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Common market makers and commonality in liquidity ☆

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Abstract

Each NYSE specialist firm provides liquidity for more than one common stock. As a result of shared capital and information among specialists within a firm, we argue that stock liquidity will co-move with the liquidity of other stocks handled by the same specialist firm, with magnitude increasing with the risk of providing liquidity. The evidence indicates that individual stock liquidity co-varies with specialist portfolio liquidity apart from information reflected by market liquidity variation. Further tests based on specialist firm size, specialist firm mergers, and market returns indicate that liquidity co-variation increases with the risk of providing liquidity.

JEL classification: D23; G14

Keywords: Liquidity; Co-movement; Specialist firms; Microstructure

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1. Introduction

Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) provide evidence of positive time-series stock liquidity co-variation. However, the underlying economic sources of this 'commonality in liquidity' are not well understood. We argue that liquidity co-variation could arise from the fact that each NYSE specialist firm provides liquidity for many stocks. Common adjustments in the provision of liquidity arise because specialists within each firm trade from a common pool of capital and share inventory and profit information. The argument also implies that the degree of liquidity co-variation should be positively related to specialist firm capital constraints or, more generally, to the firm-level risk of providing liquidity. Our cross-sectional and time-series evidence supports these arguments.

Understanding the source of common liquidity movements is important for many market participants. Because systematic liquidity variation is most likely a priced source of risk (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Jones, 2002; Pástor and Stambaugh, 2003), understanding the causes of liquidity co-variation will help investors bear this risk with greater efficiency. Empirical evidence regarding this issue will aid academics to advance their understanding of liquidity dynamics and also aid regulators, exchanges, and other participants seeking to improve market design.

Broadly speaking, commonality in liquidity is induced by common variation in the demand for liquidity, the supply of liquidity, or both. Demand-generated commonality in liquidity could arise as variation in a common factor stimulates systematic variation in the desire to transact. In contrast, supply-generated commonality in liquidity could arise from systematic variation in the costs of providing liquidity. It is difficult, however, to think of systematic factors that would not simultaneously alter the demand and supply of liquidity. For example, an interest rate shock could stimulate a shared desire to rebalance portfolios and thus stimulate a systematic increase in the demand for liquidity. Concurrently, however, an interest rate shock would also alter the cost (and risk) of supplying liquidity. In the normal course of events, liquidity co-variation most likely arises from a complex interplay among demanders of liquidity, market makers, and other liquidity suppliers (e.g., those placing public limit orders).

The purpose of this paper is to provide empirical evidence regarding the existence and relative importance of supply-generated liquidity co-variation. To do so, we highlight the fact that market makers (NYSE specialists) employ shared capital and information, and we argue that this organizational arrangement can induce liquidity co-variation. For example, suppose information regarding firm values contains no common component and arrives randomly across stocks, yielding uncorrelated demands for liquidity. Even in this extreme case, common liquidity adjustments could still arise if market makers allow gains or losses in one stock to influence the provision of liquidity to other stocks in their portfolio.

Prior research provides useful guidance for thinking about the specialist firm characteristics most likely to influence liquidity co-variation. Ho and Stoll (1983) and Gehrig and Jackson (1998) argue that the risk of providing inventory is negatively related to the degree of specialist portfolio diversification. Strobl (2002) notes that, while inventory costs could decrease with specialist portfolio diversification, adverse selection costs could increase. Apart from portfolio composition, Coughenour and Deli (2002) find that specialist firm organizational form influences liquidity provision, in which firms that employ relatively low-cost capital tend to provide liquidity as if they are more willing or able to bear risk.

The common thread through these studies is that the risk of providing liquidity can vary systematically across specialist firms, implying that a given specialist can assume more risk if its specialist firm employs lower cost capital across a well-diversified portfolio. Accordingly, we argue that stocks handled by specialist firms with these characteristics will display less liquidity co-variation. For example, with greater specialist firm diversification, a negative profit shock in one stock is less likely to influence the liquidity provided to their other stocks. Similarly, specialists facing relatively moderate capital constraints (by employing lower cost capital) are more likely to provide liquidity independent of variation in market and specialist portfolio liquidity.

Our basic methodology follows that used by Chordia et al. (2000). One difference between our studies, however, is that we use intraday aggregates that allow us to account for well-known intraday spread variation (e.g., McInish and Wood, 1992). Initially, we replicate the liquidity market model estimated by Chordia et al. (2000) and find a similar positive mean liquidity beta between individual stock and market portfolio liquidity variation. An important difference, however, is that our data yields R^2's over 22%, compared with the R^2's of roughly 1% reported by Chordia et al. (2000).[1] This result indicates that the degree of liquidity co-variation is greater than that implied by the analyses of Chordia et al. (2000) and Hasbrouck and Seppi (2001), lending greater support to recent studies arguing that systematic liquidity variation is a priced risk factor (e.g., Pástor and Stambaugh, 2003).

Our central results are obtained by incorporating information about the specialist firm portfolio into the liquidity market model used by Chordia et al. (2000). In each model, we substitute the variation of market portfolio liquidity with variation of each stock's specialist portfolio liquidity and find a significant positive specialist-liquidity beta that is roughly two-thirds the size of the market-liquidity beta. When we isolate variation in specialist portfolio liquidity from variation in market liquidity (by joint estimation), the evidence reveals a significant positive specialist-liquidity beta that is roughly one-eighth the size of the market-liquidity beta. This evidence indicates that liquidity co-variation induced by information related solely to specialist portfolio liquidity is significant, but less important than factors associated with market liquidity variation.

We conclude with tests that examine whether the degree of liquidity co-variation is positively related to the risk of providing liquidity. The first two tests focus on specialist firm size. We argue that specialists employed by larger firms can provide

[1] We verify that the different R^2's stem from the aggregation period by repeating the test with our data aggregated at daily intervals. Doing so causes the adjusted R^2's to fall from 22% to roughly 3%.

liquidity with greater independence owing to greater diversification benefits and lower capital constraints. If so, we should observe an inverse relation between specialist firm size and degree of liquidity co-variation. In the first test we estimate specialist portfolio liquidity co-variation with market portfolio liquidity and find a significant negative relation between the co-variation estimates and specialist firm size. In the second test we focus on eight specialist firm mergers and find that liquidity co-variation estimates significantly decrease after the mergers.

The final test considers whether the degree of liquidity co-variation is related to the sign and magnitude of market returns. During periods with large negative returns, we argue that shared capital constraints are likely to be more binding and the cost (and risk) of supplying liquidity should increase.[2] Therefore, if specialists provide liquidity with less independence when the risk of doing so increases, the degree of specialist portfolio liquidity co-variation should be greater during periods with negative market returns. Consistent with this argument, the evidence indicates that individual stock liquidity co-variation with specialist portfolio liquidity is significantly greater during periods with relatively large negative market returns.

In summary, the evidence indicates that commonality in liquidity is generated from the fact that stocks share common market makers. On average, individual stock liquidity variation is significantly related to variation in specialist firm portfolio liquidity. This relation, however, is roughly one-eighth of that found with respect to market liquidity variation, implying that factors which influence market wide liquidity typically play a greater role in explaining individual stock liquidity dynamics. Further tests indicate that specialist firm characteristics explain cross-sectional and time-series variation in the degree of liquidity co-variation, consistent with our hypothesis that liquidity co-variation increases with the risk of supplying liquidity. Finally, the use of intraday aggregates yields evidence that the degree of commonality in individual stock liquidity is greater than previously reported.

The remainder of this paper proceeds as follows. In Section 2 we provide background information about NYSE specialist firms and review related research. Section 3 describes the data. Section 4 presents evidence regarding the co-variation of individual stock liquidity with market and specialist portfolio liquidity. Section 5 presents evidence from tests regarding the relation between liquidity co-variation and specialist firm characteristics. Section 6 concludes with a summary of the results and a discussion of some remaining issues.

2. Background

In this section we describe the evolution and current structure of NYSE specialist firms and relate our study to research examining liquidity co-variation and to research examining the influence of specialist firms on liquidity provision.

[2] As stock prices drop, returns become more volatile and inventory-holding costs increase. More generally, because specialist firms tend to have net long positions, capital constraints are stressed and specialist firm wealth is reduced during market downturns.

2.1. Evolution and characteristics of NYSE specialist firms

The NYSE specialist system commenced soon after the exchange introduced continuous trading in 1871.[3] With continuous trading, floor brokers found it profitable to 'specialize' in a particular stock by maintaining a fixed position at a post on the NYSE floor and execute orders for other brokers. As of 1933 (the date of the earliest specialist directory available in the NYSE archives) there appeared to be 123 unique specialist firms, which typically contained no more than a handful of partners.[4] Specialist firms were formed as a means for individual specialists to share capital and risk. This capital and risk-sharing aspect of specialist firms drives the hypotheses examined in this paper.

During the 1900s, the NYSE changed its rules three times to allow specialist firms to raise greater amounts of capital at lower cost. In 1953 the NYSE allowed member firms to incorporate. In 1970 the NYSE voted to let member firms sell securities to the public. Then in 1997 the NYSE amended its rules so that the parent organization of a specialist firm could conduct other transactions with the listed firm.[5]

These rule changes allowed NYSE specialist firms to evolve from small, closely held firms that employ their own capital to larger firms owned by public corporations. This evolution was accelerated after several specialist firms failed following the large drop in market valuations during October 1987 (from October 1987 through June 1999 the number of specialist firms decreased from 65 to 31). During our sample period, June 1999 through December 2000, 13 of the 31 remaining specialist firms were acquired. Of the 18 remaining firms four are relatively large; LaBranche and Co. is itself a publicly traded corporation, and Fleet Specialists, Goldman Sachs (Spear, Leeds, and Kellogg), and Bear Stearns (Bear Hunter) are all large publicly traded firms with a specialist firm subsidiary. The remaining specialist firms are relatively smaller partnerships organized as limited liability companies.

Recent research indicates that specialist firms do not provide liquidity in equal manners. Cao et al. (1997) and Corwin (1999) document differences in bid–ask spreads, trading halt rates, and market stabilization rates across specialist firms. Their results suggest that specialists, grouped by specialist firm, differ in their incentives or ability to bear the risk of providing liquidity. In support of that conjecture, Coughenour and Deli (2002) find liquidity provision to be a function of specialist firm organizational form, which influences the risk-bearing incentives of specialists.

