39	-0.0064	-4.22
Rm (t-5,t-1)	-0.0010	-0.07	-0.1370	-14.33	-0.0281	-9.49	-0.0080	-1.12	0.1000	11.84	0.0018	1.26
OIB (t-1)	0.1790	97.92	0.2478	106.77	0.0349	6.51	0.1911	82.84	-0.1646	-55.50	0.1045	32.20
OIB (t-2)	0.0589	38.16	0.0768	45.44	0.0261	8.31	0.0898	50.40	-0.0719	-31.23	0.0466	20.16
OIB (t-3)	0.0385	27.39	0.0443	27.60	0.0455	15.80	0.0697	41.04	-0.0258	-13.55	0.0415	21.44
OIB (t-4)	0.0236	16.45	0.0332	20.39	0.0188	6.73	0.0562	33.89	-0.0057	-3.22	0.0355	18.87
OIB (t-5)	0.0221	14.93	0.0234	15.01	0.0067	2.43	0.0587	38.30	0.0119	6.88	0.0347	20.44

Table 2.4 -Continued

	Institutions		Regular program trades		Index arbitrage program trades		Individuals		Specialists		Other market makers	
	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t
Panel B: Order imbalances and previous-week daily returns												
Intercept	0.0047	8.35	0.0049	14.66	0.0007	9.93	-0.0075	-16.48	0.0005	2.26	-0.0008	-9.92
Residual Ret (t-1)	-0.6089	-28.66	-0.6032	-36.74	-0.0012	-0.37	-0.1179	-16.51	0.3406	24.71	-0.0060	-4.20
Residual Ret (t-2)	-0.1969	-10.14	-0.0750	-6.10	0.0052	1.58	-0.0896	-12.10	0.2014	19.26	-0.0044	-1.21
Residual Ret (t-3)	0.0075	0.43	0.0420	3.92	-0.0022	-0.74	-0.0747	-9.32	0.1038	9.74	-0.0071	-2.88
Residual Ret (t-4)	0.0126	0.84	0.0870	7.02	-0.0018	-0.50	-0.0628	-8.95	0.0755	8.82	-0.0085	-6.16
Residual Ret (t-5)	0.0251	1.95	0.1130	10.50	-0.0057	-1.46	-0.0550	-8.21	0.0530	6.30	-0.0056	-2.60
Rm (t-1)	0.0569	1.65	-0.5166	-22.41	-0.1360	-11.93	0.0225	1.36	0.2156	10.35	0.0033	0.98
Rm (t-2)	-0.0793	-2.58	-0.1585	-7.40	-0.0067	-1.02	-0.0188	-1.21	0.1550	8.83	0.0117	3.27
Rm (t-3)	-0.0786	-2.47	0.0477	2.35	0.0624	10.45	-0.0437	-2.70	0.0798	4.28	-0.0086	-2.37
Rm (t-4)	0.0048	0.15	0.0215	1.06	0.0308	4.95	0.0092	0.60	0.0001	0.01	-0.0009	-0.27
Rm (t-5)	0.0834	2.94	-0.0964	-4.81	-0.0963	-15.27	-0.0008	-0.05	0.0469	2.78	0.0032	0.87
OIB (t-1)	0.1820	103.25	0.2469	114.15	0.0547	10.86	0.1921	84.28	-0.1440	-47.91	0.1064	32.72
OIB (t-2)	0.0648	41.55	0.0836	50.41	0.0308	9.83	0.0932	52.20	-0.0559	-24.15	0.0490	20.97
OIB (t-3)	0.0415	28.63	0.0476	29.04	0.0419	14.97	0.0714	41.53	-0.0206	-10.40	0.0420	21.68
OIB (t-4)	0.0246	16.70	0.0372	22.53	0.0081	3.02	0.0573	34.29	-0.0079	-4.25	0.0359	18.68
OIB (t-5)	0.0209	13.97	0.0245	16.08	0.0113	3.91	0.0595	38.38	0.0035	2.02	0.0351	19.91

Table 2.4 -Continued

	Institutions		Regular program trades		Index arbitrage program trades		Individuals		Specialists		Other market makers	
	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t
Panel C: Order imbalances and previous-week cumulative returns by size quartiles (using Panel A regression, only average return coefficients shown)												
Size quartile 1 (smallest)												
Residual Ret (t-5, t-1)	-0.1691	-8.66	-0.1070	-8.65	-0.0051	-1.46	-0.1407	-15.43	0.2484	12.09	-0.0082	-5.10
Rm (t-5,t-1)	-0.0112	-0.26	-0.1274	-4.66	0.0070	0.90	-0.0231	-0.88	0.0703	2.40	-0.0037	-0.75
Size quartile 2												
Residual Ret (t-5, t-1)	-0.2324	-6.44	-0.1366	-8.82	-0.0086	-1.72	-0.0923	-12.40	0.2228	14.46	-0.0010	-0.17
Rm (t-5,t-1)	-0.0539	-2.12	-0.2006	-10.17	-0.0168	-3.68	-0.0166	-1.78	0.1928	14.01	0.0010	0.50
Size quartile 3												
Residual Ret (t-5, t-1)	-0.1465	-10.62	-0.1114	-8.22	-0.0016	-0.70	-0.0593	-11.46	0.1126	15.61	-0.0075	-7.81
Rm (t-5,t-1)	-0.0001	-0.01	-0.1479	-9.76	-0.0289	-9.97	0.0000	-0.01	0.1014	15.55	0.0029	1.83
Size quartile 4 (largest)												
Residual Ret (t-5, t-1)	-0.0856	-10.35	-0.0239	-4.01	0.0105	5.04	-0.0365	-16.73	0.0517	17.21	-0.0090	-12.55
Rm (t-5,t-1)	0.0612	5.07	-0.0723	-8.67	-0.0736	-15.14	0.0077	2.41	0.0356	10.65	0.0069	6.91

Consistent with Kaniel, Saar, and Titman (2007), we find that individuals trade as contrarians relative to a stock's returns during the previous week. Only specialists trade in the direction of previous-week returns, apparently in response to the contrarian demand by the other trader types.

While regular institutional and individual imbalances are not sensitive to market returns, we find that institutional program and index arbitrage imbalances are contrarian with respect to market returns. In fact, these imbalances are more sensitive to market returns than to idiosyncratic returns. This is a notable and intuitive result, suggesting that institutions use program trades to respond to market movements.

Panel C demonstrates that the return effects are present in each size quartile (size quartiles are based on the time-series average market value of equity). Only the largest firms (quartile 4) show somewhat different coefficients on market returns. In this quartile, institutions and individuals are still contrarian with respect to idiosyncratic returns, but they are momentum traders with respect to market returns. The counteracting influences of market and security returns in the top size quartile could potentially reconcile the differences between our results and those in Griffin, Harris, and Topaloglu, because their analysis does not allow market returns to affect order imbalances directly.[8] Their sample consists of all Nasdaq 100 stocks between May 1, 2000 and February 28, 2001. During this period, the Nasdaq 100 index declined by

[8] Griffin, Harris, and Topaloglu control for market movements by regressing order imbalances on excess returns, defined as security returns net of market returns. When we repeat this approach on our data, the coefficient on excess returns are very similar to those reported in Table 2.4. In particular, institutional imbalances are still significantly negatively related to past (excess) returns. Therefore, allowing the coefficient on market returns to vary does not cause the different results. We also obtain similar results when we include unadjusted security returns (and omit market returns).

50.7%. If institutional trading decisions depend on market returns as in Panel C, this pronounced decline should prompt large negative institutional imbalances for large stocks. Put differently, we would expect a positive correlation between security returns and imbalances during the Nasdaq decline this period. It is, therefore, possible that the momentum behavior documented in Griffin, Harris, and Topaloglu is driven by selling due to these pronounced market-wide price moves and not a response to security-specific returns.

Finally, we note that our results are related to the cross-sectional institutional momentum patterns documented at the quarterly horizon (see Grinblatt, Titman, and Wermers, 1995, or the review in Sias, 2005). One could view these longer-horizon results as describing institutional investment decisions, while our results describe institutional trading decisions. This distinction is important for two reasons. First, we believe that decisions about long-term holdings could differ from decisions about daily trading strategies and their relationship to prior returns need not be the same. Second, information on institutional holdings is only available with quarterly frequency. While this is sufficient to characterize institutional investment decisions, our findings illustrate that higher-frequency information is desirable when analyzing institutional trading decisions.

C.2. Price impact: order imbalances and contemporaneous stock returns

In this section, we ask how daily order imbalances affect contemporaneous returns. This analysis allows inferences about potential differences in order aggressiveness, and, by implication, about differences in informedness and liquidity provision across trader types. In general, traders with short-lived information need to trade actively so their orders execute before their information gets otherwise impounded into prices. Impatient, active traders tend to move prices in the direction of the order. For example, a market buy order should lead to a price increase. In contrast, patient traders can afford to trade passively. For example, a limit buy order that is priced below the current ask price only executes once prices have sufficiently declined. Upon execution, the active part of this trade (the sell order) should generally exert downward pressure on price. In this case, the buyer provides liquidity to the market. In general, we expect a stronger positive relationship between imbalances and returns for trader types who, on average during a trading day, are more informed; we expect a negative relationship for trader types who, on average, supply liquidity to the market.

We estimate the following regression model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \sum_{k=0}^{4} \gamma_{ik} OIB_{i,t-k} + \varepsilon_{it} \qquad (2.2)$$

where the variables are as defined in Equation (2.1). We believe it is important to control for market returns, because we would like to capture return movements that are idiosyncratic to the order imbalances we examine. We also repeat the estimation with a different risk adjustment and use the three Fama-French factors instead of market returns. The results are qualitatively identical and therefore not reported. Another concern about the specification in model (2.2) is that OIB_t depends on current and past returns, which could bias the estimated coefficients. We address this issue by adding four lags of the dependent variable to model (2.2). Because this extension does not materially affect the price impact coefficients, we do not report the results here.[9]

Keim and Madhavan (1995) document considerable heterogeneity in trading styles based on past price movements. Some institutions pursue trend-chasing strategies while others tend to adopt contrarian strategies; thus, the overall effect of institutional trading strategies on contemporaneous prices could also differ substantially. Unfortunately, we do not have information on trader identity beyond the account types and cannot differentiate between institutions likely to trade frequently on private information (perhaps hedge funds and other active traders) and others (such as index funds). This naturally makes it difficult to isolate information-based trading by looking at institutions as a group.

C.2.1. Basic price impact results

Table 2.5 contains results on the relationship between imbalances and contemporaneous price changes. We report cross-sectional averages of the security-specific time-series coefficients. Controlling for persistence in order imbalances, the coefficient on contemporaneous institutional imbalances is positive. Thus, institutional buying is associated with a greater price increase than implied by the simple market-model adjustment, and institutional selling is associated with a greater price decline. This result is consistent with institutions having information that affects prices when they trade.

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[9] A potential problem with this specification is that market returns are correlated with imbalances, as shown in Table 2.4, so model (2.2) is subject to multicollinearity. As a robustness check, we estimate a regression without market adjustment and another regression of excess returns (over R_m) on current and lagged order imbalances and obtain qualitatively identical results in both cases. Therefore, we present results from (2.2) and do not impose the restriction that the coefficient on R_m equals one.

The effect of institutional imbalances on returns depends on the order type institutions use. While regular institutional trading has a positive contemporaneous effect on prices, institutional program trade imbalances have a negative effect, and index arbitrage imbalances have no effect. These observations make economic sense. It is unlikely that program trades of either type are motivated by private information about individual securities, because they involve simultaneous orders in at least fifteen different securities.[10] Buy-side institutions typically often use program trades to change the scale of their portfolio. For example, when institutions experience inflows or outflows, they could be indifferent between trading several specific stocks and prefer (initially) to change their holdings of those where they obtain the best price. This could be achieved by a passive trading strategy that places a set of limit orders for a range of stocks (which, for sufficient size and at least fifteen stocks, would be classified as a program strategy). Depending on which orders execute, the institutions can then cancel the remaining orders and/or resubmit new ones to remain close to its desired target portfolio. Such a strategy would supply liquidity to the market, consistent with a negative price impact for program trades.

[10] Strategies such as "pairs trading," where traders attempt to arbitrage price differences between two similar securities often involve informed traders. But pairs trading would not generally be classified as program trading.

Table 2.5
The Price Impact of Order Imbalances

For each security, we regress daily close-to-close quote-midpoint returns, R (t), on contemporaneous market returns, Rm (t), and current and lagged order imbalances, OIB (t-k). Order imbalances are measured in dollars and scaled by total dollar volume. Market returns are computed as the equally-weighted average of close-to-close midpoint returns across all sample stocks. The reported coefficients are cross-sectional averages of the time-series regression coefficients. The sample includes 1300 NYSE common stocks from January 2000 to April 2004. Panel B uses the same model as Panel A, but provides separate average coefficients for each size quartile (using the time-series mean market value of equity for each firm). T-stats are corrected for cross-sectional correlations (Chordia and Subrahmanyam, 2004).

	Institutions		Regular program trades		Index arbitrage program trades		Individuals		Specialists		Other market makers	
	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t
Panel A: Price impact regression												
Intercept	-0.0001	-2.55	0.0001	1.60	0.0000	-0.64	-0.0001	-1.96	0.0000	-0.23	-0.0001	-2.71
Rm (t)	0.9783	82.01	0.9927	82.45	0.9806	81.09	0.9730	82.46	0.9152	80.54	0.9656	83.54
OIB (t)	0.0028	4.47	-0.0189	-19.65	0.0193	0.84	-0.0608	-20.46	-0.1271	-34.93	-0.2666	-3.02
OIB (t-1)	0.0017	6.19	-0.0002	-0.30	-0.0254	-1.00	0.0212	16.50	-0.0264	-21.05	0.4199	1.13
OIB (t-2)	-0.0003	-1.30	0.0012	2.52	0.0013	0.06	0.0110	10.97	-0.0078	-6.74	-0.1109	-1.12
OIB (t-3)	0.0001	0.34	0.0007	1.60	0.0121	0.55	0.0078	9.36	-0.0038	-3.74	-0.1999	-1.02
OIB (t-4)	0.0000	0.16	0.0006	1.18	0.0050	0.46	0.0079	8.40	-0.0002	-0.23	-0.1846	-1.37
Panel B: Price impact by size quartile (using Panel A regression, only average coefficients of contemporaneous OIB shown)												
Size quartile 1 (smallest)												
OIB (t)	0.0061	6.19	0.0088	5.43	0.1597	2.20	-0.0101	-7.00	-0.0769	-34.60	-0.4055	-1.15
Size quartile 2												
OIB (t)	-0.0011	-1.51	-0.0118	-10.98	-0.0243	-4.22	-0.0227	-12.79	-0.0875	-28.45	-0.0618	-3.61
Size quartile 3												
OIB (t)	-0.0009	-0.84	-0.0287	-17.00	-0.0234	-0.47	-0.0508	-14.31	-0.1241	-20.46	-0.1659	-10.03
Size quartile 4 (largest)												
OIB (t)	0.0071	3.79	-0.0439	-23.69	-0.0347	-1.43	-0.1596	-17.84	-0.2199	-20.02	-0.4334	-19.81

Individuals, specialists, and other market makers' imbalances have a significantly negative association with contemporaneous returns. These trader types appear to provide liquidity to the active institutional traders. The negative price impact for specialists and other market makers is what we expect from bona fide market making activities, which is consistent with Herdershott and Seasholes (2006). The negative price impact for individuals suggests that they buy when prices are falling and sell when prices are rising. As suggested by Kaniel, Saar and Titman (2007), this trading pattern makes individuals natural liquidity providers to institutions. They note that the liquidity provision from individuals does not necessarily mean that individuals trade actively like market makers to profit from making two-sided markets. It may be the case that individuals happen to take the other side of the market when institutional trades start moving prices. It is important that the negative contemporaneous relationship with returns does not imply that individuals and market makers lose, on average. If the price pressure generated by institutional traders is temporary, individuals and market makers can reverse their positions when the pressure subsides and, at a minimum, earn the spread on their trades.

Panel B of Table 2.5 shows average price impact coefficients for the same model, but computed separately for each size quartile. Coefficients for individuals and market makers are largely consistent with those in Panel A, but the disaggregation provides a partial explanation for the skewness of institutional price impacts. Panel B shows that institutional price impacts differ significantly across size quartiles. Positive impacts are strongest in the smallest quartile. In fact, institutional imbalances cause price moves in small firms whether they arise from regular or program trades. The skewness in coefficients appears to be driven by the largest size quartile. It is well known that institutions tend to invest more in larger firms, so institutional trading in the small quartile could be dominated by information-based active traders. In the large quartile, information-based traders are likely to co-exist with passive institutional traders (including program traders), so the overall price impact coefficient is more ambiguous. We have no good explanation for why institutional price impacts are zero in the middle quartiles – perhaps the effect of informed order flow is dominated by the effect of liquidity-motivated orders. Overall, we note that only individuals and market makers consistently do *not* move prices in the direction of their imbalances.

C.2.2. Price impacts and information asymmetry

Lacking information on the type of institution, one way to address the heterogeneity across institutions is to relate firm-specific price impact coefficients to cross-sectional characteristics of the securities. In particular, if the positive coefficients arise because of information-based trading, we would expect them to be larger for firms that are characterized by greater information asymmetry. Following Llorente et al. (2002), we regress the price impact coefficients (the coefficient on *OIB (t)* in Panel A of Table 2.5) on proxies for information asymmetry.

