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Cleaning house: Stock reassignments on the NYSE

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Abstract

A frequently occurring, yet unexplored, phenomenon of the New York Stock Exchange specialist system is that of reassignments of stocks by specialist firms on the floor of the Exchange. These events change the portfolios at the individual specialist level by reassigning one or more stocks from one individual specialist portfolio to another. We find that reassigned stocks have unusually wide spreads before reassignments and experience a decline in spreads to levels comparable to matched stocks after the reassignment. This improvement in liquidity is associated with a reduced cost of capital for the reassigned firms. We find that portfolio size, and industry and size concentration of the individual specialist portfolios are associated with the decision of specialist firms to reassign stocks.

JEL classifiacation: G20

1. Introduction

A frequently occurring, yet unexplored, phenomenon of the New York Stock Exchange (NYSE) specialist system is that of the reassignment of stocks by specialist firms on the floor of the exchange.[1] These events change the portfolios at the individual specialist level

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[1]Other studies such as Corwin and Coughenour (2008) and Chakrabarty and Moulton (2008) mention the phenomenon of stock reassignments within specialist firms but there has been no examination of these events in the literature.

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by reassigning one or more stocks from one individual specialist to another. We document 194 such events involving 884 stocks over a three-year period.[2] These reassignments stand in stark contrast to the almost total absence of stock reallocations across specialist firms by the NYSE. Thus, even though the NYSE follows an elaborate matching process of new listings with the "right" specialist firms, it rarely reallocates stocks (see, for example, Corwin, 1999).[3]

Given the importance of the specialist system for the liquidity of stocks traded on the NYSE (and increasingly on exchanges around the world), it behooves us to better understand these events. Toward that end, we study the possible factors determining stock reassignments, and show the impact of these specialist firm decisions on market quality and the cost of capital of the reassigned stocks. The specialist system is pervasive in international equities and options markets. For instance, equity markets ranging from the hybrid structure of the NYSE, to completely electronic systems such as those of Euronext, Toronto Stock Exchange, Stockholm Stock Exchange, etc. include a designated market maker. In fact, Charitou and Panayides (2007) note that all major international equity markets, with the exception of the Tokyo Stock Exchange, rely on some form of a designated market maker to facilitate trading. Similarly, most of the options markets in the United States assign each option to a designated market maker. The significance of the specialist system, over time and across markets, is also reflected in the number of academic studies devoted to studying various aspects of a specialist.[4] A number of empirical studies of the specialist system focus on comparing the market quality of securities traded in a specialist system with those traded under an alternative market mechanism, or on specialist trades and inventory management.[5] More recently, attention has been paid to the fact that specialists are employed by large specialist firms, who in turn are responsible for maintaining a "fair" market in their assigned stocks. Cao et al. (1997), Corwin (1999), and Coughenour and Deli (2002) establish the influence of specialist firms on market quality. Recent availability of post and panel data from the NYSE (identifying individual specialist portfolios) has allowed researchers a more detailed view of the workings of the specialist system. Battalio et al. (2007) find that a change in the individual specialist's relationships can impact market quality. Corwin and Coughenour (2008) show that the limited attention of an individual specialist (and hence the portfolio composition at the individual specialist level) can adversely affect trading costs on the NYSE. Thus, specialist firms and their decisions have real consequences for the market quality of the traded securities.

[2]To put this number in perspective, there were 2,642 companies listed on the NYSE at the end of our sample period.

[3]Such inaction is surprising given the extensive efforts expended on monitoring by the NYSE. For example, the NYSE revamped the specialist performance evaluation to include objective measures that "will permit comparisons by stock, panel and post, as well as by firm, and thus will more clearly distinguish between strong and weak performance." (Nancy Reich, VP at the market surveillance unit of NYSE, as quoted in "UPDATE: NYSE seeks to reform specialist allocation," CNN Money, June 29, 2005).

[4]Glosten (1989) and Benveniste et al. (1992) provide theoretical models where the presence of the specialist mitigates adverse selection. Hasbrouck and Sofianos (1993), Madhavan and Smidt (1993), and Madhavan and Sofianos (1998) provide empirical analyses of specialist profitability and inventory control. Venkataraman (2001), Anand and Weaver (2006), and Venkataraman and Waisburd (2007) provide evidence that a specialist system adds value to the market when compared to an electronic system or a multiple market maker system.

[5]See, for example, Hasbrouck and Sofianos (1993), Bessembinder and Kaufman (1997), Bessembinder (1999, 2003), Madhavan and Sofianos (1998), and Panayides (2007), among others.

Our analysis contributes to the literature in three ways: First, we shed light on a critical control mechanism of the NYSE specialist system not previously studied in the literature. We note that other exchanges using the specialist system and NASDAQ market-making firms face the problem of portfolio monitoring at the level of the individual market-maker as well. Ellis et al. (2002) point to the trend of large market-making firms (categorized as wholesalers) trading thousands of stocks. Our analysis of stock reassignments should be useful in the formation and monitoring of portfolios for other specialist and market-making firms as well. Second, we study the market quality and cost of capital implications for the listed firms whose stock is reassigned by the specialist firm. Third, we provide insight into the factors that specialist firms consider relevant in making the decision to reassign some stocks and not others.

We identify specialist reassignments using three years of post and panel data, from 2002 to 2004, provided by the NYSE. Our analysis of conventional liquidity measures shows that reassigned stocks have higher quoted and effective spreads before reassignments, relative to similar stocks that are traded by the reassigning specialist firm and are matched on share price, trading volume, volatility, and market value of equity. Quoted and effective spreads of the reassigned stocks decline around the reassignment date to a level below that of the matched stocks, but then stabilize to levels very similar to those of the matched stocks' spreads about 10 trading days after the reassignment. Similarly, reassigned stocks have lower quoted depths than matched stocks in the comparison period before reassignments. The quoted depth rises after reassignment to levels close to that of matched stocks. We find that the reduction in spreads is due to a decline in the adverse selection component of the spread. These findings are consistent with reassigned stocks having problems with their liquidity, which are corrected by reassignments within specialist firms. An event study analysis around the day of stock reassignments reveals statistically significant abnormal returns associated with these reassignments, indicating that listing firms benefit from stock reassignments. We find that an average firm in our sample experiences a five-day cumulative abnormal return (day 0 to day +4) of 0.90% in excess of a similar sample of control stocks. Given that our average stock has a market value of \$5.05 billion, these abnormal returns translate into an increase in value of \$45.5 million for the average firm. We use regression analysis to establish that the abnormal returns are significantly related to the decline in spreads (i.e., stocks that experience a higher decline in spreads also show higher five-day cumulative abnormal returns).

Further, we explore the possible reasons for stock reassignments. Since the implementation of the new allocation plan by the NYSE in 1997, specialist firms have placed particular emphasis on their relationships with listed firms (see Corwin, 2004). Specialist firms increasingly offer a wide array of services to their listed firms, but the promise of superior market quality remains at the core of this relationship.[6] Thus, the market quality of the stock is vital to the relationship of the specialist firm with the listing firm, forcing the specialist firms to monitor market quality measures, and correct any problems. In this analysis, we focus on individual specialist portfolio characteristics and stock characteristics that are associated with the reassignment decision. Our results indicate a prominent role for the industry and size concentration of the individual specialist portfolios in the decision of specialist firms to reassign stocks. Specifically, we find that portfolios affected by reassignments have significantly lower industry and size

[6] For instance, on the website for Van Der Moolen Specialists (www.vdm-usa.com), the firm promises, "…our commitment to utilize that capital to maintain high quality markets for the companies we represent."

concentrations before the reassignments relative to portfolios that were not affected by the reassignments. These concentrations increase after the reassignment, to levels very similar to that of the unaffected portfolios. The increase in industry concentration indicates a preference for assigning similar stocks to individual specialists. This result is consistent with theoretical models of Caballe and Krishnan (1994) and Strobl (2001), which indicate that specialists would prefer assets with correlated payoffs. The increase in size concentration indicates that specialist firms prefer individual specialist portfolios dominated by larger firms (consistent with the findings of Corwin and Coughenour, 2008). Further, the narrowing of the difference between affected and unaffected portfolios after reassignments suggests that specialist firms pay attention to these measures in the composition of individual specialist portfolios.

Our results are also consistent with anecdotal evidence, drawn from our conversations with a former CEO of Van Der Moolen Specialists, suggesting that specialist firms are concerned about market quality, and base the reassignment decisions on several factors including the overall volume handled by an individual specialist and the informational advantages that accrue from trading stocks in the same industry (with the caveat that too high a level may create an overload for the specialist in times of significant industry-specific news).[7] Overall, our results provide evidence of the economic benefits of stock reassignments by specialist firms.