[3] NYSE (1976) provides a detailed discussion of specialist firm history.

[4] Unlike current specialist directories, the exact number of firms were not provided in the 1933 specialist directory. Instead, it contains the stock symbol and specialist name (typically the list of firm partners). Therefore, we hand-counted the number of unique sets of partners and cross-checked against the 1933 *NYSE Directory of Members*.

[5] These rule changes are detailed in NYSE (1953, 1970, 1987) and summarized by Coughenour and Deli (2002).

2.2. Comparison of research questions and methods with recent studies

Studies by Chordia et al. (2000) and Hasbrouck and Seppi (2001) highlight stock liquidity co-variation. By examining common liquidity movements, they extend microstructure research that had primarily focused on an individual market maker's problem of providing liquidity while bearing inventory costs (e.g., Garman, 1976; Stoll, 1978; Ho and Stoll, 1981; O'Hara and Oldfield, 1986) and adverse selection costs (e.g., Copeland and Galai, 1983; Glosten and Milgrom, 1985; Easley and O'Hara, 1987).

Chordia et al. (2000) test for common liquidity movements across 1,169 stocks over 253 trading days during the 1992 calendar year. They focus on the variation of daily changes of various liquidity measures (quoted spreads, effective spreads, and quoted depths) with changes in market liquidity (the equally weighted average liquidity of all other stocks in the sample). Applying a market model regression to each stock, they find a strong average positive relation between changes in individual stock liquidity and changes in market liquidity.

In addition, Chordia et al. (2000) examine whether liquidity co-variation is the result of systematic variation in inventory or adverse selection costs, or both. Although market wide price and volatility shocks could lead to common changes in inventory risk, they argue that it is less likely that traders are privately informed about market wide price movements. Therefore, they test for common variation in adverse selection costs by examining whether individual stock liquidity is correlated with changes in industry portfolio liquidity (with the reasoning that traders could possess private information about industry returns). They conclude that common variation in both inventory and adverse selection costs induces common liquidity movements.

Hasbrouck and Seppi (2001), however, report weaker evidence of liquidity co-variation from a sample of 24 stocks that are each components of the Dow Jones Industrial Average during the 1994 calendar period. In contrast to Chordia et al. (2000), they analyze liquidity levels instead of changes, they sample over 15-minute intervals instead of daily intervals, and they do not test for a relation between individual stock liquidity and market liquidity because this imposes an a priori restriction on the common factor. They conduct a principal component and canonical correlation analysis that does not require assumptions about the distributions between returns, signed order flow (transaction price relative to quote midpoint), and liquidity.

From the principal component analysis, Hasbrouck and Seppi (2001) report that one common factor explains roughly 13% of variation in the quote slope (a liquidity estimate that incorporates both the quoted spread and depth) and roughly 12% of variation in the percentage quoted spread (log spread). Although this explanatory power is similar to that found for signed order flow (11.2% for all signed trades, and 13% for signed small dollar volume trades), the overall evidence leads them to conclude that common factors in liquidity are less evident and weak. This is important because it casts doubt on recent research indicating that liquidity variation is a priced source of risk (e.g., Pástor and Stambaugh, 2003). They note, however, that stronger liquidity co-variation could exist between stocks with different market capitalizations.[6]

We attempt to combine favorable elements of both studies. As explained in Section 3, we aggregate data at intraday intervals for 470 NYSE-listed securities over the 19-month period ending December 2000. In a fashion similar to Chordia et al. (2000), we consider the relation between changes in liquidity relative to the change in market and specialist portfolio liquidity. Although this pre supposes common factors, it allows us to test hypotheses with respect to variation in specialist portfolio liquidity that is independent of variation in market liquidity. Following Hasbrouck and Seppi (2001), we conduct our analysis on intraday liquidity estimates to capture well-known intraday variation in transaction costs (e.g., McInish and Wood, 1992) that is smoothed by daily aggregation. We note, however, that the precision of liquidity estimates decreases with finer aggregation periods, especially for stocks that trade less frequently. Therefore, we use three intraday liquidity estimates: morning, midday, and afternoon.

Although we employ prior techniques, our hypotheses differ markedly. Our primary hypothesis considers whether the simple sharing of a common market maker induces common liquidity movements between stocks, a test of supply-generated commonality. If a group of specialists share common financial constraints their tolerance for bearing inventory or adverse selection costs should be correlated, giving rise to positive liquidity co-variation.

Conversations with NYSE specialists provide anecdotal support of this argument. On monitors at each trading panel, NYSE specialists observe their current profit or loss on each stock they handle. Then, for example, specialist firms such as LaBranche and Co. can monitor this information across all its stocks. Although LaBranche specialists state that their firm is extremely well capitalized, they also note that they cannot freely take any position. For example, before taking an abnormally large position a specialist could seek permission from one of the LaBranche floor captains (who are also specialists). In turn, the floor captain could call LaBranche directors off the exchange floor for guidance. For our purposes, this process illustrates that information about inventory and profits is shared and that firm capital constraints and other characteristics can affect the provision of liquidity.

Several theoretical studies suggest which specialist firm characteristics could influence the degree of liquidity co-movement. Ho and Stoll (1983) argue that dealer behavior will be a function of a given stock's inventory in relation to the inventories of all other stocks handled by the dealer firm. Gehrig and Jackson (1998) show that inventory cost savings are obtained when specialist firms handle stocks with relatively low trading correlation. Strobl (2002) considers the trade-off between the diversification benefits of handling securities with uncorrelated payoffs, with the lower adverse selection costs obtained when specialists handle stocks with correlated payoffs.

[6] For example, Chan (1993) argues that, with less order-flow information about small stocks, small stock traders and market makers will rationally choose to learn, and update their quotes, by observing transactions of larger stocks.

Apart from specialist portfolio composition issues, Coughenour and Deli (2002) argue that specialist firm organizational form influences a firm's cost of capital, and thus the degree it is willing to bear market-making risk. In particular, their evidence indicates that specialists from firms that employ corporate-owned capital (instead of capital owned directly by the specialists) provide liquidity as if they can bear greater inventory risk.

These economic rationales prompt three additional tests for supplier-generated commonality based on the risk of providing liquidity. The first two tests focus on specialist firm size. Because larger specialist firms tend to have greater diversification benefits and tend to employ lower cost capital, we expect stocks handled by larger specialist firms to display less liquidity co-variation. We test this by examining whether specialist portfolio commonality estimates decrease with specialist firm size and by examining whether individual stock commonality estimates decrease when the stock's specialist firm increases in size following a specialist firm merger.[7]

The final test is based on market direction. When market valuations decrease, the stress on shared capital constraints is likely to increase as specialist firm wealth decreases (specialist firms tend to have net long stock positions). For example, the large drop in market indices during October 1987 brought several specialist firms to the brink of failure. Consequently, we expect greater joint management of liquidity within a specialist firm portfolio during periods with negative market returns. Therefore, we test whether liquidity co-variation between stocks handled by the same specialist firm is larger during periods with greater absolute negative market returns.[8]

3. Data

In this section we characterize the composition of the specialist firm portfolios, discuss issues related to the measurement of liquidity, and characterize the level and changes of several liquidity variables.

3.1. Stock and specialist firm characteristics

We use NYSE Trade and Quote data to estimate all liquidity and control variables, and we use daily NYSE specialist directory files to match each stock in our sample with its specialist firm. Given that the daily specialist directory files did not exist prior to June 1999, the analysis examines the 19-month period from June 1, 1999 through December 31, 2000. To be included in the sample each stock had to pass the following five filters. Each stock had to be among the 500 largest (market

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[7] Hatch and Johnson (2002) find an improvement in market quality after specialist firm mergers (but not relative to a control sample). While their paper examines changes in market quality (spreads and other liquidity measures) following specialist firm mergers, we examine changes in the degree liquidity co-varies after specialist firm mergers.

[8] We are grateful to the referee for suggesting the size-based test using specialist portfolio liquidity and the final test based on market direction.

capitalization) stocks that were continuously listed on the NYSE from January 1999 through December 2000. Each stock had to be continuously listed in the NYSE specialist directory files. Each stock had to trade at least twice every intraday period and average at least 20 trades per intraday period (the sample mean is 252.4 trades per period, with mean dollar volume over $19.7 million per period). Each stock's price had to always exceed $4 per share and be less than $200 per share. The trading activity filters are necessary because we aggregate data at intraday intervals. The filters on price are necessary to remove stocks that yield extreme percent changes in bid–ask spreads. Thirty stocks failed to pass one or more of these filters, leaving a sample of 470 common stocks.

Table 1 provides a description of the specialist firms operating during our sample period. The first column lists the 31 specialist firms in operation on June 1, 1999. During our sample period, however, 13 specialist firms were acquired. The second column lists the last date that the NYSE specialist directory reports stocks handled by the acquired firms. The third column illustrates the distribution of all 3,060 common stocks across the 31 specialist firms at the beginning of the sample. The fourth and fifth columns provide the distribution of our filtered 470-stock sample across specialist firms on the first and last day of our sample, respectively, to illustrate the degree of change in the specialist firm population.

The final column on Table 1 lists our working sample stocks. The working sample contains stocks handled by the same specialist firm throughout the 19-month sample period, in which the specialist portfolio contains at least ten stocks meeting the original filters. From the set of 470 filtered stocks, the working sample contains 259 stocks from ten specialist firms. We use the working sample throughout the study to measure liquidity co-variation between stock j and its own specialist portfolio (all stocks in the specialist portfolio except stock j) and with the market portfolio (all stocks from the 470 stock sample not handled by stock j's specialist firm). We constrain ourselves to these 259 stocks to assure that our specialist portfolio liquidity estimates are not overly influenced by any particular stock. This constraint is not overly costly because inference based on the 259 stock sample covers a broad range of industries and size (as shown below in Table 2). The limiting aspect of this constraint is that forthcoming cross-sectional tests will be based on a sample of ten specialist firms. The results indicate, however, that this trade-off is not problematic, for large and significant cross-sectional variation is revealed. In addition, our cross-sectional sample size reflects more recent consolidation that has left only seven specialist firms operating on the NYSE floor.