We measure information asymmetry in two different ways. First, we calculate intraday proxies for information asymmetry. Higher information asymmetry is typically associated with greater relative effective spreads, defined as twice the absolute difference between the execution price and the quote midpoint prevailing when the trade was reported (see Bessembinder, 2003). However, effective spreads also increase for non-informational reasons. We attempt to separate the two effects by decomposing effective spreads into a temporary component (realized spreads) and a permanent component (the trade-to-trade price impact). Realized spreads are typically associated with inventory effects and are measured as the price change from the trade price to the quote midpoint five minutes after the trade (multiplied by -1 for sell-signed trades). Trade-by-trade price impacts provide an estimate of the degree of informed trading in a security and are defined as the change in quote midpoints from just before a trade to five minutes afterwards. We compute daily equally-weighted averages of these variables and use their time-series averages as regressors. If information asymmetries are driving institutional price impact coefficients, we expect that they are positively related to the permanent component of spreads in the cross-section of stocks. Second, we use a firm's R&D expenditures and intangible assets to proxy for its information asymmetry. Because of larger degree of uncertainty associated with the outcomes of R&D, firms with high R&D are more difficult to value, and subject to greater information asymmetry. We obtain data on R&D investments (scaled by sales) and intangible assets (scaled by total assets) for the last reports preceding our sample period (year-end 1999). Several firms have missing values for these variables and it is not always clear whether the data item is truly missing or actually zero. In our analysis, we assume that all missing items represent zeroes but add a dummy variable that is one for observations with non-missing R&D data, and zero otherwise.

The estimates in Table 2.6 are broadly consistent with an information-based explanation for institutional price impact coefficients. Coefficients on effective spreads are positive in Panel A, controlling for firm size. Thus, greater information asymmetry associated with larger effective spreads also increases with the price impact of institutional order imbalances. When we decompose spreads into temporary and permanent components, only the permanent component is related to institutional price impacts. Therefore, as we would expect, informed trading activity appears to be the main driver of institutional price impacts.[11] Panel B presents a similar picture. While price impacts are unrelated to intangibles, larger price impacts are found in firms with higher R&D expenditures. This suggests that the greater information asymmetry associated with R&D investments makes prices more sensitive to the information in institutional trading decisions.

[11] Our inferences from Table 2.6 Panel A could be tautological. We can only interpret effective spreads as proxies for information asymmetry if we *assume* that informed trading moves prices in the appropriate direction. Therefore, given the price impact coefficients estimated in Table 2.5, a negative coefficient on effective spreads in Table 2.6 would be difficult to explain. Nevertheless, we find it helpful to demonstrate that these presumed relationships exist in the data. In unreported tests we regress price impact coefficients on effective spreads (and their components) measured at the beginning of our sample period. This avoids the endogeneity issue and we obtain qualitatively similar results (RES and the permanent component have significantly positive coefficients, although the temporary component also becomes significantly positive). Overall, this implies that the relation in Table 2.6 Panel A is not mainly driven by a tautology.

Table 2.6
Explaining the Price Impact of Institutional Order Imbalances

The sample includes 1300 NYSE common stocks from January 2000 to April 2004. We estimate cross-sectional regressions to explain the security-specific coefficient on institutional share imbalances in a regression of returns on contemporaneous market returns, contemporaneous institutional share imbalances, and lagged institutional share imbalances (see Table 5). The independent variables are R&D expenditures scaled by sales, intangible assets scaled by total assets, relative effective spreads (RES), their decomposition into temporary and permanent components, and firm size. Spreads are computed as time-series average of a stock's daily equally-weighted relative effective spreads over the sample period.

	Coefficient	t	Coefficient	t
Panel A: Intraday proxies for information asymmetry				
Intercept	-0.0031	-3.78	-0.0051	5.02
RES	1.2786	9.05		
Temporary component of RES			0.3147	0.97
Permanent component of RES			5.7454	5.73
Size * 10^{12} ($)	0.1997	7.71	0.2140	8.18
adjusted R^2	0.083		0.091	
Panel B: Financial statement proxies for information asymmetry				
Intercept	0.0030	3.32	0.0008	0.07
R&D/Sales in Dec 1999	0.1151	5.14	0.0898	3.88
R&D nonmissing dummy	-0.0026	-1.72	-0.0030	-2.16
Intangible/TA in Dec 1999			-0.0047	-1.33
Intangible nonmissing dummy			0.0028	0.26
adjusted R^2	0.021		0.013	

C.3. Predictability: order imbalances and future stock returns

A more direct way to evaluate the average information advantage of particular trader groups is to estimate return movements on the day following an order imbalance. Chordia and Subrahmanyam (2004) show that trade-based order imbalances predict next-day returns. In this section, we investigate which trader types are driving this predictability. There is some prior evidence of such predictive ability for certain traders. Boehmer, Jones, and Zhang (2007) show that institutional shorting activity is more informative than shorting by other trader types.

A positive relationship between current imbalances and future returns could also arise if traders split their order across days and the resulting autocorrelation in imbalances is not immediately reflected in prices. Evidence in Chordia, Roll, and Subrahmanyam (2005) shows, however, that at least for large stocks this is not the case – this type of information is rapidly impounded into prices. Despite predictability in imbalances over several days, they find little evidence of predictability in returns for intervals longer than about 30 minutes. Therefore, it is unlikely that order splitting alone could drive a positive relationship between imbalances and subsequent returns at the daily horizon. We also note that any apparent predictability based on trader-group specific imbalances could not be exploited by market participants, because information on group-specific order flow is not publicly disclosed.[12]

We estimate the following model:

$$R_{i,t} = \alpha_i + \beta_i R_{mt} + \sum_{k=1}^{5} \gamma_{ik} OIB_{i,t-k} + \varepsilon_{it} \tag{2.3}$$

where the variables are as defined in Equation (2.1). Similar to the forecast regressions used in Chordia and Subrahmanyam (2004), we regress a stock’s return on five lags of a trader type’s imbalances and the market return. We obtain qualitatively similar results

[12] The specialist can observe whether an order is part of a program trade, but cannot see any of the other account types.

when we add lagged security returns as explanatory variables, or when we use excess returns over market as the dependent variables (and omit market return on the right hand side).

Table 2.7 reports the results. Inconsistent with Griffin, Harris, and Topaloglu (2003), who find no predictability on Nasdaq, institutional imbalances resulting from regular (non-program) trades have some predictive ability in our data. This suggests, largely consistent with the estimates reported in Chordia and Subrahmanyam (2004), that institutions have some information about future returns on NYSE-listed stocks. But as implied by the evidence in Table 2.5, institutional imbalances only contain information when they result from regular trades. When institutions decide to use program trades, their imbalances are not informative. This corroborates our argument that institutions use program trades primarily for liquidity-motivated trading.[13]

[13] Our result that program trades are negatively related to contemporaneous and future returns differ from earlier findings by Harris, Sofianos, and Shapiro (1994) and Hasbrouck (1996), who both argue that program trades contain information based on intradaily analysis. The differences could also be due to different samples and different periods. The former study uses aggregate information on program trades from 1989 to 1990, and the latter study uses program trades on a small sample of firms over three months from November 1990. It is likely that trading strategies have changed since then, especially the use of limit-order strategies. During the 1989 and 1990 sample periods, specialists had no obligation to display limit orders immediately, which probably made them less attractive to traders. But without limit orders, a main argument for the liquidity-supplying nature of today's program trades does not apply. During our 2000-2004 sample period, limit orders are the dominant order type and their use has increased after the NYSE started to display its order book publicly in 2002 (see Boehmer, Saar, and Yu, 2005).

Table 2.7
The Predictive Power of Order Imbalances for Returns

For each security, we regress daily close-to-close quote-midpoint returns, R (t), on contemporaneous market returns, Rm (t), and five lagged daily order imbalances, OIB (t-k). Market returns are computed as the equally-weighted average of close-to-close midpoint returns across all sample stocks. Order imbalances are measured in dollars and scaled by total dollar volume. The reported coefficients are cross-sectional averages of the time-series regression coefficients. The sample includes 1300 NYSE common stocks from January 2000 to April 2004. Panel B uses the same model as Panel A, but provides separate average coefficients for each size quartile (using the time-series mean market value of equity for each firm). T-stats are corrected for cross-sectional correlations (Chordia and Subrahmanyam, 2004).

	Institutions		Regular program trades		Index arbitrage program trades		Individuals		Specialists		Other market makers	
	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t	Mean	t
Panel A: Predictive regressions												
Intercept	-0.0001	-1.54	0.0000	0.20	0.0000	-0.66	0.0001	1.76	-0.0001	-1.07	0.0000	-0.21
Rm (t)	0.9792	81.68	0.9807	82.67	0.9785	82.32	0.9791	81.81	0.9789	82.45	0.9785	82.27
OIB (t-1)	0.0018	7.07	-0.0059	-10.90	-0.0265	-1.04	0.0075	8.00	-0.0059	-5.53	0.3859	1.05
OIB (t-2)	-0.0002	-0.67	-0.0002	-0.38	-0.0014	-0.06	0.0044	4.74	-0.0003	-0.29	-0.1318	-1.32
OIB (t-3)	0.0002	0.96	0.0000	0.03	0.0114	0.54	0.0028	3.41	-0.0016	-1.51	-0.1987	-1.07
OIB (t-4)	0.0001	0.54	0.0002	0.30	-0.0012	-0.10	0.0033	3.53	0.0005	0.42	-0.1985	-1.43
OIB (t-5)	0.0000	0.03	-0.0008	-1.67	-0.0413	-1.24	0.0008	1.06	-0.0005	-0.47	-0.3565	-1.00
Panel B: Predictive regressions by size quartile (using Panel A regression, only average coefficients of OIB (t-1) shown)												
Size quartile 1 (smallest)												
OIB (t-1)	0.0010	2.06	-0.0080	-4.83	-0.1559	-2.06	0.00291	3.23	-0.0038	-3.60	1.4067	0.96
Size quartile 2												
OIB (t-1)	0.0007	1.85	-0.0054	-9.82	-0.0075	-0.82	0.00427	2.61	-0.0023	-1.93	0.09548	1.16
Size quartile 3												
OIB (t-1)	0.0013	2.49	-0.0048	-4.64	0.0453	0.68	0.00571	3.02	-0.0045	-2.53	0.01222	1.10
Size quartile 4 (largest)												
OIB (t-1)	0.0042	7.12	-0.0052	-7.27	0.0121	1.07	0.01727	6.64	-0.0131	-3.71	0.02908	3.85

Consistent with Kaniel, Saar, and Titman (2007), Table 2.7 also shows that individuals have predictive ability. Their imbalances are, on average, informative about returns during the next few days. Specialists do not appear to have private information or cannot trade to exploit it – their market making function implies that they buy in declining markets and sell in rising markets to satisfy the trading demand of other market participants. As a result, their imbalances are negatively related to next-day returns. In Panel B, we compute separate coefficients for each size quartile and find largely similar results. In particular, institutional and individual imbalances tend to predict next-day returns, while program and specialist imbalances do not.

C.4. Robustness checks

We perform a battery of tests to check the robustness of our main results. First, because these trader types' trading tends to be correlated with each other, we use Seemingly Unrelated Regressions to estimate the determinants of order imbalances. In addition, the total order imbalances from these six trader types in a stock sum up to zero in the system, we follow classic Almost Ideal Demand System (AIDS) model by omitting the equation of other market makers to avoid the singularity issue. The contrarian trading behavior among institutions and individuals is still present.

Second, we perform Vector Auto Regressions to capture the dynamic relations among returns and order imbalances. This method allows for lagged endogenous effects. Specifically, for each trader type, we estimate the following system of equations:

$$OIB_{i,t} = \alpha_i + \sum_{k=1}^{5} \beta_{ik} OIB_{i,t-k} + \sum_{k=1}^{5} \gamma_{ik} R_{i,t-k} + \varepsilon_{i,t}$$
$$R_{i,t} = \alpha_i + \sum_{k=1}^{5} \lambda_{ik} OIB_{i,t-k} + \sum_{k=1}^{5} \eta_{ik} R_{i,t-k} + \delta_{i,t} \tag{2.4}$$

where $OIB_{i,t}$ is scaled dollar imbalances of stock i on date t and $R_{i,t}$ is the quote midpoint return net of market returns for ease of interpretation.[14] The VAR coefficient are similar to those reported in separate regressions.[15] We also examine cumulative impulse responses to orthogonalized shocks, and the general picture is virtually identical.

Third, we conduct empirical analysis based on the model in Llorente, Michaely, Saar and Wang (2002) for robustness checks on the predicative power of order imbalances for returns.[16] They develop a multi-period, heterogeneous-agent, rational expectations model to study the dynamics of trading volume and returns. Traders can trade for speculation on private information and risk sharing. Returns generated by different trading motives exhibit different dynamics. Returns generated by speculative information tend to continue themselves as private information later becomes public through trading, while returns generated by hedging tend to reverse themselves. Following Llorente, Michaely, Saar and Wang (2002), we implement the following model specification:

$$R_{i,t} = \alpha_i + \gamma_i R_{i,t-1} + \theta_i OIB_{i,t-1} * R_{i,t-1} + \varepsilon_{it} \tag{2.5}$$

If institutional orders are generally informative, the average θ should be positive. We find that the coefficient of the interaction term is significantly positive, suggesting that

[14] Similar results obtain with unadjusted returns.
[15] For each trader type , we also run the dynamic structural VAR model (i.e., include contemporaneous OIB in the return equation) and obtain qualitatively identical results.
[16] We thank Jiang Wang for this suggestion.

returns on high institutional buying (selling) days tend to continue to go up (down). We interpret this as evidence of overall institutional trading being informative.

D. Summary

Microstructure theory predicts that order flow affects prices (Kyle, 1985; Glosten and Milgrom, 1985). While this prediction is well documented empirically, we know little about which traders drive this relationship. Trading strategies and information differ across traders and, therefore, we also expect that the relationship between order flow and prices differs across traders. We provide new evidence on this issue using NYSE data on daily order imbalances for different trader groups. For all common stocks between 2000 and April 2004, we observe buys and sells for institutions, individuals, and market makers, and can further distinguish regular institutional trades from institutional program and index-arbitrage program trades. Institutions account for 77% of total share volume during this period, individuals for 5%, and specialists for about 18%. Thus, institutions clearly are the most important trader group.

First, we document that institutions are contrarians with respect to returns on the previous day. This finding contrasts to evidence based on quarterly holdings, which suggests that institutions are momentum traders at longer horizons (see Sias, 2005). These results are not necessarily inconsistent; but because momentum trading would arguably be most destabilizing at shorter horizons, our results appear to alleviate such concerns about institutional trading behavior. We further show that individuals are contrarians as well, consistent with Kaniel, Saar, and Titman (2007). In fact, only specialists trade as if they are momentum traders on a daily basis – but this is a plausible result of bona fide market-making activity. A positive-return day is typically characterized by positive order imbalances and market makers may need to short to satisfy this demand. When returns reverse on the next day, they can purchase shares to rebalance their inventory.

Second, we document that order imbalances from different trader types play distinctly different roles in price formation. While institutions and individuals are contrarians, they differ in the effect their order imbalances have on contemporaneous returns. Institutional imbalances are positively related to contemporaneous returns, and we provide cross-sectional evidence that this relationship is likely to be the result of firm-specific information institutions have. In contrast, the imbalances of individuals, specialists, and institutional program traders are negatively related to contemporaneous returns. This suggests that these trader types provide liquidity to actively trading institutions. Moreover, this result suggests a special role for institutional program trades. Institutions appear to choose regular trades when they have firm-specific information, but they choose program trades when they do not and can, therefore, afford to trade passively. As a result, program trades provide liquidity to the market.

Third, both institutional non-program and individual imbalances have predictive power for next-day quote-midpoint excess returns. In contrast, specialist and program trade imbalances are negatively related to next-day returns. These results do not imply that profitable trading strategies exist, because trader-type information is not publicly (or even privately) disseminated. They do suggest, however, that institutions often have private information when their trading results in order imbalances. But because their imbalances also move prices contemporaneously, their trading profits appear to be bounded. This scenario is consistent with prior evidence that institutions have some stock-picking ability (see, for example, Daniel et al., 1997) and that institutions improve the informational efficiency of share prices (see Boehmer and Kelley, 2006). Moreover, our results also suggest that institutions use program trades when they do not have private information. This makes intuitive sense, because by packaging orders into baskets institutional traders can signal to the market that they are uninformed, which should result in lower execution costs.

During our sample period, institutional non-program trades generate 56% of share volume in the average stock. Our results imply that this portion of trading activity tends to be more informed than other trades. Therefore, institutional trading appears to drive the generally positive relationship between order flow and prices. Individuals provide 5% of volume and, on average, also tend to be informed. But the price impact results reveal that institutions trade more aggressively than individuals. Thus, consistent with Kaniel, Saar, and Titman's (2007) interpretation, individuals appear to provide liquidity to institutions. Their order volume is far too small, however, to satisfy institutional imbalances. We find that the remainder of these imbalances is filled by market makers and, in particular, by other institutions who are apparently not privately informed and use program trades.

CHAPTER III

SHORT SELLING AND THE INFORMATIONAL EFFICIENCY OF PRICES

A. Introduction

One of the continuing controversies in financial markets is the potential effect of short selling on the informational efficiency of share prices. Academics generally view short sellers as good candidates for rational, sophisticated arbitrageurs, and as such, they should help stabilize stock prices by bringing misvalued securities closer to their fundamental values (Friedman (1953)). However, some market observers adopt a different view on short sellers, often blaming this group of traders for market crises or large downward price movements.[17] This controversy is further fueled by accusations from some firms claiming that short sellers manipulate stock prices for unethical profits (see Lamont (2004) for examples). These accusations suggest that short sellers exert destabilizing influence on the market by driving stock prices away from their fundamentals.