Our findings have implications for the specialist system. We show the significance of the specialists and the composition of the specialists' portfolios in the market quality of stocks. Specific to the NYSE, we provide evidence that specialist firms monitor stock trading and take corrective action to improve market quality. Furthermore, the results also indicate that the mechanism is effective even without any overt action on the part of the exchange. However, the results can also be interpreted differently. The improvement in market quality indicates that the stocks were not trading optimally prior to the reassignments. Hence, it could be argued that the specialist system can lead to situations when the stocks do not experience the best levels of market quality possible. Recent studies (Venkataraman and Waisburd, 2007; Anand et al., 2008; Bessembinder et al., 2006) have shown the benefits of introducing specialists in electronic order-driven markets. Our results add to the findings of these studies in showing that the creation and monitoring of individual specialist portfolios is important, beyond the introduction of specialists in the market.

Our plan for the rest of the paper is as follows. Section 2 presents a discussion of the institutional details, the data, and the nature of stock reassignments by specialist firms. Section 3 presents the results on the impact of these events on market quality and returns of reassigned stocks. Section 4 presents an analysis of the determinants of stock reassignments, and Section 5 concludes.

2. Institutional details, data, and methodology

Specialists, on the NYSE, are individuals who facilitate trading in the stocks they are assigned. Thus, they not only match buyers and sellers, but also trade in and out of their

[7] We are grateful to Robert Fagenson for his many comments and conversations on the paper. Other factors mentioned as reasons for reassigning stocks are specialist profitability and matching stock characteristics with individual specialist talents. We are unable to comment on these factors since publicly available data do not allow us to measure specialist profitability or specialist talent.

personal inventories to ameliorate market volatility during periods of illiquidity. A specialist performs four vital roles: auctioneer, catalyst, agent, and principal. As an auctioneer, the specialist displays the best bids and offers, and matches buyers with sellers. As a catalyst, the specialist keeps track of the trading interests of different buyers and sellers on the floor of the exchange and continually updates them. As an agent, the specialist acts as the broker for all electronically routed orders to the NYSE floor. Floor brokers can also leave an order with the specialist, freeing themselves up to take on other orders. As a principal, the specialist acts as a major party to a transaction. These roles, combined with the specialists' responsibility to maintain fair and orderly markets, create a significant impact of specialist performance on market liquidity. While the above description applies to individual specialists, over the years the specialist business has seen significant consolidation. Thus, all specialists in the NYSE are currently employed by seven specialist firms. Each of these firms assigns a portfolio of stocks to a distinct panel. For instance, as of November 30, 2002, these firms distributed their stocks into 360 different panels. LaBranche assigned its stocks among 84 different panels on the NYSE floor, while Van Der Moolen had its stocks trading over 44 panels. Consistent with Battalio et al. (2007) and Corwin and Coughenour (2008), we use these panels to identify individual specialist portfolios. The reassignments of stocks, within specialist firms, across these panels form the basis of our study.

We use the NYSE post and panel data for a three-year period (2002–2004) to construct our sample of stock reassignments by specialist firms. This daily data-set specifies the post and panel a particular stock is traded on. A unique combination of post and panel identifies an individual specialist portfolio. Specialist firms periodically reorganize their portfolios by reassigning stocks across individual specialist portfolios. A change in the post-panel combination associated with a particular stock helps us identify stock reassignments. We choose our sample period to avoid two kinds of significant confounding effects: the decimalization in the US markets and the significant consolidation among the specialist firms on the NYSE. Specialist firm mergers caused significant movement of stocks across specialist posts, and can impact their trading due to the increased capitalization of specialist firms.[8] Our sample period largely avoids the wave of consolidation among specialist firms. There is only one specialist firm merger during our sample period. We exclude any reassignment events around this merger, particular to the merging specialist firms, that occur within 60 trading days (i.e., day -60 to day $+60$) of the merger, to avoid introducing any confounding effects in our analysis.[9] Further, we find that some of the reassigned stocks in our data are either reassigned back to the original post and panel within a few days, or move again to a different post and panel. Our conversations with NYSE officials suggest that a large number of these observations represent possible data errors. To avoid the confounding effect of data errors, and to allow

[8]We thank an anonymous referee for suggesting these filters on the sample. In an earlier version, we had studied the 2000–2002 period. During this period, the number of specialist firms declined from 17 to 7. In contrast, in the 2002–2004 period, the number of specialist firms was relatively constant, going from 8 to 7. Our results from the two samples are substantively similar. See also Hatch and Johnson (2002) for an analysis of specialist firm mergers.

[9]We were sensitive to any reassignments that occurred due to a planned or an actual specialist firm merger. Hence, we applied this filter (of excluding any reassignments within 60 days of the merger) for the announcement date, as well as the effective date of the merger. This leads to our eliminating 148 stocks reassigned by the merging specialist firms around the merger.

an analysis over the window used in this study, we exclude from our analysis any stock that is reassigned again within six months of the initial reassignment date. We verify that the results are qualitatively similar without applying the filter, or with using a 10-day, 30-day, or 60-day filter instead of the 6-month filter. Additionally, Battalio et al. (2007) argue that the reassignment of an entire panel of stocks from one location on the floor to another indicates that the specialist moves with the panel as well. Since our focus is on reassignments where the specialist portfolio changes, we eliminate all instances where the entire panel of stocks is reassigned.

We restrict our sample to common stocks only; that is, we exclude units, warrants, preferred stocks, and REITs from our analysis since their trading characteristics are likely to differ from those of common stocks. To account for the possibility that specialist reassignments are motivated by certain expected unusual market conditions on a particular day, we exclude stocks with reassignment dates within five days of listed firm mergers (announcement as well as actual dates), share repurchase announcements, and earnings announcements.[10] Furthermore, in case there are some events that affect trading but do not show up in conventional databases, we also delete stocks with unusual spike in volume around the event day. Specifically, a stock is dropped from the sample if the daily trading volume of the stock on any day around the event day (days -5 to $+5$), is equal to, or higher than, 150% of the average daily trading volume during a benchmark period (days -60 to -40).

We use the NYSE's trades and quotes (TAQ) data to measure market quality,[11] and CRSP data to calculate abnormal returns. We require our sample stocks to be present in both the TAQ and CRSP databases. We also use Securities Data Company (SDC) data to identify corporate announcements such as mergers, and the I/B/E/S data for earning announcement dates.

Table 1 describes our final sample comprising 884 stocks reassigned by eight firms over our sample period in 194 distinct reassignment events.[12] These 884 stocks represent our sample after applying the various filters. As mentioned earlier, we eliminate the 148 firms that are reassigned by the merging specialist firms around the one merger during our sample period. The combination of the other filters that eliminate stocks that move again after the initial reassignment, stocks that experience unusual volume changes, stock that move as entire panels, and stocks that are reassigned close to earnings and other corporate

[10]The five-day period is chosen to eliminate the possibility of such corporate events confounding our analysis while still keeping a reasonable sample. The issue is particularly relevant for earnings that are announced every quarter. Hence, picking a long enough window would conceivably cover every trading day. In our tests, we do not find evidence that reassignment dates cluster unusually around earnings announcement dates, and eliminating reassignments within 15 days of an earnings announcement (a 30-day window) does not change any of our conclusions. For non-earnings related corporate events (mergers and share repurchases), we also used longer time windows (60 days) with no qualitative effect on the results.

[11]We eliminate possible data errors by omitting the following trades and quotes in the TAQ database: quotes if either the bid price or the ask price is non-positive; quotes if either the bid size or the ask size is non-positive; quotes if the bid-ask spread is greater than \$5 or negative; quotes associated with designated order imbalance or trading halts; quotes and trades if they are out of time sequence, involve an error, or involve a correction; off-trading hours quotes and trades; trades if the price or volume is non-positive; quotes if bid quote, b_t, satisfies $|(b_t - b_{t-1})/b_{t-1}| > 0.10$; quotes if ask quote, a_t, satisfies $|(a_t - a_{t-1})/a_{t-1}| > 0.10$; trades if trade price p_t satisfies, $|(p_t - p_{t-1})/p_{t-1}| > 0.10$.

[12]The same stock can appear more than once in the sample if it is reassigned again by the specialist firm during the three-year sample period, subject to the previously mentioned constraint that the stock is excluded from our sample if it is reassigned within a six-month period.

Table 1
Descriptive statistics: (a) Panel A: Specialist firm reassignment events; (b) Panel B: Reassigned and matched stocks.