A related concern is the distribution of stocks across size and industry classifications within each specialist firm portfolio. If specialist portfolios are highly concentrated with stocks containing a certain characteristic, common liquidity variation between stocks within the specialist firm could be the result of common adjustments in the demand for the liquidity of these type stocks, instead of factors associated with the liquidity supplier. Two characteristics likely to be associated with common surges in the demand for liquidity are stock industry and size. For example, there are numerous cases of information releases that primarily affect stocks in a particular industry, and common demand for liquidity could be periodically

Table 1

NYSE specialist firms from June 1, 1999 to December 31, 2000. The data are collected from the merged NYSE daily specialist directory files and NYSE Trade and Quote files. There were 31 specialist firms on June 1, 1999. As a result of 13 mergers, 18 specialist firms were in operation at the end of 2000. The specialist firms are sorted according to the total number of common stocks handled on June 1, 1999. The 470 sample stocks are the largest 500 (market capitalization) stocks listed from January 1, 1999 through December 31, 2000 that passed several price and trade activity filters (see Section 3). To illustrate the degree specialist firm composition changes during our sample period, we report the distribution of the sample stocks at the beginning and end of the sample. The 259 stock working sample contains those filtered stocks that remain with the same specialist firm throughout the sample period and have at least nine other stocks in the specialist portfolio (to obtain more reliable estimates of specialist portfolio liquidity). Throughout the paper, the 470 stock sample is used to estimate market portfolio liquidity and returns, while the 259 working stock sample is used to estimate liquidity co-variation with market and specialist portfolio liquidity. A dash (—) in the column denotes a zero.

Specialist firm	Date specialist firm ceases to exist	Total stocks (June 1, 1999)	Sample stocks (June 1, 1999)	Sample stocks (December 30, 2000)	Working sample stocks
Fleet Specialist	October 27, 2000	355	72	—	—
Spear, Leeds, and Kellogg LLC		293	57	80	57
LaBranche and Co.		291	44	73	44
Wagner Stott Mercator, LLC		171	28	48	28
RPM Specialist Corp		170	28	29	28
Henderson Brothers Inc.	June 6, 2000	139	26	—	—
M.J. Meehan and Co. LLC		106	23	95	23
Equitrade Partners	June 21, 1999	172	23	—	—
Bear Hunter Specialists LLC		123	21	21	21
CMJ Partners	October 20, 1999	104	19	—	—
Benjamin Jacobson and Sons LLC		94	19	19	19
Lawrence, O Donnell, Marcus		86	15	32	15
Bocklet and Co. LLC		66	14	14	14
Scavone, McKenna, Cloud and Co.		65	10	10	10
Corroon, Lichtenstein	March 10, 2000	59	9	—	—
Fagenson/Frankel/Streicher	June 1, 2000	92	9	—	—
Lyden, Dolan, Nick and Co., LLC		80	7	7	—
Walter N. Frank and Co. LLC		75	6	6	—
Einhorn and Co.	July 19, 1999	59	5	—	—
Phoenix Partners L.L.C.	November 3, 2000	53	5	—	—
Surnamer, Weissman, and Co.	July 19, 1999	41	4	—	—
WEBCO Securities Inc.	March 10, 2000	40	4	—	—

Table 1 (*continued*)

Specialist firm	Date specialist firm ceases to exist	Total stocks (June 1, 1999)	Sample stocks (June 1, 1999)	Sample stocks (December 30, 2000)	Working sample stocks
Susquehanna Specialists		43	4	12	—
Performance Specialist Group, L.P.		47	3	9	—
Stuart, Scotto, Cella Co./MJM	October 13, 2000	24	3	—	—
Buttonwood Specialists LLC		33	3	3	—
Freedom Spec./Adrian/RPM Spec.		31	3	3	—
Stern and Kennedy		43	3	3	—
Weiskopf, Silver Specialists, LLC		56	2	2	—
M.J. Cohen and Co.	October 20, 1999	21	1	—	—
KV Specialists LLC	June 21, 1999	28	—	—	—
Total		3,060	470	470	259

size-based because many portfolio managers focus on stocks within particular market capitalization categories.

In Table 2 we list the highest number of stocks sharing Standard Industrial Classification (SIC) code digits for each specialist firm. For example, no more than 13 of 44 sample stocks handled by LaBranche and Co. share the same first SIC code digit; no more than four of 44 share both the first and second SIC code digits, etc. In the final four columns we report the distribution of stocks across mean daily dollar volume quartiles. The quartiles are defined as Q1 $\leqslant$ \$12.5 $<$ Q2 $\leqslant$ \$25 $<$ Q3 $\leqslant$ \$50 $<$ Q4 (\$ millions). Although two specialist firms (LaBranche and Bear Hunter) are weighted toward the more active stocks, the remainder appears well diversified. Therefore, any cross-sectional differences in liquidity co-variation are not likely to be the result of differences in the demand for liquidity across stocks in different specialist portfolios.[9]

3.2. Liquidity measurement and summary statistics

The liquidity of a stock's market is measured using standard methods. At the time of each transaction let P denote transaction price, t denote transaction time, a denote

[9] Related to this point, Corwin (2004) reports that a primary determinant of a specialist firm receiving a stock allocation is the queue (time since prior allocation was received). This process results in little correlation of the types of stocks allocated to any given specialist firm. We also help assure that variation in the demand for liquidity does not influence results by controlling for variation in market portfolio liquidity in the regression analysis.

Table 2
Distribution of stocks within specialist firms by Standard Industrial Classification (SIC) code and trading volume. The degree of stock concentration by SIC code and trading volume is provided for the working stock sample. The SIC codes are from the Securities and Exchange Commission Edgar database, and the trading volume data are obtained from the NYSE Trade and Quote database. The first set of columns list the greatest number of sample stocks sharing SIC codes at different digit levels (e.g., a "5" under "First digit" indicates that no more than five stocks share a particular first SIC code digit; a "2" under "All four digits" indicates that no more than two stocks share a complete SIC code; a "1" indicates that no SIC digits are shared). The volume quartiles are defined on mean daily dollar volume between the following intervals ($ millions): $Q1 \leqslant 12.5 < Q2 \leqslant 25 < Q3 \leqslant 50 < Q4$.

Specialist firm	Stocks	Highest number of sample stocks sharing SIC code digits				Percent of stocks within each trading volume quartile			
		First digit	First two digits	First three digits	All four digits	Q1 (Low)	Q2	Q3	Q4 (High)
Spear, Leeds and Kellogg LLC	57	17	5	5	3	22.81	22.81	26.31	28.07
LaBranche and Co.	44	13	4	3	3	9.09	25.00	22.73	43.82
Wagner Stott Mercator, LLC	28	7	5	3	3	21.43	25.00	21.43	32.14
RPM Specialist Corp	28	10	4	2	2	21.43	21.43	32.14	25.00
M.J. Meehan and Co. LLC	23	5	3	2	2	17.39	21.74	8.69	52.17
Bear Hunter Specialists LLC	21	6	5	3	3	9.52	9.52	19.05	61.91
Benjamin Jacobson & Sons LLC	19	6	2	2	2	36.84	10.52	26.32	26.32
Lawrence, O Donnell, Marcus	15	4	2	1	1	33.33	33.33	13.33	20.00
Bocklet and Co. LLC	14	4	2	2	2	50.00	7.14	28.57	14.28
Scavone, McKenna, Cloud & Co	10	3	2	1	1	30.00	30.00	30.00	10.00
Total	259								
Mean						25.18	20.65	22.86	31.31

the ask price, b denote the bid price, and m denote the bid–ask midpoint. Then the effective half spread (ehs_t) equals $|P_t – m_t|$, the percentage effective half spread ($pehs_t$) equals $100 \cdot ehs_t/m_t$, the quoted half spread (qhs_t) equals $(a_t – b_t)/2$, and the percentage quoted half spread ($pqhs_t$) equals $100 \cdot qhs_t/m_t$.[10] The mean spread is estimated from the trade and quote data across three intraday periods (first hour, last hour, and midday) for each stock, each day. The final sample contains 560,373 observations from 470 sample stocks covering 401 trading days.[11]

Market liquidity is measured using equally weighted estimates from the 470 sample stocks not handled by a given stock's specialist firm during each observation period. This results in an equivalent market portfolio for stocks in the same specialist firm, but not for stocks handled by different specialist firms. Any cross-sectional difference in the variation of market liquidity created by this procedure is slim because firm-specific liquidity variation is largely diversified away within the larger market portfolios. As a result, the market liquidity estimates are not significantly different for stocks handled by different specialist firms. For example, the correlation between the estimated market portfolio effective spread for stocks handled by Spear, Leeds, and Kellogg and for stocks handled by Scavone, McKenna and Cloud is 0.998.[12]

Throughout the paper we estimate liquidity commonality using changes in the effective half spread. This is done for several reasons. First, our depth estimate lacks accuracy. Therefore, inference based on our estimate of depth variation is likely to be inaccurate and unreliable.[13] Second, the evidence obtained using changes in quoted spreads is not substantially different from that obtained using effective spreads.[14] Third, the effective half spread has several desirable properties. Because it is based on transactions, and because specialists participate in a substantial number of price-improved trades, it is the liquidity measure most likely to reflect specialist actions. Furthermore, the effective spread is arguably a more accurate measure of market liquidity because it reflects unquoted depth from the exchange floor.

We estimate four different changes in the effective half spread, as defined in Table 3, Panel A. We measure the dollar change in the dollar effective spread (*DL1*), the point change in the percentage effective spread (*DL2*), the proportional change in

[10] Before spread estimation, transactions were eliminated if the quoted spread exceeds \$5, the transaction price is more than 12.5 cents greater than (less than) the ask price (bid price), the transaction, bid, or ask price is more than 25% larger than (or less than 75% of) the preceding transaction, bid, or ask price, respectively, or if it was the first transaction of the day.

[11] The number of total observations is less than 565,410 ($470 \times 401 \times 3$) because of days with early market closings and the removal of three days around holidays that had abnormally low volume (November 24, 1999; November 26, 2000; and December 28, 2000).