One reason for this controversy might be that there is little direct evidence on how short sellers affect price efficiency heretofore. The primary goal of this paper is to conduct a formal and direct test on whether short sellers contribute to the informational efficiency of transaction prices, an important dimension of market quality. Such an investigation is interesting in and of itself, and it takes on an added importance given the concerns from market regulators. The U.S. Securities and Exchange Commission (SEC) recently mandated a pilot program Regulation SHO (Reg SHO) with an aim to “study

[17]For example, many blame short sellers for the Crash of 1929. Rule 10a-1(a) under the Securities Exchange Act of 1934 is instituted in response to concerns over short selling.

the effects of relatively unrestricted short selling on market volatility, price efficiency, and liquidity."[18]

Based on daily shorting flow data published by the NYSE for a large sample of common stocks for the period from January 2005 through August 2005, I show that shorting activity significantly improves the relative informational efficiency of stock prices in the sense that their transaction prices resemble a random walk more closely when shorters are more active. This result is fairly robust to various measures of shorting activity, econometric methodologies and model specifications. The efficiency-enhancing effect of shorting suggests that short sellers play an important role in price discovery. This direct evidence complements indicative results in Diether, Lee and Werner (2005) and Boehmer, Jones and Zhang (2007). Diether, Lee and Werner (2005) show that short sellers exhibit contrarian trading behavior on a daily basis which suggests that short sellers stabilize prices, and thus potentially contribute to price efficiency. Boehmer, Jones and Zhang (2007) use proprietary flow data on shorting for NYSE listed stocks during 2000-2004, and find that shorting flow is quite informative about future stock returns. They posit that "short sellers possess important information and their trades are important contributors to more efficient prices."

I also provide some evidence on how trade motivation of short sellers is related to the effect shorting has on price efficiency. While one cannot directly distinguish between informed and uninformed short sellers, the NYSE shorting data allow me to

[18] Regulation SHO-Pilot Program (April 19 2005) at http://www.sec.gov/spotlight/shopilot.htm. The SEC has chosen a subset of stocks with varying levels of trading volume from the Russell 3000 index as of June 25, 2004 to be pilot stocks (for more details, see Section II). For these pilot stocks, Reg SHO temporarily suspends the provisions of Rule 10a-1(a) under the Securities Exchange Act of 1934 and any short sale price test of any exchange or national securities association.

separately identify short sales that are exempt from the Uptick Rule. Exempt transactions are not likely to be information motivated, because they are primarily the result of market making activity or bona-fide arbitrage transactions defined by the SEC. One expects that exempt shorting should not affect the informational efficiency of prices. On the other hand, at least a meaningful fraction of non-exempt shorting might come from informed traders, and efficiency-enhancing shorting should primarily originate from this group. These conjectures are broadly supported by the data.

Finally, I examine the relationship between shorting and price efficiency in the context of the suspension of the Uptick Rule for Reg SHO pilot stocks.[19] Relative to control stocks, pilot stocks experience significantly more shorting after the tick restriction was suspended. The suspension of the tick test results in more shorting, perhaps because it gives short sellers more discretion about how to place their orders (as suggested by Diether, Lee and Werner (2006), Alexander and Peterson (2007)). Further analysis indicates some improvement in the informational efficiency of pilot stocks associated with increased shorting following the suspension of the tick test. The overall evidence suggests that the Uptick Rule constrains short selling to some extent and therefore reduces the informational efficiency of prices.

The above analysis is made possible by employing daily shorting flow data published by the NYSE. Using daily flow data on shorting can be a significant improvement over monthly short interest snapshots if some short sellers adopt short-term

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[19] The Uptick Rule, often referred to as tick test, requires that short selling in exchange-listed stocks occur only at an uptick or a zero-plus tick. That is, short sales in these stocks need to transact above the last trade price or at the last trade price if the last trade price is higher than the most recent trade at a different price. See Rule 10a-1 under the Securities and Exchange Act of 1934.

trading strategies, but flow data on shorting is relatively unexplored in the literature due to data unavailability.[20] A drawback is that the recent nature of the Pilot program and the resulting short time series of publicly disclosed shorting data may limit inferences from my analysis. In particular, I cannot use proxies for price efficiency that require longer time series to estimate (for example, price delays as in Hou and Moskowitz (2005)). To the extent that short sellers have information pertaining to a longer horizon, however, daily analysis actually reduces the power of finding any relationship between shorting and price efficiency. But even at daily level, the efficiency-enhancing effects of shorting are still present, indicating that short sellers play an important role in price discovery even within shorter horizons. This is consistent with recent studies suggesting that short sellers can be short-term traders.[21]

This paper adds to an expanding empirical literature on the informativeness of short selling. Most prior empirical work examines whether monthly short interest predicts stock returns over a variety of time horizons (see for example, Dechow, et al. (2001), Desai, et al. (2002), Asquith, Pathak and Ritter (2005), Boehme, Danielsen and Sorescu (2006)). Another strand of empirical literature in this field focuses on direct shorting costs and equity lending market (D'Avolio (2002), Geczy, Musto and Reed

[20] Academic papers studying shorting flow data (including proprietary data) include Angel, Christophe and Ferri (2003), Christophe, Ferri and Angel (2004), Daske, Richardson and Tuna (2005), Diether, Lee and Werner (2005), and Boehmer, Jones and Zhang (2007).

[21] For example, Reed (2003) finds that durations in the equity lending market (as represented by a large security lender) have a median (mode) of 3 (1) days during his sample period from November 1998 to October 1999. Boehmer, Jones and Zhang (2007) estimate that the average holding period for short positions is only 37 trading days, versus 1.2 years for long positions in 2004. In addition, Diether, Lee and Werner (2005) report an average of 25% of short selling volume and only 3.3% of short interest in stocks listed on Nasdaq in the first quarter of 2005. They conjecture that a large portion of recent short selling activity is short-term and even intradaily. Jones (2003) provides some evidence on intradaily shorting activities in the early 1930s. He documents an average of over 4% of daily trading volume for short sales established and covered in the same day.

(2002), Jones and Lamont (2002), Cohen, Diether and Malloy (2005)). More recently, some researchers show that shorting flow is quite informative about short-term returns (Christophe, Ferri and Angel (2004), Diether, Lee and Werner (2005), Boehmer, Jones and Zhang (2007)). The above work provides indirect evidence on short sellers' potential contribution to price efficiency. Lastly, two recent papers provide some international evidence on shorting constraints and price efficiency. Bris, Goetzmann and Zhu (2006) conduct a country-level analysis, and find that stock markets where shorting is practiced are more efficient compared to countries where short selling is prohibited. Saffi and Sigurdsson (2007) provide international firm-level evidence showing that less short sale constrained firms (i.e., firms with high lending supply and a low borrowing fee) are more efficiently priced in the sense that they have less price delays with respect to market shocks.

The remainder of the paper is organized as follows. Section B describes the data and construction of variables. Section C analyzes the relation between short selling and the informational efficiency of prices. Section D presents additional evidence from examining the effect of Reg SHO on price efficiency. Section E concludes the paper.

B. Data and construction of variables

This section begins with the construction of the sample. I then describe how I measure the relative informational efficiency of transaction prices.

B.1. The sample

The shorting flow data are published by the NYSE as part of the requirements under Reg SHO. The data are available from January 2005 – so this study covers the period from January 2005 through August 2005, four months before and after the implementation of Reg SHO on May 2, 2005. I aggregate the NYSE shorting transactions data into daily data.[22] One noteworthy feature of the shorting data is an indicator of short type (exempt or non-exempt from the Uptick Rule). Aggregate shorting volume in a stock is then grouped into two types: exempt and non-exempt. Exempt short orders mainly result from (presumably uninformed) market-making activity.[23] This allows me to contrast these shorts from non-exempt shorts, which presumably include more informed orders. One limitation of the shorting data is that information about purchases from short sellers to cover their short positions is not available. Therefore it is not possible to know exactly the length of the open short positions.

For Reg SHO, the SEC has chosen a subset of stocks with varying levels of volume from the Russell 3000 index as of June 25, 2004 to be pilot stocks and the rest of Russell 3000 to be control stocks.[24] My initial sample starts with NYSE-listed securities that are members of both Russell 3000 index of 2004 and 2005. This requirement intends

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[22] Short trades that occur outside the normal trading hours are excluded.

[23] For example, any sale by an odd-lot dealer or an exchange with which it is registered for such security, or any over-the-counter sale by a third market maker to offset odd-lot orders of customers can be exempted. The SEC defines arbitrage as "an activity undertaken by market professionals in which essentially contemporaneous purchases and sales are effected in order to lock in a gross profit or spread resulting from a current differential in pricing." For example, convertible arbitrage is considered consistent with the SEC definition. For more details, see 17CFR240.10a-1.

[24] The SEC selected pilot securities from Russell 3000 index as of June 25, 2004. First, 32 securities in the Russell 3000 index that are not listed on the American Stock Exchange (Amex), or on the New York Stock Exchange (NYSE), or not Nasdaq national market securities (NNM) are dropped. Securities that went public after April 30, 2004 are also excluded. The remaining securities are then sorted into three groups by marketplace, and ranked in each group based on average daily dollar volume over the one year prior to the issuance of the order. From each ranked group, SEC selected every third stock to be a pilot stock starting from the 2nd stock. The remaining stocks are suggested to be used as the control group where the price test restriction still applies. Of all pilot stocks, 50%, 2.2% and 47.8% are from NYSE, Amex, and Nasdaq NNM, respectively. For more information about Reg SHO, see SEC Release No. 50104/July 28, 2004.

to eliminate potential confounding effects from index deletions/additions (Barberis and Shleifer (2003)). Only domestic, common stocks (share codes 10, 11) listed on the NYSE are included. Stocks that experience ticker changes due to mergers and acquisitions during the sample period are also excluded. This requirement attempts to eliminate confounding effects of merger arbitrage short selling (Baker and Savasoglu (2002), Mitchell, Pulvino and Stafford (2004)). Security-specific characteristics such as consolidated trading volume, closing prices, and market capitalization are obtained from the Center for Research in Security Prices (CRSP). If a stock's closing price is above $900, the stock is excluded from the sample to avoid potential influence of unusually high prices.[25] Sample stocks are also required to have trading data in every month during the sample period to facilitate comparisons around Reg SHO. Finally, I use transactions data from the NYSE's Trades And Quotes (TAQ) database to compute daily price efficiency measures (see Section B for details). Since very few time-series observations in the estimation can distort the calculation of price efficiency measures, a stock is required to have a daily average of more than 100 trades during the sample period to be included in the analysis. This process yields a sample of 1,217 (407 pilot and 810 control) stocks used in the main analysis.

For part of the empirical analysis on the effect of the tick test on price efficiency, I use a matched sample of pilot and control stocks. I match on three dimensions: pre-Reg SHO averages of market capitalization (MktCap), closing prices (Prc) and consolidated

[25] It turns out the lowest stock price in the sample is above $2. I do not exclude stocks with an average price below $5 (29 stocks) because the data show that they may not be very difficult or impossible to short as the average shorting activity with respect to daily trading volume in these low-priced stocks is about 13%.

trading volume (Volume). Specifically, for each pilot stock, I try to find a control stock that produces the minimum pair-wise absolute matching error:

$$\text{Matching error} = |\text{MktCap}_p\text{-MktCap}_c| \,/\, \text{MktCap}_p + |\text{Prc}_p\text{-Prc}_c| \,/\, \text{Prc}_p + |\text{Volume}_p\text{-Volume}_c|/\text{Volume}_p \qquad (3.1)$$

where p and c refer to pilot and control stocks, respectively. Such a matched sample ensures that the effects attributed to the Pilot do not simply arise from market-wide changes in shorting and informational efficiency. To mitigate the adjustment traders might have to make due to the new rule, I exclude four weeks around May 2, 2005 (i.e. 04/18/2005 - 29/04/2005 and 05/02/2005 - 05/13/2005). The 407 matched pairs of pilot and control stocks are used in studying the effect of Reg SHO on price efficiency.

B.2. Measures of the informational efficiency of prices

This study focuses on the *relative* informational efficiency of transaction prices, not market efficiency in an absolute sense. For my analysis, I follow Boehmer and Kelley (2006) to investigate the relative informational efficiency of prices, defined as how closely observable transaction prices follow a random walk.[26] This approach is appealing in several aspects. First, it is consistent with basic market efficiency concept. The idea is that the more efficient stock prices are, the more random the sequence of

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[26] Alternative proxies for the informational efficiency of prices include price delays and R^2. Price delays reflect the sensitivity of a firm's returns to contemporaneous and lagged market returns (Hou and Moskowitz (2005)) and has been used as a proxy for price efficiency to examine how quickly information is reflected into stock prices (see, for example, Griffin, Kelly and Nardari (2007), Saffi and Sigurdsson (2007)). The R^2 from a market model regression is suggested as a proxy for price efficiency in Morck, Yeung and Yu (2000) and Durnev, et al. (2003). They argue that lower R^2 indicates more firm-specific information and can thus be used as a measure of information efficiency of stock prices. However, recent work shows that R^2 does not capture information well (Kelly (2005), Ashbaugh, Gassen and LaFond (2006), Griffin, Kelly and Nardari (2007), Saffi and Sigurdsson (2007))). Both of these measures, however, require long time-series data for estimation, so they cannot be reliably computed with my sample.

price changes is. Second, this approach can capture the continuous nature of information flow and order flow as suggested in many microstructure models. Third, this approach is built on recent empirical evidence. Chordia, Roll and Subrahmanyam (2005) suggest that “astute traders” follow the market intently, and information is generally incorporated into prices through their trading within 30 minutes. Building on these insights, I use intraday transactions data to compute price efficiency measures. Specifically, to proxy for the informational efficiency of prices, I calculate (1) the pricing error as suggested in Hasbrouck (1993), and (2) the absolute value of 30-minute quote midpoint return autocorrelations. These measures are briefly discussed below.

B.2.1. The pricing error

An intuitive measure of the informational efficiency of prices is the dispersion of the pricing error as suggested in Hasbrouck (1993).[27] In this section, I discuss the economic interpretation of the pricing error (see the Appendix for a detailed estimation). To study price discovery, Hasbrouck (1993) focuses on the “efficient” price of a security defined as its expected value conditional on a given information set where it allows both public information and some private information inferred by a market maker from the order flow. Since the efficient price is not observable, Hasbrouck uses information about (signed) trade size and execution prices for all transactions in a stock to conduct a variance decomposition procedure through a Vector AutoRegression (VAR) model to identify changes in the efficient price and transient price changes. The efficient price,

[27] Boehmer, Saar and Yu (2005) apply Hasbrouck (1993) method to study the effect of adopting Openbook on the NYSE on stock price efficiency. Boehmer and Kelley (2006) find that institutions contribute to price efficiency using similar approaches. Hotchkiss and Ronen (2002) examine the informational efficiency of corporate bond prices using a simplified procedure of Hasbrouck (1993).

which only changes in response to new information, is assumed to follow a random walk. The pricing error, which measures the temporary deviation between actual transaction price and the efficient price, reflects information-uncorrelated frictions in the market (such as price discreteness, inventory control effects, non information-related fraction of transaction costs, etc.). It is assumed to have a zero-mean covariance-stationary process. The dispersion of the pricing error, $\sigma(s)$, reflects how closely actual transactions prices conform to the efficient price, and can thus be interpreted as a measure of price efficiency. Because the dispersion of the pricing error is inversely related to price efficiency, a smaller value indicates greater efficiency.

In the empirical analysis, $\sigma(s)$ is scaled by the standard deviation of intradaily transaction prices, $\sigma(p)$, to control for cross-sectional differences in the return variance. Henceforth, this ratio $\sigma(s)/\sigma(p)$ is referred to as the "pricing error" for brevity.

B.2.2. Autocorrelations

An alternative measure of price efficiency is the absolute value of quote midpoint return autocorrelations. The intuition is that if the quote midpoint is the market's best estimate of the equilibrium value of the stock at every point in time, a more efficient price implies that the quote midpoints are closer to a random walk, and therefore should exhibit less autocorrelation in both positive and negative directions.

Chordia, Roll and Subrahmanyam (2005) show prices are generally not quite efficient within 30-minute intervals in the sense that lagged order imbalances have some predictive power with respect to subsequent returns. To capture the extent of these potential inefficiencies, I compute 30-minute quote midpoint return autocorrelations, excluding overnight returns. The absolute value of the return autocorrelations, |AR30|, is used in the analysis. A random walk is characterized by zero autocorrelations. Thus, the smaller the absolute value is, the more closely the return process resembles a random walk.

It is worth pointing out that pricing errors, by construction, only attribute non-information-based price changes to departures from a random walk, whereas autocorrelations do not distinguish between information-correlated and information-uncorrelated price changes. For example, splitting a large order by an informed trader would produce a zero pricing error as information from order flow is incorporated into prices, but would generate a positive autocorrelation. In this regard, the pricing error appears to be a better proxy for the informational efficiency of prices.

C. Does shorting contribute to the informational efficiency of prices?

Before proceeding with the formal tests on the relationship between shorting and relative price efficiency, I present some recent indirect evidence on short sellers' potential contribution to efficiency. Diether, Lee and Werner (2005) find that short sellers act in a contrarian way with respect to past stock returns. This evidence runs counter to accusations that short sellers destabilize prices. Most recently, Boehmer, Jones and Zhang (2007) show that stocks with heavy shorting flow significantly underperform lightly-shorted stocks at various short-term horizons. They conclude that "short sellers possess important information and their trades are important contributors to more efficient prices." From the above indicative results, it follows that as information is impounded into prices through short sellers' daily trading activity, higher shorting flow implies greater informational efficiency.

To formally test the relationship between short selling and price efficiency on a daily basis, the following multivariate regression is specified:

$$\text{Efficiency}_{i,t} = \alpha_t + \beta_t \text{Shorting}_{i,t-1} + \gamma_t \text{Controls}_{i,t-1} + \varepsilon_{i,t} \quad (3.2)$$

The dependent variable is a proxy for relative price efficiency, either the pricing error or |AR30|. Shorting, the key variable of interest, is measured as a stock's daily shorted shares scaled by its trading volume. This standardization makes shorting volume comparable across stocks with different trading activities. If shorting contributes to greater price efficiency and thus smaller deviation from a random walk, β should be negative.