(a)

	2002	2003	2004	Overall
Number of reassignment events	69	46	79	194
Number of specialist firms affected	8	7	7	8
Average number of stocks per event	4.23	4.39	4.94	4.56
Total number of reassigned stocks	292	202	390	884
Minimum number of stocks per event	1	1	1	1
Maximum number of stocks per event	41	23	25	41

(b)

	Reassigned sample			Matched sample		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Price ($)	27.02	21.47	21.14	26.98	21.66	18.85
Volume (thousand shares)	753	714	1,925	760	658	2,337
Market value of equity ($ M)	5,051	3,779	12,757	5,233	4,139	10,253
Volatility	0.0207	0.0252	0.0128	0.0215	0.0264	0.0142

This table summarizes the sample used in the study. We use the daily NYSE post and panel data for a three-year period (2002–2004) to construct our sample of stock reassignments. This daily data-set specifies the post and panel a particular stock is traded on. A unique combination of post and panel identifies an individual specialist portfolio. We restrict our sample to common stocks only. Panel A provides the number and frequency of reassignments by specialist firms. Panel B presents summary statistics of reassigned stocks and matched stocks. For each reassigned stock, we pick an NYSE stock traded by the same specialist firm as the one reassigning the sample stock as the matched stock with the requirement that the matched stock is not reassigned with 60 trading days before and after the date of reassignment and minimizes the following index:

$$index = \sum_{k=1}^{4} [(Y_k^{REAS} - Y_k^{MTCH})/\{(Y_k^{REAS} + Y_k^{MTCH})/2\}]^2$$

where Y_k represents share price, trading volume, market value of equity, and volatility. The superscripts, $REAS$ and $MTCH$, refer to reassigned and matching stocks, respectively.

announcements, leaves us with the 884 stocks studies here.[13] We also present the annual breakdown of these reassignment events. The maximum number of reassignment events by specialist firms (79 events affecting 390 stocks) occurs in 2004, while the minimum occur in 2002 (69 events affecting 292 stocks). These numbers indicate that reassignments occur frequently, affect a large number of stocks, and are used by all the specialist firms on the NYSE. We also document that these stock reassignments by specialist firms can affect one stock or be a more significant overhaul of their portfolios, as seen in the wide range of stocks affected by these reassignments (from 1 to 41).

[13]As a result of these filters, we exclude 215 stocks that are reassigned close to corporate events, and 382 stocks due to the combination of other filters used (subsequent reassignment within six months of the initial reassignment, unusual volume changes, and stocks that move as entire panels). In an earlier version of the paper, we had only applied the filter of eliminating reassignments around specialist firm mergers. While that gave us a larger sample, the results were qualitatively similar (and statistically more significant) to the ones presented here. Hence, we are confident that these filters are not affecting our conclusions.

For our analysis focusing on market quality and abnormal returns of the reassigned stocks around the reassignment, we use a period from trading day −60 to trading day +60 (where day 0 is the reassignment date) to isolate any changes in our measures. Our events are distributed over a three-year period, which reduces the chances of any individual market-wide factor confounding the results. However, to further ensure the validity of the results, we use a control sample of stocks not affected by these events. To obtain the control sample, we first calculate the following composite match index for each reassigned stock in our sample against each NYSE stock *within* the reassigning specialist firm that is not subject to reassignment within 60 days (days −60 to +60) of the event date:

$$index = \sum_{k=1}^{4} [(Y_k^{REAS} - Y_k^{MTCH})/\{(Y_k^{REAS} + Y_k^{MTCH})/2\}]^2, \tag{1}$$

where Y_k represents share price, trading volume, market value of equity, and volatility; the superscripts, *REAS* and *MTCH*, refer to reassigned and matching stocks, respectively; and $\sum$ denotes the summation over the matching criteria used. Then, for each reassigned stock, we select the control stock traded by the same specialist firm that has the lowest value of the above index. Panel B in Table 1 presents summary statistics for the reassigned and control stocks calculated over our benchmark period (days −60 to −40, where day 0 is the event day). The reassigned and control samples are very similar in their matched characteristics: the average stock in our sample trades approximately 753,000 shares on an average day, at \$27.02 per share, and has a market capitalization of \$5.05 billion. The average stock in the control sample trades approximately 760,000 shares per day, at \$26.98 per share, with a market capitalization of \$5.23 billion.

3. Results

3.1. Market quality

If stock reassignments by specialist firms lead to better individual specialist portfolios, we would expect enhanced liquidity for the affected stocks following the reassignment. Further, if the improvement in liquidity is a result of stock reassignments, we would expect the improvement in market quality for affected stocks to be greater than that for the control sample of stocks. We analyze commonly used measures of market quality—quoted spreads, quoted depths, and effective spreads—to conduct our analysis. Quoted spreads and depths measure the ex-ante displayed liquidity available to traders who seek immediacy, while effective spreads measure actual (i.e., ex-post) trading costs incurred by the trader by factoring in trades inside or outside the quoted spread. For each of these measures, we calculate a benchmark value computed as an average from day −60 to day −40, where day 0 is the event date. We then measure abnormal levels as the difference between the daily measure and the benchmark period average for each of the days −30 to +60. Quoted spreads (Ask price–Bid price) are time weighted (i.e., weighted by the time the quote is valid for) daily averages, while effective spreads are volume weighted (i.e., weighted by the number of shares in the trade) daily averages.[14]

[14]We calculate the effective spread for stock i at time t as $Effective\ Spread_{it} = 2D_{it}(P_{it} - M_{it})$, where P_{it} is the transaction price for stock i at time t, M_{it} is the prevailing quote midpoint for stock i at time t, and D_{it} is a binary

Panel A in Table 2 presents the results for quoted percentage and dollar spreads for our sample and control stocks. The table presents three different analyses. First, we compare the quoted percentage and dollar spreads of sample and control stocks during the benchmark period (days −60 to −40). Earlier, we proposed that specialist reassignments may be a corrective mechanism. Possible symptoms of problems in the trading of certain stocks are spreads being wider than those for other similar stocks traded on the exchange. The comparison during the benchmark period, which is a full two months before the event day (based on approximately 20 trading days in a month) allows us to analyze if this is indeed the case. During the benchmark period, the average quoted percentage spread for our sample stocks is 43 basis points, which is around 4 basis points higher than that for our control sample of stocks (statistically significant at the 1% level). Quoted dollar spreads compare at \$0.07 for the reassigned sample stocks against \$0.06 for the control sample (statistically higher at the 1% level).

Next, we document changes in spreads in the period surrounding the event day (days −30 to +60). Our analysis of quoted spreads indicates that spreads are similar to the benchmark period spreads over days −30 to −20, but decline significantly starting at day −5. By day 0, quoted percentage spreads have declined to approximately 35 basis points (compared to approximately 43 basis points in the benchmark period). The third column in Panel A of Table 2 shows that the difference in abnormal quoted percentage spreads in the sample and control stocks is statistically significant starting with day −5, indicating that the decline in spreads for the reassigned stocks is greater than the decline in matched sample stocks. An interesting aspect of the abnormal spread results is that the difference between the changes in reassigned and matched stocks peaks around the event day and starts to diminish thereafter. Even so, the decline in spreads is higher on day +60 for reassigned stocks compared to control sample stocks. A comparison of the difference in the level of the spreads (instead of the changes), in the second column, sheds more light on the above mentioned result. We find that, although, around the event day, spreads for reassigned stocks decline to levels lower than those of control stocks, by day +10 the difference between the two samples is no longer statistically significant. Recall that spreads are higher for sample stocks vis-à-vis control stocks over the day −60 to −40 benchmark period. Hence, the picture that emerges from this analysis is that spreads for reassigned stocks are initially higher, but decline significantly following reassignments to a new level that is similar to the level of spreads of the stocks in our control sample. These results indicate that reassignments appear to correct the issues with stocks' liquidity by bringing them more in line with similar stocks traded by the specialist firm. The results for quoted dollar spreads are similar.

In Table 2, Panel B, we analyze the other dimension of ex-ante liquidity—quoted depth. The patterns are similar to those seen above for quoted spreads. We find that in the benchmark period, reassigned stocks have an average quoted depth of 3,556 shares, which is statistically significantly smaller than the average depth of 3,781 shares for the control sample. Depth increases significantly for the reassigned sample around day −5 and by day +10 settles to a level that is not statistically different than that of the matched sample.

(*footnote continued*)
variable that equals +1 for buyer-initiated trades and −1 for seller-initiated trades. We use the Lee and Ready (1991) algorithm as modified by Bessembinder (2003) to classify a trade as either buyer or seller initiated.

Table 2
Liquidity measures: (a) Panel A: Quoted spreads; (b) Panel B: Depth; (c) Panel C: Effective spreads; (d) Panel D: Trading volume.