[12] Chordia et al. (2000) create a market portfolio that includes all stocks except the stock of interest. Similarly, their market portfolio estimates are technically different for each stock, but because of diversification the differences are of no consequence.

[13] Depth is measured as the sum of shares available at the quoted bid and ask price. This measure of depth does not capture the willingness of people to trade at other prices in the limit order book or the unstated willingness of people to trade from the NYSE floor. Bacidore et al. (2002) illustrate that unquoted depth on the floor is significant. We also note that Chordia et al. (2000) found no evidence of significant depth co-variation.

[14] Evidence using variation in quoted spreads was provided to the referee and is available upon request.

Table 3

Liquidity variable definitions and distributions. At the time of each transaction, let P denote transaction price, t denote transaction time, a denote the ask price, b denote the bid price, and m denote the bid–ask midpoint. Then the effective half spread (ehs_t) equals $|P_t–m_t|$, the percentage effective half spread ($pehs_t$) equals $100 \cdot ehs_t/m_t$, the quoted half spread (qhs_t) equals $(a_t–b_t)/2$, and the percentage quoted half spread ($pqhs_t$) equals $100 \cdot qhs_t/m_t$. Before spread estimation transactions were eliminated if the quoted spread exceeds $5; the transaction price is more than 12.5 cents greater than (less than) the ask price (bid price); the transaction, bid, or ask price is more than 25% larger than (or less than 75% of) the preceding transaction, bid, or ask price, respectively; or if it was the first transaction of the day. All variables are aggregated across three intraday periods (first hour, midday, and last hour) for each stock, each day. The final sample contains 560,373 observations from 470 sample stocks covering 398 trading days.

Notation	Definition	Description
Panel A: Definition of changes in liquidity		
DL1	*ehs*–lag(*ehs*)	Dollar change in the mean effective half spread
DL2	*pehs*–lag(*pehs*)	Point change in the mean percentage effective half spread
DL3	(*ehs*/lag(*ehs*))–1	Proportional change in the mean effective half spread
DL4	(*pehs*/lag(*pehs*))–1	Proportional change in the mean percentage effective half spread

Statistic	*ehs*	*pehs*	*qhs*	*pqhs*	*DL1*	*DL2*	*DL3*	*DL4*
Panel B: Distribution of liquidity variables ($N = 560{,}373$)								
Mean	0.0650	0.2002	0.1337	0.3937	0.0000	0.0000	0.0503	0.0506
Percentile								
100% Maximum	1.0798	5.2691	1.8437	7.5512	0.9896	4.9383	58.1249	58.2453

99%	0.1452	0.7455	0.3210	1.2951	0.0602	0.2560	1.2954	1.2996				
95%	0.1119	0.4599	0.2334	0.8388	0.0340	0.1149	0.6641	0.6651				
90%	0.0993	0.3590	0.2014	0.6703	0.0236	0.0715	0.4465	0.4475				
75% Q3	0.00806	0.2444	0.1598	0.4750	0.0102	0.0267	0.1885	0.1884				
50% Median	0.0603	0.1632	0.1244	0.3317	–0.0005	–0.0013	–0.0099	–0.0098				
25% Q1	0.0442	0.1094	0.0960	0.2395	–0.0108	–0.0286	–0.1684	–0.1684				
10%	0.0359	0.0787	0.0751	0.1817	–0.0228	–0.0702	–0.2979	–0.2979				
5%	0.0325	0.0656	0.0639	0.1550	–0.0316	–0.1097	–0.3750	–0.3751				
1%	0.0269	0.0478	0.0457	0.1155	–0.0553	–0.2399	–0.5243	–0.5246				
0% Minimum	0.0000	0.0000	0.0053	0.0127	–0.9745	–3.9555	–1.0000	–1.0000				
Statistic	*ehs*	*pehs*	*qhs*	*pqhs*	*DL1*	*DL2*	*DL3*	*DL4*	|*DL1*|	|*DL2*|	|*DL3*|	|*DL4*|
Panel C: Cross-sectional statistics for time-series means ($N = 470$)												
Mean	0.0650	0.2002	0.1337	0.3937	0.0000	0.0000	0.0503	0.0506	0.0149	0.0489	0.2427	0.2432
Median	0.0636	0.1754	0.1287	0.3528	0.0000	0.0000	0.0423	0.0426	0.0139	0.0390	0.2297	0.2303
Standard Deviation	0.0118	0.0964	0.0329	0.1633	0.0000	0.0001	0.0276	0.0276	0.0045	0.0321	0.0638	0.0637

the dollar effective spread (*DL3*), and the proportional change in the percentage effective spread (*DL4*). Examining the point and proportional change in the percentage spread (*DL2* and *DL4*) allows us to examine liquidity co-variation relative to the price of each stock, while the dollar and proportional difference in dollar spreads (*DL1* and *DL3*) help assure that evidence is not driven by common variation in prices.[15]

A few properties of the change in effective spread distributions are worth mentioning. First, the minimum effective half spread and percentage effective spreads are zero (see Table 3, Panel B). In these cases, each trade during a period for a particular stock occurred at the quote midpoint. As a result, when the spread drops to zero the proportional change in the dollar effective spread and percentage effective spread (*DL3* and *DL4*) equals –1.0 (the minimum), but when spreads rise from zero the proportional changes are undefined. Also, when spreads rise from near-zero (which occurs fairly often), a relatively modest dollar change in the spread can yield exceptionally large proportional changes (the maximum percent change in effective spreads is over 5,800 times). Thus, the change in effective spread from zero or near-zero is captured well by the dollar change in the dollar spread or point change in the percentage spread (*DL1* and *DL2*). To assure that the evidence is robust to the measurement of liquidity change, each test is estimated using these four methods.

Finally, before estimating the degree of liquidity co-variation we remove liquidity variation observations (*DL1–DL4*) that are greater than the 99th percentile and lower than the 1st percentile of its own distribution. We do this because any remaining data errors are most likely contained in the distribution tails, and because we want the evidence to depict the degree of commonality without the undue influence of outliers.

The cross-sectional distribution of the 470 stock time-series means of each liquidity variable is reported in Table 3, Panel C. The mean effective half spread is 6.5 cents and the mean quoted half spread is roughly 13.4 cents. The mean percentage effective half spread is 0.2% and the mean percentage quoted half spread is almost 0.4%. The mean dollar change in the dollar effective spread (*DL1*) and the mean point change in the percentage effective spread (*DL2*) are both zero, while the mean percentage changes (*DL3* and *DL4*) are both about 5% (with difference driven largely by the truncation of *DL3* and *DL4* at –1.0).

The cross-sectional mean of the absolute dollar change of dollar spreads ($|DL1|$) is 1.49 cents and the mean absolute point change in percentage spreads ($|DL2|$) is 4.89 points. The mean absolute proportional change in the dollar effective spread and percentage effective spread ($|DL3|$ and $|DL4|$) are both slightly over 24% per period, which are slightly lower than the 31% mean absolute changes reported by Chordia et al. (2000). This difference could stem from different sample periods (1992 versus 1999–2000) between which there were many structural changes (tick size, display rules, increased competition for order flow) and changes in overall market activity

[15] Borrowing from Chordia et al. (2000), we let *D* denote 'difference' and *L* denote 'liquidity.' We use the numbers 1–4 to easily refer to method used to calculate the change in liquidity. Chordia et al. (2000) also measured two changes in effective spreads, the proportional change in dollar and percentage spreads (our *DL3* and *DL4*).

that has led to lower transaction costs (Bessembinder, 1999, 2003). Similar to Chordia et al. (2000), however, the low cross-sectional standard deviation of the mean absolute changes in the effective spread indicate that time-series spread variation is common across stocks.

4. Empirical evidence of common liquidity variation

In this section we report estimation of individual stock liquidity co-variation with the market portfolio and separately with the specialist firm portfolios, we report the simultaneous estimation of individual stock liquidity co-variation with market and specialist portfolio liquidity, and we present a test checking the assumption underlying the basic model specification.

4.1. Evidence regarding commonality with market liquidity

The market model method employed by Chordia et al. (2000) is used for our initial estimates of liquidity co-variation, which we report for comparison purposes. The model,

$$DL_{i,j,t} = \sum_{p=1}^{3} \alpha_{i,j,p} P_p + \beta_{i,j} DML_{i,j,t} + XB + \varepsilon_{i,j,t}, \tag{1}$$

yields the market-liquidity beta estimate ($\hat{\beta}_{i,j}$) for each stock j in the working sample ($N=259$), across each of the four (i) methods of estimating the change in effective spread (where $DL_i = DL1,\ldots,DL4$). The change in market liquidity (DML_{ijt}) is the ith change in the average effective spread using the 470 filtered sample stocks that are not in stock j's specialist firm. In addition, we estimate a vector of control variable coefficients (B), which includes lead and lag estimates of the change in market liquidity; the current, lead, and lag market return; and the current change in the squared return of stock j. The control variables are intended to hold constant any relation between spreads, market returns, and individual stock price movement that is unrelated to changes in market liquidity. Finally, we allow the intercept to vary to control for the intraday variation of transaction costs. The indicator variable P_1 equals one if the observation is aggregated from data during the first hour of trade and is zero otherwise. Likewise, indicator variables P_2 and P_3 equal one if the observation is aggregated from the middle of the day and final hour, respectively, and zero otherwise.

If individual stock liquidity co-varies with market liquidity the mean beta coefficient estimated from Eq. (1) will be significantly different from zero. Following Chordia et al. (2000), we test the hypothesis $\bar{\beta}_i = 0$ using a cross-sectional t-test.[16] To convey the cross-sectional distribution of the sign and significance of the individual liquidity beta estimates we also report the percent of positive and significantly positive coefficients estimated from the individual regressions.

[16] As Chordia et al. (2000) note, the cross-sectional t-statistic for the β estimates is calculated under the assumption that the estimation errors are uncorrelated across the individual stock regressions. The specification check reported in Table 6 supports this assumption.

The mean market-liquidity betas are reported in the first four columns in Table 4. The average market-liquidity beta ranges from $\bar{\beta}_2 = 0.66$ (t-statistic $\cong$ 30) to $\bar{\beta}_3 = 0.81$ (t-statistic $\cong$ 47), and for each measure of spread variation, over 90 percent of the individual market-liquidity betas are significantly positive. This initial evidence indicates a strong degree of common liquidity variation in our sample.