Prior literature suggests several control variables. I include relative effective spreads (measured as twice the distance between the execution price and the prevailing quote midpoint scaled by the prevailing quote midpoint) to control for trading costs.[28] Large transaction costs increase the costs of arbitrage, and should be inversely related to efficiency. Volume-weighted average price (VWAP) controls for differences in price discreteness that can potentially affect efficiency.[29] Market capitalization controls for

[28] Controlling for relative effective spreads serves another purpose in the pricing error regression. The pricing error reflects the information-uncorrelated (i.e. temporary) portion of total price variance. Since the effective spread measures the total price impact of a trade and thus could conceivably be related to the pricing error, controlling for it can help isolate changes in efficiency from changes in liquidity.
[29] Using closing prices produces qualitatively identical results.

differences in firm size. Trading volume controls for differences in trading activity, as more actively traded stocks may be more efficiently priced.[30]

Boehmer and Kelley (2006) find that institutional investors improve the informational efficiency of stock prices. Thus it is necessary to control for their holdings, obtained from the 13F filings in the CDA Spectrum database and standardized by shares outstanding (adjusted for stock splits).[31] Because analyst coverage might improve a firm's informational environment, I also control for the number of sell-side analysts producing annual forecasts of firm earnings, obtained from monthly I/B/E/S (Brennan and Subrahmanyam (1995)).[32] To control for persistence in the price efficiency measures, the lag of the dependent variable is also included. Finally, all explanatory variables are lagged by one period to mitigate the potential influence of changes in price efficiency on these contemporaneous explanatory variables.[33]

Table 3.1 presents time-series means of the cross-sectional summary statistics of the variables. Relative shorting volume accounts for over 20% of total trading volume during the sample period. Compared to an average of about 13% (of NYSE system trading volume) documented in Boehmer, Jones and Zhang (2007) from 2000 to 2004, the above number suggests a tremendous increase in shorting activity in recent years. A 10% standard deviation reveals large variation in shorting volume across stocks. Price

[30] Trading volume and firm market capitalization have a positive correlation of 0.78. To mitigate this multicollinearity issue, I use residuals from regressing log of market capitalization on log volume in the reported regression results. Results remain qualitatively similar when no orthogonalization is employed.
[31] I also use the (log of) number of institutional owners instead of percentage ownership in the regressions and the main results remain largely unchanged.
[32] Note that institutional ownership (analyst) data are observed at quarterly (monthly) frequency, and thus may have low explanatory power with a short sample period.
[33] As suggested by Boehmer and Kelley (2006), one can interpret the lagged value of these explanatory variables as instrument variables for the contemporaneous values. Results using contemporaneous values remain qualitatively similar.

efficiency measures also exhibit some cross sectional variations. Firm size, trading volume, share prices, institutional ownership and the number of analysts are quite skewed, thus the natural logarithms of their values are used in regressions.

Table 3.1
Summary Statistics on Shorting and Price Efficiency

The sample includes 1,217 NYSE-listed common stocks for the period from January 2005 to August 2005. This table reports time-series means of daily cross-sectional summary statistics. Shorting is calculated as shares shorted standardized by trading volume on a given stock day. $\sigma(s)$ is the standard deviation of the discrepancies between log transaction price and the efficient price, and $\sigma(p)$ is the standard deviation of intraday transaction prices. |AR30| is the absolute value of the 30-minute quote midpoint return autocorrelation. Volume is daily share trading volume expressed in millions. RES is daily equally-weighted relative effective spreads. VWAP is daily volume-weighted average price. Price is a stock's daily closing price. Size is the market value of equity expressed in billions of dollars. InstOwn is the fraction of shares outstanding owned by institutions. NumAnalyst is the number of analysts that covers a firm.

	Mean	Median	Std
Shorting	20.71%	19.24%	10.32%
$\sigma(s)/\sigma(p)$	0.0859	0.0599	0.0860
|AR30|	0.2481	0.2177	0.1769
Volume (millions)	1255.327	479.043	2768.752
RES	0.00083	0.00062	0.00069
VWAP($)	35.86	32.14	21.09
Price($)	35.85	32.15	21.08
Size ($billion)	8.736	2.197	24.931
InstOwn	0.746	0.772	0.206
NumAnalyst	10.300	9.000	7.160

I proceed to examine the relationship between shorting and the informational efficiency of prices. The effect of aggregate shorting flow on price efficiency is investigated first, followed by a comparative analysis on the effect of exempt vs. non-exempt shorting on efficiency.

C.1. Short selling and the relative informational efficiency of prices

Table 3.2 reports Fama and MacBeth (1973) two-step regression of price efficiency on shorting. Specifically, daily cross-sectional analysis is performed first, and then time-series averages of the regression coefficients are reported. T-statistics are based on Newey-West standard errors to correct for potential autocorrelations.[34] Model 1 reports a significantly negative coefficient of shorting flow on the pricing error. It suggests that, controlling for other variables, more shorting is associated with greater relative informational efficiency (i.e. smaller pricing errors). This evidence is consistent with the view that short sellers are primarily informed traders and their trading contributes to price efficiency. Other control variables show signs consistent with previous studies. For example, higher relative effective spreads are associated with less efficient prices (i.e., larger pricing errors). Model 2 further controls for institutional ownership and the number of analysts. Both variables are inversely related to efficiency, but shorting is still significant (although the magnitude of its coefficient is slightly smaller). Thus, shorting appears to have a distinct effect on price efficiency.

[34] Various lags are used for the Newey-West standard errors. Results are not sensitive to the number of lags used. I report statistics adjusted with 5 lags.

Models 3 and 4 use (the log of) |AR30| to proxy for price efficiency.[35] Shorting has a significantly negative coefficient in both models, indicating more short selling is associated with smaller autocorrelations in either positive or negative direction. This provides further evidence that shorting contributes to greater price efficiency.

Table 3.2
Cross-Sectional Regressions of Price Efficiency on Shorting

This table reports daily Fama-MacBeth regression results for 1,217 NYSE-listed common stocks during the sample period from Januray 2005 to August 2005. $\sigma(s)$ is the standard deviation of the discrepancies between log transaction price and the efficient price, and $\sigma(p)$ is the standard deviation of intraday transaction prices. |AR30| is the absolute value of the 30-minute quote midpoint return autocorrelation. Shorting is shares shorted standardized by shares traded on a given stock day. RES is daily equally-weighted relative effective spreads. VWAP is daily volume-weighted average price. Size is the market value of equity expressed in billions of dollars. Volume is orthogonalized daily share trading volume with repespct to size. DV is the dependent variable. InstOwn is the fraction of shares outstanding owned by institutions. NumAnalyst*100 is the number of analysts that covers a firm (scaled up by 100). Ln refers to the natural logarithm. T-statistics are based on Newey-West standard errors adjusted for 5 lags.

Dependent variable	$\sigma(s)/\sigma(p)_t$ Model 1		$\sigma(s)/\sigma(p)_t$ Model 2		$Ln\|AR30\|_t$ Model 3		$Ln\|AR30\|_t$ Model 4	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Intercept	0.1723	41.48	0.1780	38.99	-1.5709	-28.25	-1.5521	-26.68
$Shorting_{t-1}$	-0.0223	-9.15	-0.0183	-8.65	-0.0870	-3.65	-0.0803	-2.84
$LnVolume_{t-1}$	-0.0183	-35.78	-0.0159	-34.89	-0.0195	-3.93	-0.0178	-3.29
RES_{t-1}	34.0464	33.17	31.7433	29.2	9.7289	1.45	3.1260	0.47
$LnVWAP_{t-1}$	-0.0099	-20.71	-0.0095	-21.79	-0.0198	-2.13	-0.0210	-2.16
$Lnsize_{t-1}$	-0.0069	-34.43	-0.0063	-29.43	-0.0090	-2.90	-0.0049	-1.30
DV_{t-1}	0.3134	36.60	0.3077	41.28	0.0025	1.16	0.0011	0.45
$LnInstOwn_{t-1}$			-0.0058	-11.24			0.0085	1.13
$LnNumAnalyst*100_{t-1}$			-0.0026	-10.73			-0.0109	-1.87

[35] Using the absolute value of autocorrelations produces qualitatively similar results.

To check the robustness of the above results, alternative measures of shorting activity and methods are used. First, I use daily shorting decile ranks in the analysis. Specifically, each day, stocks are sorted into deciles according to relative shorting volume, and the rank value is used in the regression. This approach can potentially reduce the influence of outliers. A significantly negative coefficient of shorting is documented in all model specifications. Stocks with higher ranks in terms of relative shorting flow have significantly smaller pricing errors and autocorrelations. Since these results are qualitatively similar, they are not reported here.

Second, “abnormal” shorting is constructed as another alternative measure of shorting activity. Each day, a stock’s shorting activity is measured relative to its own moving average over the past week to determine whether the shorting is more intense. This measure helps identify stocks that experience a shock in their own shorting activity over a short period. It can factor in potential persistence in shorting activity in a certain stock. Using this measure yields qualitatively identical results in all models: stocks with more abnormal shorting are priced more efficiently as shown by smaller pricing errors and autocorrelations.

Finally, I also conduct panel regressions as additional sensitivity checks. The overall results largely mirror those obtained through Fama-MacBeth regressions. Taken together, these results present direct evidence on the efficiency-enhancing effect of short sellers in price discovery. Short sellers are relatively well informed traders, and their trading contributes to more efficient prices in the sense that stocks with higher shorting activity track more closely with their fundamental value. This direct evidence complements the indicative results in Boehmer, Jones and Zhang (2007) and ties well with the contrarian trading behavior of short sellers documented in Diether, Lee and Werner (2005).[36]

C.2. Exempt vs. non-exempt short selling

The aggregate shorting in a stock lumps together all types of short sellers who might be more or less informed about the stock. I now provide some additional evidence on how different information is related to the effect shorting has on price efficiency. While one cannot distinguish informed from uninformed short sellers directly, the NYSE shorting data allow me to identify short sales that are exempt from the Uptick Rule. Exempt shorting primarily includes broker-dealer market-making activities or bona-fide arbitrage transactions defined by Rule 10a-1(a) under the Securities Exchange Act of 1934. Shorting in the course of market making, by definition, should not have as much information content as shorting by other traders. Similarly, shorting due to convertible arbitrage should be less informed as well, because it mainly exploits information about other securities (Asquith, Pathak and Ritter (2005)). Therefore, exempt shorting should have a smaller effect on price efficiency than non-exempt shorting.

A caveat related to the data is in order. The exempt vs. non-exempt categorization is clean in both pilot and control stocks in the pre-Reg SHO period, but only in control stocks in the post-Reg SHO period. This categorization is contaminated for pilot stocks after the implementation of Reg SHO. According to Reg SHO, all short

[36] The price-efficiency enhancing effect of short selling is also consistent with the argument that "pairs trading" helps maintain price efficiency (Gatev, Goetzmann and Rouwenhorst (2006)).

sales in pilot stocks in the post period should be exempt from the Uptick Rule. However, some short orders in pilot stocks are not marked “Short Exempt” when they should have been.[37] Thus a comparative analysis of exempt vs. non-exempt shorting on price efficiency is performed and reported using all stocks in the pre-Reg SHO period.

Non-exempt shorting dominates total shorting activity on the NYSE. In the Pre-Reg SHO period, the average relative non-exempt shorting (measured as non-exempt shorting volume scaled by total trading volume) accounts for 20.71% of total trading volume, while relative exempt shorting (measured as exempt shorting volume scaled by total share volume) accounts for only 0.07% of total trading volume.

Table 3.3 presents cross-sectional effect of exempt and non-exempt shorting flow on price efficiency. The results show that exempt shorting is not significantly associated with price efficiency measures. This suggests that exempt shorting is not likely to be driven by information, and therefore contributes little to price efficiency. In contrast, non-exempt shorting has much stronger effect on price efficiency. Higher levels of non-exempt shorting are significantly associated with smaller pricing errors. This lends support to the view that non-exempt short selling is more likely to be motivated by information. The result with autocorrelation measures is weak, though.

To check the sensitivity of the relation between non-exempt vs. exempt shorting flow and price efficiency, I repeat the tests only on uncontaminated reporting of control stocks. Non-exempt shorting is significantly associated with greater price efficiency

[37] See Letter from SEC to SIA, January 2 2005 and Letter from SEC to SIA, April 15 2005.

using either proxy for price efficiency, while exempt shorting is not consistently associated with price efficiency.

Table 3.3

Cross-Sectional Regressions of Price Efficiency on Exempt vs. Non-Exempt Shorting

This table reports daily Fama-MacBeth regression results for 1,217 NYSE-listed common stocks for the period from Januray 2005 to April 2005. σ(s) is the standard deviation of the discrepancies between log transaction price and the efficient price, and σ(p) is the standard deviation of intraday transaction prices. |AR30| is the absolute value of the 30-minute quote midpoint return autocorrelation. Exempt (Non-Exempt) shorting refers to daily exempt (non-exempt) shares shorted standardized by total trading volume. RES is daily equally-weighted relative effective spreads. VWAP is daily volume-weighted average price. Size is the market value of equity expressed in billions of dollars. Volume is orthogonalized daily share trading volume with repespct to size. DV is the dependent variable. InstOwn is the fraction of shares outstanding owned by institutions. NumAnalyst*100 is the number of analysts that covers a firm (scaled up by 100). Ln refers to the natural logarithm. T-statistics are based on Newey-West standard errors adjusted for 5 lags.

Dependent variable	$\sigma(s)/\sigma(p)_t$ Model 1		$\sigma(s)/\sigma(p)_t$ Model 2		Ln|AR30| $_t$ Model 3		Ln|AR30| $_t$ Model 4	
	coef.	t	coef.	t	coef.	t	coef.	t
Intercept	0.1688	31.04	0.1716	29.04	-1.6124	-18.03	-1.6185	-17.8
Non-exempt shorting $_{t-1}$	-0.0125	-5.34	-0.0115	-4.82	-0.0587	-1.61	-0.0285	-0.66
Exempt shorting $_{t-1}$	0.1430	1.51	-0.0781	-1.33	-1.8850	-1.17	-1.9992	-1.05
LnVolume $_{t-1}$	-0.0192	-37.93	-0.0165	-31.19	-0.0227	-2.97	-0.0211	-2.52
RES $_{t-1}$	35.3522	27.57	33.4211	23.81	10.4735	0.96	7.4792	0.68
LnVWAP $_{t-1}$	-0.0102	-17.78	-0.0091	-15.05	-0.0255	-1.83	-0.0265	-1.74
Lnsize $_{t-1}$	-0.0069	-23.44	-0.0066	-19.57	-0.0058	-1.14	-0.0009	-0.15
DV $_{t-1}$	0.2943	42.75	0.2909	43.46	0.0001	0.03	-0.0008	-0.29
LnInstOwn $_{t-1}$			-0.0066	-7.45			0.0154	1.34
LnNumAnalyst*100 $_{t-1}$			-0.0018	-6.21			-0.0097	-1.04

Consistent with the priors, the overall evidence suggests that exempt shorts do not contribute to price efficiency in a consistent manner, while a large portion of non-exempt shorting appears to be driven by information and therefore enhances the informational efficiency of stock prices. This contrast indicates the importance of trade motivation in affecting price efficiency. Since non-exempt shorting dominates shorting activity, shorting in general is an important contributor to more efficient prices.

D. Additional evidence from suspending the Uptick Rule

The analysis so far suggests that short selling enhances the relative informational efficiency of stock prices in a general setting. I now provide some additional evidence from evaluating the effect of suspending the Uptick Rule on the informational efficiency of pilot stocks designated for the Reg SHO experiment.

There are several potential event dates associated with the Reg SHO Pilot program.[38] For the purpose of this study, what matters most is the actual date when traders can carry out shorting in pilot stocks without the uptick restriction, May 2, 2005. For this part of analysis, a matched sample as discussed in the data section is used. Panel A of Table 3.4 presents summary statistics on the matching variables. Pilots and their matched controls are quite similar in price, volume and size. The (untabulated) mean (median) matching error of 0.27 (0.23) suggests that they are matched well.

[38] Reg SHO was adopted on September 7, 2004 and the compliance to the rules was originally intended to start on January 3, 2005. But the pilot was postponed until May 2, 2005. The termination date of the pilot was originally set to April 28, 2006, but has been postponed to August 6, 2007. See Securities Exchange Act of 1934 Release No. 53684.

D.1. Changes in shorting activities around Reg SHO

Panel B of Table 3.4 compares the relative shorting activity between pilot and control stocks. Cross-sectional means (medians) in the Pre-Reg SHO period are compared to those in the post period to evaluate the effect of Reg SHO. To mitigate possible time-trends arising from market-wide changes in shorting and informational efficiency, differences between post-pre changes in pilot stocks and corresponding post-pre changes in matched control stocks are examined.[39] In the pre-Reg SHO period, pilot (control) stocks have an average of 20.89% (20.35%) shorting relative to the consolidated trading volume. These numbers suggest tremendous amount of shorting activity in the stock market despite the presence of the Uptick Rule. Note that pilot stocks do not differ significantly from control stocks in shorting activity in the pre-Reg SHO period.

Shorting activity increases in pilot stocks after the uptick restriction is suspended. The mean (median) shorting in pilot stocks climbs to 21.63% (21.31%) of total trading volume, whereas shorting in control stocks has declined slightly in the post-Reg SHO period. Relative to the change in control stocks, the increase in shorting activity for pilot stocks has a mean (median) of 1.58% (1.8%) of total volume. The differences of differences tests show that these increases are significant, suggesting that the uptick restriction does constrain short selling to some extent.

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[39] Alternatively, I test the post-pre change in the difference between pilot and control stocks and document similar results.

Table 3.4
Summary Statistics on the Matched Pairs of Pilot and Control Stocks

This table reports summary statistics of 407 matched pairs of pilot and control stocks listed on the NYSE from January 2005 to August 2005. Panel A reports the pre-Reg SHO daily average of the matching variables. Each pilot stock is matched with a control stock that produces the minimum pairwise matching error along three dimensions based on pre-event period averages: market capitalization (MktCap), month-end share price (Prc) and consolidated trading volume (Volume). Matching error = |MktCapp-MktCapc| / MktCapp + |Prcp-Prcc| / Prcp + |Volumep-Volumec| / Volumep, where symbols p, c refer to pilot and control stocks, respectively. Panel B reports shorting activity of these matched pairs in the pre- (post-) Reg SHO period. Shorting is measured as daily shares shorted standardized by daily trading volume. Pilot - Control is the difference between post-pre change in pilot stocks and post-pre change in matched control stocks. Mean (median) differences are tested using t-tests (Wilcoxon signed rank tests). Asterisks *,**,*** indicate significance at 0.1, 0.05, 0.01 level, respectively. The pre- (post-) Reg SHO period refers to the period from January 2005 to April 2005 (from May 2005 to August 2005) where the four weeks around 05/02/2005 are excluded.