(A)

Day	Quoted % spread for reassigned sample	Quoted % spread for matched sample	Difference in abnormal quoted % spread (Reassigned−Matched)	Quoted \$ spread for reassigned sample	Quoted \$ spread for matched sample	Difference in abnormal quoted \$ spread (Reassigned−Matched)
−60 to −40	0.4304%	0.3920%[a]		\$0.0701	\$0.0625[a]	
−30	0.4464%	0.3914[a]	3.89%**	\$0.0722	\$0.0621[a]	3.65%**
−20	0.4442	0.3931[a]	2.93**	0.0717	0.0610[a]	4.10**
−10	0.4175	0.3884	−2.07	0.0674	0.0616	−2.25
−5	0.3805**	0.3900[a]	−11.08**	0.0604**	0.0629[a]	−14.49**
−4	0.3843**	0.3949[a]	−11.43**	0.0593**	0.0625[a]	−15.47**
−3	0.3753**	0.3980[a]	−14.35**	0.0588**	0.0619[a]	−15.19**
−2	0.3622**	0.3900[a]	−15.35**	0.0589**	0.0627[a]	−16.18**
−1	0.3676**	0.3938[a]	−15.06**	0.0580**	0.0622[a]	−16.66**
0	0.3541*	0.3870[a]	−16.45**	0.0571**	0.0624[a]	−18.03**
1	0.3602**	0.3928[a]	−16.51**	0.0579**	0.0631[a]	−18.36**
2	0.3666**	0.3957[a]	−15.77**	0.0586**	0.0619[a]	−15.38**
3	0.3649**	0.3881[a]	−14.23**	0.0589**	0.0623[a]	−15.62**
4	0.3707**	0.3946[a]	−14.55**	0.0594**	0.0628[a]	−15.58*
5	0.3632**	0.3869[a]	−14.31**	0.0598**	0.0624[a]	−14.53**
10	0.3790**	0.3880	−10.92**	0.0605**	0.0614[a]	−11.83**
20	0.3716**	0.3803	−10.67**	0.0595**	0.0609	−12.60**
30	0.3722**	0.3708	−8.10**	0.0600**	0.0584	−7.80**
40	0.3726**	0.3712	−8.11**	0.0597**	0.0598	−10.49**
50	0.3764**	0.3707	−7.12**	0.0594**	0.0602	−11.57**
60	0.3781**	0.3786	−8.75**	0.0584**	0.0592	−11.35**

(B)

Day	Depth for reassigned sample	Depth for matched sample	Difference in abnormal depth (Reassigned−Matched)
−60 to −40	3556 shares	3781[b] shares	
−30	3448	3800[b]	−3.52%
−20	3462	3831[b]	−3.96
−10	3602	3741	2.36
−5	3903**	3789[b]	9.57**
−4	3950**	3831[b]	9.76**
−3	3938**	3774[b]	10.93**
−2	3941**	3785[b]	10.74**
−1	3908**	3733[b]	11.16**
0	4082**	3802[b]	14.26**
1	4072**	3831[b]	13.20**
2	4076**	3778[b]	14.70**
3	4070**	3896[b]	11.39**
4	4056**	3811[b]	13.25**
5	4117**	3841[b]	14.18**

Table 2 (*continued*)

10	4027**	3968	8.30**
20	4075**	4029	8.03**
30	4071**	4003	5.97**
40	4113**	4092	7.45**
50	4101**	4157	5.38**
60	4140**	4094	8.15**

(C)

Day	Effective % spread for reassigned sample	Effective % spread for matched sample	Difference in abnormal effective % spread (Reassigned−Matched)	Effective $ spread for reassigned sample	Effective $ spread for matched sample	Difference in abnormal effective $ spread (Reassigned−Matched)
−60 to −40	0.3458%	0.3136%[c]		$0.0418	$0.0366[c]	
−30	0.3561	0.3117[c]	3.58%**	0.0431	0.0362[c]	4.25%**
−20	0.3567	0.3139[c]	3.07**	0.0437	0.0371[c]	3.09**
−10	0.3351	0.3117	−2.46	0.0400	0.0358	−1.96
−5	0.3046**	0.3180[c]	−13.31**	0.0358**	0.0374[c]	−16.63**
−4	0.2909**	0.3153[c]	−16.41**	0.0360**	0.0376[c]	−16.51**
−3	0.2972**	0.3147[c]	−14.41**	0.0348**	0.0365[c]	−16.38**
−2	0.2933**	0.3123[c]	−14.75**	0.0346**	0.0368[c]	−17.55**
−1	0.2847**	0.3120[c]	−17.16**	0.0345**	0.0366[c]	−17.15**
0	0.2807**	0.3107[c]	−17.86**	0.0341**	0.0367[c]	−18.54**
1	0.2831**	0.3125[c]	−17.75**	0.0348**	0.0369[c]	−16.94**
2	0.2933**	0.3150[c]	−15.62**	0.0359**	0.0365[c]	−13.71**
3	0.2919**	0.3153[c]	−16.12**	0.0344**	0.0364[c]	−17.01**
4	0.2897**	0.3103[c]	−15.17**	0.0356**	0.0378[c]	−17.92**
5	0.2917**	0.3119[c]	−15.06**	0.0360**	0.0376[c]	−16.51**
10	0.2895**	0.3005	−12.09**	0.0356**	0.0361	−13.43**
20	0.2870**	0.2925	−10.28**	0.0338**	0.0341	−12.34**
30	0.2837**	0.2904	−10.57**	0.0341**	0.0344	−12.23**
40	0.2854**	0.2824	−7.49**	0.0349**	0.0338	−8.69**
50	0.2917**	0.2908	−8.36**	0.0333**	0.0339	−12.93**
60	0.2880**	0.2921	−9.83**	0.0339**	0.0342	−12.32**

(D)

Day	Volume for reassigned sample in thousand shares	Volume for matched sample in thousand shares	Difference in abnormal volume (Reassigned−Matched)
−60 to −40	753	760	
−30	751	754	0.52%
−20	748	761	−0.80
−10	746	763	−1.32
−5	751	757	0.13
−4	749	755	0.13
−3	758	767	−0.26
−2	756	757	0.79
−1	759	764	0.27
0	758	762	0.40
1	756	761	0.27
2	757	759	0.66
3	757	760	0.53
4	751	766	−1.06

Table 2 (*continued*)

5	753	765	−0.66
10	754	765	−0.53
20	757	762	0.27
30	759	758	1.06
40	752	760	−0.13
50	759	774	−1.05
60	759	763	0.40

This table summarizes changes in quoted percentage spreads, quoted dollar spreads, quoted depths, effective percentage spreads, effective dollar spreads, and trading volume around the day of stock reassignments. The abnormal spread is calculated as $(SP_{EVT}-SP_{NORM})/SP_{NORM}$, where SP_{NORM} is the average spread over days −60 to −40, and SP_{EVT} is the spread as of a particular day around the event date. We calculate the abnormal spreads for each day for both reassigned and matched stocks. We then compute the difference in abnormal spreads between the reassigned and matched stocks for each day. Abnormal depth and abnormal trading volume are calculated in the same manner. Panel A shows the results for quoted percentage and quoted dollar spreads. Panel B reports the results for quoted depths. Panel C reports the results for effective percentage spreads and effective dollar spread. Panel D presents the results for trading volume. We calculate the effective spread for stock i at time t as $\textit{Effective Spread}_{it} = 2D_{it}(P_{it}-M_{it})$, where P_{it} is the transaction price for stock i at time t, M_{it} is the prevailing quote midpoint for stock i at time t, and D_{it} is a binary variable which equals +1 for buyer-initiated trades and −1 for seller-initiated trades. Trades are classified as buys or sells using the Lee and Ready (1991) algorithm as modified by Bessembinder (2003).

**Significant at the 1% level.

*Significant at the 5% level.

[a]The difference in the level of spreads between the reassigned and matched sample (Reassigned−Matched) is significant at the 1% level.

[b]The difference in the level of depths between the reassigned and matched sample (Reassigned−Matched) is significant at the 1% level.

[c]The difference in the level of spreads between the reassigned and matched sample (Reassigned−Matched) is significant at the 1% level.

While quoted spreads and depths measure ex-ante liquidity, executions frequently occur inside (due to price improvement) or outside the spread (for orders larger than the quoted depth). Effective spreads capture these effects as they compare the execution price to the midpoint of the prevailing bid-ask spread. Panel C of Table 2 presents our results for effective percentage and dollar spreads. The results for the effective spreads are very similar to those discussed above for quoted spreads. Effective spreads for the reassigned sample stocks are higher than those for the control sample stocks in the day −60 to −40 benchmark period. Spreads decline significantly around the event day, dropping below that of matched stocks, but by day +10 stabilize to a level similar to that of matched stocks. This result again shows that reassignments appear to remedy situations where stocks have higher spreads than they should (as determined by the spreads of similar stocks traded by the specialist firm).