Table 4
Commonality in liquidity with market and specialist firm portfolios. The change in the effective spread of stock j is regressed on the concurrent, lag, and lead change in the market portfolio effective spread (where the market excludes stock j and stocks in the same specialist firm) or on the change in the specialist portfolio effective spread (where the specialist portfolio excludes stock j). The specifications are described in the text as Eqs. (1) and (2). The dependent variable is *DL1*, *DL2*, *DL3*, or *DL4*, representing the four methods of estimating spread changes (see Table 3, Panel A). The regression is estimated for each of the 259 stocks in the working sample. The cross-sectional average time-series coefficient $\bar{\beta}$ is the estimate of co-variation with market portfolio liquidity, and $\bar{\gamma}$ is the estimate of co-variation with specialist portfolio liquidity (with t-statistics in parentheses). 'Percent positive' is the percent of positive coefficients, and 'Percent + significant' is the percent with t-statistic greater than + 1.645, the 5% critical level in one-tailed test. Sum = concurrent + lead + lag coefficients. The p-value is a sign test of H_0: Sum median = 0. Regressors not reported include the period intercepts, lead, lag, and concurrent equally weighted market returns, and the proportional change in individual stock squared return.

	Eq. (1) dependent variable				Eq. (2) dependent variable			
	DL1	*DL2*	*DL3*	*DL4*	*DL1*	*DL2*	*DL3*	*DL4*
Concurrent-market ($\bar{\beta}$)	0.7777	0.6615	0.8079	0.7393				
(t-statistic)	(43.98)	(30.40)	(46.84)	(45.28)				
Percent positive	98.06	98.46	98.45	98.45				
Percent + significant	94.98	92.66	94.21	94.21				
Concurrent-specialist ($\bar{\gamma}$)					0.4718	0.4016	0.4060	0.3321
(t-statistic)					(31.79)	(22.85)	(28.35)	(25.72)
Percent positive					97.29	97.68	96.52	94.98
Percent + significant					90.73	86.87	83.01	81.46
Lag	0.0028	0.0224	–0.0368	–0.0143	–0.0046	–0.0057	0.0032	0.0028
(t-statistic)	(0.23)	(1.84)	(–3.22)	(–1.34)	(–0.55)	(–0.72)	(0.45)	(0.44)
Percent positive	50.96	58.30	45.17	50.96	46.71	47.87	52.12	52.51
Percent + significant	7.72	11.58	5.02	5.01	8.49	10.42	5.01	3.86
Lead	–0.0033	0.0136	–0.0115	–0.0119	–0.0039	–0.0068	0.0143	0.0039
(t-statistic)	(–0.35)	(1.44)	(–1.29)	(–1.36)	(–0.58)	(–1.08)	(2.24)	(0.68)
Percent positive	50.57	54.82	47.10	45.17	49.03	52.12	53.28	51.73
Percent + significant	4.24	9.65	3.47	4.24	4.63	5.01	6.17	5.02
Mean sum	0.7772	0.6976	0.7549	0.7130	0.4633	0.3891	0.4235	0.3388
(t-statistic)	(30.89)	(23.05)	(35.74)	(35.60)	(24.05)	(18.86)	(23.79)	(21.02)
Median	0.8150	0.6652	0.8300	0.7681	0.4674	0.3470	0.4351	0.3499
p-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Mean adjusted R^2	0.2497	0.2388	0.2225	0.2204	0.2317	0.2191	0.2089	0.2063
Median adjusted R^2	0.2418	0.2302	0.2142	0.2119	0.2234	0.2127	0.2015	0.1988

Because this test replicates Chordia et al. (2000), it is worth pausing for a comparative discussion. First, Chordia et al. (2000) use the proportional change in the dollar effective spread and percentage effective spread (same as our *DL3* and *DL4*). While the signs and significance of the commonality coefficients are similar, the difference in the degree of individual liquidity variation explained is substantial. The mean adjusted R^2's reported by Chordia et al. (2000) are slightly greater than 1%, while ours are slightly greater than 22%. This difference appears to be primarily the result of different aggregation periods. We assess the degree different aggregation periods have on explained variation by re-aggregating our data at daily intervals and re-estimating Eq. (1). The resulting mean coefficients fell slightly, ranging from $\bar{\beta}_2 = 0.60$ (t-statistic $\cong$ 15) to $\bar{\beta}_1 = 0.71$ (t-statistic $\cong$ 21). The four mean adjusted R^2 estimates, however, now range from 2.9% (*DL1* regressions) to 3.9% (*DL2* regressions), which is much closer to the average adjusted R^2 of 1.4% reported by Chordia et al. (2000). As a result, we conclude that our initial evidence is consistent with this previous study but that the degree of commonality is greater than previously reported.[17]

4.2. Evidence regarding commonality with specialist portfolio liquidity

The degree of liquidity co-variation within specialist firms is estimated in two ways. First, we simply replace variation in market portfolio liquidity (DML_i) in Eq. (1) with variation in specialist portfolio liquidity (DSL_i),

$$DL_{i,j,t} = \sum_{p=1}^{3} \alpha_{i,j,p} P_p + \gamma_{i,j} DSL_{i,j,t} + XB + \varepsilon_{i,j,t}, \tag{2}$$

where specialist firm liquidity is measured as the mean of all other stocks in the specialist firm except stock j, and where all other variables are defined above. The evidence is reported in the final four columns of Table 4. The average sensitivity of individual stock liquidity to specialist portfolio liquidity ranges from $\bar{\gamma}_4 = 0.33$ (t-statistic $\cong$ 25) to $\bar{\gamma}_1 = 0.47$ (t-statistic $\cong$ 32), and over 80 percent of the 259 individual regression coefficients are significantly positive for each measure of liquidity variation. The regression R^2's indicate that approximately the same degree of individual stock liquidity variation is explained by specialist portfolio liquidity as was found with market portfolio liquidity.

The liquidity co-variation estimates with only the market or specialist portfolios, however, should be interpreted with caution because much variation in the specialist and market portfolio liquidity is likely the result of common information.[18] Therefore, we estimate liquidity co-variation based on variation that is not shared

[17] The evidence using daily aggregates was provided to the referee and is available upon request.

[18] The average correlation coefficient between the change in market portfolio spreads and specialist portfolio spreads is roughly 0.70. Because they are never perfectly correlated, we have no identification problem, and least squares remains the best linear unbiased estimator. However, near-multicollinearity can influence the precision of the coefficient estimates. As a rule of thumb, Greene (1990) suggests that if the R^2 in the multivariate regression is less than any individual R^2 then near-multicollinearity could influence the precision of the coefficient estimates (see Greene, 1990, p. 280). Because this is not true in our case, we believe any precision problems are marginal.

between the two portfolios. The model is,

$$DL_{i,j,t} = \sum_{p=1}^{3} \alpha_{i,j,p} P_p + \beta_{i,j} DML_{i,j,t} + \gamma_{i,j} DSL_{i,j,t} + XB + \varepsilon_{i,j,t}, \tag{3}$$

where all variables are as previously defined.

The joint commonality estimates obtained from Eq. (3) are reported in Table 5. Across the four (i) methods of measuring the change in effective spreads, liquidity co-variation with both the market and specialist portfolios is positive and significant. The market commonality coefficients now range from $\bar{\beta}_2 = 0.59$ (t-statistic $\cong$ 27) to $\bar{\beta}_3 = 0.74$ (t-statistic $\cong$ 40). Although the sensitivity of individual stock liquidity to market liquidity falls slightly, the cross-section of commonality estimates remain significantly different from zero; and the estimates remain positive and significant in over 86% of the individual regressions. In contrast, the specialist commonality coefficients decrease substantially but remain significantly positive, ranging from $\bar{\gamma}_3 = 0.0756$ (t-statistic $\cong$ 6.71) to $\bar{\gamma}_4 = 0.0783$ (t-statistic $\cong$ 7.83).

This evidence indicates that individual stock liquidity is less sensitive to information associated exclusively with variation in the specialist firm portfolio. To assess this difference, we test the restriction that $\hat{\beta}_{i,j} = \hat{\gamma}_{i,j}$ for each of the four (i) methods of measuring the change in effective spreads, for each of the $j = 259$ individual stock regressions. This restriction is rejected in over 62% of the sample regressions (mean F-values range from 6.07 to 7.25, and mean p-values range from 0.16 to 0.18 across the four i regression sets). Based on this evidence, we conclude that the liquidity of the typical individual stock is more sensitive to variation in market portfolio liquidity than to variation in specialist portfolio liquidity. The significant specialist portfolio co-variation estimates indicate, however, that factors associated with liquidity suppliers generate liquidity co-variation.

4.3. *A specification check*

Before analyzing the relation between specialist firm characteristics and liquidity co-variation, we report a specification check with regard to the initial evidence. Above, we use t-tests to determine if the average commonality coefficients ($\bar{\beta}_i$ and $\bar{\gamma}_i$) were significantly different from zero. For this test to be reliable, the residuals across regressions need to be independent. We test for error independence using a method similar to that used by Chordia et al. (2000). First, we save the residuals from the joint estimation of commonality, Eq. (3), for each of the 259 individual regressions, and assign each residual series a number, j, using a random number generator. The relation between the residuals for stock j+1 with the residuals for stock j are estimated as

$$\varepsilon_{j+1,t} = \delta_{j,0} + \delta_{j,1}\varepsilon_{j,t} + \xi_{j,t} \quad (j = 1, \ldots, 259). \tag{4}$$

This allows us to create a random set of error sensitivities with mean $\bar{\delta}_1$. As reported in Table 6 the evidence indicates that there is very little cross-equation dependence. The full sample average coefficient ($\bar{\delta}_1$) is –0.0066 with a mean t-statistic of –0.18 and

Table 5
Joint estimation of liquidity co-variation with market and specialist firm portfolios. The change in the effective spread of stock *j* is regressed on the concurrent, lag, and lead change in the market portfolio effective spread (where the market excludes stock *j* and stocks in the same specialist firm) and on the change in the specialist portfolio effective spread (where the specialist portfolio excludes stock *j*). The specification is described in the text as Eq. (3). The dependent variable is *DL1*, *DL2*, *DL3*, or *DL4*, representing the four methods of estimating spread changes (see Table 3, Panel A). The regression is estimated for each of the 259 stocks in the working sample. The cross-sectional average time-series coefficient $\bar{\beta}$ is the estimate of co-variation with market portfolio liquidity, and $\bar{\gamma}$ is the estimate of co-variation with specialist portfolio liquidity (with *t*-statistics in parentheses). 'Percent positive' is the percent of positive coefficients, and 'Percent + significant' is the percent with *t*-statistic greater than +1.645, the 5% critical level in one-tailed test. Sum = concurrent + lead + lag coefficients. The *p*-value is a sign test of H_0: Sum median = 0. Regressors not reported include the period intercepts, the lead, lag, and concurrent equally weighted market returns; the lead and lag change in market and specialist portfolio liquidity; and the proportional change in individual stock squared return. We test the restriction that $\hat{\beta}=\hat{\gamma}$ within each individual regression and report the mean (median), *F*-value, *p*-value, and the percent of *p*-values less than 0.10.