Panel A: Pre-Reg SHO (excluding two weeks prior to 05/02/2005) daily averages of matching variables.

	Pilot		Control	
	Mean	Median	Mean	Median
Size ($billion)	8.409	2.229	7.769	2.098
Price ($)	35.93	32.51	34.73	32.81
volume (million)	1308.418	539.247	1206.083	552.053

Panel B: Shorting activity in the pre-(post-) Reg SHO period

	Pilot				Control				Pilot - Control	
	Post	Pre	Post-pre		Post	Pre	Post-pre			
Shorting (Mean)	21.63%	20.89%	0.74%	***	19.50%	20.35%	-0.84%	***	1.58%	***
Shorting (Median)	21.31%	20.71%	0.82%	***	19.47%	20.13%	-0.60%	***	1.80%	***

D.2. (How) Does the Uptick Rule affect price efficiency?

Given the increase in shorting activity following the suspension of the tick test, a natural question to ask is whether the relative price efficiency of pilot stocks also changes. I examine this issue using the following panel data estimation:

$$\text{Efficiency}_{i,t} = \alpha + \delta\text{Pilot} + \phi\text{Post} + \eta\text{Pilot*Post} + \beta\text{Shorting}_{i,t-1} + \theta\,\text{Pilot*Post* Shorting}_{i,t-1} + \gamma\text{Controls}_{i,t-1} + \varepsilon_{i,t} \quad (3.3)$$

Pilot, a dummy variable equal to one for pilot stocks and zero for control stocks, is included to control for potential differences between pilot and control stocks during the sample period. Post, a dummy variable equal to one for the period after May 2 and zero before this date, controls for potential time trends in the market. The interaction term of Pilot*Post intends to capture the shorting-unrelated effect on the efficiency of pilot stocks after the suspension of the uptick rule. The interaction term of Pilot*Post*Shorting reflects the corresponding effect that is directly related to shorting activity. To ease interpretation, shorting is defined as a dummy equal to one if a stock's standardized shorting volume is above the daily cross-sectional median and zero otherwise.[40]

Random effects panel estimation is used as it has the advantage of allowing time-invariant variables in the regression. Table 3.5 reveals several interesting results. First, note that shorting is significantly negative in most cases, with varying magnitudes as model specifications change. This confirms the earlier result that shorting contributes to more efficient prices.

[40] Using relative shorting activity produces qualitatively similar results.

Table 3.5
Reg SHO and Price Efficiency

This table reports random effects panel estimation results for 407 matched pairs of pilot and control stocks listed on the NYSE during the period from January 2005 to August 2005. σ(s) is the standard deviation of the discrepancies between log transaction price and the efficient price, and σ(p) is the standard deviation of intraday transaction prices. |AR30| is the absolute value of the 30-minute quote midpoint return autocorrelation. Shorting is a dummy equal to one if a stock's relative shorting volume is above the cross-sectional median and zero otherwise on a given day. Volume, RES, VWAP, and Size are daily share trading volume, equally-weighted relative effective spreads, volume-weighted average prices, and market value of equity, respectively. Pilot is a dummy variable equal to one for pilot stocks and zero for control stocks. Post is a dummy variable equal to one after 5/2/2005 and zero before that date. InstOwn is the fraction of shares outstanding owned by institutions. NumAnalyst*100 is the number of analysts that covers a firm (scaled up by 100). DV is the dependent variable. Ln refers to the natural logarithm.

Dependent variable	$\sigma(s)/\sigma(p)_t$		$\sigma(s)/\sigma(p)_t$		Ln|AR30| $_t$		Ln|AR30| $_t$	
	Model 1		Model 2		Model 3		Model 4	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Intercept	0.3758	30.48	0.3657	27.60	-1.5495	-24.40	-1.5734	-21.52
Shorting $_{t-1}$	-0.0021	-4.78	-0.0018	-4.15	-0.0145	-1.84	-0.0108	-1.29
Pilot	-0.0014	-0.60	-0.0017	-0.69	-0.0073	-0.75	-0.0098	-0.90
Post	0.0039	2.20	0.0034	2.02	-0.0106	-0.51	-0.0096	-0.45
Pilot*Post	-0.0007	-0.83	-0.0002	-0.29	0.0180	1.20	0.0175	1.11
Pilot*Post*Shorting $_{t-1}$	-0.0030	-3.86	-0.0029	-3.66	0.0120	0.84	0.0072	0.47
LnVolume $_{t-1}$	-0.0089	-5.83	-0.0078	-4.77	-0.0201	-2.28	-0.0127	-1.25
RES $_{t-1}$	-0.0108	-28.48	-0.0100	-25.82	-0.0158	-3.22	-0.0119	-2.12
lnVWAP $_{t-1}$	-0.0096	-10.16	-0.0086	-8.11	0.0024	0.45	0.0006	0.10
LnSize $_{t-1}$	11.9059	18.07	12.9336	18.10	11.4880	1.55	10.8183	1.18
DV $_{t-1}$	0.1598	52.37	0.1557	48.15	-0.0034	-1.14	-0.0070	-2.23
LnInstOwn $_{t-1}$			-0.0033	-3.72			0.0014	0.18
LnNumAnalyst*100 $_{t-1}$			-0.0031	-3.75			-0.0049	-0.71

Second, the coefficients of Pilot*Post are not statistically significant, suggesting that Reg SHO has little effect on pilot stocks that is unrelated to shorting. Third and more importantly, the negative θ associated with Pilot*Post*Shorting suggests that a pilot stock with above median shorting activity following the suspension of the tick test has significantly smaller pricing errors, indicating that pilot stock prices become relatively more efficient through the channel of more short selling. While results using autocorrelations are weak, the evidence on pricing errors suggests increases in the relative informational efficiency of pilot stocks. These efficiency improvements are attributable to increased shorting activity after the tick test is suspended.

As a robustness test, I partition the matched sample into Pre- and Post-Reg SHO periods and conduct Fama and MacBeth (1973) two-step regressions similar to Equation (3.2). If the suspension of the tick test improves price efficiency through the channel of shorting activity, the coefficient of shorting flow on price efficiency is expected to be stronger in the post-Reg SHO period relative to that in the pre-Reg SHO period, controlling for other factors. This is indeed the case and not reported here.

I also conduct cross-sectional analysis of post-pre changes in average price efficiency. Similar to the panel regression results, suspending the Uptick Rule has no shorting-unrelated effect on the efficiency of pilot stocks after other changes associated with Reg SHO are controlled for. However, pilot stocks exhibit more efficient prices (as shown by smaller pricing errors) that are directly related to the increased shorting.

To sum up, this section examines the shorting-efficiency relationship in the specific context of Reg SHO. There is evidence that the Uptick Rule constrains short selling. Pilot stocks that experience increases in shorting see some improvement in price efficiency, providing additional evidence to the earlier result that short sellers contribute to greater price efficiency.

E. Summary

Using a large sample of NYSE-listed common stocks with publicly available shorting flow data, I examine the relationship between short selling and the relative informational efficiency of stock prices. The main result is that short sellers contribute to greater price efficiency. Stocks with more shorting activity are relatively more efficiently priced in the sense that their transaction prices follow more closely to a random walk. This result is robust to various econometric methods and model specifications and suggests that short sellers play an important role in price discovery process. The efficiency-enhancing effect of shorting activities complements recent empirical literature on the informativeness of short selling flow.

I also provide some evidence on how shorters' trade motivation affects price efficiency. Exempt shorting, which primarily comes from broker-dealer market-making activities and bona-fide arbitrage transactions, is not associated with price efficiency in any consistent manner. In contrast, stocks with higher levels of non-exempt shorting are more efficiently priced, suggesting that this group of short sellers is relatively more informed.

Finally, I examine shorters' efficiency-enhancing activities in the context of Reg SHO. Relative to matched control stocks, pilot stocks experience increased shorting, and consequently, exhibit some improvement in price efficiency after the uptick restriction is suspended. Overall, the evidence in this paper suggests that short sellers are generally informed traders and that their trading contributes to more efficient prices. Importantly, the Uptick Rule appears to constrain short sellers’ efficiency-enhancing activities and therefore reduces the informational efficiency of prices.

CHAPTER IV

DEMUTUALIZATION AND STOCK EXCHANGE PERFORMANCE

A. Introduction

Since the early 1990s, stock exchanges around the world have been undergoing dramatic changes in their organizational form. One of the most visible trends is demutualization, a process of transforming member-owned not-for-profit cooperatives into shareholder-owned for-profit corporations where ownership of the exchange is separated from membership. The first stock exchange to demutualize in developed economies was Stockholm Stock Exchange in 1993. This initiative was partially a response to the erosion of its domestic trading due to international competition from London Stock Exchange’s SEAQ International (SEAQ-I) between 1987 and 1990, a period in which Stockholm’s turnover declined by a third and its market share shrank sharply (Domowitz and Steil (1999), Pagano (1998)). Over the past decade, almost all the major stock exchanges in developed countries have demutualized and some have gone public and listed their shares on their own exchanges (i.e. self-listing). The New York Stock Exchange (NYSE), the world’s largest stock exchange, after 214 not-for-profit years, went public by merging with Archipelago on March 8, 2006.

Given the growing importance of stock exchanges in the development of an economy, a thorough understanding of demutualization is interesting in and of itself. In this paper, we treat a stock exchange as a multi-product firm and examine how the evolution in exchange governance structure affects its competitiveness in its primary product markets: trading and listings.[41] We hand-collect data on demutualization dates as well as characteristics of the trading protocols for 132 major stock exchanges in 114 countries covering a long time period from 1990 to 2003. Our analysis reveals that exchange demutualization, particularly the initial demutualization where exchanges are transformed from not-for-profit mutual organization into for-profit corporate form, is associated with improved competitiveness in attracting trading volume (monthly dollar trading volume, turnover defined as monthly dollar trading volume divided by month-end market capitalization, dollar volume over GDP which quantifies the level of trading relative to the size of the economy). The effect on listings is relatively weak, though. These results are consistent with the view that attracting order flow is the primary goal of exchanges, as it is the major source of revenues.

Our research design of analyzing exchange performance in its primary product markets is motivated by theoretical work and supported by empirical evidence, and it enables us to extend the literature in two ways.[42] First of all, our study is the first to empirically examine the impact of the initial demutualization as well as the effect of the

[41] Di Noia (1999) notes that there are at least three views of stock exchanges: the exchange as a market; the exchange as a firm; and the exchange as a broker-dealer. The firm view of exchanges focuses on the production side. In particular, exchanges can be seen as special firms that produce a combination of two major goods: listing and trading services. Exchanges have two main direct customers: firms that want to be listed and investors that want to trade.

[42] Exchanges are modeled to compete for listings through disclosure requirements (Huddart, Hughes and Brunnermeier (1999), trading technology and listing fees (Foucault and Parlour (2004)), sponsorship serviced by dealers (Aggarwal and Angel (1997)), and reputation effects of listing standards (Chemmanur and Fulghieri (2005)). Hendershott and Mendelson (2000), Parlour and Seppi (2003), Fluck and Stompter (2003), and Ramos and von Thadden (2003) model competition for trading volume among exchanges. Easley and O'Hara (2006) examine how designing market structures to reduce ambiguity can induce greater participation from both investors and issuers. Recent survey results by World Federation of Exchanges (WFE) suggest that the key source of overall revenue for exchanges is trading/transaction revenues. As a percentage of total revenue, trading revenue of survey participant exchanges has become more and more important over time, rising from 36% in 1996 to 44% in 2002 (MondoVisione (2006)).

final self-listing on exchange performance. Aggarwal (2002) notes that the exchange demutualization process takes place in stages. An exchange first demutualizes by becoming a privately-owned for-profit corporation.[43] It then has two basic options: to stay private, or to go public by listing itself and trade like a regular public firm.[44] We believe that the initial demutualization is substantially important because it has fundamentally changed the organizational structure of an exchange, yet its effect on exchange performance has not been thoroughly analyzed in the literature.

Second, our approach utilizes information on volume and listings, which enables us to produce a large and long panel dataset covering a large number of stock exchanges in the world. This allows us to conduct panel analysis comparing demutualized exchanged to those that have not. In addition, these performance variables are relatively more standardized which make cross-country analysis more meaningful. This is an important improvement over recent studies on exchange governance. Given the recent nature of exchange demutualization, studies on this topic are relatively limited. Recent empirical work directly related to our analysis includes Mendiola and O'Hara (2004), Aggarwal and Dahiya (2005), and Otchere (2006).[45] These researchers only study the last stage of demutualization process of self-listing of exchanges, and they find that self-listing is associated with improved accounting and long-run stock performance. As

[43] In this initial process, shares are generally first distributed to members so they become legal owners of the exchange, and then the exchange raises capital through a private placement, typically from outside investors as well as members.

[44] Rather than becoming a standalone company, a demutualized exchange can also become a wholly owned subsidiary of a publicly traded company. For example, Stockholm Stock Exchange demutualized in 1993 and became a subsidiary of OM Group, a publicly traded and listed company that went public in 1987.

[45] Hazarika (2005) also studies governance change in stock exchanges, but only focus on two exchanges (London Stock Exchange and Borsa Italiana). Krishnamuri, Sequeira and Fu (2003) only examine the two stock exchanges in India.

acknowledged by the authors, accounting-based measures unavoidably suffer from differences in accounting practices across countries. Our performance measures are less subject to this criticism, and part of our results complement these existing studies.

The rest of the paper is organized as follows. Section B discusses why stock exchanges decide to demutualize in recent years. Section C presents data and empirical analysis. Section D concludes.

B. Reasons for demutualization

This section briefly discusses the economic reasons for exchange demutualization. Mendiola and O'Hara (2004) note that the traditional nonprofit cooperative structure of stock exchanges is mainly due to historical antecedents, monopoly power, and homogeneity of customers. However, over the past decade or so, rapid changes in the competitive environment have prompted exchanges to consider whether the governance structure that has evolved in the past is likely to remain appropriate for the future. Mendiola and O'Hara argue that growing divergent interests of exchange members and increasing competition brought about by the advance of technology are the primary driving forces behind the demutualization trend around the world.

First, conflicts of interest between existing exchange members have become more intensified. In the mutual structure, interests of each member have to be taken into account when making major strategic and operating decisions. Hansmann (1996) notes that the cost of collective decision making in cooperatives is minimized with homogeneous members. As markets have become more sophisticated and competitive, the interests of various member groups began to diverge. Brokers are no more of similar size and profitability, and market makers have different interests from brokers. This growing heterogeneity of exchange members in a mutual organization may impose tremendous strains in the decision making process, which can hinder the exchange's ability to adapt to changing environments. Exchange members, who derive profits mainly from intermediating non-member transactions, may resist innovations (such as electronic trading) that would reduce demand for their intermediation services even if such innovations would enhance the value of the exchange (Domowitz and Steil (1999)). For example, the former ownership structure of NYSE before its demutualization highlights these tensions: of the 1,366 seats on the NYSE, 464 were held by the specialists and another 317 by "two-dollar" brokers and 575 by the "upstairs brokers" (i.e., big Wall Street Firms). The traditional one-member-one-vote structure gives floor brokers relatively more power in decision making, and is one of the reasons that it took so long for the NYSE to adopt its electronic trading system (Direct +) and to demutualize (Aggarwal and Dahiya (2005)).[46] Hart and Moore (1996) argue that a demutualized structure with outside ownership becomes relatively more efficient than a members' cooperative as the variation across the membership becomes more skewed.

The advent of technology and growing competition from alternative trading venues such as Electronic Communication Networks (ECNs) also drive demutualization. First of all, automation of the trading market permits demutualization (Domowitz and

[46] A similar story happened in the U.K exchange industry. Tradepoint, an electronic auction trading system, started operating in London in September 1995. It has been set up by former executives of the London Stock Exchange (LSE) who tried unsuccessfully to introduce a continuous auction mechanism in that market. Tradepoint allows institutional investors to trade directly, bypassing the intermediation of broker-dealers on LSE (Pagano (1998)).

Steil (1999)). Trading without an automated trading system inevitably requires a trading floor, and limited floor space restricts access to members only. They argue that a non-automated trading floor itself is worth little more than its real estate value, and it makes economic sense for members to operate the floor as a cooperative. The automation of trading provides access to all traders and reduces the need for intermediary members. Exchanges can charge fees for this service on a transaction basis and operate on a regular commercial basis. Furthermore, as competition from alternative trading venues threatens the monopolistic positions of traditional exchanges in trading securities, exchanges are forced to invest more in advanced trading technologies. Demutualization serves as one solution to the increasing need for outside financing for these capital-intensive projects (Mendiola and O'Hara (2004)).

Exchange members in a mutual organization and the owners of a demutualized exchange differ in their incentives. Particularly, members of the mutual exchange are interested in maximizing individual profits which are a function of trading volume and bid-ask spread, whereas the owners of the demutualized exchange are interested in maximizing exchange revenues which is a function of trading volume and the transaction fees earned by the exchange. For the owners of the demutualized exchange, increasing trading volume is the primary goal. Reducing trading costs is a secondary goal, and would be desirable only to the extent that it increases trading volume (Hazarika (2005)). This leads to our main hypothesis that demutualization is associated with increased trading volume. To the extent that listing fees also generate revenues for exchanges, demutualization may be also associated with more competition for listings.

Yet recent survey shows that the fraction of revenues from listing fees is decreasing, and it is possible that we may not detect changes in this dimension (MondoVisione (2006)).