We also analyze the trading volume of the reassigned stocks in Table 2, Panel D. The trading volume of reassigned stocks is not significantly different than those of matched stocks during the benchmark period, and does not show a statistically significant change over our observation period. Thus, our results on improvements in liquidity are not accompanied by a change in volume.[15]

[15]Two sample selection issues that may impact the volume analysis should be noted here. First, we use volume as one of the matching criteria in choosing the control stocks. Second, in order to eliminate any impact of

3.2. Source of changes in spreads

We next attempt to identify the source of reduction in spreads documented above. Specifically, we follow Huang and Stoll (1996) and Battalio et al. (2007) in decomposing the effective spread into a component associated with adverse selection and another that is realized by the liquidity supplier as compensation for order processing costs and profits. If the spread reduction is due to reduced information asymmetry in the trading of the stock associated with the changes in individual specialist portfolios, then we would expect the adverse selection component of the spread to show a decline. The other possibility is that the change in the specialist portfolio reduces the component associated with the specialists' order processing costs and profits. In this scenario, we expect to see a decline in the realized spreads.

The realized spread is calculated as the product of a binary variable that equals +1 for buyer initiated trades and −1 for seller initiated trades and twice the difference between the trade price and the midpoint of the quoted spread prevailing five minutes after the trade is executed. As before, we use the Lee and Ready (1991) algorithm as modified by Bessembinder (2003) to classify a trade as either buyer or seller initiated. The difference between the effective spread and the realized spread is the price impact of the trade, which captures the change in quote midpoint caused by the trade over the five minute horizon. The price impact is our measure of the adverse selection component of the effective spread. We present the results in Table 3.

Our results are consistent with the reduction in spreads arising from a reduction in information asymmetry for the reassigned stocks. Our measure of the adverse selection component of the spread, the price impact, presents a picture very similar to that seen for effective spreads. The price impact is higher for reassigned stocks relative to the matched stocks in the benchmark period, and shows a statistically significant decline around day −5. By day +10, the price impact settles to a significantly lower value that is no longer statistically different from the price impact of matched stocks. Realized spreads, on the other hand, do not experience a decline associated with stock reassignments and are not statistically significantly different from those of the matched stocks. Thus, these results point to the liquidity improvement arising from the reduction in information asymmetry associated with the change in individual specialist portfolios.

3.3. Cost of capital

The improvement in market quality and the results of the extant literature, establishing the link between liquidity and firm valuation, imply that we may see an increase in firm value for the reassigned stocks.[16] To test this hypothesis, we calculate the abnormal returns using the market model for our sample and control stocks, using daily data, over days

(*footnote continued*)
confounding events on our analysis, we eliminate stocks from our sample that experience a sharp increase in volume (specifically, as mentioned earlier, a stock is dropped from the sample if the daily trading volume of the stock on any day around the event day (days −5 to +5), is equal to, or higher than, 150% of the average daily trading volume during the benchmark period).

[16] Amihud and Mendelson (1986) and Pastor and Stambaugh (2003) establish the link between stock returns and liquidity. Other studies (such as Amihud et al., 1997; Kalay et al., 2002; Venkataraman and Waisburd, 2007) document a positive abnormal return around liquidity enhancing events.

Table 3
Price impact and realized spreads.

Day	Price impact for reassigned sample	Price impact for matched sample	Difference in abnormal price impact (Reassigned−Matched)	Realized spread for reassigned sample	Realized spread for matched sample	Difference in abnormal realized spread (Reassigned−Matched)
−60 to −40	0.0311	0.0268[a]		\$0.0107	\$0.0098	
−30	0.0323	0.0264[a]	5.35%**	0.0108	0.0097	1.02
−20	0.0328	0.0271[a]	4.35**	0.0109	0.0100	−0.17
−10	0.0294	0.0258	−1.73	0.0107	0.0099	−1.02
−5	0.0250**	0.0277[a]	−22.97**	0.0106	0.0097	0.09
−4	0.0254**	0.0280[a]	−22.81**	0.0107	0.0097	1.02
−3	0.0241**	0.0270[a]	−23.25**	0.0106	0.0096	1.12
−2	0.0238**	0.0268[a]	−23.47**	0.0107	0.0099	−1.02
−1	0.0239**	0.0268[a]	−23.15**	0.0108	0.0098	0.93
0	0.0234**	0.0269[a]	−25.13**	0.0106	0.0097	0.09
1	0.0241**	0.0269[a]	−22.88**	0.0107	0.0097	1.02
2	0.0251**	0.0266[a]	−18.55**	0.0108	0.0098	0.93
3	0.0237**	0.0265[a]	−22.68**	0.0106	0.0098	−0.93
4	0.0249**	0.0278[a]	−23.67**	0.0107	0.0100	−2.04
5	0.0253**	0.0277[a]	−22.01**	0.0108	0.0099	−0.09
10	0.0248**	0.0262	−18.02**	0.0105	0.0097	−0.85
20	0.0230**	0.0243	−16.72**	0.0108	0.0098	0.93
30	0.0233**	0.0246	−16.87**	0.0106	0.0098	−0.93
40	0.0242**	0.0240	−11.74**	0.0107	0.0097	1.02
50	0.0226**	0.0241	−17.26**	0.0108	0.0098	0.93
60	0.0232**	0.0243	−16.07**	0.0107	0.0099	−1.02

This table summarizes changes in price impacts and realized spreads around the day of stock reassignments. The abnormal price impact is calculated as $(PIMPACT_{EVT}-PIMPACT_{NORM})/PIMPACT_{NORM}$, where $PIMPACT_{NORM}$ is the average price impact over days −60 to−40, and $PIMPACT_{EVT}$ is the price impact as of a particular day around the event date. We calculate the abnormal price impact for each day for both reassigned and matched stocks. We then compute the difference in abnormal price impact between the reassigned and matched stocks for each day. We calculate the abnormal realized spreads in a similar manner.
**Significant at the 1% level.
*Significant at the 5% level.
[a]The difference in price impacts between the reassigned and matched sample (Reassigned−Matched) is significant at the 1% level.

−300 to −40. We then calculate abnormal returns for each stock from days −30 to +60. We also calculate the cumulative abnormal returns after the event day. Consistent with our intuition, we find, from Table 4, that reassigned stocks show a significant abnormal return around the event day. The five-day (day 0 to day +4) cumulative abnormal return equals 0.92% for reassigned stocks. The difference between the abnormal returns for sample and control stocks is statistically significant. Sample stocks have a five-day CAR, over and above that of control stocks, of 0.90%. The CARs remain statistically significant until day +60. We note that the abnormal returns start to appear around day −5. These results are consistent with the decline in spreads that appears around the same time. We attribute the changes before the event day to the release of the news of the impending reassignment to

Table 4
Abnormal returns.

Day	Abnormal returns for reassigned sample	Difference in abnormal returns (Reassigned−Matched)
−30	−0.03%	−0.03%
−20	−0.03	−0.01
−10	0.04	0.04
−5	0.10*	0.09*
−4	0.11*	0.12*
−3	0.13**	0.14**
−2	0.16**	0.15**
−1	0.17**	0.17**
0	0.27**	0.26**
1	0.21**	0.20**
2	0.15**	0.15**
3	0.15**	0.14**
4	0.16**	0.15**
5	0.11*	0.11*
10	0.03	0.04
20	0.03	0.04
30	−0.01	−0.01
40	0.02	0.01
50	0.01	0.01
60	0.03	0.01
0 to 4	0.92**	0.90**
0 to 60	1.48**	1.25**

This table summarizes abnormal returns around stock reassignments by specialist firms. We calculate abnormal returns using the market model for our sample and control stocks. Our estimation period for the market model parameter is from day −300 to day −40. Results are presented for reassigned stocks and for the paired difference between the reassigned stock sample and the matched sample.
**Significant at the 1% level.
*Significant at the 5% level.

the trading community. The NYSE announces reassignments by specialist firms on its member site (www.nysedata.com). The few announcements that we were able to observe (the NYSE does not maintain an archive of these announcements) tended to be 0 to 6 days before the actual reassignment date. An apparent puzzling feature of these results is that the abnormal returns persist over the day 0 to day +4 period. Since, at the start of trading on day 0, the floor community is aware of the change, and if the change is known to be associated with a reduction in the cost of capital, we would expect the abnormal returns to disappear once the change occurs on the floor. One possibility is that these returns are within the bounds of transaction costs of a round-trip trade. To check this possibility, we create an artificial trade that buys at the opening ask price on day 0 and sells at the closing bid price of day +4. We find that such a trade would yield 0.14% on average. Thus, while bid-ask spreads reduce the abnormal returns, they do not make them disappear. However, we should note that the quoted bid-ask spreads do not include other components of transaction costs such as commissions, which would further diminish the abnormal returns.[17] The quoted depths available at the quoted prices would also limit the profitability of a trading strategy based solely on stock reassignments. These factors may significantly reduce the economic attractiveness of the trading strategy discussed above.