	Eq. (3) dependent variable			
	DL1	*DL2*	*DL3*	*DL4*
Concurrent-market ($\bar{\beta}$)	0.7114	0.5953	0.7409	0.6717
(*t*-statistic)	(37.73)	(27.05)	(39.98)	(38.98)
Percent positive	98.06	94.98	98.45	98.06
Percent + significant	87.64	86.10	87.25	86.10
Concurrent-specialist ($\bar{\gamma}$)	0.0757	0.0795	0.0756	0.0783
(*t*-statistic)	(7.01)	(7.25)	(6.71)	(7.83)
Percent positive	67.56	69.88	65.63	69.88
Percent + significant	11.58	14.28	13.51	12.35
Mean market sum	0.7110	0.6380	0.6952	0.6569
(*t*-statistic)	(25.60)	(19.07)	(27.76)	(27.34)
Mean specialist sum	0.0712	0.0698	0.0714	0.0639
(*t*-statistic)	(3.81)	(3.77)	(4.09)	(4.10)
Mean adjusted R^2	0.2507	0.2402	0.2231	0.2210
Median adjusted R^2	0.2425	0.2319	0.2146	0.2138
Test: $\hat{\beta}=\hat{\gamma}$				
Mean *F*-value	6.24	7.25	6.07	6.77
(median)	(4.32)	(4.51)	(4.54)	(5.10)
Mean *p*-value	0.1609	0.1891	0.1702	0.1713
(median)	(0.0377)	(0.0337)	(0.0332)	(0.0240)
Percent *p*-values < 0.10	62.54	62.16	63.32	64.09

Table 6
The cross-equation correlation of estimation errors. First, joint commonality is estimated using Eq. (3) for each of the 259 stocks in the working sample. Then the residuals for stock $j+1$ are compared with residuals for stock j using Eq. (4), where j is assigned using a random number generator. From these 258 paired regressions, we report the average slope coefficient, the mean and median t-statistic for the slope coefficient, and the frequency it exceeds the 5% and 2.5% critical levels. This process is then repeated on the sample subgroups sorted by total dollar volume.

Sample	Average slope coefficient	Mean t	Median t	$\lvert t\rvert > 1.645$ (%)	$\lvert t\rvert > 1.96$ (%)
All stocks	–0.0066	–0.1818	–0.1899	19.76	15.50
Quintile 5 (highest volume)	0.0152	0.5067	0.8068	27.45	21.56
Quintile 4	0.0000	0.0285	0.1369	21.56	15.68
Quintile 3	–0.0021	–0.0475	0.0819	19.60	11.76
Quintile 2	0.0057	0.1742	0.3226	23.52	15.68
Quintile 1 (lowest volume)	–0.0027	–0.0917	0.0203	20.00	12.00

a median t-statistic of –0.19. The percent of significant t-statistics at the 5% level (15.5%) is higher than expected given a normal distribution and is slightly greater than that reported by Chordia et al. (2000).

As a further check, we repeat the test on volume-sorted quintiles because heavily traded stocks could be more likely to share commonalities in order flow because of program trading and the concerted efforts of institutional investors (Hasbrouck and Seppi, 2001). As expected, the relation between residuals is strongest for the high-volume securities. However, even for this set of stocks, no evidence exists of a significant relation (mean and median t-statistics for the high-volume portfolio are 0.51 and 0.81, respectively). Because the mean cross-equation error is not significant, the evidence implies that adjustments for cross-equation dependence would yield immaterial changes.

5. Common liquidity variations and the risk of providing liquidity

In this section, we report three tests considering whether the degree of supply-generated liquidity co-variation is positively related to the risk of providing liquidity. The first two are based on specialist firm size and the last is based on the direction of market returns.

5.1. Specialist firm size and commonality in liquidity

Prior research indicates that the cost (and risk) of providing liquidity is influenced by the degree of specialist firm portfolio diversification (e.g., Gehrig and Jackson, 1998; Strobl, 2002) and specialist firm organizational form (Coughenour and Deli, 2002). With a higher degree of portfolio diversification, a given profit shock in one stock is less likely to influence the liquidity provided to other stocks in large specialist firm portfolios. In addition, because large specialist firms tend to be subsidiaries of well-diversified corporations, their specialists provide liquidity using relatively low-cost capital. As a result of both these benefits that accrue with specialist firm size, we expect the liquidity of stocks handled by large specialist firms to co-move less with market liquidity.

First, we test whether the liquidity co-variation of specialist firm portfolios with the market declines with specialist firm size. The estimation procedure is as follows. First, we estimate the change in the mean spread of each specialist firm portfolio.[19] This results in a time-series of mean spread changes for each specialist firm portfolio, which are regressed against the change in market portfolio liquidity. The model is

$$DSL_{i,s,t} = \sum_{p=1}^{3} \alpha_{i,s,p} P_p + \beta_{i,s} DML_{i,s,t} + XB + \varepsilon_{i,s,t}, \tag{5}$$

where s indicates the specialist firm portfolio.[20] As before, we control for the concurrent, lead and lag market returns, lead and lag changes in market liquidity, and the squared specialist portfolio return. We estimate the model coefficients for each specialist firm (ten times) and report the mean market-liquidity beta in Table 7, Panel A.

The evidence indicates that the specialist portfolio market-liquidity betas are slightly greater than the individual stock liquidity betas. For example, the commonality estimates for the percent change in dollar spread (*DL3*) and percentage spreads (*DL4*) are 0.81 (t-statistic $\cong$ 15) and 0.83 (t-statistic $\cong$ 11), respectively, and are significant for each specialist portfolio regression (percent positive and significant is 100%). Furthermore, the mean adjusted R^2's increase to roughly 78%. The increased explanatory power stems from the fact that idiosyncratic stock liquidity variation is largely reduced within the diversified specialist portfolios, leaving only the systematic variation in specialist portfolio liquidity to be explained by systematic variation in market liquidity.

Next, we test whether the cross-sectional variation in the specialist portfolio commonality estimates are inversely related to specialist firm size. We measure specialist firm size by the natural log of both the number of specialist firm stocks and the total dollar volume generated by stocks within each specialist portfolio. The evidence reported in Table 7, Panel B, is consistent with the hypothesis. The specialist portfolio commonality estimates significantly decrease with specialist firm size. In addition, the R^2's range from 10% to 44%, indicating that specialist firm size accounts for a large degree of the cross-sectional variation in portfolio commonality.

[19] The specialist portfolio includes all working sample stocks handled by the firm, and the change in mean effective spread is estimated using the similar four (i) methods as described above.

[20] We considered whether a market portfolio proxy that includes stocks handled by specialist firms of the same size influences the results. Because of the effects of diversification, removing these stocks from the market portfolio does not significantly alter the estimate of market portfolio liquidity variation. For consistency, and to assure that only systematic liquidity variation remains in the market portfolio proxy, we continue to use the same definition of the market portfolio.

Table 7
Specialist portfolio liquidity co-variation. Panel A reports the degree of co-variation between the change in specialist portfolio liquidity and change in market liquidity estimated using Eq. (5). The dependent variable is the change in specialist portfolio liquidity, *DSL1*, *DSL2*, *DSL3*, or *DSL4*, representing the four methods of estimating spread changes (see Table 3, Panel A). Each regression is estimated ten times (once for each specialist firm), in which each regression is based on 1,194 day-period observations. We report the mean coefficient (t-statistic), percent of positive coefficients, and percent of positive significant coefficients. Regressors not reported include the period intercepts; lead and lag changes in market liquidity; lead, lag, and concurrent market returns; and the proportional change in specialist portfolio squared return. Panel B reports the relation between the estimated portfolio commonality coefficients reported in Panel A with specialist firm size. Each cross-sectional regression is estimated using the ten estimates. We provide the plot the commonality estimates in Fig. 1 because outliers are more likely to alter small-sample regression coefficients.