C. Data and methodology

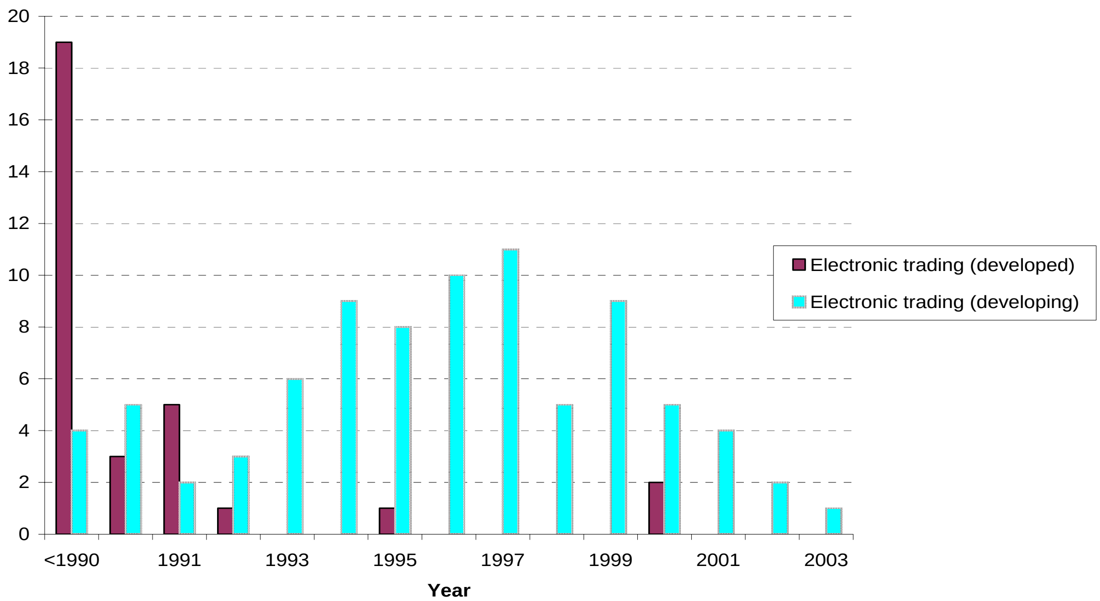
C.1. Data

We have assembled a hand-collected dataset on 132 major stock exchanges in 114 countries from various sources. We obtain dates of demutualization as well as details on major technological changes such as dates of the adoption of electronic execution systems and characteristics of the trading protocol during the last 15 years. This information is collected from various issues of *Focus*, a trade magazine published by the World Federation of Exchanges (WFE), different volumes of the Handbook of World Stock, Commodities and Derivatives Markets, and various other sources including an exchange's official website as well as email inquiries to exchange officials.

Figure 4.1 presents the number of exchanges that have adopted electronic trading technology and demutualized. Three interesting patterns emerge. First, demutualization takes place in stages. Forty stock exchanges have demutualized in recent years, and fifteen of them have listed their shares on their own exchanges. Among the self-listed stock exchanges, the process from the initial demutualization by changing the ownership structure into shareholder-owned for-profit basis to the final self-listing takes about 15 months. But overall, demutualization is a relatively recent trend and most of the events happened in late 1990s.[47]

[47] For exchanges without a prior history of mutual governance structure, the mutual structure is routinely avoided in favor of a for-profit corporation structure. The National Stock Exchange in India was established as a demutualized exchange.

A



B

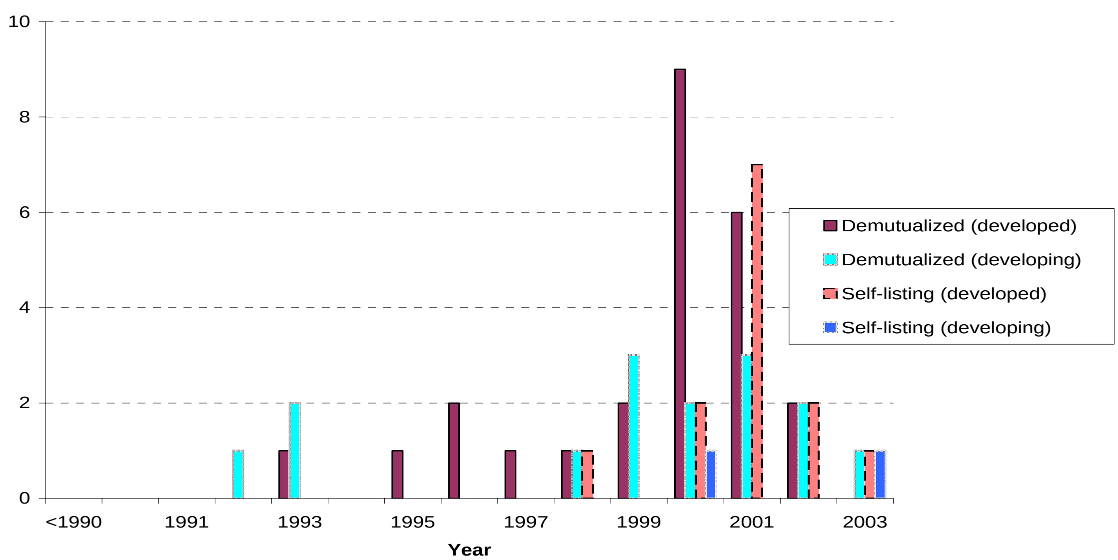


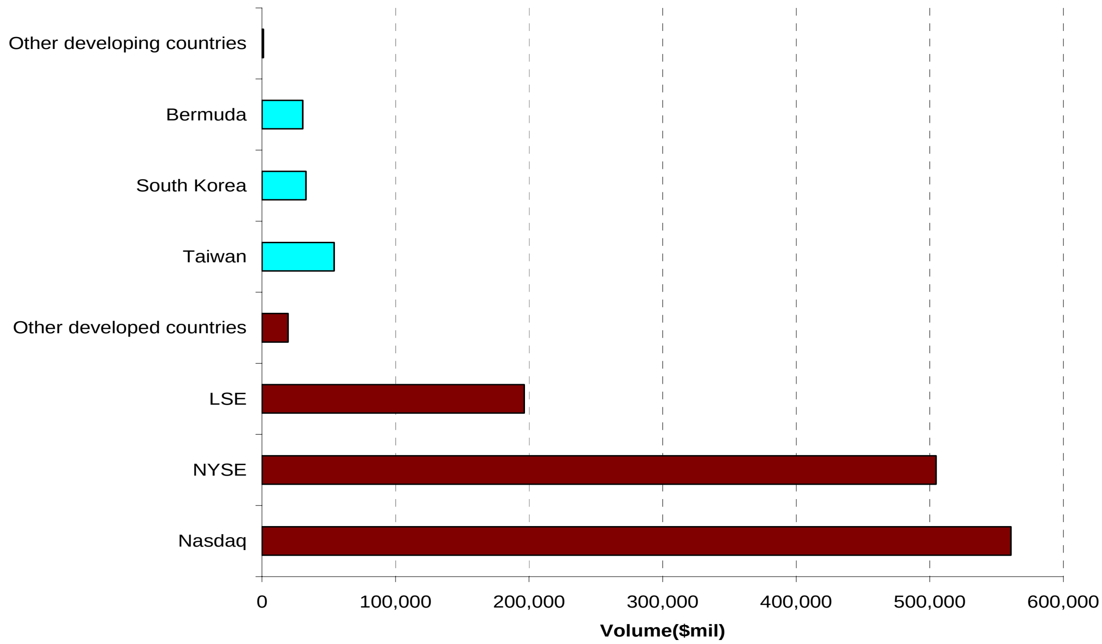
Figure 4.1. Adoption of electronic trading, demutualization/Self-listing by year. Electronic trading refers to the adoption of electronic execution of trades on an exchange. Demutualized refers to exchanges that have changed from member-owned non-profit organization into shareholder-owned for-profit organization. Self-listing refers to an exchange that lists itself as a public company.

Second, the majority of demutualized exchanges cluster in developed countries. This is probably due to more advanced technology in these countries and more intense domestic and global competition faced by these exchanges (Mendiola and O'Hara (2004)). Lastly, the adoption of electronic trading, on average, precedes the demutualization process. This is consistent with Domowitz and Steil (1999) who argue that automation permits demutualization.

Exchange performance is measured in two main dimensions: trading and listings. We obtain monthly dollar trading volume, month-end market capitalization and the number of listings from WFE for exchanges in developed countries and from the Standard and Poor's Emerging Markets DataBase (EMDB) for exchanges in developing countries. Trading is measured with three variables: monthly dollar trading volume (in millions), turnover defined as dollar trading volume standardized by month-end market capitalization, dollar volume over GDP which quantifies the level of trading relative to the size of the economy (Levine and Zervos (1996)). Our final sample spans from 1990 to 2003. Each exchange is required to have at least 24 months of data to be included in the analysis, and this leaves us with 85 stock exchanges.

Figure 4.2 reports time series means of trading volume and listings of the top 3 exchanges and the cross-sectional average of the rest exchanges in developed and developing countries, respectively. Panel A shows that dollar trading volume is substantially higher in developed economies than in developing countries. In particular, Nasdaq, New York Stock Exchange and London Stock Exchange lead world exchanges in trading volume over the sample period.

A.



B.

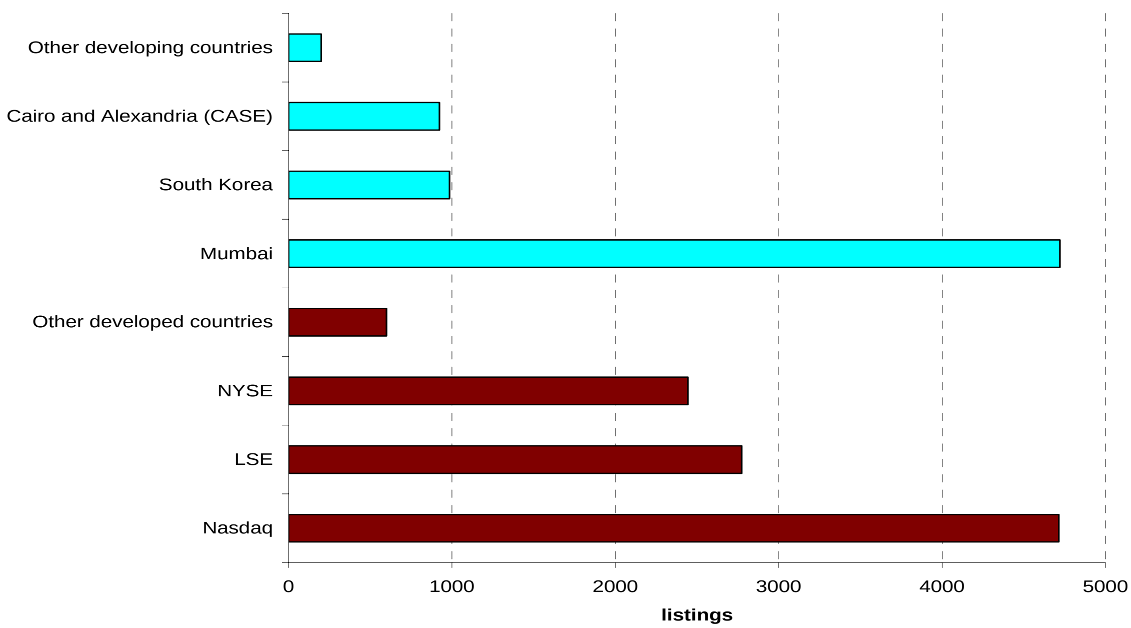


Figure 4.2. Time series averages of monthly volume and month-end listings. This figure lists the top 3 exchanges and the averages of the rest exchanges in developed and developing countries, respectively. Monthly dollar trading volume is measured in millions of dollars (A), and month-end number of companies listed on the exchange is measured in units (B). The sample period is from 1990 to 2003.

Among developing countries, Taiwan and South Korea lead in trading volume. The other dimension of competition in the exchange industry is the listings. Panel B shows that on average, exchanges in developed economies have substantially more listed companies. The three largest exchanges in terms of listings are Nasdaq, London Stock Exchange and New York Stock Exchange. In developing countries, Mumbai Stock Exchange in India has the largest number of listings.

Table 4.1 presents cross-sectional means of time-series correlations of these performance variables. The three volume variables are highly correlated with each other. Listings are positively correlated with trading, but the magnitude of correlation is modest. These simple statistics just present a general picture of the data, and we now turn to empirical analysis.

Table 4.1
Cross-Sectional Averages of Time-Series Correlations

This table reports cross-sectional averages of time-series correlations among performance measures. The variables include (natural logs of) monthly dollar trading volume (in millions), turnover defined as the monthly trading volume scaled by month-end market capitalization, Volume/GDP Ratio defined as dollar trading volume over GDP, and month-end number of companies listed on the exchange. The sample period covers 1990 - 2003.

	Ln(Volume)	Ln(Turnover)	Ln(Volume/ GDP)	Ln (No. of listed firms)
Ln(Volume)	1			
Ln(Turnover)	0.84	1		
Ln(Volume/ GDP)	0.99	0.86	1	
Ln (No. of listed firms)	0.21	0.11	0.18	1

C.2. Empirical analysis

C.2.1. Event analysis

For completeness, univariate event studies are conducted to examine changes in exchange competitiveness in attracting trading volume and listings around the demutualization. We look at changes in performance around the initial demutualization as well as the self-listing since both are important restructuring events. Specifically, the initial demutualization fundamentally changes the organizational form and the objective function of the exchange, and self-listing further opens up share ownership to the investing public. Because the specific date of demutualization for some exchanges cannot be exactly identified, the event year is excluded from analysis. We require at least 12 monthly observations for each exchange on either side of the event date, and compare three-year mean performance around the events.

Table 4.2 reports the changes in performance for demutualized exchanges. Panel A shows that following the initial demutualization, exchanges on average experience more trading volume. Other measures of performance change are on average also positive. Panel B reports the changes in exchange performance following the self-listing. The average change in exchange performance does not seem significant.

Table 4.2
Changes in Performance Around Demutualization

This table presents post-pre changes in three-year average performance around demutualization. Performance measures include monthly dollar trading volume (millions), turnover defined as the monthly trading volume scaled by month-end market capitalization, Volume/GDP Ratio defined as dollar trading volume over GDP, and month-end number of companies listed on the exchange, and natural log of these variables. Event year is excluded. Panel A (B) reports changes following the initial demutualization (self-listing). Asterisks *,**,*** represent significance at 0.1, 0.05, and 0.01, respectively.

Panel A: Changes around initial demutualization

Exchange	Volume	Turnover	Volume/GDP	No. of listed firms	Ln (Volume)	Ln(Turnover)	Ln(Volume/ GDP)	Ln (No. of listed firms)
Exchanges in developed countries:								
Australian Stock Exchange	7478 ***	0.0091 ***	0.0168 ***	37 ***	0.7258 ***	0.2307 ***	0.5570 ***	0.0305 ***
Vienna Stock Exchange	-481 ***	-0.0079 ***	-0.0031 ***	-18 ***	-0.5299 ***	-0.2784 ***	-0.6302 ***	-0.1455 ***
Euronext Brussels	486	0.0140 ***	0.0007	-68 ***	0.1263 *	0.4488 ***	0.0462	-0.2872 ***
Toronto Stock Exchange	9616 ***	0.0090 ***	0.0070 ***	-74 ***	0.2941 ***	0.1707 ***	0.1460 ***	-0.0537 ***
Copenhagen Stock Exchange	2627 ***	0.0023	0.0157 ***	20 ***	0.7750 ***	0.0479	0.6601 ***	0.0851 ***
Helsinki Stock Exchange	2632 ***	0.0123 ***	0.0236 ***		1.8282 ***	0.5037 ***	1.6779 ***	
Euronext Paris	67290 ***	0.0467 ***	0.0465 ***	-62 ***	0.8669 ***	0.5884 ***	0.7673 ***	-0.0617 ***
Deutsche Borse AG	-4391	0.0013	-0.0058 *		-0.0273	0.0115	-0.0847 *	
Hong Kong Stock Exchange	-4401	-0.0188 ***	-0.0453 **	261 ***	-0.1115	-0.3499 ***	-0.2415 **	0.3309 ***
Italian Stock Exchange	51896 ***	0.0516 ***	0.0476 ***	35 ***	1.7635 ***	0.7679 ***	1.6865 ***	0.1364 ***
Tokyo Stock Exchange	22301	0.0255 ***	0.0038	228 ***	0.2515 **	0.5180 ***	0.2187 *	0.1122 ***
Osaka Stock Exchange	-6849 **		-0.0015 ***	-4	-0.3322 **		-0.3655 **	-0.0042
Euronext Amsterdam	32032 ***	0.0301 ***	0.0842 ***	-72 ***	1.3848 ***	0.5517 ***	1.2371 ***	-0.1755 ***
New Zealand Stock Exchange	0	-0.0085 **	-0.0015	18 ***	0.0194	-0.1871 **	-0.0893	0.0930 ***
Oslo Stock Exchange	908 **	-0.0026	0.0032	-27 ***	0.2016 **	-0.0083	0.1332 *	-0.1285 ***
Euronext Lisbon	-1326 ***	-0.0236 ***	-0.0146 ***	-41 ***	-0.5139 ***	-0.4861 ***	-0.6025 ***	-0.3359 ***
Singapore Stock Exchange	1022 **	0.0032	0.0005	98 ***	0.1896 **	0.1031	0.0212	0.3036 ***
Barcelona Stock Exchange	116		-0.0003	389 ***	0.0390		-0.0625	0.6474 ***
Bilbao Stock Exchange	-570		-0.0031	165 ***	0.3314		0.2299	0.4671 ***
Madrid Stock Exchange	-13329 **	-0.0515 ***	-0.0314 **	1073 ***	-0.1269	-0.3081 **	-0.2202	1.0446 ***
Stockholm Stock Exchange	6560 ***	0.0332 ***	0.0318 ***		1.4346 ***	0.9616 ***	1.3896 ***	
Swiss Stock Exchange	909	0.0107 **	0.0004	-2	0.0205	0.1286 **	0.0041	-0.0064
London Stock Exchange	108226 ***	0.0612 ***	0.0565 **	-93 ***	0.4108 ***	0.4791 ***	0.3058 ***	-0.0323 ***
Nasdaq Stock Market	133059 **	0.0398 ***	0.0077	-1346 ***	0.2462 ***	0.1488 ***	0.1370 *	-0.3028 ***