3.4. Regression analysis

Our results so far show that market quality improves, and the cost of capital declines, following the reassignments of stocks to a different specialist. In this section, we verify that the decline in the cost of capital (as seen by the significant CARs) is related to the improvement in market quality in a multiple regression framework. In addition to including the change in spreads on the right-hand side of the regression equation, we also include stock specific characteristics in the regression—the price, volume, and market capitalization of the stock as of the event day. Our stock-specific variables serve as proxies for firm size and allow for the fact that a change of specialists may have different impact for firms of different size (for example, Neal, 1992 shows that specialists benefit small firms more than large firms). Our primary focus in this analysis is to test whether the change in spreads is related to abnormal returns after controlling for any cross-sectional effects. Specifically, we estimate the following equation:

$$\begin{aligned} CAR_i = {} & \beta_0 + \beta_1 AVGABQSP_i (\text{or } AVGABESP_i) \\ & + \beta_2 (1/PRICE_i) + \beta_3 \log(VOL_i) + \beta_4 \log(MVE_i) + \varepsilon_i, \end{aligned} \tag{2}$$

where CAR_i is the five-day cumulative abnormal return from days 0 to +4 for stock i, $AVGABQSP_i$ ($AVGABESP_i$) is the average daily abnormal quoted (effective) dollar or percentage spread from days 0 to +4 for stock i, representing the change in market quality, $PRICE_i$ is the share price, VOL_i is the dollar volume, and MVE_i is the market value of equity for stock i.

Table 5 presents the results of the estimation. Our variables of interest, abnormal quoted and effective spreads, both have a negative and significant coefficient, implying that the stocks that experience a greater improvement in market quality also experience a higher CAR. This further lends support to our result that the improvement in market quality is associated with a decline in the listed firm's cost of capital.

4. Factors affecting stock reassignments

4.1. Background

The findings discussed above indicate that reassignments by specialist firms have significant economic consequences for investors and listing firms. We also find that reassigned stocks initially have higher spreads than control sample stocks which, after reassignment, decline to the same level as those for the control stocks. Thus, there appears to be some evidence that higher spreads of the (soon to be) reassigned stocks contribute to the reassignments. In this section, we attempt to understand the other factors specialist firms might use in deciding which stocks to reassign.

[17] Institutional commissions are on average 4 to 5 cents a share (see Goldstein et al., 2008, Fig. 1, and "The extra burden on brokers," *Financial Times Mandate*, September 2006). With the median price of a stock at \$21 in our sample, this translates into about 0.24% of the stock price. Individual commissions are presumably even higher.

Table 5
Regression analysis: abnormal returns and spreads.

	Results based on quoted spreads		Results based on effective spreads	
	CUMABR	*CUMABR*	*CUMABR*	*CUMABR*
Intercept	0.0001 −0.01	−0.0036 (−0.21)	0.0009 (0.05)	−0.003 (−0.17)
AVGABQ$SP	−0.0329** (−5.63)			
AVGABQ%SP		−0.0195** (−3.84)		
AVGABE$SP			−0.0245** (−4.54)	
AVGABE%SP				−0.0152** (−3.25)
1/PRICE	0.0360** (2.90)	0.0353** (2.74)	0.0350** (2.79)	0.0395** (3.03)
log(*VOL*)	0.0049** (2.92)	0.0054** (3.16)	0.0052** (3.07)	0.0054** (3.22)
log(*MVE*)	−0.0049* (−2.19)	−0.0052* (−2.30)	−0.0053* (−2.33)	−0.0068* (−2.36)
R^2	0.0738	0.0466	0.0691	0.0396

This table relates five-day (day 0 to day +4, where day 0 is the event day) cumulative abnormal returns around stock reassignments by specialist firms to changes in spreads. We calculate abnormal returns using the market model for our sample and control stocks. Our estimation period for the market model parameter is from day −300 to day −40. The five-day cumulative abnormal return from days 0 to +4 is computed by adding abnormal returns over the five-day period. The regression equation estimated is:

$$CUMABR = \beta_0 + \beta_1 AVGABQ\$SP(\text{or } AVGABQ\%SP \text{ or } AVGABE\$SP \text{ or} AVGABE\%SP) \\ + \beta 2(1/PRICE) + \beta_3 \log(VOL) + \beta_4 \log(MVE) + \varepsilon,$$

where *CUMABR* is the cumulative abnormal returns from days 0 to +4 for the stock, *AVGABQ$SP* (*AVGABQ%SP*) is the average daily abnormal quoted dollar (percentage) spread from days 0 to +4 for the stock, *AVGABE$SP* (*AVGABE%SP*) is the average daily abnormal dollar (percentage) effective spread from days 0 to +4 for the stock, *PRICE* is the share price for the stock, *VOL* is the dollar volume for the stock and *MVE* is the market value of equity for the stock. Price, dollar volume and market value of equity are as of the event day. Numbers in parentheses are *t*-statistics.
*Significant at the 5% level.
**Significant at the 1% level.

We draw on the extant literature and anecdotal evidence for the possible factors that determine which stocks are reassigned by specialist firms. In this analysis, we focus on the observable characteristics of stocks and individual specialist portfolios affected by these reassignments.[18]

[18]Stocks could conceivably be taken away from a specialist if a mismatch developed between the particular skills of the individual specialist and the emergent characteristics of a stock. We are, however, not able to measure the specialist skill-set in order to be able to comment on this particular reason for stock reassignments.

The models of Caballe and Krishnan (1994) and Strobl (2001) emphasize the role of industry concentration in specialist portfolio formation. In particular, Caballe and Krishnan (1994) provide a model of informed traders trading in multiple, and correlated, risky assets. The authors show that correlated risky assets traded by the same specialist allow for welfare improvement for the market by improving the trading space of both informed and uninformed traders, as well as allowing diversification for the specialist across the various stocks. The diversification for the specialist in this case occurs because order flow for one asset contains information for the other correlated asset. Thus, a specialist who has a complete view of the order flow of similar securities is better able to assess the demand for correlated securities than if only the order flow for one of these securities is observed.

Strobl (2001) addresses the question of how securities with correlated payoffs should be optimally allocated to dealers in a specialist system. Using a static (single period) exchange economy with informed and uninformed traders (all agents are risk averse), the author shows that specialists always prefer portfolios of highly correlated assets even if handling such portfolios increases their inventory costs resulting from greater payoff uncertainty. The author also finds that specialists and investors can both be better off in situations where stocks with correlated payoffs are assigned to the same specialist. In his model, the benefit of information in trading similar assets is traded off against the cost of lower competition if substitutable assets are traded by the same specialist. In our context, the benefits are likely to be even higher than the costs since our focus is on the individual specialist portfolio, which typically contains too few stocks to impose any substantive monopoly costs on the market. Strobl (2001) notes that stocks within a single industry are likely to have correlated payoffs. An implication flowing from both the Caballe and Krishnan (1994) and Strobl (2001) models is that higher correlation across risky assets is preferred in specialist portfolios and should also improve market welfare. We draw on these theoretical foundations in testing for whether correlations in asset payoffs (proxied by industry concentration of portfolios) play a role in the formation of individual specialist portfolios, and whether the portfolio changes that result from stock reassignments are associated with changes in the market quality of the stocks.

In empirical analyses, Cao et al. (1997) show that specialist firms subsidize illiquid stocks from their trading in the liquid stocks in their portfolio. Huang and Liu (2004) find that this cross-subsidization from liquid to illiquid stocks exists within an individual specialist's portfolio as well. Under the assumption that size and liquidity are correlated, the implication of these findings for us is that we should expect to see a mix of large and small stocks assigned to every specialist on the NYSE. Further, Corwin and Coughenour (2008) find that the limited ability of individuals to focus on multiple tasks has adverse consequences for the less active stocks in individual specialist portfolios. They term this the ''limited attention'' hypothesis. Similarly, Hatch et al. (2005) find that quote adjustments by specialists are faster for stocks that constitute a higher fraction of trading in the individual specialist's portfolio, implying that these higher volume stocks receive more attention from the specialist. Based on these studies, we conjecture that the portfolio composition, with respect to the size of the firms in the portfolio, of the individual specialist is important to the performance of the specialist. Hence, multiple large stocks in an individual specialist's portfolio competing for the specialist's attention would be expected to have a negative effect on the liquidity of the stock. We, therefore, focus on the size composition of the portfolio as one of the possible reasons for reassigning a stock.