	Eq. (5) dependent variable							
	DSL_1	DSL_2	DSL_3	DSL_4				
Panel A: Specialist portfolio commonality								
Concurrent ($\bar{\beta}$)	0.8790	0.9148	0.8110	0.8359				
(t-statistic)	(37.71)	(17.06)	(15.26)	(11.14)				
Percent positive	100.00	100.00	100.00	100.00				
Percent + significant	100.00	100.00	100.00	100.00				
Mean adjusted R^2	0.7862	0.7465	0.7515	0.7159				
Median adjusted R^2	0.7655	0.7445	0.7350	0.7216				
	Dependent variable, coefficients estimated from Eq. (5)							
	$\hat{\beta}_{PDL1}$	$\hat{\beta}_{PDL2}$	$\hat{\beta}_{PDL3}$	$\hat{\beta}_{PDL4}$	$\hat{\beta}_{PDL1}$	$\hat{\beta}_{PDL2}$	$\hat{\beta}_{PDL3}$	$\hat{\beta}_{PDL4}$
Panel B: Cross-sectional regressions of portfolio commonality estimates on specialist firm size estimates ($N=10$)								
Intercept	1.1329	1.4253	1.3086	1.3988	1.1884	1.6597	1.4245	1.6753
(t-statistic)	(10.75)	(5.42)	(4.98)	(3.49)	(9.97)	(6.31)	(4.76)	(3.90)
ln(spec firm stocks)	–0.0764	–0.1536	–0.1498	–0.1694				
(t-statistic)	(–2.45)	(–1.97)	(–1.92)	(–1.43)				
ln(spec firm dollar volume)					–0.0496	–0.1196	–0.0985	–0.1348
(t-statistic)					(–2.63)	(–2.87)	(–2.08)	(–1.98)
Adjusted R^2	0.3570	0.2426	0.2308	0.1033	0.3960	0.4452	0.2689	0.2447

Because each of the above cross-sectional regressions are based on only ten specialist portfolio commonality estimates, the slope estimate is more likely to be influenced by outliers. To examine this potential problem we plot the coefficients in Fig. 1. From this plot, we believe it would be difficult to argue that outliers generate the negative relation. For each measure of effective spread change, the market liquidity betas generally decline with specialist firm size. In addition, we find a significant negative relation between all the portfolio commonality estimates and specialist firm size (regression reported on Fig. 1). We conclude that this evidence is consistent with a negative relation between specialist firm size and degree of portfolio liquidity co-variation.

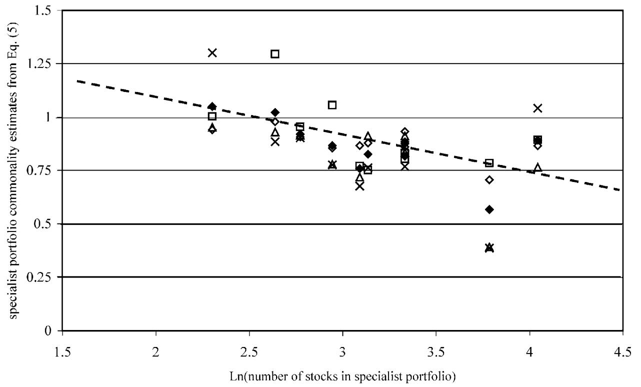

Fig. 1. Plot of specialist portfolio liquidity commonality estimates on specialist firm size. The co-variation coefficients ($\hat{\beta}_s$) are estimated using Eq. (5) separately for each specialist firm (reported in Table 7). The commonality coefficient estimates for DML_1, DML_2, DML_3, and DML_4 (the four measures of market liquidity variation) are denoted with a ◇, □, Δ, and ×, respectively. Thus, each column of plot points belongs to the same specialist firm (with the mean of each specialist firm's coefficients denoted with the solid diamond, ◆). We also estimate a simple regression through all coefficient estimates: $\hat{\beta} = 1.4044 - 0.1734 \cdot ln(stocks) + e$, slope t-statistic = –3.64, and $R^2 = 0.2395$.

5.2. Specialist firm mergers and commonality in liquidity

The second size-based test focuses on specialist firm mergers. If larger specialist firms enjoy greater diversification and capital cost benefits, the degree the liquidity of stocks within the original parent firm co-varies with market portfolio liquidity and with each other (parent specialist portfolio liquidity) should decrease after the merger effective date. To test this hypothesis, we compare the degree of commonality using one-month windows around each merger.

Thirteen specialist firm mergers occurred during our sample period. Of these mergers, eight involved five of our ten specialist firms in the working sample. In total, 167 stocks in our working sample experienced a time when their specialist firm grew in size through a merger. The parent specialist firm, target specialist firm, merger effective date (first trading day the target firm is not listed in the daily specialist directory files), and the window of analysis are reported in Table 8, Panel A.

We extend Eq. (3) to allow the commonality estimates to vary after the merger by interacting an indicator variable A, which equals one if the observation is after the merger and zero otherwise, with the change in market and specialist portfolio liquidity variables. The model is

$$DL_{i,j,t} = \sum_{p=1}^{3} \alpha_{i,j,p} P_p + \beta_{i,j} DML_{i,j,t} + \beta_{A,i,j} A \cdot DML_{i,j,t} + \gamma_{i,j} DSL_{i,j,t} + \gamma_{A,i,j} A \cdot DSL_{i,j,t} + XB + \varepsilon_{i,j,t}, \quad (6)$$

Table 8

Change in liquidity co-variation following specialist firm mergers. The sample includes the 167 stocks in the working sample whose specialist firm grew through merger or acquisition during our sample period. Panel A describes our merger parent firms, target firms, effective date, and window of analysis. Panel B reports the mean regression estimates from Eq. (6) on each of the 167 stocks, where coefficients β_A and γ_A estimate the post-merger difference in liquidity co-variation with market and specialist portfolio liquidity. The specialist portfolio is constrained to the set of sample stocks prior to the merger. In this manner we estimate the effect of an increase in specialist firm size on the degree liquidity co-varies across the same stock set. Regressors not reported include the period intercepts; lead and lag changes in market liquidity; lead, lag, and concurrent market returns; and the proportional change in individual stock squared return.

Parent firm	Stocks	Target firm	Effective date	Window of analysis
Panel A: Sample of specialist firm mergers				
Spear, Leeds and Kellogg	57	Equitrade Partners	June 21, 1999	± 1 month
Lawrence, O'Donnell, Marcus	15	Surnamer Weissman and Co., and Einhorn and Co.	July 19, 1999	± 1 month
Wagner, Stott, Mercator	28	CMJ Partners	October 20, 1999	± 1 month
LaBranche and Co.	44	Henderson Brothers	March 6, 2000	
		Webco Securities Inc.	March 19, 2000	1 month before March 6, 2000 and 1 month after March 10, 2000
M.J. Meehan and Co.	23	Stuart, Scotto, Cella Co.	October 16, 2000	
		Fleet Specialist	October 27, 2000	1 month before October 16, 2000 and 1 month after October 27, 2000

	Eq. (6) dependent variable					
	DL3	*DL3*	*DL3*	*DL4*	*DL4*	*DL4*
Panel B: Regression estimates of change in liquidity co-variation after specialist firm mergers ($N=167$)						
Concurrent-market ($\bar{\beta}$)	0.7315		0.7729	0.6851		0.7041
(t-statistic)	(11.73)		(7.07)	(10.58)		(7.70)

Percent positive	83.83		73.65	81.43		76.04
Percentage + significant	40.71		23.95	39.52		20.95
Concurrent-market after ($\bar{\beta}_A$)	–0.1170		–0.2361	–0.1329		–0.2158
(t-statistic)	(–2.61)		(–1.84)	(–2.93)		(–2.06)
Percent negative	58.68		55.68	58.08		53.89
Percent–significant	14.37		16.17	14.97		16.17
Concurrent-specialist ($\bar{\gamma}$)		0.3973	–0.0374		0.3427	–0.0018
(t-statistic)		(9.26)	(–0.41)		(7.83)	(–0.02)
Percent positive		78.44	53.29		73.65	53.89
Percent + significant		28.14	7.18		26.94	8.98
Concurrent-specialist after ($\bar{\gamma}_A$)		–0.0973	0.1172		–0.1218	0.0800
(t-statistic)		(–2.34)	(1.00)		(–3.03)	(0.86)
Percent negative		58.68	49.10		57.48	50.89
Percent–significant		16.17	8.38		16.17	7.78
Mean adjusted R^2	0.2234	0.2146	0.2328	0.2215	0.2119	0.2311
Median adjusted R^2	0.1994	0.2013	0.2172	0.1973	0.1973	0.2147

where all variables are as earlier defined. We estimate this regression for each of the 167 individual stocks originally held by the set of parent specialist firms. To be consistent with the hypothesis, the evidence should reveal a significant decrease in mean commonality after the merger ($\bar{\beta}_{A,i} < 0$ and $\bar{\gamma}_{A,i} < 0$).

The evidence is reported in Table 8, Panel B. In the first two columns we regress the proportional change in dollar spreads (*DL3*) on changes in the market or specialist portfolio liquidity separately [similar to Eqs. (1) and (2)]. In this case, the evidence indicates that the degree of liquidity co-variation with the market portfolio and specialist portfolio drop significantly after the specialist firm mergers.

When estimating joint specialist and market portfolio commonality [similar to Eq. (3)] the degree of liquidity co-variation with the market portfolio falls significantly after the mergers. For example, the mean change in the market-liquidity beta, $\bar{\beta}_{A,i}$, equals –0.23 (t-statistic = –1.84) and –0.21 (t-statistic = –2.06) for the proportional change in dollar (*DL3*) and percentage effective spreads (*DL4*), respectively. However, the degree of liquidity co-variation with the specialist portfolio does not significantly change after the mergers. Consistent with the cross-sectional specialist portfolio tests, the evidence using mergers indicates that the degree of liquidity co-variation with the market portfolio decreases as specialist firm size increases.

The hypothesis tested in this subsection is that stocks handled by larger specialist firms will display less liquidity co-variation. This is based on the idea that larger specialist firms tend to have a lower cost of capital and, because they handle more stocks, individual liquidity shocks have less influence on specialist firm wealth and capital constraints. Overall, the evidence from the two size-based tests is consistent with this hypothesis. The cross-sectional test based on portfolio commonality indicates that market liquidity betas are significantly lower for larger specialist firms. Similarly, the time-series test indicates that individual stock market liquidity betas decrease after specialist firms grow through mergers.

5.3. Variation in market returns and commonality in liquidity

In this section we use the sign and magnitude of returns to isolate times when the risk of providing liquidity is likely to be relatively high. Relative to periods with rising market valuations, specialist firm wealth is likely to contract and capital constraints are more likely to be stressed during periods with falling market valuations. Therefore, if specialists are more likely to share inventory and profit information during falling markets in an effort to manage firm wealth, we expect specialist portfolio liquidity co-variation to increase with the absolute size of negative returns.