Table 4.2 - Continued

Exchange	Volume	Turnover	Volume/GDP	No. of listed firms	Ln (Volume)	Ln(Turnover)	Ln(Volume/ GDP)	Ln (No. of listed firms)
Exchanges in developing countries:								
Tallinn Stock Exchange	-9	-0.0303 **	-0.0031 *	-11 ***	-0.1139	-0.7703 ***	-0.3207	-0.5600 ***
Athens Stock Exchange	2219 ***	-0.0121 **	0.0171 **	102 ***	0.8140 ***	-0.2378 **	0.6639 ***	0.3707 ***
Budapest Stock Exchange	-180	-0.0167 **	-0.0056 **	-14 ***	-0.1226	-0.2460 **	-0.2291	-0.2541 ***
Riga Stock Exchange	-4	-0.0155 *	-0.0007	-6 ***	-0.2922	-0.9835 **	-0.5002	-0.1019 ***
Vilnius Stock Exchange	8 *	0.0054	0.0006		0.5756 **	0.2394	0.4423 *	
Stock Exchange of mauritus	-3 **	-0.0007	-0.0010 **	0 ***	-0.3085 **	-0.0540	-0.5057 ***	-0.0056 ***
Philippine Stock Exchange	-816 ***	-0.0184 ***	-0.0118 ***	10 ***	-1.5153 ***	-1.2461 ***	-1.6596 ***	0.0441 ***
Mean	13452 **	0.0053	0.0076	22.19	0.2679 **	0.0266	0.1552	0.0448

Panel B: Changes around self-listing	Volume	Turnover	Volume/GDP	No. of listed firms	Ln (Volume)	Ln(Turnover)	Ln(Volume/ GDP)	Ln (No. of listed firms)
Exchanges in developed countries:								
Australian Stock Exchange	7034 ***	0.0082 ***	0.0131 ***	143 ***	0.5008 ***	0.1781 ***	0.3447 ***	0.1117 ***
Euronext Brussels	-635 **	0.0090 ***	-0.0039 **	-68 ***	-0.1248 **	0.3202 ***	-0.1792 **	-0.2900 ***
Toronto Stock Exchange	-799	-0.0015	-0.0053		0.0037	-0.0151	-0.0780	
Euronext Paris	28525 ***	0.0325 ***	0.0178 ***	-167 ***	0.3823 ***	0.4408 ***	0.3121 ***	-0.1657 ***
Deutsche Borse AG	-38721 ***	0.0038	-0.0230 ***		-0.2898 ***	0.0404	-0.3250 ***	
Hong Kong Stock Exchange	-4401	-0.0188 ***	-0.0453 **	261 ***	-0.1115	-0.3499 ***	-0.2415 **	0.3309 ***
Euronext Amsterdam	17864 ***	0.0601 ***	0.0430 ***	-83 ***	0.3683 ***	0.6222 ***	0.3226 ***	-0.2521 ***
Oslo Stock Exchange	908 **	-0.0026	0.0032	-27 ***	0.2016 **	-0.0083	0.1332 *	-0.1285 ***
Euronext Lisbon	-1421 ***	-0.0232 ***	-0.0151 ***	-35 ***	-0.5894 ***	-0.4994 ***	-0.6630 ***	-0.2914 ***
Singapore Stock Exchange	-375	-0.0024	-0.0137 *	127 ***	-0.0223	-0.0342	-0.1520	0.3526 ***
London Stock Exchange	16325	0.0409 ***	-0.0051	-90 ***	0.0729	0.3018 ***	-0.0093	-0.0316 ***
Nasdaq Stock Market	-555426 ***	-0.0557 ***	-0.0612 ***	-1288 ***	-0.6107 ***	-0.1963 ***	-0.6786 ***	-0.3194 ***
Exchanges in developing countries:								
Athens Stock Exchange	-4364 ***	-0.0414 ***	-0.0444 ***	94 ***	-0.5050 **	-0.7690 ***	-0.6609 ***	0.3297 ***
Mean	-41191	0.0007	-0.0108	-103	-0.056	0.0024	-0.144	-0.032

Note that these averages are only suggestive because factors such as market designs, general market movements and time trends might confound these summary statistics. For example, Nasdaq experienced a large reduction in listings following the demutualization in 2000, but this is probably due to the burst of the tech bubble in 2001 which resulted in many delistings on Nasdaq. It could also be the case that many firms shifted to unlisted venues following Sarbanes-Oxley reforms. These and other potential confounding factors are addressed through more rigorous tests that follow.

C.2.2. Panel data analysis

In this section, we investigate the effects of demutualization on exchange performance in a multivariate setting. The dependent variables are the exchange performance measures. The natural log of these measures is used to mitigate the skewness of the data. The key variable of interest is an exchange's initial demutualization (self-listing), an indicator variable switching from zero to one following initial demutualization (self-listing) date.

Given the time-series and cross sectional nature of a panel dataset, we conduct exchange-fixed effects models with year dummies.[48] This has a number of advantages. First, the exchange-fixed effects control for time-invariant differences in performance due to unobservable factors that differ across stock exchanges. Second, year dummies control for potential business cycles and time trends. Third, this specification is a generalization of the difference-in-differences approach where the effect of demutualization is estimated as the difference between the change in performance before

[48] Results based on random-effects panel estimation are qualitatively identical.

and after demutualization with the difference in performance for a control group constructed from a set of exchanges not experiencing demutualization.

Table 4.3 reports regression results with year dummies to control for potential time trends. To save space, coefficients for these year dummies are not tabulated. Panel A reports the effect of initial demutualization. All measures of performance increase significantly following the initial demutualization, suggesting that the initial demutualization strengthens an exchange's competitiveness in its product markets. Panel B examines the effect of self-listing. Exchanges appear to attract more trading volume after they list themselves as a public company. Note the magnitude of the self-listing coefficients is smaller than that associated with the initial demutualization. There is no significant change in listings, though. The weaker results associated with self-listing could also be due to low power as it may take more time to detect significant changes.

Table 4.3
Effects of Demutualization on Exchange Performance, Controlling for Time Trends

This table reports exchange-fixed effects of demutualization on performance, controlling for time trends. Performance measures include (natural logs of) monthly dollar trading volume (in millions), turnover defined as the monthly trading volume scaled by month-end market capitalization, Volume/GDP Ratio defined as dollar trading volume over GDP, and month-end number of companies listed on the exchange. Panel A (B) reports effects of initial demutualization (self-listing). Initial demutualization (Self-listing) is an indicator variable switching from zero to one following the date of initial demutualization (self-listing). The sample period covers 1990 - 2003.

Panel A: Effects of initial demutualization on performance

	Ln(Volume)		Ln(Turnover)		Ln(Volume / GDP)		Ln (No. of listed firms)	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Initial demutualization	0.2963	8.68	0.1098	3.92	0.3127	9.20	0.0495	4.03
R2: within	0.35		0.1112		0.2734		0.1826	
between	0.19		0.0313		0.1128		0.0287	
overall	0.002		0.006		0.0265		0.0006	
Exchange dummies	yes		yes		yes		yes	
Year dummies	yes		yes		yes		yes	

Panel B: Effects of self-listing on performance

	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Self-listing	0.1231	2.49	0.0840	2.14	0.1335	2.72	0.0014	0.08
R2: within	0.344		0.1103		0.2682		0.1812	
between	0.279		0.076		0.2014		0.049	
overall	0.0002		0.0025		0.014		0.0001	
Exchange dummies	yes		yes		yes		yes	
Year dummies	yes		yes		yes		yes	

We next control for some features of market designs because research suggests that they can affect an individual stock's trading activity, which in turn may affect exchange performance. First, Pagano (1998) and Domowitz and Steil (1999) show that the adoption of automated trading systems in the continental exchanges during1989-1991 helps recover some market share in their competition with the London Stock Exchange. Jain (2005) presents some evidence that the adoption of an electronic trading system by exchanges enhances stock turnover. We include an indicator variable switching from zero to one following the introduction of the electronic trading system.[49]

Another potentially important aspect of market design relates to exchange models for trading: order-driven vs. quote-driven. Order-driven markets are the ones where the orders of some public participants establish the prices at which other public participants can trade. Quote-driven markets are the ones where dealer quotes establish the prices at which all public participants trade. Swan and Westerholm (2004) show that the electronic limit order book design is associated with higher trading volume. We use an indicator variable equal to one for order-driven markets and zero for quote-driven markets.

Grossman and Miller (1988) show that the continuous presence of a specialist can enhance the liquidity of thinly-traded stocks. Parlour and Seppi (2003) also point out that specialists can supplement liquidity through ex post price improvement after a market order has arrived. Empirical evidence seems to support the theoretical arguments. Nimalendran and Petrella (2003) show that thinly-traded stocks benefit from specialist liquidity provision in the Italian stock market. Venkataraman and Waisburd (2006) also document improved volume of transactions for low liquidity stocks in Euronext Paris following the introduction of market makers in these stocks. We control for this by using an indicator variable equal to one if an official liquidity provider is present with contractual obligations to post continuous bid-ask quotes and zero otherwise.

[49] In many cases, floor and electronic coexist for some time and the complete switch takes place only after the abolition of trading floor. Following Jain (2005), we use the initial date on which the option to trade electronically became available to traders as the starting date of electronic trading.

Table 4.4 presents summary statistics of the exchange market design variables. By the end of 2003, 115 exchanges have adopted some form of electronic trading. However, not all exchanges with electronic trading have completely eliminated floors, and about 33% of stock exchanges still have trading floors. The majority of the exchanges are order-driven, with only six exchanges being quote-driven dealer markets. Thirty-one stock exchanges have official liquidity providers to maintain an orderly market.

Table 4.4
Summary Statistics on Market Structures

This table presents summary statistics on market designs of the sample stock exchanges. Electronic trading refers to the electronic execution availability. Floor refers to the existence of floor trading. Order-driven refers to markets where orders of some public participants establish the prices at which other public participants can trade. Official liquidity provider refers to the existence of liquidity providers with contractual obligations to post bid-ask quotes within certain parameters. Multiple domestic stock exchanges refer to the existence of more than two major stock exchanges within a country.

Market design	Mean	Frequency	No. of exchanges
Electronic trading	87.1%	115	132
Floor	32.6%	43	132
Order-driven	95.3%	121	127
Official liquidity provider	28.0%	31	111
Multiple domestic stock exchanges	21.2%	28	132

We now examine the effects of demutualization on exchange performance with these additional controls for market structures. Panel A of Table 4.5 focuses on the initial demutualization. The initial demutualization dummy remains significantly positive for all three measures of trading volume. The adoption of electronic execution of orders is positive in these models, suggesting that the introduction of such technology, which is associated with faster execution of orders, can increase an exchange's competitiveness in attracting order flow. Order-driven exchanges are positively related to higher trading volume, consistent with Swan and Westerholm (2004). The existence of official liquidity providers has positive coefficient on trading volume, largely consistent with Nimalendran and Petrella (2003) and Venkataraman and Waisburd (2006). With regards to listings, there is no significant change associated with the initial demutualization.

Panel B reports the effects of self-listing on exchange performance. The self-listing dummy is positively associated with higher trading volume, while the number of listings sees no significant changes. The overall results in Table 4.5 suggest that both the initial demutualization and the final self-listing of exchanges seem to be able to strengthen an exchange's competitiveness in its core business of trading. In addition, the effects of the initial demutualization seem to be stronger as the coefficients are larger in magnitude.

Table 4.5
Effects of Demutualization on Exchange Performance, Controlling for Time Trends and Market Structures

This table reports exchange-fixed effects of demutualization on performance, controlling for time trends and market designs. Performance measures include (natural logs of) monthly dollar trading volume (millions), turnover defined as the monthly trading volume scaled by month-end market capitalization, Volume/GDP Ratio defined as dollar trading volume over GDP, and month-end number of companies listed on the exchange. Panel A (B) reports the effect of initial demutualization (self-listing). Initial demutualization (Self-listing) is an indicator variable taking the value of one following the date of initial demutualization (self-listing). Electronic trading is a dummy switching from zero to one following the adoption of electronic trading. Order_driven is a dummy with a value of one for order-driven markets and zero for quote-driven markets. Official liquidity provider is an indicator variable taking a value of one following the introduction of official liquidity providers. The sample spans from 1990 to 2003.

Panel A: Effects of initial demutualization on performance

	Ln(Volume)		Ln(Turnover)		Ln(Volume/ GDP)		Ln (No. of listed firms)	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Initial demutualization	0.3413	9.76	0.1548	5.54	0.3559	10.24	0.0066	0.50
Electronic trading	0.1908	5.82	0.0100	0.38	0.1856	5.69	-0.0682	-5.56
Order_driven	0.4793	4.75	0.4062	5.02	0.5008	4.99	0.0502	0.81
Official liquidity provider	0.1894	3.54	-0.0092	-0.22	0.2087	3.93	-0.1677	-8.16
R2: within	0.3425		0.098		0.2689		0.1890	
between	0.0231		0.0096		0.0005		0.2105	
overall	0.0195		0.0044		0.0650		0.0201	
Exchange dummies	yes		yes		yes		yes	
Year dummies	yes		yes		yes		yes	

Panel B: Effects of self-listing on performance

	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Self-listing	0.2062	4.19	0.1065	2.74	0.2137	4.36	0.0035	0.20
Electronic trading	0.1524	4.66	-0.0050	-0.19	0.1454	4.47	-0.0684	-5.57
Order_driven	0.5190	5.11	0.4232	5.22	0.5424	5.37	0.0507	0.82
Official liquidity provider	0.2026	3.77	-0.0029	-0.07	0.2224	4.17	-0.1679	-8.17
R2: within	0.3373		0.0959		0.2626		0.1889	
between	0.0760		0.0575		0.0138		0.2126	
overall	0.0095		0.0003		0.0417		0.0205	
Exchange dummies	yes		yes		yes		yes	
Year dummies	yes		yes		yes		yes	

We next consider potential effects of country-specific institutional and legal environment characteristics on exchange performance. Bekaert, Harvey and Lundblad (2003) and Bekaert and Harvey (2000) show that financial market liberalization is associated with higher market liquidity. Liberalization can also increase order flow if it induces foreign investors to participate in the stock market. To control for the effect of liberalization, an indicator variable is included which changes from zero to one following the official liberalization date.[50]

Bhattacharya and Daouk (2002) and Daouk, Lee and Ng (2005) document increased turnover after the enforcement of the insider trading laws. Thus an indicator variable is used that takes the value of one after the enforcement (evidenced by the first insider trading prosecution) was recorded and zero before the enforcement.

Privatization of state-owned enterprises is also included because it may affect both listings and trading volume. First, the privatization generally results in an increase in the number of publicly listed firms. Second, many privatizations involve distributing shares to retail investors, which encourage them to trade on the stock exchange. This increased supply of shares might lead to higher trading volume. But it is also possible that mass privatization in some countries might inflate the market capitalization and decrease turnover in the short run if the majority of stocks listed are traded only occasionally (Fungacova (2005)). Thus to control for the effect of privatization, we

[50] We obtain the liberalization dates from Bekaert, Harvey and Lundblad (2003), Bekaert and Harvey (2000) and Campell Harvey's website.

include an indicator variable switching from zero to one following the date of the first privatization of state-owned enterprise.[51]

Table 4.6 reports the demutualization effect on exchange performance after controlling for exchange market structures and country characteristics.[52] The results largely mirror the findings documented earlier. Both the initial demutualization and the self-listing dummies retain their significance, suggesting that the effect of demutualization on increased competitiveness in attracting trading volume is robust.

The country-level control variables have signs largely consistent with prior literature. Liberalization has positive effect on exchange performance, suggesting that the opening up of financial markets to international investors can attract more trading volume and listings to exchanges. Insider trading laws enforcement is positively associated with exchange performance measures, indicating that exchanges in countries with protection from insider trading perform better. Privatization increases volume level and the listings, but decreases turnover, consistent with the priors.

Collectively, the above results suggest that demutualized exchanges appear to be able to enhance their competitiveness in their core business of trading. This strengthened competitiveness is founded to be associated with both the initial demutualization and final self-listing of exchanges.

[51] Dates on first privatization of state-owned enterprise are provided by Boehmer, Nash and Netter (2005).
[52] We also control for a country's legal origin, GDP, population, and worldwide market development, and results remain qualitatively similar.

Table 4.6
Effects of Demutualization on Exchange Performance, Further Controlling for Country Characteristics

This table reports exchange-fixed effects of demutualization on performance. Performance measures include (natural logs of) monthly dollar trading volume (millions), turnover defined as the monthly trading volume scaled by month-end market capitalization, Volume/GDP Ratio defined as dollar trading volume over GDP, and number of companies listed on the exchange at the end of each month. Panel A (B) reports the effects of initial demutualization (self-listing). Initial demutualization (Self-listing) is an indicator variable switching from zero to one following the date of initial demutualization (self-listing). Electronic trading is a dummy switching from zero to one following the adoption of eletronic trading. Order driven is a dummy with a value of one for order- driven market and zero for quote-driven market. Official liquidity provider is an indicator variable taking a value of one following the introduction of official liquidity providers. Insider trading law enforcement is an indicator variable taking the value of one following the first prosecution of insider trading case in a country. Liberalization is an indicator variable switching from zero to one following a country's liberalization. First privatization is an indicator variable equal to one following a country's first privatization of state-owned enterprise. The sample spans from 1990 to 2003.