While the above discussion is specific to the portfolio of stocks handled by the individual specialist, we also recognize that different stocks will have varying importance to the specialist firms. Coughenour and Harris (2003), for example, assert that the NYSE trades a small number of large stocks and a large number of small stocks. Furthermore, they find that both trading volume and specialist profits are skewed towards the (relatively) few large stocks. In particular, they show that, after decimalization, approximately 82% of specialist profits are earned collectively from their trading in the largest 100 stocks. The next 400 stocks contribute 14.6% of profits while the remaining 1,311 stocks earn only about 3.4% of the profits. Based on these results, we conjecture that specialist firms are likely to pay more attention to the larger stocks than the smaller stocks in their respective portfolios. Hence, within our context, any problems with the primary revenue producing stocks are more likely to be recognized and corrected.

4.2. Measures of portfolio and stock characteristics

In the previous sub-section, we hypothesize portfolio industry composition, portfolio size composition, and stock size as possible determinants of stock reassignments by specialist firms across individual specialists. We now present specific empirical measures for these factors.

We measure industry concentration (as a proxy for correlated assets) of an individual specialist portfolio as the sum of squared market value weights of industries in the portfolio, multiplied by 10,000. Specifically,

$$INDCON = \sum_{i=1}^{n} (w_i)^2 \times 10,000, \tag{3}$$

where $INDCON$ is the industry concentration index and w_i represents the market-value weight of industry i calculated as the total market value of all stocks in the same industry divided by the total market value of all the stocks in the portfolio.[19] We define an industry by the 2-digit SIC code. Thus, a portfolio with every stock from the same industry would have the highest possible industry concentration measure of 10,000. If having correlated payoffs is beneficial for the specialist, then we would expect industry concentration for portfolios that have stock reassignments to be lower than the industry concentration for the portfolios not affected by these reassignments. Furthermore, subsequent to the reassignments, we would expect the industry concentration to increase for the affected portfolios.

To fully capture the size composition of individual specialist portfolios, we use three different measures. Our primary focus is on a size concentration measure defined to capture the weight of the dominant stocks in the portfolio. The rationale here is that if individual specialist portfolios are created to have one dominant stock and other smaller stocks, then the size concentration of the portfolio would be high. However, multiple large stocks in a portfolio would cause the size concentration measure to decline. We would then expect the size concentration of portfolios affected by stock reassignments to be lower than those portfolios that the specialist firm leaves untouched. Furthermore, we would expect the size concentration to increase after the reassignments. Our measure of size

[19] This measure draws on the Herfindahl index widely used in the literature.

concentration of a portfolio is an index that equals the sum of squared market-value weights of stocks in the portfolio multiplied by 10,000. More formally,

$$SIZECON = \sum_{i=1}^{n} (w_i)^2 \times 10,000, \tag{4}$$

where $SIZECON$ is our size concentration measure and w_i represents the market-value weight of stock i calculated as the market value of the stock divided by the total market value of all the stocks in the portfolio. A single stock portfolio would give us the highest possible concentration of 10,000. Apart from this measure, we also use the combined market value of all stocks in the portfolio and the number of stocks in the portfolio as size measures. Following the limited attention hypothesis in Corwin and Coughenour (2008), we expect that reassignments are more likely to occur for stocks in larger portfolios (measured by market capitalization of all stocks in the portfolio and by the number of stocks in the portfolio).

We include the stock groups described in Coughenour and Harris (2003) to account for the varying significance of stocks for the specialist firm. Specifically, they divide their sample into large stocks (the top 100 stocks by market value), medium size stocks (next 400 stocks), and the remaining sample. Consistent with this classification scheme, we test whether a stock belonging to one of these groupings is more or less likely to be reassigned. As mentioned earlier, since the majority of the specialist firm revenue is generated from the top 100 stocks, we expect the likelihood of reassignment for these stocks to be higher.

4.3. Analysis of factors affecting stock reassignments: methodology and results

We analyze the potential factors driving stock reassignments by specialist firms in three ways. First, we compare the industry and size concentration for the affected portfolios with those of the portfolios not affected by these reassignments, both before and after reassignments. We define unaffected portfolios as those individual specialist portfolios within the *same* specialist firm that are left untouched at the time of the reassignment. We believe that this gives us the best possible control, as the same specialist firm looks at how stocks are assigned among the individual specialists, and decides to change some while leaving others alone. We impose an additional constraint that the unaffected portfolio should remain unchanged in the day -60 to day $+60$ period corresponding to the reassignment date of the affected portfolios. Second, we analyze the changes in the measures for the affected portfolios following the reassignments. Third, we use a logit regression to study how the factors discussed above affect the probability of a particular portfolio being reorganized.

The results of these comparisons are presented in Table 6. We find that the industry concentration of the portfolios affected by reassignments is significantly lower than the industry concentration for the unaffected portfolios (Panel A). After stock reassignments, the industry concentration of the affected portfolios experiences a significant increase (Panel B). Additionally, we no longer see a substantive difference between the industry concentration of the portfolios affected by the reassignments and those left unchanged by the specialist firms (Panel C). The results are very similar for our size concentration measure. Before the reassignments, affected portfolios have significantly lower size concentrations than the unaffected portfolios. After the reassignments, the size

Table 6
Changes in size and industry concentration of reassigned portfolios: (a) Panel A: Before reassignment; (b) Panel B: Before and after reassignment comparison; (c) Panel C: After reassignment.

(a)

	Reassigned portfolio	Unaffected portfolio	Reassigned–unaffected
Avg. size concentration Index	3,626	4,421	−795**
Avg. industry concentration Index	5,358	6,026	−668**

(b)

	Before reassignment	After reassignment	Before−after
Avg. size concentration Index	3,626	4,490	−864**
Avg. industry concentration Index	5,358	5,971	−613**

(c)

	Reassigned portfolio	Unaffected portfolio	Reassigned–unaffected
Avg. size concentration Index	4,490	4,432	58
Avg. industry concentration Index	5,971	5,901	70

This table presents the size and industry concentration for the portfolios with reassigned stocks. We consider both the portfolio from which the stock is reassigned and the portfolio to which the stock moves as portfolios affected by the reassignment. We also benchmark these measures with the portfolios that are unaffected by these reassignment events. We define unaffected portfolios as all those individual specialist portfolios within the same specialist firm which are left untouched at the time of the reassignment, and are not affected by a reassignment event within (before or after) 60 days of the event date. Size and industry concentration indices are calculated as follows. For each portfolio we calculate the following index:

$$\sum_{i=1}^{n}(w_i)^2 \times 10,000,$$

where w_i represents the market-value weight of stock i calculated as the market value of the stock divided by the total market value of all the stocks in the portfolio when measuring size concentration, and the total market value of all stocks in the same industry divided by the total market value of all stocks in the entire portfolio when measuring the industry concentration index. Panel A presents the size and industry concentration indices before reassignments by specialist firms for affected and unaffected portfolios, and tests for equality of means of indices of affected and unaffected portfolios. Panel B presents the results after the reassignments. Panel C compares the indices for the affected portfolios before and after the reassignments.
**Significant at the 1% level.

concentration of the affected portfolios increases significantly to a level that is more comparable to the size concentration of the unaffected portfolios.

Finally, we use the variables discussed above to analyze the decision of the specialist firm to reassign stocks within a logistical regression framework. The particular equation estimated is:

$$\begin{aligned} REASSIGN = {} & \beta_0 \log(SIZECON) + \beta_1 \log(INDCON) \\ & + \beta_2 \log(SIZE) + \beta_3 DUM100 + \beta_4 DUM400 \\ & + \beta_5 \log(NSTKS) + \varepsilon, \end{aligned} \tag{5}$$

where $REASSIGN$ is a binary variable that equals one for portfolios with reassigned stocks and zero for the unaffected portfolios described above, $SIZECON$ is the size concentration index in Eq. (5), $INDCON$ is the industry concentration index in Eq. (4), $SIZE$ is the total market value of equity for the portfolio, $DUM100$ is a binary variable that equals one for

Table 7
Factors affecting stock reassignments.