We condition liquidity co-variation estimates on market returns using indicator variables to denote which quartile a period's return observation is within the total return distribution. For example, if the return at period t falls into the quartile with the lowest returns, then *q1* equals one; otherwise *q1* equals zero, etc. To estimate the liquidity co-variation coefficients conditional on returns we modify

Eq. (3) as

$$DL_{i,j,t} = \sum_{p=1}^{3} \alpha_{i,j,p} P_p + \beta_{i,j} DML_{i,j,t} + \sum_{r=2}^{4} \beta_{qr,i,j} DML_{i,j,t} \cdot q_r + \gamma_{i,j} DSL_{i,j,t} + \sum_{r=2}^{4} \gamma_{qr,i,j} DSL_{i,j,t} \cdot q_r + XB + \varepsilon_{i,j,t}, \quad (7)$$

where r denotes the return quartile, and where all other variables are defined as above. In this manner, we estimate the difference in liquidity co-variation when returns are in the upper three quartiles relative to the degree that occurs when returns are in the lowest quartile. Given our economic rationale for liquidity co-variation between stocks in the same specialist portfolio, we expect γ_{q2}, γ_{q3}, and γ_{q4} to be negative.

We summarize the return distribution of each quartile in Table 9, Panel A, and provide the conditional liquidity co-variation evidence in Table 9, Panel B. The evidence is largely consistent with the hypothesis. We estimate Eq. (7) using each of the four changes in liquidity measures. The bottom three rows provide the difference in specialist portfolio co-variation when returns are in the upper three quartiles (γ_{q2}, γ_{q3}, and γ_{q4}). The degree of co-variation in the change in dollar spreads (*DL1*), change in percentage spread points (*DL2*), and proportional change in percentage spreads (*DL4*) is significantly less than the estimated degree of co-variation when returns are most negative. For the proportional change in dollar spreads (*DL3*), the mean degree of co-variation is also lower when market returns are in the upper three quartiles, but the difference is not significant.

In Fig. 2 we illustrate the mean specialist portfolio co-variation level for each measure of liquidity variation, across the four return quartiles. Regardless of the measure of liquidity variation, the highest estimate is associated with returns in the lowest quartile (denoted with solid black bars). Also observable is the strong increase in liquidity co-variation when returns are in the lowest quartile, even relative to the second quartile. This indicates that the degree of co-variation with the specialist portfolio increases with the magnitude of negative market returns. This is consistent with greater joint management of liquidity during periods when specialist firm constraints are most likely strained.

It is also of interest to note the different pattern in conditional market portfolio co-variation across the return quartiles. Unlike the variation in specialist portfolio commonality, market portfolio commonality is lowest when market returns are most negative. We interpret this as further evidence that variation in specialist portfolio liquidity provides unique information to specialists and that during periods with negative market returns the relative role of supplier-generated factors in causing liquidity co-variation is elevated.

6. Conclusion

In this paper we argue that common market makers induce common liquidity movements. Because specialists within the same firm share capital and information,

Table 9

The relation between liquidity co-variation and market returns. Eq. (3) is extended to allow liquidity co-variation estimates to vary by market direction, as described by Eq. (7). The dependent variables are *DL1*, *DL2*, *DL3*, or *DL4*, representing the four methods of estimating spread changes (see Table 3, Panel A). The regression is estimated for each of the 259 stocks in the working sample. The β and γ coefficient estimates the degree of liquidity co-variation with the market and specialist portfolio, respectively, when market returns are in the lowest quartile (quartile 1) of its distribution. The coefficients β_{qi} and γ_{qi} denote the estimated difference in liquidity co-variation during periods within return in the ith quartile from the quartile with the lowest returns, relative to market and specialist portfolios, respectively. Regressors not reported include the period intercepts, lead and lag commonality coefficients, lead and lag market returns, and the proportional change in individual stock squared return. Fig. 2 illustrates the co-variation estimates (instead of the differences) with the specialist portfolio liquidity across quartiles.

Statistic	Quartile 1 (lowest)	Quartile 2	Quartile 3	Quartile 4 (highest)
Panel A: Percentage period returns by quartile				
Mean	–0.576	–0.106	0.119	0.606
Minimum	–3.138	–0.238	0.006	0.255
Median	–0.472	–0.104	0.115	0.481
Maximum	–0.239	0.005	0.254	3.454

	Eq. (7) dependent variable			
	DL1	*DL2*	*DL3*	*DL4*
Panel B: Liquidity co-variation estimates by return quartile				
Concurrent market q1 ($\bar{\beta}$)	0.6742	0.5621	0.7150	0.6360
(t-statistic)	(28.41)	(22.46)	(28.29)	(30.25)
Percent positive	96.13	93.82	94.59	94.98
Percent + significant	69.88	72.59	71.04	74.90
Concurrent market–difference q2 ($\bar{\beta}_{q2}$)	0.0680	0.0337	0.0342	0.0347
(t-statistic)	(2.74)	(1.67)	(1.28)	(1.63)
Percent positive	56.75	50.96	50.96	55.59
Percent + significant	7.72	8.49	6.17	6.56
Concurrent market–difference q3 ($\bar{\beta}_{q3}$)	0.0499	0.0582	0.0428	0.0567
(t-statistic)	(2.03)	(2.40)	(1.62)	(2.53)
Percent positive	55.98	55.21	55.59	60.62
Percent + significant	7.72	8.88	5.40	6.17
Concurrent market–difference q4 ($\bar{\beta}_{q4}$)	0.0519	0.0523	0.0456	0.0672
(t-statistic)	(2.14)	(2.16)	(1.68)	(3.07)
Percent positive	49.81	53.66	52.12	57.91
Percent + significant	9.65	9.65	10.03	10.42
Concurrent specialist q1 ($\bar{\gamma}$)	0.1148	0.1125	0.0959	0.1083
(t-statistic)	(6.91)	(6.63)	(4.84)	(7.02)
Percent positive	65.25	64.48	62.16	67.56
Percent + significant	10.81	14.28	13.13	14.67
Concurrent specialist–difference q2 ($\bar{\gamma}_{q2}$)	–0.0793	–0.0477	–0.0315	–0.0418
(t-statistic)	(–3.15)	(–2.27)	(–1.21)	(–2.06)

Table 9 *(continued)*

Percent negative	56.37	57.53	53.67	55.21
Percent–significant	9.65	9.27	7.33	7.33
Concurrent specialist–difference q3 ($\bar{\gamma}_{q3}$)	–0.0374	–0.0433	–0.0274	–0.0395
(t-statistic)	(–1.56)	(–1.75)	(–1.06)	(–1.86)
Percent negative	55.21	54.44	54.05	57.14
Percent–significant	6.94	8.11	6.56	6.56
Concurrent specialist–difference q4 ($\bar{\gamma}_{q4}$)	–0.0502	–0.0427	–0.0269	–0.0383
(t-statistic)	(–2.05)	(–1.71)	(–1.02)	(–1.89)
Percent negative	50.96	52.89	53.67	56.37
Percent–significant	9.26	10.81	7.72	9.26
Mean adjusted R^2	0.2515	0.2416	0.2239	0.2219
Median adjusted R^2	0.2441	0.2304	0.2147	0.2149

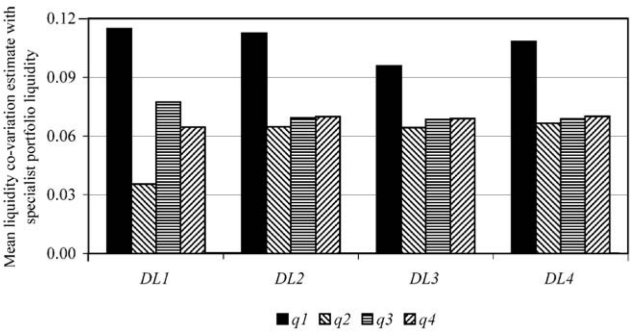

Fig. 2. Plot of mean liquidity commonality estimates with specialist portfolio liquidity conditional on market return, using Eq. (7). Market returns are sorted into quartiles, with lowest quartile denoted $q1$, etc. $DL1$, $DL2$, $DL3$, or $DL4$ denote the commonality estimates derived from each of the four methods of estimating spread changes (see Table 3, Panel A). Table 9 provides information on the statistical significance of the different magnitudes across quartiles.

the manner in which they provide liquidity is likely to be correlated. The evidence indicates that individual stock liquidity co-varies with specialist portfolio liquidity, unique from information causing co-variation with market liquidity. However, individual stock liquidity is roughly one-eighth as sensitive to specialist portfolio liquidity variation as it is to information causing market wide liquidity variation.

In extension, we argue that if shared resources cause liquidity co-variation across stocks within a specialist firm, then the degree of co-variation will increase when these resources are at most risk. Prior research indicates that the risk of providing liquidity decreases with the degree of specialist firm portfolio diversification (Ho and Stoll, 1983; Gehrig and Jackson, 1998) and increases with the specialist firm's cost of capital (Coughenour and Deli, 2002). Using specialist firm size as a proxy for firms with greater diversification and capital cost benefits, tests examining specialist firm portfolio commonality and specialist firm mergers indicate that liquidity co-variation is significantly lower for stocks handled by larger specialist firms. Evidence based on market returns indicates that liquidity co-variation increases with the absolute magnitude of negative returns, which is when shared resources such as capital are more likely to be at risk.

In addition to examining the existence and relative importance of supplier-generated liquidity co-variation, our evidence also has potentially important implications regarding asset pricing. If variation in liquidity is completely idiosyncratic, then liquidity variation can be eliminated at the portfolio level, and liquidity variation is not likely to be a source of priced risk. If this is true, it sheds doubt on research indicating that variation in liquidity is a priced risk factor. However, our study indicates that the degree of liquidity co-variation is greater than that implied by the analyses of Chordia et al. (2000) and Hasbrouck and Seppi (2001).

Our conclusions regarding common market making and common liquidity variation differs from conclusions recently reached by Naik and Yadav (2003). Naik and Yadav use a sample of 20 stocks during 1994 and find that London equity dealers appear to manage stocks independent of dealer-firm level considerations. The divergent conclusions could result from different sample time periods, sample sizes, and empirical methods. However, differences in the organizational and trading structures of London dealer firms and NYSE specialist firms could be most critical. Naik and Yadav note difficulty in information sharing across London dealers within the same firm. However, our conversations with NYSE specialists suggest that information sharing (both verbal and electronic) is not problematic. Further research considering liquidity co-variation owing to other structural characteristics at the NYSE and across a wider variety of markets would be of interest.

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