Panel A: Effects of initial demutualization on performance

	Ln(Volume)		Ln(Turnover)		Ln(Volume / GDP)		Ln (No. of listed firms)	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Initial demutualization	0.4140	11.7	0.1627	5.62	0.4244	12.06	-0.0112	-0.83
Electronic trading	0.0386	1.12	-0.0157	-0.55	0.0349	1.02	-0.1358	-10.44
Order_driven	0.5878	5.99	0.4189	5.23	0.6053	6.21	0.1325	2.15
Official liquidity provider	0.0920	1.76	-0.0585	-1.39	0.1137	2.19	-0.1812	-8.79
Liberalization	0.9407	20.7	0.3751	10.08	0.8989	19.89	0.0887	5.44
IT law enforcement	0.4440	12.79	0.1243	4.35	0.4160	12.05	0.2924	20.95
First privatization	0.2542	5.84	-0.1035	-2.9	0.2680	6.19	0.2503	14.34
R2: within	0.3952		0.1167		0.322		0.2564	
between	0.1417		0.0023		0.1553		0.0816	
overall	0.1392		0.044		0.1776		0.0728	
Exchange dummies	yes		yes		yes		yes	
Year dummies	yes		yes		yes		yes	

Panel B: Effects of self-listing on performance

	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Self-listing	0.2256	4.66	0.1132	2.91	0.2231	4.63	-0.0141	-0.78
Electronic trading	-0.0237	-0.69	-0.0364	-1.3	-0.0297	-0.87	-0.1354	-10.44
Order_driven	0.6260	6.33	0.4307	5.36	0.6460	6.57	0.1337	2.17
Official liquidity provider	0.1082	2.06	-0.0518	-1.23	0.1303	2.5	-0.1809	-8.78
Liberalization	0.9067	19.86	0.3634	9.77	0.8636	19.01	0.0888	5.45
IT law enforcement	0.4845	13.96	0.1412	4.98	0.4579	13.25	0.2919	20.95
First privatization	0.2371	5.41	-0.1113	-3.11	0.2510	5.75	0.2505	14.33
R2: within	0.3877		0.1144		0.3129		0.2564	
between	0.1011		0.0003		0.0985		0.0808	
overall	0.1205		0.0358		0.1485		0.0725	
Exchange dummies	yes		yes		yes		yes	
Year dummies	yes		yes		yes		yes	

The above analysis finds little changes in listings following exchange demutualization. This seems a little puzzling. Interestingly, Ramos (2003) reports that many of European exchanges focus more on trading volume and not on attracting listings. Schwartz and Francioni (2004) also point out today's exchanges put increasing emphasis on attracting trading volume. This is possible if trading generates more revenues for exchanges. For example, WFE reports that listing fees averaged across world-wide exchanges consist of about 10% of revenues, compared to 37% derived from trading in 2005.[53]

Overall, demutualization is associated with higher trading volume. This result largely reflects the objective function of a demutualized exchange where increasing trading volume is the primary goal.

As discussed earlier, one primary driving force behind demutualization is the increasing competition faced by exchanges. It is possible that a more competitive exchange is more likely to demutualize in anticipation of higher trading volume. If this is the case, the results documented above may be subject to a reverse causality interpretation. We now attempt to address this issue through estimating two-step treatment effect models.

In the first stage, the decision for an exchange to demutualize is estimated using a Probit model

$$D_{it} = 1 \quad \text{if} \quad \gamma Z_{it} + \eta_{it} > 0$$

$$D_{it} = 0 \quad \text{if} \quad \gamma Z_{it} + \eta_{it} <= 0$$

[53] For detailed data on listing fees and exchange revenues, see "World Federation of Exchanges Cost and Revenue Survey 2005", World Federation of Exchanges, September 2006.

where D is demutualization dummy (initial demutualization and self-listing, respectively) and Z is a set of explanatory variables. In the second stage, exchange performance is specified as

$$\text{Performance}_{it} = \alpha + \beta X_{it} + \phi D_{it} + \varepsilon_{it}$$

where X is a set of exogenous variables, and η_{it} and ε_{it} are assumed to be bivariate normal. Coefficient ϕ is the primary parameter of interest that captures the effect of demutualization on performance after correcting for potential endogeneity.

The following variables are used in the Probit model to proxy for competition faced by an exchange. Floor is a dummy variable equal to one if a trading floor exists and zero otherwise. As suggested by Domowitz and Steil (1999), the existence of a trading floor limits access to intermediary members only and it is more likely to operate the exchange as a cooperative. The second variable is a dummy variable, equal to one if there exist two or more major stock exchanges in the country and zero otherwise.[54] It is used to proxy for domestic competition from rival exchanges that compete for order flow and listings. Domestic competition can be important because if there is only one monopolistic exchange, the exchange can benefit more from higher spreads and thus has less incentive for governance change. Finally, we also include the degree of economic integration of a country with the rest of the world as a proxy for international competition. The more integrated a country is, the more competition it may face with

[54] The following countries have had more than two major stock exchanges in our panel: Brazil, Canada, Chile, China, Colombia, Ecuador, India, Japan, Korea (South), Romania, Russia, Spain, US.

other countries. Following Bhattacharya and Daouk (2002), integration is measured as the ratio of imports plus exports to GDP.

Table 4.7 reports the treatment effect regressions with exchange cluster-robust standard errors. Panel A shows that the initial demutualization still has positive effect on scaled trading volume, even after controlling for the self-selection bias. Panel B presents the effect of self-listing on performance. The results are weaker as only volume/GDP remains significant. Overall, demutualization has some positive impact on an exchange's competitiveness.

Another sensitivity check is performed on possible seasonality in performance measures. We repeat all tests including eleven calendar month dummies in the regressions, and results remain qualitatively identical. We also transform the performance series through a two-step procedure following Chordia, Sakar and Subrahmanyam (2005). In the first step, the original series is regressed on year dummies, month dummies and a dummy for Asian crisis (July 1997-December 1997) to eliminate potential time trends. In the second step, the regression residuals are regressed on demutualization dummies controlling for exchange market design and country variables. The (unreported) results remain qualitatively the same.

Table 4.7
Effects of Demutualization on Exchange Performance, Treatment Effects Regressions

This table reports two-step treatment effects regressions of exchange performance on demutualization. Performance measures include (natural logs of) monthly dollar trading volume (millions), turnover defined as the monthly trading volume scaled by month-end market capitalization, Volume/GDP Ratio defined as dollar trading volume over GDP, and number of companies listed on the exchange at the end of each month. Panel A (B) reports the effect of initial demutualization (self-listing). Initial demutualization (Self-listing) is an indicator variable taking a value of 1 following the initial demutualization (self-listing) date. Electronic trading is a dummy switching from 0 to 1 following the adoption of eletronic trading. Order driven is a dummy with a value of 1 for order- driven market and 0 for quote-driven market. Official liquidity provider is an indicator variable taking a value of 1 following the introduction of official liquidity providers. Insider trading law enforcement is an indicator variable taking the value of 1 following the first prosecution of insider trading case in a country. Liberalization is an indicator variable switching from 0 to 1 following a country's liberalization. First privatization is an indicator variable equal to 1 following a country's first privatization of state-owned enterprise. Emerging is a dummy variable equal to 1 for emerging countries and 0 otherwise. Lambda is the hazard from the first-stage Probit regression where the dependent variable is initial demutualization (self-listing) dummy and the independent variables include Floor, a dummy variable equal to 1 if floor exists and 0 otherwise, multiple domestic stock exchanges, a dummy equal to 1 if there exits more than 2 major stock exchanges in the country, and integration, ratio of imports plus exports to GDP. The sample spans from 1990 to 2003. T-stats are djusted for clustering within exchanges.

Panel A: Effects of initial demutualization on performance

	Ln(Volume)		Ln(Turnover)		Ln(Volume / GDP)		Ln (No. of listed firms)	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Initial demutualization	2.2798	1.17	2.4011	2.27	4.9957	3.38	-0.4730	-0.41
Electronic trading	0.7117	1.46	0.2412	0.88	0.4409	1.18	0.4626	1.98
Order_driven	-0.0063	-0.01	-0.0616	-0.15	0.3629	0.96	-0.7539	-1.24
Official liquidity provider	1.1862	2.37	0.5374	2.79	0.6624	1.91	0.0696	0.24
Liberalization	1.7894	3.02	0.5936	1.44	1.1634	2.07	0.1485	0.47
IT law enforcement	2.6879	6.61	1.0050	5.21	1.2058	3.96	1.0016	5.04
First privatization	-0.3130	-0.64	-0.3945	-1.26	-0.4653	-0.87	0.4754	2.41
Emerging	-1.6781	-3.31	-0.0817	-0.34	-0.3248	-0.81	-0.7983	-3
Lambda	-1.0561	-1	-1.1647	-2.06	-2.3112	-2.84	-0.0340	-0.05
year dummies	yes		yes		yes		yes	
clusters	yes		yes		yes		yes	
R2	0.5794		0.3548		0.3993		0.3672	

Panel B: Effects of self-listing on performance

	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Self-listing	-0.4014	-0.11	2.1033	1.06	9.4779	2.77	-4.7114	-1.72
Electronic trading	0.9288	1.92	0.3750	1.39	0.5485	1.44	0.6166	2.6
Order_driven	-0.0273	-0.02	-0.1117	-0.24	0.2175	0.47	-0.6828	-1.23
Official liquidity provider	1.0592	2.14	0.4610	2.37	0.5633	1.62	0.0645	0.22
Liberalization	1.7805	2.95	0.5629	1.39	1.0861	1.91	0.2035	0.61
IT law enforcement	2.6667	6.6	1.0107	5.15	1.2142	3.97	0.9734	4.87
First privatization	-0.3928	-0.8	-0.4228	-1.37	-0.4230	-0.82	0.3375	1.52
Emerging	-1.7853	-3.81	-0.1836	-0.8	-0.5261	-1.42	-0.6157	-2.37
Lambda	0.5905	0.37	-0.8604	-0.93	-4.0387	-2.43	2.4341	1.82
year dummies	yes		yes		yes		yes	
clusters	yes		yes		yes		yes	
R2	0.578		0.336		0.3909		0.3706	

To sum up, demutualization of stock exchanges is associated with higher trading volume. This provides some preliminary evidence indicating that the change in organizational structure from a member-owned nonprofit organization into a shareholder-owned for-profit company seems to be a successful move in strengthening the exchange's competitiveness in attracting trading volume.

D. Summary

Demutualization of stock exchanges, a process of transforming member-owned non-profit cooperatives into shareholder-owned for-profit corporations, is one of the most recent trends in the exchange industry around the world. In this paper, we view exchanges as special firms producing a combination of two major goods: trading and listings. We examine how demutualization (the initial demutualization and the self-listing, respectively) affects exchange competitiveness in its product markets.

Our analysis reveals that both the initial demutualization and the final self-listing of exchanges are associated with higher trading volume. In addition, the improved competitiveness in attracting trading volume following the initial demutualization seems to be stronger than that following the self-listing of exchanges. As for the effects on the number of listings on an exchange, the results are not strong. Taken collectively, these results suggest that demutualized exchanges seem to be able to enhance their competitiveness in attracting trading volume.

Given the importance of stock exchanges in the development of an economy, research on major changes in the exchange industry is promising. For example, many stock exchanges have adopted electronic trading platforms in recent years. As electronic trading can speed up the order processing time, one expects that the adoption of such a system may boost liquidity and enhance price efficiency as the information contained in the order flow can be incorporated into security prices faster. This is left for future work.

CHAPTER V

CONCLUSION

This dissertation evolves the topics on equity prices and market structures. The first essay is titled “Order Flow and Prices.” Microstructure theory predicts that order flow affects prices (Kyle, 1985; Glosten and Milgrom, 1985). While this prediction is well documented empirically, we know little about which traders drive this relationship. Trading strategies and information differ across traders and, therefore, we also expect that the relationship between order flow and prices differs across traders. We provide new evidence on this issue using NYSE data on daily order imbalances for different trader groups. First, we document that institutions are contrarians with respect to returns on the previous day. We further show that individuals are contrarians as well, consistent with Kaniel, Saar, and Titman (2007). Second, we document that order imbalances from different trader types play distinctly different roles in price formation. While institutions and individuals are contrarians, they differ in the effect their order imbalances have on contemporaneous returns. Institutional imbalances are positively related to contemporaneous returns and we provide cross-sectional evidence that this relationship is likely to be the result of firm-specific information institutions have. In contrast, the imbalances of individuals, specialists, and institutional program traders are negatively related to contemporaneous returns. This suggests that these trader types provide liquidity to actively trading institutions. Moreover, this result suggests a special role for institutional program trades. Institutions appear to choose regular trades when they have firm-specific information, but they choose program trades when they do not and can, therefore, afford to trade passively. As a result, program trades provide liquidity to the market. Third, both institutional non-program and individual imbalances have predictive power for next-day quote-midpoint excess returns.

The second essay is titled “Short Selling and the Informational Efficiency of Prices.” The potential effect of short selling on the informational efficiency of share prices is an ongoing debate in financial economics. Based on daily shorting flow data for a large sample of NYSE-listed stocks, we show that short sellers enhance the relative efficiency of transaction prices. We also provide new evidence on the recent suspension of the Uptick Rule for Regulation SHO Pilot stocks. Pilot stocks, compared to a matched sample of control stocks, see some improvement in price efficiency associated with increased shorting activity after the tick test was suspended.

The third essay is titled “Demutualization and Stock Exchange Performance.” The exchange industry around the world speeds up the demutualization process in recent years. Using panel data on 132 major stock exchanges in 114 countries from 1990 to 2003, we examine the effect of demutualization on an exchange’s performance in its primary product markets: trading and listings. There is some evidence that demutualization is associated with improved competitiveness in attracting trading volume, while results on listings following demutualization are relatively weak.

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APPENDIX

This appendix presents the estimation of the pricing error. The notations follow those in Hasbrouck (1993). Hasbrouck assumes that the observed (log) transaction price at time t, p_t, can be decomposed into an efficient price, m_t, and the pricing error, s_t:

$$p_t = m_t + s_t, \tag{A.1}$$

where m_t is defined as the security's expected value conditional on all available information at transaction time *t*. By definition, m_t only moves in response to new information, and is assumed to follow a random walk. The pricing error s_t measures the deviation relative to the efficient price. It captures non-information related market frictions (such as price discreteness and inventory control effects, etc.). s_t is assumed to be a zero-mean covariance-stationary process, and it can be serially correlated or correlated with the innovation from the random walk of efficient prices. Because the expected value of the deviations is zero, the standard deviation of the pricing error, $\sigma(s)$, measures the magnitude of deviations from the efficient price, and can be interpreted as a measure of price efficiency for the purpose of assessing market quality.

In the empirical implementation, Hasbrouck (1993) estimates the following vector AutoRegression (VAR) system with five lags:

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \ldots + b_1 x_{t-1} + b_2 x_{t-2} + \ldots + v_{1,t} \\ x_t &= c_1 r_{t-1} + c_2 r_{t-2} + \ldots + d_1 x_{t-1} + d_2 x_{t-2} + \ldots + v_{2,t} \end{aligned} \tag{A.2}$$

where r_t is the difference in (log) prices p_t, and x_t is a column vector of trade-related variables: a trade sign indicator, signed trading volume, and signed square root of trading volume to allow for concavity between prices and trades. $v_{1,t}$ and $v_{2,t}$ are zero-mean, serially uncorrelated disturbances from the return equation and the trade equations, respectively. All transactions in TAQ that satisfy certain criteria are included in the estimation.[55] Following Hasbrouck (1993), overnight returns are not included. I follow Lee and Ready (1991) to assign trade directions but make no time adjustment (Bessembinder (2003)).

The above VAR can be inverted to obtain its vector moving average (VMA) representation that expresses the variables in terms of contemporaneous and lagged disturbances:

$$\begin{aligned} r_t &= a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} + \ldots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \ldots \\ x_t &= c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-2} + \ldots + d_0^* v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + \ldots \end{aligned} \qquad \text{(A.3)}$$

To calculate the pricing error, only the return equation in (A.3) is used. The pricing error under the Beveridge and Nelson (1981) identification restriction can be expressed as:

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \ldots + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \ldots \qquad \text{(A.4)}$$

where $\alpha_j = -\sum_{k=j+1}^{\infty} a_k^*$, $\beta_j = -\sum_{k=j+1}^{\infty} b_k^*$.

The variance of the pricing error is then computed as

$$\sigma_{(s)}^2 = \sum_{j=0}^{\infty} [\alpha_j, \beta_j] Cov(v) \begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix} \qquad \text{(A.5)}$$

[55] Trades and quotes during regular market hours are used. For trades, I require that TAQ's CORR field is equal to zero, and the COND field is either blank or equal to *, B, E, J, or K. Trades with non-positive prices or sizes are eliminated. A trade with a price greater than 150% or less than 50% of the price of the previous trade is also excluded. For quotes, I include only those with positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. Quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price are also excluded. A quote with the ask greater than 150% of the bid is also excluded. For each stock, I aggregate all trades during the same second that execute at the same price and retain only the last quote for every second if multiple quotes were issued.

Since very few time-series observations in a VAR can distort the calculation of pricing errors, a stock is required to have a minimum of 100 trades on average to be included in the daily analysis. To make comparisons across stocks meaningful, $\sigma(s)$ is then scaled by the standard deviation of p_t, $\sigma(p)$, to control for cross-sectional differences in the return variance. This ratio $\sigma(s)/\sigma(p)$ reflects the proportion of deviations from the efficient price in the total variability of the observable transaction price process.[56] Therefore, it serves as a natural measure of the informational efficiency of prices. Because the pricing error is inversely related to price efficiency, the smaller this ratio is, the more efficient the stock price is.[57] In the empirical analysis, this ratio is referred to as "pricing error" for brevity.

[56] $\sigma(s)/\sigma(p)$ greater than 1 are excluded from analysis to reduce the influence of outliers.
[57] As pointed out by Hasbrouck (1993), if temporary deviations from the efficient price take too long to correct, pricing errors will be understated because deviations are erroneously attributed to changes in efficient price. This potential limitation is not a major concern in this study for two reasons. First, my analysis examines the relative efficiency of prices instead of price efficiency in an absolute sense. Moreover, the empirical tests focus on the cross-section of stocks and this potential measurement error is unlikely to be highly systematic across stocks.

VITA

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