REASSIGN	
Intercept	−13.4990** (−20.04)
SIZECON/10,000	−0.4360** (−8.84)
INDCON/10,000	−0.4465** (−7.24)
SIZE	0.5505** (14.08)
*DUM*100	0.4984** (3.51)
*DUM*400	−0.0828 (−1.15)
NSTKS	1.0012** (17.44)

This table presents the estimates of a logistical regression of the form:

$$REASSIGN = \beta_0 + \beta_1 \log(SIZECON) + \beta_2 \log(INDCON) + \beta_3 \log(SIZE) + \beta_4 DUM100 + \beta_5 DUM400 + \beta_6 \log(NSTKS) + \varepsilon,$$

where *REASSIGN* is a binary variable that equals one for portfolios with reassigned stocks and zero for the unaffected portfolios, *SIZECON* is the size concentration index in Eq. (2), *INDCON* is the industry concentration index in Eq. (3), *SIZE* is the total market value of equity for the portfolio, *DUM*100 is a binary variable that equals one for the top 100 stocks and zero otherwise, *DUM*400 is a binary variable that equals one for the next 400 stocks and zero otherwise, and *NSTKS* are the number of stocks in the portfolio. Numbers in parentheses are *t*-statistics.
**Significant at the 1% level.

the 100 largest NYSE stocks and zero otherwise, *DUM*400 is a binary variable that equals one for the next 400 stocks and zero otherwise, and *NSTKS* are the number of stocks in the portfolio. The regression includes the portfolio and stock characteristics discussed earlier.

We present the estimation results in Table 7. The coefficients indicate the impact of the independent variables on the likelihood of stock reassignments. Our estimates indicate a significant role for almost all of our independent variables in specialist firm decision-making. The signs are also in the expected directions. For example, the size concentration coefficient of −0.44 and the industry concentration coefficient of −0.45, both significant at the 1% level, indicate that a lower size or industry concentration of the portfolio increases the likelihood of the stocks in that portfolio being reassigned. Similarly, larger (in market value as well as number of stocks) portfolios are more likely to have stocks reassigned than smaller portfolios. We also find that the size of the reassigned stock plays a role in this decision. Consistent with our expectations of specialist firms paying more attention to their most profitable stocks, the 100 largest NYSE stocks are the most likely to be reassigned. The next 400 stocks do not show any significant differences from the remaining stocks in their probability of reassignment.

In sum, our results show that the industry concentration and size characteristics of individual specialist portfolios play a significant role in the specialist firms' decision to reassign stocks across individual specialists. Further, the results in Table 6 also indicate that the specialist firms appear to have some decision-making rules that cause the industry and size concentration levels of portfolios affected by reassignments to resemble those of unaffected portfolios.

We further analyze whether the changes in industry and size concentration are related to the improvement in liquidity for the reassigned stocks. Specifically, we estimate the following regression model:

$$\begin{aligned} AVGABQSP_i(\text{or } AVGABESP_i) = \beta_0 + \beta_1 \Delta PORTCON \\ + \beta_2 \log(PRICE) + \beta_3 \log(VOL) \\ + \beta_4 \log(MVE) + \varepsilon, \end{aligned} \tag{6}$$

where $AVGABQSP_i$ (or $AVGABESP_i$) is the average daily abnormal quoted dollar spread, or the average daily abnormal effective dollar spread, from days 0 to +4, $\Delta PORTCON$ is either the change in industry concentration or the change in size concentration, $PRICE$ is the share price, VOL is the dollar volume, and MVE is the market value of equity. As discussed earlier, if increasing industry and size concentration play into specialist firm decisions to reconfigure portfolios, and these changes improve market quality, then we should see a significant inverse relation between the change in industry (or size concentration) and the improvement in market quality. The results in Table 8 provide strong support for our hypothesis. The coefficients on the change in concentration measure are negative and statistically significant at the 1% level.[20]

5. Conclusion

In this study, we explore the periodic reorganizations of individual specialists' portfolios by specialist firms operating in the NYSE. The analysis of this practice also explains why the NYSE almost never reallocates stocks across specialist firms (after their initial allocation), instead letting the firms correct any temporal mismatches in-house. Our study is the first to investigate these frequently occurring events and to document their economic implications.

Using recently available post and panel level data from the NYSE over a three-year period, we report a significant improvement in market quality of the reassigned stocks. We find that quoted and effective spreads decline for the reassigned stocks to levels similar to those of matched stocks. We decompose the spreads into adverse selection and realized cost components, and find that the spread reductions are associated with the reduction in the adverse selection component. The improvement in market quality is associated with a lower cost of capital for the listed firms as seen by the abnormal returns surrounding these events. For example, we find that an average firm in our sample experiences a five-day cumulative abnormal return (day 0 to day +4) of 0.90% in excess of a similar sample of control stocks. Thus, our results indicate an alignment between the interests of the

[20]We do not include changes in industry and size concentration in the same regression model, since changes to portfolios are likely to cause the two measures to change simultaneously and hence be highly correlated, introducing multicollinearity into the regression. Empirically, we find this to be the case.

Table 8
Regression analysis: spread improvements and changes in portfolio characteristics.

	AVGABQ\$SP	*AVGABQ%SP*	*AVGABE\$SP*	*AVGABE%SP*	*AVGABQ\$SP*	*AVGABQ%SP*	*AVGABE\$SP*	*AVGABE%SP*
Intercept	−0.0094 (−1.27)	−0.0001 (−0.07)	−0.0165** (−3.19)	−0.0012 (−1.54)	−0.0094 (−1.28)	−0.0002 (−1.07)	−0.0165** (−3.20)	−0.0012 (−1.53)
$\Delta(SIZECON/10{,}000)$	−0.0190** (−3.36)	−0.0021** (−2.81)	−0.0154** (−3.90)	−0.0019** (−3.12)				
$\Delta(INDCON/10{,}000)$					−0.0165** (−2.88)	−0.0022** (−2.93)	−0.0175** (−4.37)	−0.0021** (−3.53)
log(*PRICE*)	−0.0023 (−1.50)	−0.0005** (−2.91)	−0.0019* (−2.08)	−0.0001 (−0.88)	−0.0022 (−1.63)	−0.0005** (−2.97)	−0.0019* (−1.99)	−0.0001 (−0.91)
log(*VOL*)	0.0009 (1.01)	0.0002* (2.02)	0.0017** (2.76)	0.0003** (3.43)	0.0008 (0.96)	0.0024* (2.06)	0.0016** (2.67)	0.0003** (3.44)
log(*MVE*)	−0.0004 (−0.35)	−0.0002 (−1.07)	−0.0007 (−0.92)	−0.00025* (−2.16)	−0.0003 (−0.31)	−0.0002 (−1.11)	−0.0007 (−0.85)	−0.0003* (−2.17)
R^2	0.0328	0.0396	0.0482	0.0478	0.0351	0.0421	0.0499	0.0492

This table reports the results of the following regression:

$$\begin{aligned}&AVGABQ\$SP \text{ or } AVGABQ\%SP \text{ or } AVGABE\$SP \text{ or } AVGABE\%SP\\&\quad = \beta_0 + \beta_1\,\Delta SIZECON(\text{or } \Delta INDCON) + \beta_2\,\log(PRICE) + \beta_3\,\log(VOL) + \beta_4\,\log(MVE) + \varepsilon,\end{aligned}$$

where *AVGABQ\$SP* (*AVGABQ%SP*) is the average daily abnormal quoted dollar (percentage) spread from days 0 to +4, *AVGABE\$SP* (*AVGABE%SP*) is the average daily abnormal effective dollar (percentage) spread from days 0 to +4, *PRICE* is the share price, *VOL* is the dollar volume, and *MVE* is the market value of equity. Numbers in parentheses are *t*-statistics.
**Significant at the 1% level.
*Significant at the 5% level.

specialist firms, issuing firms, and the investors since, following stock reassignments, liquidity improves while the cost of capital of the issuing firm declines.

We further identify the observable factors that determine the likelihood of stocks in a particular individual specialist portfolio being reassigned. We find that size and industry concentration of individual specialist portfolios are significant determinants of the likelihood of a portfolio being affected by a reassignment event. The overall size of the portfolio, and the revenue-generating potential of a stock, also impacts the specialist firms' decision to reassign stocks across panels. These results help in our understanding of how individual specialist portfolios are created within specialist firms. Overall, our analysis sheds light on the economic benefits of reassignments by specialist firms.

To the best of our knowledge, ours is the first piece of empirical evidence in the literature examining the factors that specialist firms take into account in reassigning stocks across panels. We leave the question of whether these decision rules stay constant over time, or shift in response to market changes, to future research. We underscore, however, that while our study focuses on the role of stock reassignments in a specialist system and the various associated effects, our results raise potentially significant questions about the specialist system on the NYSE. Our results complement recent studies focusing on the introduction of specialists in various markets, in emphasizing the need for monitoring and correction of individual specialist portfolios. Specific to the NYSE, our results indicate that the mechanism for monitoring trading is effective even without any overt action on the part of the exchange. We note that our results are also open to a different interpretation. The improvement in market quality indicates that the stocks were not trading optimally prior to the reassignments. Hence, it could be argued that the specialist system, by making the specialist so central to the trading of a stock, can lead to situations where the stocks do not experience the best levels of market quality possible, further emphasizing the need for appropriate regulatory mechanisms to minimize such situations.

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